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Do farmers' ability and community networks matter in agricultural adaptation to climate change?

A case study of Bihar

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Do Farmers' Ability and Community Networks Matter in Agricultural Adaptation to Climate Change? A Case Study of Bihar

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Abstract

Climate change is having a grave impact on agriculture in India, especially in the heavily agriculture dependent economy of Bihar. Although the state is one of the more resource-abundant one, its agricultural productivity is among the lowest in the country. Bihar is also extremely vulnerable to climate change. To reduce the impact of climate change on agriculture, adaptation measures have been favoured over mitigation. Within adaptation measures, autonomous adaptations, that is, adaptations that are not the result of any deliberate policy but are adopted spontaneously by farmers, have been gaining importance over planned adaptation in the shift towards sustainable agricultural productivity. So far, most of the existing studies as well as government policies have had the focus on technology-based planned adaptation strategies, while in reality, autonomous adaptation has gained importance to transition agriculture towards sustainability. To bridge this research gap, this study aims to tease out the role of autonomous adaptation – through the twin channels of farmer's inherent ability/ traditional knowledge and community networks – in agricultural adaptation to climate change in case of two staple crops, rice and wheat.

We have used a quantitative econometric approach to delineate the role of inherent ability and community networks based on both secondary and primary data for Bihar, while controlling for the underlying driving factors, such as social and economic characteristics, technological factors, resource availability, climate, etc. Our research finds that (i) farmers are well aware of changing climate patterns, (ii) temperatures have risen with high temperatures persisting over a long period of time over the past 20-30 years and there have been a greater number of days with very high temperatures in the more recent past, that is over the past 5-10 years, and (iii) the rainfall pattern has changed with delayed monsoons and more intense rainfall spread over a fewer number of days. To adapt to these changes in climate regimes, farmers are modifying their production decisions, placing significant reliance on traditional knowledge or inherent ability and informal community networks to undertake this adaptation. Further, from both primary and secondary data regression analyses, we find that acquired education as an indicator of planned adaptation, in general, increases both rice and wheat yields. It was also found that inherent ability and community networks as indicators of autonomous adaptation always boost both rice and wheat yields. Moreover, inherent ability and community networks act as substitutes, inherent ability and literacy act as complements, informal community networks and literacy as substitutes, and formal community networks and literacy as complements. These results have important underlying social and economic dimensions.

Keywords: Climate change, Climate regimes, Sustainable agricultural productivity, Mitigation, Planned adaptation, Autonomous adaptation, Literacy, Traditional knowledge or inherent ability, Informal community networks, Formal community networks.

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1. Background and motivation

The phenomenon of climate change signifies alterations that go beyond the common atmospheric states leading to an average rise in global temperature or what is commonly called “global warming”. These may result from natural factors such as volcanic eruptions, solar variations, ocean currents, the earth’s orbital changes or due to anthropogenic factors such as a rise in the concentration of greenhouse gases (namely, carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O), hydrofluorocarbons (HFCs), and sulphur hexafluoride (SF_6)). Climate change by global warming has emerged as a worldwide megatrend with serious ramifications for ecology, economies, and human welfare, with these impacts already underway (Kim 2010).

Global warming has proved to cause not simply changes in average temperature and precipitation regimes, but also a rise in the frequency and intensity of floods, droughts, heat waves, and storms, all of which are a consequence of changes in temperature and precipitation configurations. A recent study by researchers at the Potsdam Institute for Climate Impact Research (PIK) in Germany has traced striking historical shifts in monsoons starting from the mid-20th century, which indicate that human-driven variations have begun to dominate the more gradual natural changes that had occurred over several millennia. The study also points out that the earth’s mean surface temperature has already risen by 1.1 degrees Celsius on average in comparison with the late 19th-century, with most of the warming happening over the last five decades. Even as the 2015 Paris Agreement has directed the countries of the world to collectively cap global warming at "well below" 2 degrees Celsius (even 1.5 degrees Celsius is technically feasible), most fear that this possibility is fast receding with severe implications for rainfall patterns. This is likely to have grave consequences for the food and farming sectors (Agence France-Presse (AFP) 2021). The other significant adverse implications of climate change are also found to include a rise in sea levels due to thermal expansion, increased glacial melt, a northward movement of plant habitations, modifications in animal habitats, and reduced winters and early arrival of spring.

Successful agricultural activities are heavily reliant on a suitable selection of crops and use of appropriate farming practices for the specific agro-climatic conditions of a particular region. Since agriculture is an inherently climate dependent industry with prominent geo-climatic features, slowly altering climate patterns (changes in level and timing of temperature and rainfall regimes) and extreme climate events (heating and cooling degree days, rainfall distribution and days of extreme (high or low) rainfall, flooding, and droughts) tend to disturb agricultural production through their influence on land and the hydrology ecosystem. The specific effects on the arable system work through biological changes such as changes in flowering and harvesting seasons, modification in soil quality, shift of areas suitable for cultivation, and the incidence of infestations such as blights and pests. The effects on hydrology are generally channelized through underground water levels, water temperature, river and canal flows, and the quality of water in lakes and marshes, all of which are affected by precipitation, evapotranspiration and soil moisture content (Kim 2010). In fact, the PIK study cited above says that climate change is rendering India's monsoons more intense and erratic due to global warming than was previously anticipated, making it harder to adapt (Agence France-Presse (AFP) 2021).

The measures to cope with global warming and climate change can be broadly divided into two: there are the mitigation measures that focus on reducing and absorbing greenhouse gases, and there are adaptation options that help societies and economies minimise the adverse implications of climate change. The thrust of most approaches so far has been on mitigating greenhouse gases, as is evident from the discussions and negotiations at international environmental conventions and forums such as the United Nations Framework Convention on Climate Change (UNFCCC), the Kyoto Protocol, and the Paris Agreement, with varied degrees of consensus and success achieved by individual nations. In the case of agriculture, however, there is increasing shift in favour of adaptation measures based on the assessment of the vulnerability and risk posed by the effects of climate change on agricultural productivity and living standards of agriculture-dependent households. These include, *inter alia*, changes in crop mix and inter-cropping, modifications in the time of sowing and harvesting, greater reliance on more climate-resilient varieties, etc.

The importance of adaptation is derived from the fact that even if the emissions of greenhouse gas begin to lower, global warming will continue to occur over the next several decades due to historically emitted greenhouse gases and its concentration in the earth's atmosphere. Accordingly, agriculture being inherently climate-dependent and sensitive to climate variations (in terms of both temperature and rainfall), it is necessary to plan adaptation measures against climate change. The design and testing of suitable adaptation options for climate-smart agricultural practices could provide valuable evidence for local and national governments to draw up agricultural development plans and for vulnerable farming households to prepare their farming strategies better.

Climate change poses grave concerns for India. Average temperatures have been rising and precipitation patterns have become more uncertain and often, more intense. By 2050, annual average temperatures in India are projected to increase by 1 to 2 degrees Celsius under the climate-sensitive scenario (Representative Concentration Pathway (RCP) 4.5) and 1.5 to 3 degrees Celsius under the carbon-intensive scenario (RCP 8.5) (Mani, et al. 2018).[3] Geo-statistical analyses show that most of the meteorological sub-divisions of India have experienced a marked decline in rainfall, which, in fact, became most abrupt in the post-1960 period. If the present situation of rainfall occurrences continues unabated, the intensity of rainfall occurrences and their distribution in future is likely to worsen. Specifically, rainfall predictions for 2030 have shown a decline in the range of 5-10 per cent in overall rainfall in India (Praveen, et al. 2020).

In the context of the state of Bihar, which is the focus of this study, climatic patterns have shown notable variations over the relatively short period of the last three to four decades. The Bihar State Action Plan on Climate Change notes a minimum temperature increase of 0.6 to 1.5 degrees Celsius during December-January and a maximum temperature decline of -3.0 (Southwest) to -1.4 degrees Celsius (Northeast) during April-May over the period 1971-2000 in different parts of Bihar. The projected change in annual temperature during 2011-2040 in relation to the levels in 1961-1990 under RCPs of 8.5 will be in the range of 0.8 to 1.9 degrees Celsius, which is significant. As for the rainfall patterns, based on trends in the period 1984-2012, heavy rainfall frequency is found to be more pronounced in the month of July in Patna while Purnia displays a heavier rainfall occurrence as compared to Patna during the months of June to September. Further, meteorological drought and flood year occurrences during 1872-2010 across different parts of Bihar were observed to be 26 and 24 respectively. In the future, a 5-10 per cent change (positive or negative) in mean June-July-August rainfall (in cm) is estimated over parts of Bihar in case of RCPs of 4.5 and 8.5 (BAPCC 2015).

These changes are likely to have adverse implications for all economic sectors and will affect living standards across India (Mani, et al. 2018). Rising mean temperatures, variations in seasonal rainfall patterns, and climate extremes in particular have already affected agriculture in India and more so, the heavily agriculture dependent economy of Bihar.

As per the study by experts at the Central University of South Bihar, Gaya (CUSB), alterations in surface temperature over the state of Bihar pose grave new challenges – causing increased uncertainty – for cropping patterns with critical implications for farming activities and availability of water resources. The researchers predicted that the consequences will be felt in terms of more intense rainfall and longer dry spells in the *kharif* (monsoon) cropping season, with staple crops being affected, while in the *rabi* season, crops could face destruction in several of Bihar's districts due to

[3] The climate-sensitive scenario refers to representative concentration pathway (RCP) 4.5 that reflects a future in which some degree of collective action is undertaken to limit greenhouse gas emissions and global annual average temperatures rise to 2.4°C (in the range of 1.7°C to 3.2°C) by 2100 relative to preindustrial benchmarks. In comparison, the carbon-intensive scenario relates to RCP 8.5 that is representative of a future where no actions happen to lower emissions and global annual average temperatures increase 4.3 degrees Celsius (varying in the range of 3.2 to 5.4 degrees Celsius) by 2100 relative to preindustrial levels.

heavy rainfall and hailstorms (S. Kumar 2020). This would require serious policy interventions to promote mitigation and adaptation to climate change.

Agriculture generates 17-18 per cent of India's GDP and the proportion is even higher at over 21 per cent for the state of Bihar. It employs 50 per cent of the labour force at the all-India level, while the proportion of the labour force engaged in agriculture in Bihar is found to be an overwhelming 90 per cent. The proportion of marginal and small farmers in total is found to be 82 per cent for India as a whole and even higher at 92.5 per cent in the case of Bihar. Thus, the performance of agriculture is critical to ensure inclusive growth, poverty reduction, and food security.

In the face of climate change and extreme weather variations, a range of micro and macro policy initiatives have been announced by different tiers of the Indian government to arrest the recent trends of declining agricultural productivity and associated farmer distress. The policy landscape covers diverse programmes such as the State Action Plan on Climate Change (SAPCCs) and National Mission for Sustainable Agriculture of 2010 (to operationalise the National Action Plan on Climate Change (NAPCC) of 2008), with the latter aimed at enhancing agricultural productivity in rain-fed areas. Under a 2010 scheme called the National Initiative on Climate Resilient Agriculture (NICRA) of 2010, the government aimed to build capacity among scientists and other stakeholders in climate-resilient agricultural research and ensure the application of research results through awareness building and training programmes. Further, there is the National Agricultural Insurance Scheme (NAIS) that provides comprehensive risk insurance to farmers to cover yield losses resulting from natural disasters and extreme weather events. There also exist local initiatives such as community-based adaptation initiatives through farmers' field schools (FFSs) and farmers' clubs (FCs), where a practical, group-based approach is used to train farmers. It entails groups of farmers meeting regularly and receiving guidance/knowledge from a subject-expert trainer as well as from the experiences of other farmers to learn about agricultural adaptation options in response to climate change.

At this point, it is important to make a distinction between planned adaptation and autonomous adaptation. According to the Intergovernmental Panel on Climate Change (IPCC)'s Third Assessment Report (IPCC, Climate Change 2001. Synthesis Report 2001), planned adaptation to climate change occurs as a consequence of a deliberate policy decision, derived from the knowledge that background conditions have changed or are about to change and, therefore, action is needed to return to, to maintain, or to achieve, a desired state. In comparison, autonomous adaptation, also called spontaneous adaptation, is not an intentional response to climatic stimuli, but is triggered by ecological changes in natural systems and by market or welfare changes in human systems (IPCC, Climate Change 2001. Synthesis Report 2001). In light of the significance of the latter, our study has focused on identifying the ongoing process of autonomous adaptation to climate change, by attempting to delineate the contribution of farmers' ability (traditional/ ancestral knowledge and experience) and knowledge spill-overs among farming communities towards climate adaptation measures.

While there exists a vast body of literature on the impact of climatic variability on agricultural productivity in India ((Chand, Raju and Pandey, Growth Crisis in Agriculture: Severity and Options at National and State Levels 2007), (Chand and Parappurathu, Temporal and Spatial Variations in Agricultural Growth and its Determinants 2012), (K. Kumar, Vulnerability of Agriculture and Coastal Resources in India to Climate Change 2003), (K. Kumar, Climate Change Studies in Indian Agriculture 2007), (Kumar and Tholkappian, Relative Vulnerability of Indian Coastal Districts to Sea-Level Rise and Climate Extremes 2006), (O'Brien, et al. 2004), (Sanghi and Mendelsohn, The Impacts of Global Warming on Farmers in Brazil and India 2008), (Dell, Benjamin and Benjamin, temperature and Income Reconciling New Cross-Sectional and Panel Estimates 2009), (Dell, Benjamin and Benjamin, Temperature Shocks and Economic Growth: Evidence from the Last half Century 2012), (Hari, Khare and Subramanian 2018), (Economic Survey, Climate, Climate Change, and Agriculture 2018)), and some state governments have initiated adaptation measures, all or most of these have focused only on input/technology-based planned adaptation strategies to climate change. In a cross-country setting, an attempt has been made by some of these studies to capture the role of unobserved inherent ability of heterogeneous workers on economic growth in the context of skillbiased technical progress by incorporating environmental constraints (Das and Keswani Mehra 2019) (See Chapter 2 of the report for a more detailed discussion of existing literature). However, no research exists so far, either at the national/sub-national or cross-country level, that emphasises autonomous adaptation measures by farmers, which could be linked to the farmers' inherent ability (derived from ancestral knowledge or learning-by-doing) and/or community networks, and their effect on agricultural yields in the face of uncertainty and risks posed by climate change and extreme weather events.

Further, although education is found to affect the formation of human capital (Bathla and D'souza 2015), adaptation capability is also important to maintain agricultural productivity (Mckinsey 2009). Guiteras (2009) found that, crop yields tend to decline by 4.5-9 per cent in the short-run (2010-39) and by a whopping 25 per cent in the long-run (2070-99) in the absence of adaptation efforts (Guiteras 2009). To the best of our knowledge, there is inadequate analysis of farmers' inherent ability to adopt new techniques and almost none on community networking among farmers to improve agricultural productivity and facilitate adaptation to climate change. This research aims to fill these gaps in the existing state of knowledge by endeavouring to tease out the role of farmers' ability (traditional knowledge and learning-by-doing) and local community networks in maintaining agricultural productivity to understand adaptation strategies at the sub-national/district level.

The research questions that the study answers are:

1. How vulnerable is agricultural productivity to climate variation?
2. Is the farming community aware of climate change concerns? How do they perceive these concerns in terms of their impact on agricultural yields?
3. What are the adaptation measures (planned and autonomous) being taken by them to cope with climate change?
4. How does farmers' ability (derived from traditional knowledge and past experience) help in coping with the effects of climate change and sudden weather shocks on agricultural productivity?
5. What role do community networks (family, friends, neighbours, etc.,) play in the case of the agricultural sector that could potentially create knowledge spill-overs so as to maintain yields or improve the resilience of agriculture to climate change?
6. How do the twin channels of farmers' inherent ability and community networks interface with each other?
7. What role does gender differentiation play in terms of the significance of the two channels of climate adaptation to agriculture?
8. How can these channels and associated responses of farmers be utilised for improved policy making, including specific policy options and recommendations, for adaptation of agriculture to climate change?

The research examines climate change adaptation processes as these would have unfolded in the rice and wheat growing districts of the state of Bihar, which is located in the Eastern part of India. According to the Indian Council of Agriculture Research (ICAR) (NICRA project), Bihar is one of the states that is most vulnerable to climate change. Bihar ranks sixth in the production of both rice and wheat. Although Bihar is rich in natural resources, especially in terms of fertile land and groundwater availability, it suffers from low yields and contributes a mere 8 per cent and 4 per cent of India's rice and wheat production respectively. We propose both quantitative and mixed method analyses to delineate the role of ability and community networks, based on secondary data as well as a primary survey of two districts, while controlling for the underlying driving factors (social, economic, technological, resources' availability, climate etc.), in the adaptation of agriculture to climate change.

The methods of analyses include a mix of quantitative and qualitative approaches. The desk research involved collection of information and data to assess past trends in agricultural vulnerability and adaptation to climate change, and the role of state and local policies in such adaptation so far.

The first part of the quantitative analysis is based on secondary datasets. Since climate change is a long-term phenomenon and has a differential impact for different agro-climate locations, we have relied on panel econometric analysis of secondary data at the district-level, spanning the 30-year period of 1990-2019 for all the 38 districts of Bihar. The dependent variables are taken to be rice and wheat yields.

The role of community networks is captured through a composite index based on Principal Component Analysis (PCA) derived from specific indicators of local social networks (such as land size, caste and religious composition of the population, public call records for agricultural queries, number of self-help groups (SHGs) and voluntary organisations (VOs), credit access, etc.), as all of these help in forging social interactions and knowledge sharing for enhancing climate adaptation.

To capture the effects of the inherent ability of farmers (embodied in traditional knowledge and past experience), which is an unobservable variable, Kalman-filtering that utilises the framework of state-space time-series models for individual districts has been used. The filtered variable (extracted series) of the unobservable variable is then carried over to the panel regression analyses for rice and wheat yields. For each district, the state equation is specified for the unobservable or latent variable (here, inherent ability) as a function of its lagged values, while the observation equation specifies the dependent variable as a function of its arguments, namely, the state variable and the other independent variables. Having extracted the values of the unobservable variable, we next regress rice and wheat yields separately on a range of control variables, such as climate (average temperature, average rainfall, and number of rainfall days), natural resources (ground water availability), socio-economic factors (demography, educational attainment, literacy, etc.), use of irrigation technologies and farm equipment, utilisation of high-yielding varieties (HYVs), etc. Robustness check are also attempted by using the output growth rate of each crop – rice and wheat – as the dependent variable and all the above control variables along with the inherent ability (which is extracted from state-space Kalman-filtering) and community network index as independent variables in the panel regressions.

The Hausman test helped ascertain that a panel fixed effect model is more suitable for the rice yield specifications, and a panel random effect model for the wheat yield specifications. Further, we find that a state-fixed effect model with time trend provides a better fit to the data as compared to a state-fixed effect and state- and time-fixed effects models for the rice yield model. For the wheat yield model, we find that a random effect model with time trend provides a better fit to the data over random effect and random state- and time-fixed effect models.

An important component of our study has been the primary field survey that has helped to complement the panel regression estimations based on secondary data. For the primary survey, we have selected two districts of Bihar – Gaya and Purnia – which are fairly similar with regard to their socio-economic characteristics but belong to two different agro-climatic zones. This allows us to capture the differences in the role of ability and community networking channels of climate adaptation. For the field/ primary survey, a detailed questionnaire was drawn up to understand, through personal interviews with farmers, their understanding of climate change concerns and the coping mechanisms they rely upon and find effective. Interviews have helped in understanding the inherent ability of farmers and knowledge shared with neighbours, friends, relatives, JEEViKA,[4] government-run programmes, and engagement in community centres (farmer's field schools (FFFs), farmer clubs (FCs), *krishi vigyan kendras* (KVKs), etc.) to capture access, actual acquisition, costs, effectiveness, constraints, and intensity of preferences of each of these sub-channels of knowledge gathering for farming adaptation.

Due to travel restrictions imposed on account of the COVID-19 pandemic, the questionnaire was first pilot tested through tele-conferencing, with a pilot sample of around 15 farmers. Next, a full-fledged in-person survey of 411 farmers in both the districts – 166 in Gaya and 245 in Purnia – primarily engaged in cultivation of rice and wheat, was carried out by observing all the state-prescribed standard operating procedures and COVID-19 guidelines. The sample was selected through a process of stratified random sampling and geo-spatial information (detailed later in the report). The data thus collected were collated and analysed using mixed-survey methods (due to the presence of both continuous and categorical variables in the survey) and survey cross-sectional regression approaches.

[4] This is the Bihar Rural Livelihoods Project (BRLP), locally known as JEEViKA.

Local researchers were involved in each of the two districts during the conduct of field survey. This enabled easier communication in the local language and a better understanding of ground realities, while also providing benefits in terms of developing local capacity building that are likely to be useful beyond the duration of the study and offer potential for scalability and replicability for future research endeavours of this nature.

Secondary data on farm production, area, yields, landholding size, technology (machinery and equipment, rain-fed or irrigated), input use (labour, fertilisers, and high-yielding seeds), credit availability, access to banks/financial institutions, the number of agricultural non-governmental organisations (NGOs), irrigation infrastructure, demographic profile (caste, religion, family size, sex ratio, occupation pattern), literacy/educational attainment, exposure to climate variations (that is, temperature and rainfall means and variations, extreme weather events/natural disasters), natural resource constraints (such as groundwater availability), involvement in self-help groups (SHGs), voluntary organisations (VOs), and *kisan call centres* (KCCs), network facility by roads, community networks, etc., have been relied upon. Most data were obtained at the district-level from the state agriculture and environment departments, published statistical handbooks of central ministries, Agriculture Census, Census of India, Indian Meteorological Department (IMD), India Water Portal, and the Village Dynamics in South Asia (VDSA) database from the International Crops Research Institute for the Semi-Arid Tropics (ICRISAT).

To substantiate the analysis further, a primary in-person field survey of farmers in two different districts was carried out. The data on important variables covering social, demographic, and economic profiles and agricultural resources and technology being used were collected and collated. These include information on a household's occupational profile, family incomes, family size, literacy, sex ratio, caste, credit availability through financial institutions/banks, Prime Minister's (PM) *kisan* funds[5] and kisan credit cards (KCCs); production, area and yield for rice and wheat; production technology, input use, soil quality, water availability and its source(s); information facilities from government bodies, *gram panchayats*, farmers' portal, involvement in government run workshops, farmer field schools (FFSs), farmers' clubs (FCs), *krishi vigyan kendras* (KVKs), Agricultural Technology Management Agency (ATMA), SHGs, agriculture co-operatives; interactions with neighbours, relatives and friends, government officials, and JEEViKA; perceptions about changes in climate patterns and likely adaptation measures adopted in terms of modification of cropping pattern and other agricultural practices in response to slow and progressive climate change as well as extreme weather events.

Thus, application of mixed research survey methods for analysing the combined effects of qualitative and quantitative factors, utilising both secondary and primary data, helped answer the key research questions of the study that we have alluded to above.

The important findings of this research are as follows.

Our research finds that farming communities are discerning about climate change. Nearly 64.2 per cent of the farming households in Gaya and 63.1 per cent in Purnia believe that climate change is happening. From a broader perspective, it is perceived that temperature, rainfall, wind speed, heavy rainfall, number of hot temperate days,[6] drought, excessive hot dry winds (loo), excessive cold winds, and other climate events are changing gradually over the past 5-10 or 20-30 years. The only exception to this was the perception of rainfall in Gaya, where a majority of the farmer respondents stated that rainfall in the past was much higher than is at present. This tells us that farmers do perceive the slow and persistent changes in climate patterns. The perception of climate change is also consistent across gender. However, the responses to more specific questions on climate change were more revealing.

For instance, it was felt by the farmers that the temperature has changed towards a greater number of hot temperate days as compared to a greater intensity of hot days over a shorter span of days.

[5] This refers to the funds from Prime Minister's *Kisan Samman Nidhi* Scheme

[6] In general, Bihar has a temperate climate. That is, it is neither too hot not too cold. The term hot temperate days refers to days observed or perceived to be hotter than the average in a season.

Moreover, a changing trend towards a greater number of hot temperate days has happened in relation to the past 20-30 years, whereas the higher intensity of hot days spread over a fewer number of days has been a phenomenon of the past 5-10 years. This indicates that the greater number of hot temperate days is more of a long-run and gradual climate change phenomenon, while higher intensity of hot temperatures over fewer days is a more recent climate change trend.

The rainfall pattern has changed toward a delay in the monsoon, followed by more intense rainfall spread over a fewer number of days. Moreover, a significant (50 to even over 80 per cent) of the respondents in both the districts perceive that rainfall pattern has changed in several ways, that is, a greater number of rainy days, heavier rainfall concentrated over a fewer number of days, and shifting of monsoon rainfall in terms of both early or delayed arrival in comparison to the past 20 to 30 years. This supports the evidence of a higher number of rainy days, more intense rainfall spread over a shorter period, and shifting monsoon rainfall timings, all of which are perceptible, long-run climate change phenomena.

Over the past 20-30 years, it was revealed that changes in wind patterns have happened in terms of alterations in wind direction, excessive loo,[7] and delayed timing of monsoon winds while over the shorter time frame of 5-10 years, wind patterns are perceived to have changed in terms of more intense loo over a fewer number of days and shifting of monsoon winds to an earlier time as compared to monsoon days prevalent in the past. A small but significant proportion of respondents also perceive that wind patterns have changed towards excessively cold winds and the wind patterns have changed toward more intense colder winds spread over a fewer number of days.

This change in climate, as perceived by farming households, is not without its impact on agriculture. Our secondary data estimation results show that higher average annual temperature levels tend to boost yields of both rice and wheat (more for rice than wheat), but for both, there are threshold effects. That is, higher temperatures will boost yields but only up to a point; yields decline with further increases in temperature. Changes in the average number of rainy days and average monsoon rainfall have similar effects. Thus, excessively high temperature, monsoon rainfall or annual rainy days tend to dampen yields.

Our primary survey data estimation results also corroborate these climate related effects on yields. Evidently, both temperature and rainfall regimes seem to have surpassed their respective thresholds for rice yield gains, but these fall short of the threshold levels for wheat yields, pointing to the scope for potential gains.

Other than temperature and precipitation, wind speed, cloud cover, evapotranspiration processes and diurnal (day versus night) temperature range also have an impact on yields. An increase in any of these variables tends to lower rice yields; however, these are found to boost wheat yields.

Our primary survey data also revealed that, on the one hand, environmental hazards are perceived to be the most significant contributors to crop losses incurred by farmers, with the major environmental hazards perceived to be heavy rainfall followed by drought in Gaya and flood in Purnia. On the other hand, farmers faced more wheat than rice output losses, both in 2018 and 2019, indicating that wheat output is more vulnerable to environmental hazards than rice. However, since climate regimes have seemingly crossed the threshold levels for rice yield gains, but not for wheat, rice could also be highly vulnerable to long-run climatic variations as compared to wheat, although wheat appears to be more vulnerable with respect to ongoing extreme weather phenomena than rice.

Furthermore, most of the time, the compensation that they receive for crop losses is not adequate, as is reported by the farmers in the primary survey of the two districts.

Focusing on the gender aspect, we find that female headed households are better at managing agriculture than male headed households in both Gaya and Purnia. This differs from the findings of our secondary data-based analysis, which posits that a higher female to male population ratio tends to dampen production in the case of both crops. As stated earlier, this may be ascribed to the men in

[7] The loo is a strong, dusty, hot and dry summer wind.

farming households migrating to urban areas to seek alternative non-agricultural occupations, leaving agricultural operations in the hands of women or even hired labour. Further, secondary data analysis considers a broader dimension of gender through an overall female to male population ratio at the district level, which might be a weaker indicator of the role of women in agriculture.

Changes in climate results in farmers taking various adaptation measures in order to cope with it through both planned and autonomous adaptation strategies. A high proportion of farmer respondents of our primary survey perceived that continuous climate change has been happening and this influences their production decisions. This perception did not vary with the gender of the respondents.

Moreover, the effectiveness of planned adaptation channels to cope with climate change is found to be rather weak in the case of both the surveyed districts – Gaya and Purnia – as dissemination of knowledge and capacity building through Information and Communication Technology (ICT)-enabled extension services, government workshops, agriculture related formal social groups such as farmers' clubs (FCs), farmer's field schools (FFSs), *krishi vigyan kendra* (KVKs), etc., are quite low. This is compounded by a lower level of acquired education and lack of awareness of such formal social groups and forums. The only exceptions were the role of self-help groups (SHGs) and JEEViKA, which were stated to be very effectual. Despite the less efficacious role of planned adaptation channels, Bihar's farming households are coping with climate change, mainly through autonomous adaptation channels, such as traditional knowledge embodied in farmers' ability as well as community networks.

For our analysis, we have tried to examine the role played by inherent ability (intrinsic to ancestral knowledge and learning-by-doing) and community networks (knowledge spill-over from friends, family, relatives, neighbours, KVKs, government/ block officials, FFSs and FCs). We derive the following specific results from our research.

Our secondary and primary data regression analyses have shown that inherent ability/ancestral knowledge has a positive impact on rice and wheat yields (an exception is wheat yields in secondary data analysis where it shows a negative impact[8]). This general positive result is reinforced by the households' responses on the effectiveness of ancestral knowledge, which a majority of respondents ranked between medium and very high. Furthermore, the impact of the inherent ability channel is reinforced or supplemented by increases in literacy rate.

In fact, a higher fraction of respondents, mostly women (of the primary survey) in both districts believe that they embody ancestral knowledge in making cultivation decisions.

Further, the secondary data regressions show that community networks, in general, have a positive impact on both rice and wheat yields. This result is corroborated by households' responses on the effectiveness of formal and informal community networks, where a majority of responses ranked them between medium and very high. The impact of community networks reduces with an increase in literacy rate. This result may be due to the weakening of social and local ties as members of farming households attain higher literacy levels and move away or migrate to other locations for alternative opportunities.

As per the primary survey data regression analysis, within community networks, whenever informal community networks (such as trusted connections among neighbours, relatives, friends, big farmers, landlords, etc.) show a positive (negative) impact on yield, the role of JEEViKA as a formal community network (these are organised networks such as co-operatives, NGOs, FFSs, FCs, etc.) is negative (positive) impact. This may be because of the education factor. Wherever the impact of basic education (that is, class X education) on crop yields were found to be positive (negative), the informal community networks are found to affect crop yields negatively (positively) while formal community networks affect yields positively (negatively). This result on the role of informal community networks derived from the primary data analysis ties in well with the one derived from secondary data analysis, which points to the dampening effect of community networks with a rise in overall literacy, while that

[8] We believe that the quality of data could be responsible for some such results.

of the formal community network, represented by the role of JEEViKA, gets reinforced due to increasing literacy rate. These results indicate that higher acquired knowledge dampens the role of informal community networks but promotes the role of formal community networks and vice-versa. This is as one would expect it to be.

Farming households trust and rely more on informal community networks such as friends, relatives, and neighbours rather than formal community networks like government/ block officials, *gram panchayat* members, co-operative members, NGO members etc., for their farming decisions. The only exception to this is the trust and reliance on JEEViKA for farming decisions, which is comparable to or even more than that of informal community networks. The responses as regards the role of JEEViKA are extremely promising almost across the board. Participation in government workshops is low, even though these are stated to be beneficial, which may be due to access and cost related factors. Attendance in these workshops is also higher among male-headed households than female-headed ones, seemingly associated with social and cultural factors.

The awareness and consequent membership in social groups, like FCs, FFSs, KVKs, agricultural technology management agency (ATMA), co-operative societies, etc. is generally very low. The only social groups that a majority of people are aware of and are members of are SHGs. Awareness and membership of SHGs are higher among female-headed households than male-headed households, implying higher social connectedness among women.

An important result of our study is that inherent ability and community networks substitute each other. The higher the influence of community networks in agricultural adaptation, the lower is the impact of inherent ability and vice-versa. Furthermore, regression estimates show that, on the one hand, higher literacy rate makes ability more effective in boosting crop yields, that is, the two complement each other. On the other hand, in general, the community network index (mainly reflective of informal networks) and literacy rate are substitutes. These results indicate that higher acquired basic education dampens the effectiveness of informal community networks and makes formal community networks more effective in boosting crop yields and vice-versa. That is, higher literacy tends to reinforce the positive effect of formal community networks and works toward weakening the positive effect of informal community networks (and community networks, in general) on crop yields. This may be due to social and local ties loosening with farming communities attaining higher literacy levels, often leading to out-migration, transition to nuclear families and urbanisation. These are important sociological implications of our analysis that require more analysis.

It is also important to emphasise that climate change adaptation has been mainstreamed in public spending in India, with an increase in the allocation in union budgets from 1.45 per cent of the GDP in 2000–01 to about 2.82 per cent of the GDP in 2009–10 (V. Kumar 2018). For efficacious utilisation of public budgets, adaptation measures have to be implemented, not in isolation, but in the context of the social, economic, and cultural milieu of the communities affected by it. The current research has attempted to capture local realities and contribute locally relevant knowledge in the design of future adaptation policies.

Thus, the key academic contribution of this research is the twin assessments, qualitative and quantitative, of two channels of farmers' adaptation capacity – inherent ability (stemming from traditional knowledge and experience) and knowledge spill-over from local community networks – in determining the climate-agriculture relationship, with focus on adaptation to climate change. The results of the secondary and primary survey data analyses with regard to these two channels corroborate each other. Several policy recommendations have been derived from the results that belong to context-specific (specific to our study area) and general policy domains for local, state, and national governments.

For instance, specific policy measures should focus on providing infrastructure for early warning systems to predict climate variations and extreme weather events, ICT-enabled extension services for climate risk alerts and knowledge dissemination, formation of formal social groups at the village-level to strengthen formal community networks, institutions to strengthen village-level informal community networks, innovating new climate-resilient technologies, financial institutions at village-level to promote green credit systems as hard adaptation measures and adoption of natural and organic farming, promotion of indigenous farming practices, adoption of ICT-enabled extension services, capacity building and knowledge sharing through formal social groups along with informal community networks, as soft adaptation measures.[9] Policy should also focus on measures to preserve natural resources, such as groundwater, soil quality, and other ecosystems, etc.

We believe that detailed analyses such as this will help guide policies across all the tiers of government and its agencies to tailor make them to the specific context as regards crops, climate, technology, and information dissemination. This will enhance their efficacy and help resolve policy trade-offs better.

In Chapter 2 we provide an extensive review of literature on this subject. Chapter 3 covers the design of research, methods of analyses, and data and its sources. Chapters 4 and 5 include the results of secondary and primary data analyses carried out by us. Chapter 6 summarises the key findings and derives policy recommendations based on these research outcomes. Chapter 7 concludes.

[9] Studies emerging at the UNFCCC and the United Nations Development Programme (UNDP) categorise hard adaptive measures to involve capital-intensive, large, complex, inflexible technology and infrastructure, whereas soft adaptive measures emphasise natural capital, community control, simplicity and appropriateness to a context (Sovacool 2011).

2. Review of Literature

1.1. Overview of issues

Agriculture is the mainstay of 1.3 billion small land-holding farmers worldwide (World Bank, World Development Report 2008: Agriculture for Development 2008); it is also one of the most climate-dependent sectors (Salinger, Sivakumar and Motha 2005). Increased temperature reduces crop yields due to the reduction in crop cycles, implying early flowering and shortening the grain-filling period (Chattopadhyay 2011). According to climate models, in the near future, high day and night temperatures are likely to occur that will adversely affect food production ((Lobell, Schlenker and Costa-Roberts, Climate Trends and Global Crop Production Since 1980 2011a), (Cairns, et al. 2012), (Hijioka, et al. 2014)). Besides progressive climatic variability, more frequent extreme weather events (as is already observable) in the form of frequent and intense droughts and floods (Randhawa, Singh and Kang 2014) are predicted to affect both rain-fed and irrigated farming systems. According to the IPCC model's projections (IPCC, Summary for Policymakers 2007a), the global mean surface temperature has risen by around 0.74^0 Celsius during the 20th century and is expected to increase by an additional $1.1 – 6.4^0$ Celsius by 2100 under alternative future scenarios. Concurrently, the number of rainy days is falling, with more intense rainfall concentrated over fewer days. This rainfall variability along with rising temperature is likely to influence agricultural production and yields.

India is found to be the fifth most climate-vulnerable country in the world, according to the Global Climate Risk Index 2020, which makes it highly susceptible to weather abnormalities. This is especially relevant in view of the fact that it has a very significant number of marginal and small farmers (more than 80 per cent) with meagre coping capacity, high reliance on rainfall for irrigation (around 60 per cent of the country's net cultivated area is rain-fed), and limited technical and financial resources ((Acharya 2006), (Khan, et al. 2009), (Jain, et al. 2015), (Patnaik and Das 2017)). The climate projections indicate an increase in the annual mean temperature in India in the range of $3.5–5.5^0$ Celsius by 2080, depending on the specific scenario. This is likely to result in a relatively lower increase in the *kharif* season than in the *rabi* season (Lal, et al. 2001). Further, there will be an increase in rainfall in the *kharif* season and a decline in rainfall in the *rabi* season by 2050 ((Lal, et al. 2001), (Prabhakar and Shaw 2008), (Randhawa, Singh and Kang 2014)). All of these imply high exposure of Indian agriculture to climatic variations. As per the Government of India's (GoI's) Economic Survey, there will be an overall expected loss of annual agricultural income in the range of 15-18 per cent, which could be higher, around 20-25 per cent, in unirrigated areas (Economic Survey, Climate, Climate Change, and Agriculture 2017).

Prolonged breaks in the south-west monsoon in India have resulted in the increasing frequency of droughts across the country ((P. Udmale, et al. 2015), (Zhang, et al. 2017), (Choudhury and Sindhi 2017)). These droughts are shifting towards agriculturally important zones (Mallya, et al. 2016), one of which is the Indo-Gangetic plains (IGPs) – one of the world's most intensely farmed area due to its fertile soil and India's cereal bowl. The main crops grown in these plains are rice and wheat, which are staple foods in India and are relatively more water-intensive crops. While Bihar, located within the IGP, is a resource-abundant state of India (in terms of its sub-soil natural resources, groundwater, perennial rivers, alluvial fertile lands, and a rich history of adoption of green revolution), it is also one of the most vulnerable to climate change ((Rama Ro, et al. 2018), (Sehgal, et al. 2013)). Its agricultural productivity is one of the lowest in the country, mainly attributable to exposure to extreme weather abnormalities and continuous climate change; this is also acknowledged by the Bihar state government (BAPCC 2015). Within the state, climate variations are prominent. Northern Bihar is a highly flood-prone area, whereas Southern Bihar is highly drought-prone (BAPCC 2015). The main crops cultivated in almost all the districts of Bihar are rice and wheat, though the state ranks 6th in India in respect of its production of both these crops.

Therefore, the adoption of climate-resilient strategies is an impending need to ensure sustainable agriculture in India – more so for the state of Bihar – to attain food security and safeguard livelihoods. Sustainable agriculture is adopted by less than four per cent of Indian farmers (PTI 2021). The two most significant climate change coping mechanisms are mitigation and adaptation. However, adaptation, which is often complemented with global mitigation measures, is expected to be more effective in reducing the impact of climate change ((IPCC, Climate Change 2007b: Impacts, Adaptation and Vulnerability 2007b), (ADB 2009), (UNFCCC 2009), (MNRE 2010), (Begum, Abidin and Pereira 2011)). IPCC's approach addresses both autonomous and planned adaptations (IPCC, Climate Change 2007b: Impacts, Adaptation and Vulnerability 2007b). Most policy-based adaptation strategies are planned adaptations through technological improvements and innovations. Autonomous adaptations mainly include indigenous, local, and traditional knowledge systems and practices. For example, in Alaska, Inuit knowledge of climate variability ensured the source of food to hunters and reduced various risks ((Alessa, et al. 2008), (Ford 2009), (Weatherhead, Gearheard and Barry 2010)); in the southern Andes, Inca traditions of crop diversification, genetic diversity, raised bed cultivation, weather forecasting, water harvesting, etc., are still used in agriculture ((Goodman-Elgar 2008), (Renard, et al. 2011), (McDowell and Hess 2012)). Similarly, in Asia and Australia, autonomous adaptation, especially indigenous knowledge, plays an important role in ensuring food security ((Salick and Ross 2009), (Green, Billy and Tapim 2010), (Speranza, et al. 2010), (Kalanda-Joshua, et al. 2011), (Pareek and Trivedi 2011), (Biazin, et al. 2012)). Crop breeding for high-temperature conditions is a lucrative strategy for climate change adaptation in Asia (IPCC, Climate Change 2014: Impacts, Adaptation and Vulnerability 2014). These knowledge systems and practices under autonomous adaptation have not been incorporated consistently and efficiently in existing adaptation efforts. Integrating these knowledge systems and practices with existing practices increases the effectiveness of adaptation (IPCC, Climate Change 2014: Impacts, Adaptation and Vulnerability 2014). In line with the focus of this research, the review of literature will centre round autonomous agricultural adaptation by farming communities.

In what follows, the review of literature focuses on the climate change impact on agriculture and the associated adaptation strategies to cope with climate change.

The effects of climate change on agriculture are now well established ((Lobell, Schlenker and Costa-Roberts, Climate Trends and Global Crop Production Since 1980 2011a), (Auffhammer and Schlenker, Empirical Studies on Agricultural Impacts and Adaptation 2014), (Campbell, Vermeulen, et al. 2016), (Khanal and Mishra, Enhancing Food Security: Food Crop Portfolio Choice in response to Climatic Risk in India 2017)). Studies have shown that the productivity levels of main crops (namely, rice, wheat, maize, etc.) are likely to fall significantly in developing countries due to global warming and rise in climate variability ((Challinor and Wheeler, Crop Yield Reduction in the Tropics Under Climate Change: Processes and Uncertainties 2008), (Sanghi and Mendelsohn, The Impacts of Global Warming on Farmers in Brazil and India 2008), (Guiteras 2009), (Thornton and Gerber, Climate Change and the Growth of the Livestock Sector in Developing Countries 2010), (Lobell, Sibley and Ortiz-Monasterio, Extreme Heat Effects on Wheat Senescence in India 2012), (Auffhammer, Ramanathan and Vincent, Climate Change, the Monsoon, and Rice Yield in India 2012), (Bennett, et al. 2014), (Calzadilla, et al. 2014), (Campbell, Thornton, et al. 2014), (Gupta, Sen and Srinivasan 2014), (Rahman and Rahman 2015)). Similarly, Challinor et al. (2014) have shown that in the absence of adaptation, yields of rice, wheat, and maize are predicted to fall in both tropical and temperate regions under different climate change scenarios (Challinor, Watson, et al. 2014). Asseng et al. (2014) and Porter et al. (2014) have found that for each 1^0 Celsius rise in global mean temperature, wheat yields might decline by as much as 6 per cent ((Asseng, et al. 2014), (Porter, et al. 2014)). Further, an expected increase in the frequency of shorter periods of extreme heat ((Battisti and Naylor 2009) and (Wegren 2011)) have shown that there could be devastating effects on crop production, as seen during the hottest summer season in Russia during 2010. While a global study estimates higher negative impacts on global aggregate production of wheat and maize, these effects are much smaller for rice and soybean yields (Lobell, Schlenker and Costa-Roberts, Climate Trends and Global Crop Production Since 1980 2011a). Again, Iqbal et al. (2009) have shown that increasing mean temperature resulted in shortening the maturity period of a crop (Iqbal, Goheer and Khan 2009), resulting in reduced grain yields when high temperatures occurred during flowering (Moriondo, Giannakopoulos and Bindi 2011) and there was increased water stress throughout the growing cycle (Lobell, Hammer, et al. 2013a). Further, it has been found that wheat and maize yields declined with $1\text{-}2^0$ Celsius of local warming in the tropics. However, temperate maize and tropical rice yields were less affected at a lower temperature increase but significantly affected with a warming of 3-5^0 Celsius (IPCC, Climate Change 2014: Impacts, Adaptation and Vulnerability 2014). Contrary to these trends, global warming has benefitted crop production in some high-latitude cold regions, such as Northeast China or the United Kingdom ((Jaggard, Qi and Semenov 2007), (Chen, et al. 2010), (Supit, et al. 2010), (Gregory and Marshall 2012)). It has been found that rice yields in China have been positively correlated with temperature in some regions and negatively correlated in other regions ((Zhang, Zhu and Yang, et al. 2008), (Zhang, Zhu and Wassmann, Responses of Rice Yields to Recent Climate Change in China: An Empirical Assessment Based on Long-Term Observations at Different Spatial Scales (1981-2005) 2010)).

As in the case of temperature variations, rainfall variations also have adverse effects on crop production. A higher frequency of heavy precipitation leads to run-off (Stocker, et al. 2013), whereas low precipitation results in drought that lowers the ability to plan any given crop season (Hochman, et al. 2009). Furthermore, in semi-arid areas, rain-fed agriculture may be positively or negatively responding to climate change (Ratnakumar, et al. 2011). Thornton et al. (2009b) found that the crop yields are not too responsive to increase in rainfall in the drylands of East Africa, an outcome that could be explained by the fact that a wetter climate is typically associated with warmer temperature, and warmer temperatures tend to lower crop yields (Thornton, Jones, et al. 2009b). As a result, precipitation becomes less important as a predictor of crop yields on a broader scale ((Lobell and Field, Global Scale Climate-Crop Yield Relationships and the Impacts of Recent Warming 2007), (Li, et al. 2010)). Similarly, Lobell and Burke (2008) have shown that projected changes in precipitation from climate models tended to be more spatially variable than changes in temperature (Lobell and Burke, Why Are Agricultural Impacts of Climate Change So Uncertain? The Importance of Temperature Relative to Precipitation 2008). Further, the influence of rising temperature on yields started to dominate over that of variations in precipitation with the increase in irrigation over time (Hawkins, et al. 2012). That is, rising temperatures are found to have more detrimental effects due to the combined heat and drought stress than either of these by themselves, and these are also are much harder to control for in field trials (Pradhan, et al. 2012).

Furthermore, extreme weather events also affect agricultural production adversely (IPCC, Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation 2012). For example, dry spells, droughts and floods lower both crop production and crop yields through an outbreak of pests and diseases ((Easterling, et al. 2007), (Gormall, et al. 2010)), changes in soil fertility ((Tang, et al. 2008), (Clair and Lynch 2010)) and levels of moisture content ((Turral, Nurke and Faures 2011), (Misra 2014), (Malek, et al. 2018)), etc.

There exist many studies for India that focus on the determinants of declining agricultural productivity at the state and national levels among which climate variability is found to be an important one ((Chand, Raju and Pandey, Growth Crisis in Agriculture: Severity and Options at National and State Levels 2007), (Chand and Parappurathu, Temporal and Spatial Variations in Agricultural Growth and its Determinants 2012)). Climate change projections indicate that the rise in temperature is likely to be in the range of 1-4 degrees Celsius and the increase in precipitation 9-16 per cent in India by the 2050s (Krishna Kumar, et al. 2011). It is evident that high temperatures raise crop respiration rates and evapotranspiration, thus lowering crop duration, fertiliser use efficiency, and crop yields ((Aggarwal and Kalra, Analyzing the Limitations Set by Climatic Factors, Genotype, and Water and Nitrogen Availability on Productivity of Wheat II. Climatically Potential Yields and Management Startegies 1994), (Peng, et al. 2004), (Hundal 2007), (Randhawa, Singh and Kang 2014), (Anand and Khetarpal 2015)). In the case of rice, each 1^0 Celsius rise in minimum temperature is likely to lead to a 19 per cent fall in yield, and a 1^0 Celsius rise in mean temperature causes it to fall by 15 per cent (Peng, et al. 2004). As for wheat, grain yield declines due to a rise in maximum temperature ((Aggarwal and Kalra, Analyzing the Limitations Set by Climatic Factors, Genotype, and Water and Nitrogen Availability on Productivity of Wheat II. Climatically Potential Yields and Management Startegies 1994), (Hundal 2007), (Anand and Khetarpal 2015)). Specifically, the decline for wheat yields is estimated to be around 3-7 per cent in India for every 1^0 Celsius rise in temperature (Aggarwal, Global Climate Change and Indian Agriculture. Case Study from ICAR Network Project 2009). To combat climate change, it is crucial to examine the climate vulnerability of Indian agriculture, and this has been done by Kumar (2003, 2007) and Kumar and Tholkappian (2006) ((K. Kumar, Vulnerability of Agriculture and Coastal Resources in India to Climate Change 2003), (K. Kumar, Climate Change Studies in Indian Agriculture 2007), (Kumar and Tholkappian, Relative Vulnerability of Indian Coastal Districts to Sea-Level Rise and Climate Extremes 2006)). O'Brien et al. (2004) also identify the most agriculturally vulnerable regions in the face of climate change in India (O'Brien, et al. 2004). As per the Government of India's National Communication (NATCOM 2004), India will be highly affected due to climate change between now and 2100. In particular, floods are likely to increase both in frequency and intensity and wheat production is predicted to decline by 4-5 million metric tons with an increase in temperature of 1degrees degree Celsius (NATCOM 2004). Similarly, evidence from literature indicates that climate change has already adversely affected Indian agriculture ((Kumar and Parikh, Socio-Economic Impacts of Climate Change on Indian Agriculture 2001a), (Kumar and Parikh, Indian Agriculture and Climate Sensivity 2001b), (K. Kumar, Climate Sensitivity of Indian Agriculture: Do Spatial Effects Matter? 2009), (Sanghi and Mendelsohn, The Impacts of Global Warming on Farmers in Brazil and India 2008), (Dell, Benjamin and Benjamin, temperature and Income Reconciling New Cross-Sectional and Panel Estimates 2009), (Dell, Benjamin and Benjamin, Temperature Shocks and Economic Growth: Evidence from the Last half Century 2012), (World Bank, World Development Report 2008: Agriculture for Development 2008), (Economic Survey, Climate, Climate Change, and Agriculture 2018)).

Notwithstanding its resource abundance, the agricultural sector of Bihar is highly vulnerable on account of its already low productivity, high climate-vulnerability, recurrent floods and droughts, higher proportion of marginal and small farmers, low literacy rate, high rural population, high dependence on agriculture for livelihoods, lower access to irrigation and credit infrastructure, poor extension services and high levels of poverty (BAPCC 2015). Rainfall during the monsoon season (June–September) is the primary source of water for Bihar's rain-fed agricultural regions. According to the annual rainfall reports of the IMD, there has been a rise in the number of no rainfall days in the state and a deficiency in rainfall volume in the past few decades. As per the Standardised Precipitation Index (SPI), the rate of increase in the number of dry days in Bihar is almost one day per year (M. Khan 2019). According to agricultural scientists and climate change experts, rain-fed rice and *rabi* wheat will be affected by moisture variations in the soil due to declining rainfall. Further, the non-profit initiative called the Action on Climate Today (ACT) in its value chain analysis of Bihar has predicted that longer dry spells in monsoon tend to impact the *kharif* crop and heavy deficiency in rainfall affects rabi crops; farmers will face more loss of the *rabi* than the *kharif* crop due to drying land and lower scope for irrigation (ACT 2018). While Tesfaye et al. (2017) predict an increase in rainfall per day, particularly in the monsoon season resulting in more exposure to flash floods, they have also predicted a higher rise in future temperature for October-January and February-May seasons, implying more effects on *rabi* and spring crops (Tesfaye, et al. 2017). Kumar et al. (2011) have estimated a decline in wheat yields in Bihar by 5-6 per cent due to changes in maximum temperature levels alone by the 2080s (Kumar, et al. 2011). Moreover, the current maximum temperature in Bihar is already close to its maximum threshold for *kharif* (rice) and *rabi* (wheat) crops (Anand and Khetarpal 2015).

Since the effect of climate change on agriculture is evident, and its severity is expected to increase in the near future with developing nations being the most affected (IPCC, Climate Change 2014: Impacts, Adaptation and Vulnerability 2014), it is eminently desirable to mainstream adaptation along with mitigation to attain sustainable agricultural productivity. Although the review covers both types of adaptation measures – planned and autonomous/spontaneous – the focus of our research is mainly on the autonomous channel.

2.3. Adaptation Strategies

Planned Adaptation

To prevent the adverse effects of climate change, agricultural practices would have to transition to climate-smart agriculture (CSA), conservation agriculture (CA) and precision farming (PF) technologies while also minimising input costs and utilising information communication technology (ICT)-enabled extension services. Many studies have focused on the promotion of low-cost sustainable land care strategies, such as CA, PF, etc., mostly for Africa and Europe, and found low rates of adoption for these technologies due to a range of factors ((Giller, et al. 2009), (Teklewold, Kassie and Shiferaw 2013), (Pannell, Llewellyn and Corbeels 2014), (Andersson and D'Souza 2014), (Zarco-Tejada, Hubbard and Loudjani 2014), (Manda, et al. 2016), (OECD 2016)). Similarly, some recent studies examine the drivers of adoption of PF technologies in Europe in more detail ((Paxton, et al. 2011), (Pierpaoli, et al. 2013), (Watcharaanantapong, et al. 2014)). Khataza et al. (2018) have identified the factors that determine the timing of adoption of CA in Malawi and have tried to identify farmers who could be potential users of innovative agricultural technologies (Khataza, et al. 2018). Among all factors responsible for low adoption, farmers' lack of information is found to be a key reason responsible for slow diffusion of new technologies in different geographical regions ((Pannell, Llewellyn and Corbeels 2014), (Andersson and D'Souza 2014), (Parks, Christie and Bagares 2015)). Thus, the adoption of ICT-enabled CSA technologies is a pre-requisite to reduce agricultural vulnerability to climate change ((Aggarwal, Bhatta, et al. 2013), (Sehgal, et al. 2013), (Aryal, Farnworth, et al. 2014)). Although the benefits of CSA for both economic reasons and for climate change adaptation are evident ((Aryal, Sapkota, et al. 2015), (Erenstein, et al. 2008), (Khatri-Chhetri, et al. 2016), (Sapkota, et al. 2015)), the adoption of adaptive measures for resilient agriculture through CSA is subject to frequent exposure to droughts in coastal regions, intrusion of salt water with a rise in sea level, and the size of the farm holding (Saroar and Filho 2016). Besides the availability of information and the socio-demographic characteristics of farmers like age, education, experience, confidence, and access to finance have also been identified as factors that determine the adoption of climate-resilient agricultural technologies ex-ante, (Pierpaoli, et al. 2013), while farm ownership, its tenure, geography and soil quality are factors that influence uptake ex-post (Paxton, et al. 2011). Further, the increasing likelihood of drought conditions in many cropping regions of the world (Olesen, et al. 2011) has raised the importance of breeding additional drought-tolerant crop varieties ((Naylor, et al. 2007), (Mutekwa 2009), (Tao and Zhang, Climate Change, Wheat Productivity and Water Use in the North China Plain: A New Super-Ensemble-Based Probabilistic Projection 2011a)), enhancing storage and access to irrigation water, ensuring improved and efficient water delivery systems and irrigation techniques, ensuring more effective water harvesting, adopting agronomic practices that increase soil water retention, and more effective decision support ((Verchot, et al. 2007), (Lioubimtseva and Henebry 2009), (Luo, et al. 2009), (Falloon and Betts 2010), (Piao, et al. 2010), (Olesen, et al. 2011)), among many other possible adaptation strategies. These planned adaptation strategies could well lead to between 10 and 20 per cent yield benefits on average, under persistently drier conditions (Deryng, et al. 2011).

As per the Economics of Climate Adaptation (ECA)'s projections, Indian agriculture could suffer a production loss of more than US$7 billion in 2030, which in turn, could severely affect the income of around 10 per cent of its population (ECA 2009). This loss could be reduced by as much as 80 per cent if cost-effective climate-smart adaptation measures are implemented efficiently. In India, the main challenges to the adoption of climate-resilient adaptation technologies are the lack of information and financial support. Maheswari et al. (2008), Zarco-Tejada et al. (2014), and OECD (2016) have also found lack of finance and credit to be the main barriers to the adoption of PF technologies ((Maheswari, Ashok and Prahadeeswaran 2008), (Zarco-Tejada, Hubbard and Loudjani 2014), (OECD 2016)). To tackle these barriers, Mittal and Hariharan (2018) suggested that mobile-based agro-advisory services be initiated to reduce information gaps and to improve the adoption of climate-resilient technologies by generating awareness (Mittal and Hariharan 2018). This was based on their study of the impact of mobile-based climate services on farmers' ability to adopt climate-resilient technologies in two of the states of India — Haryana and Bihar. Further, an ongoing project of Deutsche Gesellschaft fur Internationale Zusammenarbeit (GIZ) with the Division for Rain-fed Agriculture, Ministry of Agriculture, GoI, is trying to reinforce the existing extension systems and local networks to provide high-quality information on climate change, agricultural production, agricultural markets, and extreme weather events in a timely manner. Having experienced success, this knowledge exchange pilot will be expanded to other regions of India (BMZ and GoI 2013-2017). In 2016, the United States Agency for International development (USAID) had saved India from incurring the loss of 25 per cent of the total crop harvest of Bihar and Eastern Uttar Pradesh together by suggesting, through the Cereal Systems Initiative for South Asia (CSISA) platform (USAID 2016), to farmers to sow wheat early. Again, the adoption of improved crop varieties with higher survival rates, lower water consumption needs, high yield, and drought and flood-resistance is also one of the strategies for climate-resilient adaptation ((Roy and Hirway 2007), (P. Udmale, et al. 2014), (Singh, Anand and Khan, Micro-Level Perception to Climate Change and Adaptation Issues: A prelude to Mainstreaming Climate Adaptation into Developmental Landscape in India 2018a)).

To minimise climate risk and to maintain household living standard, rural households often engage in diverse livelihood generation activities outside the agriculture sector ((Davis, et al. 2010), (Patnaik and Das 2017)) such as opening up of small shops, provision stores, repair workshops, etc. (Tripathi and Mishra 2017), participating in employment-generating government programmes like MGNREGA ((Banerjee, et al. 2013), (P. Udmale, et al. 2015), (Singh, et al. 2018b)), seasonal migration to urban agglomerations for work ((McLeman and Hunter 2010), (Bhatta and Aggarwal, Coping with Weather Adversity and Adaptation to Climate Variability: A Cross-Country Study of Smallholder Farmers in South Asia 2016), (Singh, et al. 2018b), (Rama Ro, et al. 2018)), etc. Due to this strategy of moving to non-agricultural occupations, rural non-farm employment in India has recorded an increase of 12 per cent between 1999-2000 and 2011-2012 (Saha and Verick 2016).

In spite of its challenges, the state of Bihar has recently exhibited some initial trends towards increasing willingness to adopt new agricultural technologies, use of phosphatic and potassic fertilisers (instead of excessive reliance on nitrogenous fertiliser), use of micro-nutrients along with NPK, and increasing awareness of the need for balanced use of chemical fertilisers due to the wider availability of soil testing services at local points and massive extension services by non-governmental organisations (NGOs) and the state government (BAPCC 2015). Although extension services in the state have been rather poor prior to the 11th Five-Year Plan (FYP), in recent years, the state government has embarked upon promotion of CSA by initiating massive training and knowledge sharing programmes for farmers through "*kisan pathsala', "kisan vikash shibir'*, mini kit demonstration in camps at *panchayat* or village levels, and by attracting a large number of farmers and public representatives towards agricultural development schemes by organising *kharif* and *rabi mahostsavs* and '*kisan melas*' (BAPCC 2015). Meanwhile, a significant improvement in credit facilities through *kisan credit cards* (KCCs) has been achieved (this was stated to be as high as 89.3 per cent of its target in 2009-10 and 70.14 per cent in 2010-11) where several lakh farmers got financial benefits (BAPCC 2015). Further, public and private agencies and academia jointly introduced a project, called Bundled Solutions of Index Insurance with Climate Information and Seed Systems to Manage Agricultural Risks (BICSA), which aims to help farmers by providing many complementary solutions for drought and flood insurance, improved seed varieties, weather forecasting services, and climate-smart farming practices (Amarnath 2019). Similarly, the CGIAR is also trying to integrate CSA into village development plans to enhance sustainable agricultural growth and food security through its research programme called Climate Change, Agriculture and Food Security (CCAFS), which is expected to enhance community resilience to climatic shocks by ensuring household food and livelihood security (CCAFS and CIMMYT 2014). Further, smartphones are changing farming decisions by providing information related to unprecedented weather, crop diseases, suitable harvest timings, favourable inputs, access to agricultural markets, best crop to harvest according to their soil quality through soil health cards, etc. (Mishra 2019). Although access to credit facilities, ICT-enabled extension programmes, and bridging knowledge gap programmes are improving in Bihar, a large proportion of farm households have been found to work as wage labourers in non-farm activities (Bhatta, Aggarwal and Shrivastava, Livelihood Diversification and Climate Change Adaptation in Indo-Gangetic Plains: Implication of Rainfall Regimes 2015). The state government, in collaboration with the World Bank, is also trying to mobilise and help the rural population by providing them access to markets, public services, and financial services through the Bihar Rural Livelihoods Project (BRLP), known as JEEViKA, which will scale up farm and non-farm value chain interventions by diversifying both – agricultural and non-agricultural -- occupations along with setting up of women-owned farmers producer companies (World Bank, Government of India and World Bank Sign Agreement to Diversify and Enhance Household Income in Bihar 2016). In view of the increasing success of JEEViKA, the World Bank is planning to expand this initiative across all blocks of the six operational districts of Bihar (Muzaffarpur, Gaya, Madhubani, Purnia, Nalanda, and Khagaria); this project has also been adopted at the national level by the National Rural Livelihood Mission (NRLP) (BAPCC 2015). In fact, JEEViKA is aware of the current research and the results of the study will be shared with them.

Besides planned adaptation, mainstreaming autonomous adaptation is found to be essential to cope with climate change impacts, a channel less considered in the NAPCC and most SAPCCs. This research emphasises two distinguishable autonomous adaptation strategies, namely, inherent ability (traditional knowledge) and community networks, both of which have also been advocated by other studies as well (V. Kumar 2018) as significant drivers of spontaneous adaptation process.

Autonomous adaptation

Role of traditional knowledge in autonomous adaptation

There is increasing evidence that farmers are already adapting to observed climate change in some regions by altering cultivation and sowing times, crop cultivars and species, and marketing arrangements ((Fujisawa and Koyabashi 2010), (Olesen, et al. 2011)). Across studies, it has been seen that changing planting/sowing dates might increase crop yields by a median of 3-17 per cent with substantial variations ((Krishnan, Swain, et al. 2007), (Deressa, et al. 2009), (Magrin, et al. 2009), (Mary and Majule 2009), (Meza and Silva 2009), (Tingem and Rivington 2009), (Travasso, et al. 2009), (Laux, et al. 2010), (Shimono, Kanno and Sawano 2010), (Stockle, et al. 2010), (Tao and Zhang, Adaptation of Maize Production to Climate Change in North China Plain: Quantify the Relative Contributions of Adaptation Options 2010), (Van de Geisen, Liebe and Jung 2010), (Olesen, et al. 2011), (Cho, et al. 2012)). Further, early sowing with improved machinery and techniques such as dry sowing, seeding transplanting, seed priming, etc., can improve cultivars' tolerance to high temperature (Passioura and Angus 2010) and is frequently identified as an adaptation strategy for almost all crops and environments as high temperatures are known to dampen both crop yields and output quality ((Krishnan, Swain, et al. 2007), (Challinor, Wheeler and Hemming, et al. 2009), (Luo, et al. 2009), (Wassmann, et al. 2009a), (Shimono, Kanno and Sawano 2010), (Stockle, et al. 2010)). Again, changes in land use, for example, adjusting the location of crop production, is a potential adaptation response to climate change (IPCC, Climate Change 2007b: Impacts, Adaptation and Vulnerability 2007b).

In India, farmers are highly dependent on their traditional knowledge (ancestral knowledge) about the agriculture and climate change nexus that guide their decision making to combat climate stress (Jodha, Singh and Bantilan 2012). In response to perceived climatic variations, farmers automatically shift planting schedules and harvesting timings ((Salau, Onuk and Ibrahim 2012), (P. Udmale, et al. 2014), (Varadan and Kumar 2014), (USAID 2016)). It has been seen that, by early sowing of wheat in Bihar and Eastern Uttar Pradesh, India has succeeded in staving off losses, which were put at around 25 per cent of the total crop harvest of both the states in 2016 (USAID 2016). Tripathi and Mishra (2017) have shown farmers' perception of and adaptation to climate change using content analysis and group information in eastern Uttar Pradesh and note different passive responses like changing the sowing and harvesting time, cultivation of crops of short duration varieties, intercropping, changing to cropping pattern, investment in irrigation, agroforestry, etc., which indicate the presence of autonomous adaptation strategies (Tripathi and Mishra 2017).

Another commonly adopted method of reducing climate risk by Indian farmers is crop diversification, specifically intercropping and mixed cropping ((Singh, Bantilan and Byjesh, Vulnerability and Policy Relevance to drought in the Semi-Arid Tropics of Asia - A Retrospective Analysis 2014), (Jain, et al. 2015), (Reddy, et al. 2015)). It is evident that intercropping and mixed cropping result in greater productivity and profitability as compared mono-cultivation, especially in rain-fed regions ((Chandra, et al. 2010), (Singh, Bantilan and Jayatilaka, et al. 2015), (Khanal and Mishra, Enhancing Food Security: Food Crop Portfolio Choice in Response to Climatic Risk in India 2017)).

Role of community networks as drivers of autonomous adaptation

Community networks play an important role in agricultural technology diffusion and adoption ((Rogers 1995), (Conley and Udry 2001), (Bandiera and Rasul, Social Networks and Technology Adoption in Northern Mozambique 2006), (Foster and Rosenzweig 2010), (Hartwich and Scheidegger 2010), (Genius, et al. 2014), (Krishnan and Patnam, Neighbours and extension Agents in Ethiopia: Who Matters More for Technology Adoption? 2014), (Bolden, et al. 2018)). It is noticeable that farmers learn about CA performance by observing the plots of early adopters or through interaction with other farmers who are familiar with such technologies ((Moser and Barrett 2006), (Maertens and Barrett 2012), (Krishnan and Patnam, Neighbours and extension Agents in Ethiopia: Who Matters More for Technology Adoption? 2014)). Blasch et al. (2018) studied farmers' willingness to adopt PF technologies in a sample of Italian farmers using a choice experiment and found that knowledge of other farmers who adopted the technology first positively influenced the willingness of another group of farmers to do so, highlighting the importance of network effects (Blasch, et al. 2018). Kate et al. (2010) also examined the influence of social networks on technology adoption in an extended version of the Technology Acceptance Model (TAM) developed by Venkatesh et al. in 2003 (Venkatesh, et al. 2003) and found strength, network density, and network centrality as the factors determining the strength of social influence in technology adoption (Kate, et al. 2010). Further, Burlig and Stevens (2017) analysed the impact of network size using a natural field experiment in the US by comparing US counties between 1959 and 1964 and found similar results in line with the theoretical models of technology adoption (Burlig and Stevens 2018). Social learning has been found to be an important channel of adaptation. Conley and Udry (2001) have explained the social learning process in Ghana and Northern Mozambique, in which farmers observe each other's actions, communicate with each other, and update their beliefs (Conely and Udry 2001). Similarly, Bandiera and Rasul (2006) have examined farmers' propensity to adopt a new crop as a function of the number of adopters in the social network of farmers (family and friends) and found a U-shaped relationship between the probability of adopting a new crop and the number of adopters in the network, that is, the influence of having an additional adopter in the network is positive if there are a few adopters; otherwise, it is negative (Bandiera and Rasul, Social Networks and Technology Adoption in Northern Mozambique 2006). Further, Ramirez (2013) has studied different types of network relationships that could potentially influence farmers' adoption behaviour and found family relationships, landowner-tenant relationship, and interaction with professional associations as different channels (Ramirez 2013) of influence. However, Rugaimukamu et al. (2018) have examined the role of membership of community-based networks (of the savings and credit co-operative societies (SACCOSs) and self-help groups (SHGs)) in Tanzania on households' energy transition and found that households having at least one member who is a part of community-based networks are more likely to adopt modern cooking fuels (Rugaimukamu, Muchapondwa and Thiam 2018). Karim and Thiel (2017) have examined the linkage of participation in such social networks and forums with community-based adaptation (CBA) to climate change by analysing the participation process in the local village disaster management community (VDMC) and concluded that more than 80 per cent of VDMC and around 40-55 per cent of non-VDMC households agreed on the success of CBA (Karim and Thiel 2017).

Community networks have played a crucial role in the Indian economy as well, apparently in the transition from trade to manufacturing (Gupta, et al. 2017). To substantiate that community networks are highly significant for substantial economic growth, data from farming households in rural India have been analysed, which suggest the need for further refinement of indicators of social networks by accounting for the quality of links (i.e., frequency of communication, completeness of information, trust etc.) between farmers (Maertens and Barrett 2012).

To summarise, climate change has severe effects on agricultural productivity, which is mostly negative, and climate-resilience measures, such as adaptation, are effective ways to counter these adverse effects. There are many channels of adaptation measures, such as planned adaptation and autonomous adaptation and, within autonomous adaptation strategies, intrinsic ability and community networks are widely visible. While there exists a large body of literature on the impact of climatic variability on agricultural productivity in India, and governments have initiated adaptation policies, all or most of these have focused only on input/ technology-based adaptation strategies, which are a part of planned adaptation approaches. While adaptation capability is crucial to maintain agricultural productivity (Mckinsey 2009), farmers' ability to adopt appropriate adaptation strategies gets constrained due to under-developed human capital ((Nelson, et al. 2009), (Wright, et al. 2014)), whereas education is necessary for the formation of human capital (Bathla and D'souza 2015). To the best of our knowledge, there is inadequate or almost insignificant rigorous analyses of farmers' inherent ability to adopt new techniques, which are through the channel of autonomous adaptation strategies, and almost none on community networking among farmers towards maintaining or improving agricultural productivity at the national- and state-levels and facilitating adaptation to climate change. While it is evident that capacities to adapt to climate change are highly influenced by innate coping ability and socially acquired knowledge along with a wide range of socio-economic factors and infrastructure ((Patnaik and Das 2017), (Singh, et al. 2018b)), little or no region specific quantitative evidence exists to date on the role played by these two channels to adapt to climate change. This research has attempted to fill this important gap. It attempts to tease out the role of farmers' ability and community networks in the adoption of adaptation strategies to understand adaptation strategies at the district-level for the state of Bihar.

Thus, the key academic contribution of this research is a quantitative as well as mixed method assessment of the twin channels of farmers' adaptation capacity – inherent ability and local community networks – in determining climate-agriculture relationships, with a focus on adaptation to climate change. Several interesting results are obtained, which can be used to design specific policies at the local, state and national levels to enhance the adoption and effectiveness of these two channels of adaptation. We also believe that the knowledge generated from the findings of this research can be closely dovetailed with community-based initiatives such as farmers' field schools (FFSs) and farmers' clubs (FCs). In particular, the findings of the field survey of farmers in the chosen districts, by involving local researchers and policy actors, has the potential to flow directly into agriculture and climate policy design and implementation.

3. Research design, methods of analyses and data utilised

3.1. Key research questions

As discussed in Chapter 1, the key questions that the study attempts to answer are the following.

1. How vulnerable is agricultural productivity to climate-variation?
2. Is the farming community aware of climate change concerns? How do they perceive these concerns in terms of their impact on agricultural yields?
3. What are the adaptation measures (planned and autonomous) being adopted by them to cope with climate change?
4. How does farmers' ability (derived from traditional knowledge and experience) help in coping with the effects of climate change and sudden weather shocks on agricultural productivity?
5. What role do community networks (family, friends, neighbours etc.) play that could potentially create knowledge spill-overs in the case of the agricultural sector so as to maintain yields or improve the resilience of agriculture to climate change?
6. How do the twin channels of farmers' inherent ability and community networks interface with each other?
7. What role does gender differentiation play in terms of the significance of these two channels of climate adaptation?
8. How can these channels and associated responses of farmers be utilised to improve policy making related to the adaptation of agriculture to climate change, including specific policy options and recommendations?

3.2. Site details

We have attempted to find answers to these questions based on the analyses of climate change adaptation processes as these have unfolded in the predominantly rice and wheat growing districts of Bihar. The state of Bihar is located in the north-eastern part of India. It covers a geographical area of 94,163 sq. km with co-ordinates bounded by 24º20'N to 27º31'N latitude and 83º20'E to 88º18'E longitude. The state is entirely land-locked and has a mean elevation of about 150 metres above sea level. The state is flanked by Nepal in the north, the state of West Bengal in the east, Jharkhand in the south and Uttar Pradesh in its west. In terms of topography, Bihar can be apportioned into three regions – the sub-Himalayan foothills, the Indo-Gangetic Plain, and the Southern Plateau region.

The soil is the fertile alluvial variety with abundant water resources, especially groundwater resources. Bihar has 38 districts, spread across its three important agro-climatic zones: North-West, North-East, and South. The North-West zone has 13 districts and receives annual rainfall in the range of 1040-1450 millimetres (mm), with soil being mostly loam and sandy loam. The North-East Zone comprises 8 districts and receives rainfall ranging from 1200-1700 mm and is endowed with loam and clay loam soils. The South Zone has 17 districts, receives an average annual rainfall varying between 990-1300 mm, and has sandy loam, loam, clay, and clay loamy soils ((Tesfaye, et al. 2017), (IMD 2011)) (see Annexure A for details).

The agriculture sector accounts for 21.3 per cent of Bihar's GDP, provides a source of income and livelihood for an overwhelming 90 per cent of its population and, thus, plays a critical role in the economic development of the state. Rice, wheat, and maize are the major cereal crops. Rice is the main monsoon crop (in *kharif* season) and is cultivated in almost all the districts of Bihar. Wheat has been progressively sown by Bihar's farmers in the post-green revolution period and is currently a major *rabi* crop. Bihar ranks sixth in India in terms of production of both rice and wheat. Maize has also been grown, with production increasing over the years. The other crops include pulses such as *moong* bean, peas, and lentils, which are mostly grown in the southern parts of Bihar. Bihar is one of the most climate-sensitive states in India due to its geographical location, hydro-meteorological uncertainties, dependence of a large proportion of the rural population on agriculture, and high levels of poverty. The Government of Bihar has recognised climate change as one of the key challenges for its agriculture sector and has been striving to transform agriculture and its allied sectors into a climate-resilient, sustainable sector to ensure food and nutritional security ((Tesfaye, et al. 2017), (IMD 2011)).

With the agriculture sector of Bihar as the focus, this research has attempted to delineate the role of farmers' ability and community networks in adapting to climate change while controlling for the underlying driving factors (social, economic, technological, availability of natural resources, climate, etc.). To this end, distinct analyses using secondary and primary survey data have been carried out. The secondary data analysis relies on quantitative estimations of rice and wheat yields for all the 38 districts of Bihar for the period spanning 1990-2019 using state-space time-series models and panel regressions. The primary data, collected from a stratified random sample survey of individual farmers carried out in two agro-climatically differentiated districts, namely, Gaya and Purnia (which are similar in other respects), has been analysed using mixed methods to find answers to our research questions. In what follows immediately, we discuss in detail the methods of analyses used in this study.

3.3. Methods of analyses

After carrying out desk research to collect background facts and figures, the key concerns surrounding research questions, results of other studies and methods and data used, the important components of the analyses – based on secondary and primary data – comprise two distinct methods. These are discussed below.

Secondary data analyses methods

Using panel data techniques, the study has done quantitative estimations to extract the effect of farmers' inherent ability (traditional knowledge and past experience) and community networks (social connections) on adaptation to newer farming technologies in response to climate change, while controlling for variables, such as availability of local natural resources, demographic and socio-economic characteristics, farming technology, labour, equipment and other agricultural inputs, and climate variables (temperature and precipitations levels and fluctuations in these), etc.

Given that changes in climate (temperature and rainfall patterns) are a long-run phenomenon and also display geographical variations even within a state, static panel data regressions by utilising secondary data at the district-level, spanning the period 1990-2019 have been estimated. Since the key research questions pertained to teasing out the channels of innate ability and community networks for climate change adaptation, the methods used for the treatment of indicators of these two channels have been examined first.

Principal component analysis

To begin with, how the role of farmers' community networks, climate index and education index have been captured has been discussed. This is done by forming three distinct composite indices for each of these variables for individual districts and years. To come up with a combined index for each district and year, a statistical method called the Principal Component Analysis (PCA), that reduces the number of variables (dimensions) of a large set of interrelated variables while retaining as much of the information (variation) as possible has been used. PCA calculates an uncorrelated set of variables (components or PCs) that are ranked so that the first few components encapsulate most of the variation present in all the original variables.

The method of calculating the index is the following. The first involves normalising the original variables to render them unit and scale free for comparison purposes. For variables that have a positive functional relationship with the respective indicators, the normalisation is carried out using equation (1) below:

$$Normalisation = \frac{Actual\ value - Minimum\ value}{Maximum\ value - Minimum\ value} \quad (1)$$

For variables that influence the respective indicators negatively, the following normalisation method is used (equation (2)):

$$Normalisation = \frac{Maximum\ value - Actual\ value}{Maximum\ value - Minimum\ value} \quad (2)$$

This implies that the normalised variables now lie in the unit interval [0,1].

The next step is to ascribe weights to these normalised variables to work out the composite index, for which PCA has been utilised. This is an econometric approach that rests on the assumption of a linear relationship among the underlying variables. For this, the criterion mentioned in Kaiser (1960) (of choosing only those PCs that have an Eigen value of more than one) that capture the maximum variation in the data has been followed (Kaiser 1960). These are estimated by first using equation (3):

$$X_{itk} = \Omega_{tk} F_{tk} + \varepsilon_{tk}, \quad (3)$$

where X_{tk} represents the vector of all the variables (each represented by i) influencing community networks in year t across district k, Ω_{tk} is the common factor, F_{tk} is the factor loading, and ε_{tk} is the idiosyncratic error-term. The calculation of weights follows from equation (4):

$$W_i = \sum |L_{ij}| E_j, \quad (4)$$

where W_i is the weight of the ith variable, E_j is the Eigen value of the jth factor and L_{ij} is the loading value of the ith variable on the jth factor in any time period.

Finally, these calculated weights for each variable for each district k in period t are used to calculate the composite index value as:

$$PCAIndex_{tk} = \frac{\sum_i X_{itk} W_i}{\sum_i W_i}, \quad (5)$$

where X_{itk} is the normalised value of ith variable and W_i is the weight of the ith variable.

For the community network index, the following specific variables were used as the basis: distribution of farmers by land holding size, caste-based groupings, and religion-based groupings; involvement in SHGs and voluntary organisations (VO); accessibility to bank branches; number of calls made for agricultural queries to *kisan call centres* (KCCs), and length of roads for each of the 38 districts. For the climate index, the variables included for PCA were other than those pertaining to temperature and precipitation, that is, wind speed, cloud cover, evapotranspiration, and diurnal temperature range. For the education index, enrolment in primary, middle and secondary/ higher secondary schools have been used as the basis for estimating it through PCA.

State space modelling using Kalman filtering

The next step was to capture the role of an unobservable variable such as the inherent ability of farmers, which may have been derived from traditional knowledge or experience with farming practices, on climate adaptation strategies. For extracting this variable, state-space models using Kalman filtering have been relied on.

State-space models are extensively applied to include unobserved variables, such as measurement errors, missing observations, and unobserved components (cycles and trends), mainly in time series data. Specifically, state space models permit unobserved variables (known as the state variables) to be incorporated, and estimated along with the model based on observable variables, using an effective recursive algorithm known as the Kalman filter (named after one of its developers, Rudolf E. Kalman). Kalman filtering is also called linear quadratic estimation (LQE). This is an algorithm that utilises a series of measurements viewed over time, containing statistical noise and other errors, and produces estimates of unknown variables that tend to be more precise than those based on a single measurement alone. It works by estimating a joint probability distribution over the variables for each timeframe.

In what follows, a brief discussion of the specification and estimation of a linear state-space model has been presented. A linear state-space representation of the dynamics of the vector y_t is given by the system of equations in (6) and (7):

$$y_t = c_t + Z_t\alpha_t + \epsilon_t \quad (6)$$

$$\alpha_t = d_t + T_t\alpha_{t-1} + \nu_t, \quad (7)$$

where α_t is a vector of unobserved state variables, c_t, Z_t, d_t and T_t are the concordant vectors and matrices, and ϵ_t and ν_t are vectors of Gaussian disturbances with mean zero. Here, the unobserved state vector is assumed to move over time as a first-order vector autoregressive process. Importantly, equation (6) is referred to as the "signal" or "observation" equation and equation (7) is the "state" or "transition" equation. As can be seen from equation (7), filtered Kalman residuals have been preferred instead of the one-step ahead Kalman residuals in the model so that any cyclical or trend parts present in the model can be excluded.

Further, the disturbance vectors ϵ_t and ν_t are taken to be serially independent, with contemporaneous variance structure as follows (equation (8));

$$\Gamma_t = var\begin{bmatrix}\epsilon_t \\ \nu_t\end{bmatrix} = \begin{bmatrix}H_t & G_t \\ G_t' & J_t\end{bmatrix}, \quad (8)$$

where H_t and J_t are symmetric variance matrices, and G_t is a matrix of covariances.

After estimating the signal and the state equations in (6) and (7), the final state vector and final state covariance matrix are obtained by evaluating them at the estimated parameters.

For our purpose, in particular, the equations corresponding to (6) and (7) have been specified for each district to be:

Signal Equation: $Dependent\ Variable_t = \sum_{i=1}^{n}(c_i * Regressor_i)_t + sv1_t$ (9)

State Equation: $sv1_t = (c_{n+2} * sv1_{t-1}) + [var = exp(c_{n+1})]$ (10)

In equation (9), the dependent variable is the logarithmic transformation of rice or wheat yields, and the regressors are the logarithmic transformations of the following variables: proportion of irrigated area, groundwater depth, proportion of cultivated area under HYVs, number of pump sets, number of tractors, number of power tillers, NPK fertiliser usage, number of main and marginal agricultural labourers employed, index of education (as calculated), climate index (as calculated), mean annual temperature (level and its squared term), mean annual rainfall (level and its squared term), average number of rainy days annually (level and its squared term), and the community network index calculated earlier using PCA. Further, in equations (9) and (10), $sv1$ is the state variable or the unobservable variable, which for our case is inferred to be inherent ability. The state equation is set up as a first-order autoregressive process. Finally, $c_i, i = 1, 2, \ldots\ldots, n+2$ are the coefficients that are estimated. The values of the final state vector (or unobservable variable) are displayed at these estimated parameter values, and this series is extracted for each district to include the unobservable variable (inherent ability) in the panel regression estimation in the next step. Thus, for our purpose, ability is the unobservable variable that is extracted from the state-space model after controlling for other farm characteristics, district-level variables and time-variant characteristics in the observation equation as listed above.

Panel data estimations

In the final step of the secondary analysis, panel data regressions have been carried out. Panel data refer to longitudinal data that capture the same cross-section (here, variables pertaining to the agriculture sector in each of the districts of Bihar) over time (here, years). A balanced panel of 38 districts over 1990-2019 has been considered. The use of panel data estimations will permit taking into account explicitly the heterogeneity across different cross-sections (here, districts), and the analysis of the repeated cross sections of districts will be better suited to capture the time dynamics of yields due to a range of regressors, such as cultivation technology, capital equipment, consumable inputs (fertiliser usage and agricultural labour), socio-economic characteristics, educational attainment, climate, innate ability/ traditional knowledge and community networks.

The panel data regressions can be done using panel fixed effects (FE) or random effects (RE) methods. The general form of FE model with cross-sectional FE is specified as:

$$y_{it} = \beta_1 x_{it1} + \beta_2 x_{it2} + \cdots \dots \dots + \beta_k x_{itk} + a_i + u_{it}, \quad t = 1,2, \dots \dots, T. \quad (11)$$

where y_{it} in equation (11) is the dependent variable, $x_{itj}, j = 1, 2, \dots, k$ are the regressors, a_i is the unobserved FE for the ith cross-section and u_{it} is the error term. The specification in equation (11) says that the intercept may differ across different cross-sections (here, 38 districts) but each cross-section's intercept is time invariant.

For this study, rice/ wheat yields have been used as the dependent variable and the percentage of irrigated area, groundwater depth during *kharif/rabi* season (depending on whether it is rice or wheat crop), percentage of cultivated area under HYVs, number of equipment (pump sets (diesel and electric), tractors and power tillers), NPK fertiliser usage, number of main and marginal agricultural labourers engaged, household size, sex ratio (female to male ratio), literacy rate, education index, climate index, mean annual temperature (level and square), mean annual rainfall (level and square), mean number of rainy days annually (level and square), average annual monsoon rainfall (level and square), average annual monsoon rainy days (level and square), community network index, ability (anti-logarithm of estimated filtered value extracted from state-space modelling and Kalman filter in the previous stage), adaptation 1 (representing interaction of community network index and ability), adaptation 2 (reflecting interaction of ability and literacy rate), adaptation 3 (representing interaction of community network index and literacy rate) and time trend (level and square) as the regressors.

Besides, cross sectional/ district FE, we have also estimated the state and time FE models as follows (equation (12).

$$y_{it} = \beta_1 x_{it1} + \beta_2 x_{it2} + \cdots \dots \dots + \beta_k x_{itk} + a_i + \theta_t + u_{it}, \quad t = 1,2, \dots \dots, T. \quad (12)$$

Here, the assumption of time-invariant intercepts for the individual cross section i is relaxed. So, in comparison to equation (11), the specification in equation (12) includes another variable, θ_t to denote a different intercept for each time period. Usually, these capture the influence of factors, such as technological change, changes in government policies, and other external effects, which are time-variant. The specification of variables remains the same as in the case of the pure district (cross-section) FE model.

An alternative specification that is estimated is the panel RE model, without and with time variant effects. Starting with the following FE model, an intercept term is now included:

$$y_{it} = \beta_0 + \beta_1 x_{it1} + \beta_2 x_{it2} + \cdots \dots \dots + \beta_k x_{itk} + a_i + u_{it}, \quad t = 1,2, \dots \dots, T, \; j = 1,2, \dots, k. \quad (13)$$

where it is assumed that a_i is now uncorrelated with each of the explanatory variables. That is, $Cov(x_{itj}, a_i) = 0, \; t = 1,2, \dots, T; \; j = 1,2, \dots, k$. Put differently, as in (13), the ideal RE assumptions include all of the fixed effects assumptions plus the additional requirement that a_i is independent of all explanatory variables in all the time periods of analysis.

The next step is to define the composite error term as $v_{it} = a_i + u_{it}$; then, (13) can be written as

$$y_{it} = \beta_0 + \beta_1 x_{it1} + \beta_2 x_{it2} + \cdots \dots \dots + \beta_k x_{itk} + v_{it}, \quad t = 1,2, \dots \dots, T, \; j = 1,2, \dots, k. \quad (14)$$

Notably, the composite error term v_{it} comprises two components, a_i, which is the cross section, or district-specific, random error component, and u_{it}, which is the combined time series and cross-sectional error component. The term error components model (ECM) for RE derives its name from the composite error term $v_{it,}$ which is the sum of two (or more) error components. The usual assumptions of the ECM follow, that is, the individual error components are not correlated with each other and neither cross section/districts nor time series units are auto-correlated. .

Like (12), the time variant RE model used assumes the form:

$$y_{it} = \beta_0 + \beta_1 x_{it1} + \beta_2 x_{it2} + \cdots \ldots \ldots + \beta_k x_{itk} + \theta_t + v_{it}, \quad t = 1,2,\ldots \ldots,T, \quad j = 1,2,\ldots,k. \quad (15)$$

For the purpose of the study, the individual regressors and regressands are taken to be the same as in the FE model, as explained above.

To decide between the FE and RE models, estimates can be tested for whether there is correlation between the a_i and the $x_{itj}s$, assuming that the idiosyncratic errors and explanatory variables are uncorrelated across all time periods. The Hausman test (Hausman 1978) was done to decide between the two, as this is routinely computed by most econometric packages. The results of these tests indicated that an FE model will work better than RE for rice yields estimations, whereas an RE model will work better than FE for wheat yields estimations. Some of these outcomes change when an alternative specification is tested, where the RE model may turn out to be better than the FE model. The details of the test results are provided in **Error! Reference source not found.** in Annexure B.

Further, using the widely deployed Modified Wald Test (for group wise heteroscedasticity in the FE model), Wooldridge-Drucker (for serial correlation in panel models), Friedman's and Pesaran's Tests (for cross-sectional independence in the FE model) and Breusch-Pagan LM Test (heteroscedasticity in the RE model), it was found that there is presence of cross-sectional dependence, heteroscedasticity and first-order serial correlation in the case of both the rice and wheat yield regressions. Due to the presence of these problems in the models, the Feasible Generalised Least Squares (FGLS) and Panel Corrected Standard Error (PCSE) methods have been done to correct for heteroscedasticity, serial correlation and cross-sectional dependence. Between FGLS and PCSE, the former is said to be appropriate if the number of time periods (T) exceeds the number of cross-sections (N), i.e., $T > N$, while the latter is suitable when $N > T$. Since in our data set the number of time periods and cross-sections are almost equal, the results with FGLS and PCSE for both rice and wheat yields regressions were almost similar.

Only in the case of some alternative specifications of the model (by choosing an alternative dependent variable, such as growth of crop output) was there no problem of heteroscedasticity and autocorrelation. More discussion on these alternative models can be found in the next chapter. Notwithstanding these cases, we have attempted FGLS and PCSE methods. This also provided a way to do robustness checks for the initial regressions. Indeed, the results of both the FGLS and PCSE models were similar to the RE estimations, that is, similar in terms of coefficients, their signs, and almost similar in significance levels. The results of all these tests and the estimations are provided in **Error! Reference source not found.** in Annexure B.

Further, it is to be noted that, when the correlation test for the extracted (filtered) inherent ability/traditional knowledge variable was done with the extracted error terms of all of the above regression models focused on, all the correlation coefficient values were found to be either weakly correlated or uncorrelated. This validates the necessary condition of choice of the instrumental variable for the inherent ability indicator variable (filtered out through the Kalman filtering approach).

In what follows, the methods used for the field survey data analyses are discussed.

Survey design and primary data collection

The field survey comprised the following specific activities:

The first was the appointing of an enumeration/ survey agency. The surveyors were identified for the primary survey based on their extensive experience in carrying out field surveys in Bihar and eastern parts of India. Several discussions and virtual meetings were held with them, and the draft questionnaire and survey design were fine-tuned.

A detailed questionnaire was prepared and regular meetings of the project team with the survey agency as well as pilot testing of the questionnaire helped fine tune it. The final version questionnaire used in the survey is attached with the report separately.

Next, district selection for the primary survey was undertaken. A detailed analysis of the agro-climatic and soil conditions of the different zones in Bihar was carried and the following two districts, differentiated by these features, were selected – Gaya (drought-prone) and Purnia (flood-prone). These displayed heterogeneity in terms of agro-climatic conditions, soil variability, climate variability (average temperature, average rainfall, and average rainy days), sensitivity to extreme weather events, and crop yields (see Annexure A for a detailed classification).

More precisely, Gaya was located in agro climatic zone IIIB (South-west) and Purnia in the agro climatic zone II (North-east). Due to differing agro-climatic features, their soil texture is also dissimilar. The average annual temperature and diurnal temperature range in Gaya are a little higher than in Purnia. Annual and monsoon (June-October) average rainfall levels are found to be about one and a half times higher in Purnia than in Gaya. Accordingly, groundwater tables in Gaya are lower than in Purnia. Besides, both annual and monsoon (June-October) average rainy days are observed to be a little higher in Purnia than in Gaya. These significant differences in temperature and rainfall levels along with a little difference in rainy days between the two districts indicate that rainfall intensity in a day is much higher in Purnia than in Gaya, indicating that Purnia is a more flood-prone district and Gaya a more drought-prone district. Although much higher average annual and monsoon rainfall levels have been found in Kishanganj, which is also located in the agro-climatic Zone II, crop yields (mainly for rice) are much lower in Kishanganj. Furthermore, grain production is more challenging in Purnia due to the more coarse and rocky soil texture as compared to the soil texture in Kishanganj. Hence, Gaya and Purnia were chosen for our primary survey. The data supporting this discussion are presented in Table 22 included in Annexure A.

Due to the COVID-19 pandemic, the questionnaire could be pilot tested only telephonically. The piloting of the questionnaire was done on a sample of 15 farmers, and it was revised in light of the responses received.

The criteria underlying the survey design are now discussed. The primary survey has been designed, based on the systematic stratified random sampling method. First, stratification has been carried by the number of farming households at the district-level with a margin of error around 6-7 per cent. For this level, the two strata were the two districts – Gaya and Purnia – with a survey sample size of 166 for Gaya and 245 for Purnia (the respective farmer population sizes according to Agriculture Census 2010-11 are 751,817 and 381,890).[10] For the next sub-level, the strata were the blocks in each of the two districts, then villages, and finally, households. The blocks in a district were chosen so as to be consistent with the distribution of farming households (in terms of their density) for that district. Finally, household selection was done by a mix of random sampling and snowball sampling. The design of the selection of blocks, villages, and households was accomplished as follows.

A geo-spatial analysis was used to identify three blocks with high forest cover within the two selected districts. In the absence of publicly available shapefiles[11] for the blocks, the identification was done visually through the land use and land cover (LULC) maps. The LULC maps for both the districts of Bihar – Gaya and Purnia – are shown in Figure 1. From these, it is clear that the North-Western region of Gaya, consisting of Konch, Tikari, Guraru, and Paraiya blocks, and the central region of Purnia, consisting of Jalalgarh, Srinagar, Kasba, Krityanand Nagar, Purnia East, and Dagarua blocks are rich in green space, and thus, have been chosen for the survey. The district maps based on their block division are presented in Figures 36 and 37 in Annexure A.

[10] The planned sample size for each of the districts was 200. However, due to some technical issues, some surveyed responses had to be dropped. Unfortunately, these could not be replaced with alternative household responses due to the rising COVID-19 cases in the district.

[11] The shapefile format is a geospatial vector data format for geographic information system software.

Figure 1: LULC classification of the two surveyed districts of Bihar – Gaya and Purnia

The top three blocks from visual analysis for the selected districts were then checked for the percentage of households with agricultural land using the Socio Economic and Caste Census (SECC 2011) database. This step was done to ensure that the choice of the block derives from geo-spatial analysis such that top three blocks having the maximum concentration of farming households are selected for the survey (see Table 1 below). Among these, the top two blocks per district were selected.

Table 1: Block selection in each district

	District	Block 1	Block 2	Block 3
Name	Gaya	Konch	Guraru	Paraiya
% of households with land	38.75	32.84	51.97	39.54
	District	**Block 1**	**Block 2**	**Block 3**
Name	Purnia	Jalalgarh	Dagarua	Purnia East
% of households with land	30.29	44.63	38.61	34.23

Source: (SECC 2011)

The *gram panchayats* for the selected blocks were then listed and three of the *gram panchayats*[12] were selected using systematic random sampling based on the data on the total number households with farming as the primary occupation from the Socio Economic and Caste Census (SECC 2011) (see Table 2 for details).

Table 2: Selected *gram panchayats* in each of the chosen blocks

District	Block	Panchayat	Number of farming households
Gaya	Guraru	Deokali	434
		Kanausi	533
		Rauna	233
	Paraiya	Ajmat Ganj	287
		Mangarawan	615
		Solara	853
Purnia	Jalalgarh	Chak	52
		Jalalgarh	114
		Ram Deli	109
	Dagarua	Babhani	106
		Dariapur	196
		Mathor	102

Source: (SECC 2011)

Within each of the gram *panchayats*, specific villages were identified using local knowledge. For this purpose, block project managers (BPMs), cluster level federation (CLF) co-ordinators and village resource persons (VRPs) were consulted to identify villages that had a representative composition of marginal, small, medium, and large-scale farmers.

Within each village, individual farming households were selected using a mixture of random sampling (that relied on a right-hand rule of selecting every third household) and snowball sampling. The snowball sampling was required to capture more of the medium and large farmers since households in the villages were found to be mostly skewed toward marginal and small farmers. As mentioned earlier, the field survey was completed for 166 farmers in Gaya district and 245 in Purnia district, amounting to an aggregate of 411 farmers. Further, for our sample, an attempt has been made to maintain the ratio of small to large farmers in each stratum in a manner that the number of small and large farmers surveyed were 125 and 41 respectively for Gaya, and 170 and 75 for Purnia.

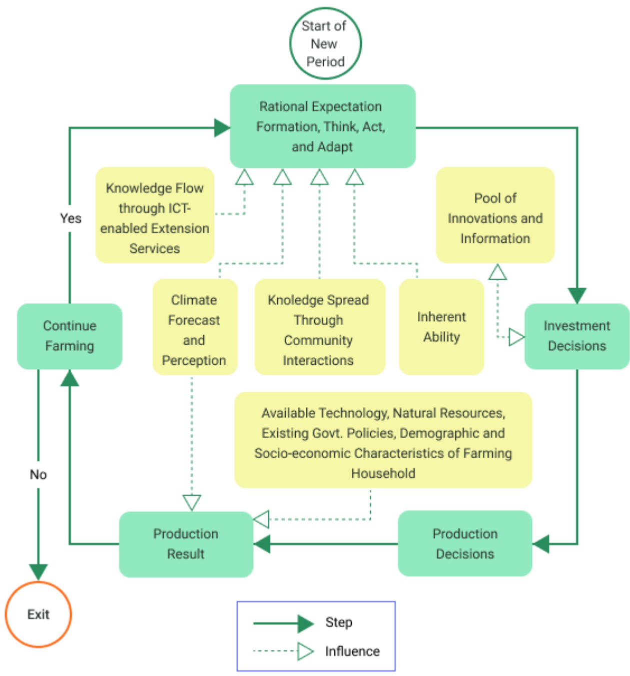
[12] *Gram panchayat* (or village council) is a basic village governing institution in Indian villages. It is a democratic structure at the grass-roots level in rural India that allows for self-governance.

Consequently, the sample size for larger farmers for Gaya is smaller since the ratio of large farmers to small farmers in lower in Gaya as compared to Purnia.

Conceptual framework and primary data analyses methods

Our study is based on the conceptual framework of agent-based models (ABMs) where agents, that is, farmers in our case, make production decisions, namely, maximization of crop yields/ productions based on rational expectation based on past years' farming performance as well as available knowledge at present, both of which help the farming individual to form a belief about yields/ productions and think, act, and adapt accordingly. Moreover, the process of adaptation gets enhanced by inherent ability, that is, the perceptions gathered from traditional knowledge ascertained by past experience of learning-by-doing and social learning through interactions among agents through the two autonomous adaptation channels considered in our study ((Berger, Schreinemachers, & Woelcke, 2006) and (Acosta-Michlik & Espaldon, 2008)). Depending on this process of understanding and adaptation, farmers make investment decisions on which available technology or inputs they should invest in as well as production decisions relating to changing cropping patterns, sowing, and harvesting timings, shifting land from more water-intensive to less water-intensive crops, adopting new climate-resilient seeds, technologies, inputs, etc. Lastly, crop yield/ production is maximized subject to constraints relating to technology, natural resources, socio-economic background of the farming household, existing government policies at national, state, or local-levels, climate forecasts and perceptions. Based on this optimized outcome, farming agents either continue cultivating in the next period or exit. Moreover, literature points to the fact that ABMs, which constitute the conceptual basis of our study, have been strongly recommended by many researchers ((Babli & Giupponi, 2009), (Patt & Siebenhuner, 2005), (Moss, Pahl-Wostl, & Downing, 2001)) as important tools of analyses of agricultural adaptation to climate change because these allow an in-depth understanding of the processes determining the extent and speed of adaptation by including different adaptation channels like social learning, interaction among agents, etc. to cope with the effects of changing climate. A schematic for this process is shown in Figure 2.

Figure 2: Individual farm agent flow chart of activities under the agent-based model



Based on this conceptual ABM framework, the quantitative basic descriptive statistics have been worked out for both continuous and categorical variables for the analysis of the primary survey data collected from the field. As mentioned, the field survey has covered a sample of 411 farmers and used the perception research approach to examine their perception and observations of the ground-reality about climate change (temperature, rainfall, extreme climate events, wind speed, etc.) impacts on rice and wheat yields, and the role of the twin channels of inherent ability (determined by ancestral knowledge and learning-by-doing) and community networks (knowledge spill-overs from social interactions with friends, family, neighbours and others in farming occupations) in enhancing coping capacities, technology and policy efficacy, etc.

On the data thus collected, a mix of perception and quantitative econometric analyses have been used. For the perception analysis, responses to questions that involve categorical variables (such as binary, multiple rankings, groupings, intrinsic orderings, etc., as can be seen in Table 6 to

Table *9* below) have been relied on to perform basic calculations, like percentage or proportion analysis of responses received – separately for Gaya and Purnia. In comparison, for the quantitative analysis, basic descriptive statistics, such as mean, range, variation/ dispersion analyses of continuous variables and normal quantile-quantile (QQ) plots (which show the distribution of continuous variables for the overall sample) have been done. Statistical analysis has also been attempted by interacting categorical and continuous variables wherever it was felt that plausible linkages/interdependencies exist between them.

In addition to the above analyses, cross-sectional econometric regression equations have been estimated, using household and farmer level responses to questions in the survey on agricultural yields, technology, climate variables, ancestral knowledge, and community networks for both the districts strata and for each of the crops – rice and wheat, separately. The specific form of the model estimated is as follows:

$$\begin{aligned}(\text{Crop Yield})_{ij} = {} & a + b_1.(\text{Labour Input})_{ij} + b_2.(\text{Capital Inputs})_{ij} \\ & + b_3.(\text{Agricultural Technology})_{ij} + b_4.(\text{Soil Information})_{ij} \\ & + b_5\,.(\text{Household Characteristics})_{ij} + b_6.(\text{Socio}-\text{economic Factors})_{ij} \\ & + b_7.(\text{Climate Factors})_{ij} + b_8.(\text{Traditional Knowledge or Ability})_{ij} \\ & + b_9.(\text{Community Networks})_{ij} + u_{ij} \qquad (16)\end{aligned}$$

where i denotes farmer respondent and j represents the district.

The specific variables included as regressors are capital equipment and machinery for land preparation, soil fertility, irrigation, and harvesting, use of HYV technology, labour, NPK usage, credit, demographic characteristics (gender of household head, family size, joint or nuclear family), land ownership, landholding size, climate variables (temperature and rainfall), education level, ancestral knowledge, informal community networks, and role of JEEViKA as a formal community network. More details on these can be found in the section on survey data and data sources below.

3.1. Data and data sources

Secondary data and data sources

Annual data on rice and wheat yields for 38 districts of Bihar for the period spanning 1990-2019 on the following variables: area-production-yield (A-P-Y), land utilisation, proportion of land irrigated, proportion of land under HYVs, agricultural cultivator/ labourer, distribution of farmers by landholding size, agricultural equipment used, usage of agricultural inputs, access to credit/loan facilities, irrigation infrastructure, involvement in SHGs, and VOs, *kisan call centres* (KCC), road network, demographic characteristics of farming households (literacy, caste, family size, sex ratio and religion), climate characteristics (average temperature, diurnal temperature range, average rainfall, number of rainy days, cloud cover, evapotranspiration and wind speeds), and local natural resources (groundwater depth) were collected.

Most of the data were obtained from the following sources: Ministry of Agriculture and Farmers' Welfare (MoAFW), State Government of Bihar; Bihar Statistical Handbooks (various issues), Directorate of Economics and Statistics (DE&S), Agriculture Census, Census of India, Indian Council of Agricultural Research (ICAR), India Water Portal, Indian Meteorological Department (IMD) data supply portal, Pune; and Village Dynamics in South Asia (VDSA) database from the International Crops Research Institute for the Semi-Arid Tropics (ICRISAT).

Table 3 to Table 5 below provides more specific details.

Table 3: Variables used for state space modelling through Kalman filter for rice and wheat crops

Variable	Unit	Data source
Dependent variable		
Rice/wheat yield	Metric tons/ hectare	DE&S
Independent variables		
Share of irrigated area	Proportion of cultivated area	DE&S and VDSA Database
Ground water depth during ***kharif*** (for rice)/***rabi*** (for wheat) season	Metres below ground level	India Water Portal
Share of area under HYV technology	Proportion of cultivated area	VDSA Database
Pump sets (Diesel + electric)	Nos.	Agriculture Census and VDSA Database
Tractors	Nos.	Agriculture Census and VDSA Database
Power tillers	Nos.	Agriculture Census and VDSA Database
NPK fertiliser application	Tons	Bihar Agriculture Department and VDSA Database
Marginal agricultural labourers employed	Nos.	Census of India
Education index	Index	Calculated using PCA
Climate index	Index	Calculated using PCA
Soil quality index	Index	Calculated using PCA
Average annual temperature (calculated from monthly averages for a year)	Degree Celsius	India Water Portal and IMD
Square of average annual temperature (calculated from monthly averages for a year)	Degree Celsius	India Water Portal and IMD
Average annual rainfall (calculated from monthly averages for a year)	Millimetres	India Water Portal and IMD
Square of average annual rainfall (calculated from monthly averages for a year)	Millimetres	India Water Portal and IMD
Average annual rainy days (calculated from monthly averages for a year)	Nos.	India Water Portal and IMD
Square of average annual rainy days (calculated from monthly averages for a year)	Nos.	India Water Portal and IMD
Community network index	Index	Calculated using PCA

Table 4: Variables included in calculation of individual indices

Name of index	Variables used for calculating the index	Components & units	Data source
Community Network Index	Herfindahl Hirschman Index for farmer category by landholding size	Proportion of large, medium, semi-medium, small and marginal farmers –proportion	Agriculture Census and VDSA Database
	Herfindahl Hirschman Index for caste	Proportion of rural scheduled caste (SC), scheduled tribe (ST), general & other backward classes (OBC) population – proportion	Census of India
	Herfindahl Hirschman Index for religion	Proportion of rural population with Hindu, Muslim, and Other religious faiths –proportion	Census of India
	Functioning commercial bank branches	Nos.	Ministry of Finance Database, Reserve Bank of India
	Calls for agricultural purposes	Nos.	KCC Database
	Self-help groups (SHGs)	Nos.	JEEViKA Database
	Voluntary organisations	Nos.	JEEViKA Database
	Road length	Km	Bihar Statistical Handbooks
Climate index (for other climate variables)	Wind speed	Kilometres/hour (km/h)	India Water Portal and IMD
	Cloud cover	Hours	India Water Portal and IMD
	Potential evapotranspiration	Millimetres	India Water Portal and IMD
	Diurnal temperature range	Degree Celsius	India Water Portal and IMD
Soil Quality Index	Moderately shallow to deep soil depth greater than 50 cm	Per cent	WRIS
	Nearly level soil slope between 0-3 per cent	Per cent	WRIS
	Slight soil erosion	Per cent	WRIS
Education index	Primary school enrolment	Nos.	Education Department, Government of India (GoI)
	Middle school enrolment	Nos.	Education Department, GoI
	Secondary and higher secondary enrolment	Nos.	Education Department, GoI

Table 5: Variables used for panel data estimations – for both rice and wheat crops

Variable	Unit	Data source
Dependent Variable		
Rice/wheat yield (in MT per Hectare)	Metric ton/hectare	DE&S
Independent Variables		
Share of irrigated area	Per cent of cultivated area	DE&S and VDSA Database

Ground Water Depth during ***kharif*** (for rice)/***rabi*** (for wheat) season	Meters below ground level	India Water Portal
Share of area under HYV technology	Per cent of cultivated area	VDSA Database
Pump sets (Diesel & Electric)	Nos.	Agriculture Census and VDSA Database
Tractors	Nos.	Agriculture Census and VDSA Database
Power tillers	Nos.	Agriculture Census and VDSA Database
NPK fertiliser application	Metric tons	Bihar Agriculture Department and VDSA Database
Main agricultural labourers employed	Nos.	Census of India
Household size	Nos.	Census of India
Sex Ratio	Female to Male ratio of population	Census of India
Literacy rate	Per cent	Census of India
Education Index	Index	Calculated using PCA
Soil Quality Index	Index	Calculated using PCA
Climate Index	Index	Calculated using PCA
Average annual temperature (calculated from monthly averages for a year)	Degree Celsius	India Water Portal and IMD
Square of average annual temperature (calculated from monthly averages for a year)	Degree Celsius	India Water Portal and IMD
Average annual rainy days (calculated from monthly averages for a year)	Nos.	India Water Portal and IMD
Square of average annual rainy days (calculated from monthly averages for a year)	Nos.	India Water Portal and IMD
Average monsoon rainfall (calculated from monthly averages for monsoon months)	Millimetres	India Water Portal and IMD
Square of average monsoon rainfall (calculated from monthly averages for monsoon months)	Millimetres	India Water Portal and IMD
Annual Frequency of Highest Maximum Temperature (HMAX)	Nos.	India Water Portal and IMD
Annual Frequency of Lowest Minimum Temperature (LMIN)	Nos.	India Water Portal and IMD
Annual Frequency of Heaviest Rainfall in Last 24 Hours (HVYRF)	Nos.	India Water Portal and IMD
Community network index	Index	Calculated using PCA
Inherent ability	Anti-log of estimated filtered value	Extracted from rice/ wheat Kalman filter analysis
Rice/ wheat adaptation 1	Interaction term	Interaction of community network index & inherent ability
Rice/ wheat adaptation 2	Interaction term	Interaction of inherent ability & literacy rate
Rice/ wheat adaptation 3	Interaction term	Interaction of community network index & literacy rate
Trend	t = 1, 2, ….., 30 (for 1990-2019)	Time variable
Trend Square		Square of time variable

Primary survey data by type

Based on the questionnaire prepared for the primary field survey of farmers, the data gathered can be broadly grouped into four categories:

- household characteristics (demographic and gender composition, caste, religion, land-holding size, education, occupation, reasons for multiple occupations, income from farming of rice and wheat, income from multiple cropping);
- agriculture-related information (land ownership status, irrigated and unirrigated area, irrigation source, sown area, soil type, soil quality, reasons for soil degradation, information about soil health card, adoption of pest control, cropping pattern at present and in the past 10-20 years, reasons for multiple cropping, use of HYV and its composition, total crop production, produced grain saved for own consumption, amount of produced crop for sale, crop selling options and their prices, usage of NPK, number of agricultural labourers employed, utilisation of different agricultural equipment and machineries, credit facilities and their drawbacks, crop insurance, reasons for post-harvest loss and details of crop loss in last two years including reasons for crop loss, percentage crop loss, compensation received and compensation sources);
- climate characteristics and perceptions about pattern of change over short, medium and long time frames (rainfall, temperature, wind speeds and direction, extreme temperature, excessive rain, hailstorm, excessively hot/cold winds, and hot days);
- ongoing agricultural adaptation (through different autonomous adaptation channels, knowledge flow through ICT-enabled services, involvement in government-held workshops and their effectiveness or drawbacks, information about different social groups and their membership status, informal community networks such as connections with neighbours, relatives, friends, big farmers, landlords, etc., formal community networks, namely, trusted connections with JEEViKA, co-operatives, NGOs, *gram panchayat* members, etc., different adaptation strategies/ channels and their rankings, most effective adaptation channels and their rankings).

Each of these has been listed, along with the type of variable (continuous or categorical), in the tables below (Table 6 to

Table *9*).

Table 6: Data on household characteristics

Variable	Type of variable	Units (if continuous)	Variable code (if categorical)
District name	Categorical		Gaya = 0, Purnia = 1
Practise agriculture or not	Categorical		No = 0, Yes = 1
Cultivate rice or not	Categorical		No = 0, Yes = 1
Cultivate wheat or not	Categorical		No = 0, Yes = 1
Total land holding size	Continuous	Hectares	
Farmer type	Categorical		Marginal/Small = 1, Semi-medium/Medium/Large = 0
Age of respondent	Continuous	Nos.	

Variable	Type of variable	Units (if continuous)	Variable code (if categorical)
Gender of family head	Categorical		Male = 0, Female = 1
Religion	Categorical		Hindu = 1, Muslim = 0
Caste	Categorical		SC = 1, ST = 2, OBC = 3, GEN = 4
Origin	Categorical		Did not Migrate = 0, Migrated = 1
Years since migration	Continuous	Nos.	
Current family type	Categorical		Nuclear = 0, Joint = 1
Past family type	Categorical		Nuclear = 0, Joint = 1
Changed family type	Categorical		Did not Change = 0, Nuclear to Joint = 1, Joint to Nuclear = 2
Family size	Continuous	Nos.	
Proportion of adult males	Continuous	Per cent	
Proportion of adult females	Continuous	Per cent	
Number of earning family members	Continuous	Nos.	
Number of family members who have passed class 10	Continuous	Nos.	
Number of family members who have passed class 12	Continuous	Nos.	
Number of family members who have attended higher education	Continuous	Nos.	
Dependency ratio	Continuous	Per cent	
Occupation – Rank wise	Categorical		Cultivation = 1, Allied agriculture = 2, Agri. wage labour = 3, Non-agri. wage labour = 4, Artisan = 5, Petty shop/ Small business = 6, Organised trade/ Business = 7, Govt. salaried employment = 8, Non-govt. salaried employment = 9, Pension/Rent/Dividend = 10, Others = 11
At Rank 1	Categorical		
At Rank 2	Categorical		
At Rank 3	Categorical		
At Rank 4	Categorical		
Occupation Type	Categorical		No = 0, Yes = 1
Cultivation	Categorical		
Allied agriculture	Categorical		
Agricultural wage labour	Categorical		
Non-agricultural wage labour	Categorical		

Variable	Type of variable	Units (if continuous)	Variable code (if categorical)
Artisan	Categorical		
Petty shop/small business	Categorical		
Organised trade/business	Categorical		
Govt. salaried employment	Categorical		
Non-govt. salaried employment	Categorical		
Pension/rent	Categorical		
Any other	Categorical		
Any other occupation, specifically	Categorical		None = 0, Home tutor = 1, Practise medicine in village = 2, Ward member = 3
Total annual income	Continuous	INR	
Reasons for multiple occupations	Categorical		No = 0, Yes = 1
Low market price	Categorical		
High input cost	Categorical		
More climate vulnerable	Categorical		
Higher number of family members	Categorical		
Any other	Categorical		
Any other reason for multiple occupation, specifically	Categorical		None = 0, To Pay-off loans = 1
income from farming in rice season	Continuous	INR	
Income from farming in wheat season	Continuous	INR	
Practise multi-cropping or not	Categorical		No = 0, Yes = 1
Income from multi-cropping	Continuous	INR	

Table 7: Agriculture-related information

Variable	Type of variable	Units (if continuous)	Variable code (if categorical)
District	Categorical		Gaya = 0, Purnia = 1
Ownership status of land	Categorical		No = 0, Yes = 1
Own land	Categorical		
Lease-in	Categorical		
Lease-out	Categorical		
Having uncultivable land or not	Categorical		No = 0, Yes = 1
Area of uncultivable land	Continuous	Acres	
Times of land sown	Categorical		No = 0, Yes = 1
Once	Categorical		
Twice	Categorical		
Thrice	Categorical		
More than thrice	Categorical		
Irrigate land or not	Categorical		No = 0, Yes = 1
Irrigated area	Continuous	Acres	
Unirrigated area	Continuous	Acres	
Source of irrigation	Categorical		No = 0, Yes = 1
Open well	Categorical		
Bore well	Categorical		
Canal	Categorical		
Tank	Categorical		
Submersible pump	Categorical		
Hand pump	Categorical		
Rivers	Categorical		
Others	Categorical		
Type of soil present or not	Categorical		No = 0, Yes = 1
Halki mitti	Categorical		
Kewal mitti	Categorical		
Domat mitti	Categorical		
Balsundari mitti	Categorical		
Rehada mitti	Categorical		
Balusahi mitti	Categorical		
Other *mitti*	Categorical		
Soil fertility	Categorical		No = 0, Yes = 1
Very high	Categorical		
High	Categorical		
Medium	Categorical		
Low	Categorical		

Variable	Type of variable	Units (if continuous)	Variable code (if categorical)
Very low	Categorical		
Soil moisture	Categorical		No = 0, Yes = 1
Very high	Categorical		
High	Categorical		
Medium	Categorical		
Low	Categorical		
Very how	Categorical		
Slope of land	Categorical		No = 0, Yes = 1
Levelled	Categorical		
Slant	Categorical		
Medium	Categorical		
High	Categorical		
Soil Degradation is Happening or Not	Categorical		No = 0, Yes = 1
Reasons for soil degradation	Categorical		No = 0, Yes = 1
Soil Erosion	Categorical		
Nutrient Depletion	Categorical		
Water Logging	Categorical		
Salinity/Acidity	Categorical		
Having Soil Health Card (SHC) or not	Categorical		No = 0, Yes = 1
Getting any soil related information from SHC or not	Categorical		No = 0, Yes = 1
If do not get soil related information from SHC, then other sources of getting soil related information	Categorical		No = 0, Yes = 1
Krishi Bhavan	Categorical		
Co-operative Societies	Categorical		
NGOs	Categorical		
KVKs	Categorical		
Agriculture Universities	Categorical		
JEEViKA	Categorical		
Other	Categorical		
Adopt pest control or not	Categorical		No = 0, Yes = 1
No. of times pest control undertaken in a year	Continuous	Nos.	
Crops cultivated at present – Rank wise	Categorical		Rice = 1, Wheat = 2, Maize = 3, Barley = 4, Millet = 5, Sorghum = 6, *Moong* = 7, Masoor = 8, Arhar = 9, Chana = 10, Matar/ Peas Dal = 11,

Variable	Type of variable	Units (if continuous)	Variable code (if categorical)
			Mustard = 12, Other Pulses = 13, Vegetables = 14, Potato = 15, Onion = 16, Fruits = 17, Others = 18
At Rank 1	Categorical		
At Rank 2	Categorical		
At Rank 3	Categorical		
At Rank 4	Categorical		
Types of crops cultivated at present	Categorical		No = 0, Yes = 1
Rice	Categorical		
Wheat	Categorical		
Maize	Categorical		
Barley	Categorical		
Millet	Categorical		
Sorghum	Categorical		
Moong	Categorical		
Masoor	Categorical		
Arhar	Categorical		
Chana	Categorical		
Matar/Peas dal	Categorical		
Mustard	Categorical		
Other pulses	Categorical		
Vegetables	Categorical		
Potato	Categorical		
Onion	Categorical		
Fruits	Categorical		
Others	Categorical		
Crops cultivated in past 10-20 years - Rank wise	Categorical		Rice = 1, Wheat = 2, Maize = 3, Barley = 4, Millet = 5, Sorghum = 6, *Moong* = 7, *Masoor* = 8, *Arhar* = 9, *Chana* = 10, *Matar*/Peas Dal = 11, Mustard = 12, Other Pulses = 13, Vegetables = 14, Potato = 15, Onion = 16, Fruits = 17, Others = 18
At Rank 1	Categorical		
At Rank 2	Categorical		
At Rank 3	Categorical		
At Rank 4	Categorical		
Types of crops cultivated in past 10-20 years	Categorical		No = 0, Yes = 1
Rice	Categorical		
Wheat	Categorical		
Maize	Categorical		
Barley	Categorical		

Variable	Type of variable	Units (if continuous)	Variable code (if categorical)
Millet	Categorical		
Sorghum	Categorical		
Moong	Categorical		
Masoor	Categorical		
Arhar	Categorical		
Chana	Categorical		
Matar/Peas dal	Categorical		
Mustard	Categorical		
Other pulses	Categorical		
Vegetables	Categorical		
Potato	Categorical		
Onion	Categorical		
Fruits	Categorical		
Others	Categorical		
Shifted cropping pattern from rice to other crops or not	Categorical		No = 0, Yes = 1
Shifted cropping pattern from wheat to other crops or not	Categorical		No = 0, Yes = 1
Crops under multi-cropping – Rank wise	Categorical		Rice = 1, Wheat = 2, Maize = 3, Barley = 4, Millet = 5, Sorghum = 6, *Moong* = 7, *Masoor* = 8, *Arhar* = 9, *Chana* = 10, *Matar*/Peas Dal = 11, Mustard = 12, Other Pulses = 13, Vegetables = 14, Potato = 15, Onion = 16, Fruits = 17, Others = 18
At Rank 1	Categorical		
At Rank 2	Categorical		
At Rank 3	Categorical		
At Rank 4	Categorical		
Types of crops under multi-cropping	Categorical		No = 0, Yes = 1
Rice	Categorical		
Wheat	Categorical		
Maize	Categorical		
Barley	Categorical		
Millet	Categorical		
Sorghum	Categorical		
Moong	Categorical		
Masoor	Categorical		
Arhar	Categorical		
Chana	Categorical		
Matar/Peas dal	Categorical		
Mustard	Categorical		
Other pulses	Categorical		
Vegetables	Categorical		

Variable	Type of variable	Units (if continuous)	Variable code (if categorical)
Potato	Categorical		
Onion	Categorical		
Fruits	Categorical		
Others	Categorical		
Reasons for multi-cropping	Categorical		No = 0, Yes = 1
Own consumption needs	Categorical		
Better utilisation of available resources such as soil, water, fertilisers, etc.	Categorical		
To increase soil fertility	Categorical		
To become self-sufficient	Categorical		
Crops cultivated during non-season of rice/wheat – Rank wise	Categorical		Rice = 1, Wheat = 2, Maize = 3, Barley = 4, Millet = 5, Sorghum = 6, *Moong* = 7, *Masoor* = 8, *Arhar* = 9, *Chana* = 10, *Matar*/Peas Dal = 11, Mustard = 12, Other Pulses = 13, Vegetables = 14, Potato = 15, Onion = 16, Fruits = 17, Others = 18
At Rank 1	Categorical		
At Rank 2	Categorical		
At Rank 3	Categorical		
At Rank 4	Categorical		
Types of crops cultivated during non-season of rice/wheat	Categorical		No = 0, Yes = 1
Rice	Categorical		
Wheat	Categorical		
Maize	Categorical		
Barley	Categorical		
Millet	Categorical		
Sorghum	Categorical		
Moong	Categorical		
Masoor	Categorical		
Arhar	Categorical		
Chana	Categorical		
Matar/Peas dal	Categorical		
Mustard	Categorical		
Other pulses	Categorical		
Vegetables	Categorical		
Potato	Categorical		
Onion	Categorical		
Fruits	Categorical		
Others	Categorical		

Variable	Type of variable	Units (if continuous)	Variable code (if categorical)
Use HYV seeds or not	Categorical		No = 0, Yes = 1
Composition of usage of HYV seeds	Categorical		All are HYV seeds = 1, All are normal seeds = 2, Combination of HYV and normal seeds = 3
If the composition is a combination of HYV and normal seeds, then share of usage of HYV seeds	Categorical		More HYV than normal seeds = 1, Less HYV than normal seeds = 2
Rice irrigated area	Continuous	Acres	
Rice unirrigated area	Continuous	Acres	
Total amount of rice produced	Continuous	Kilogram	
Amount of rice saved for self-consumption	Continuous	Kilogram	
Amount of rice sold	Continuous	Kilogram	
Rice selling places	Categorical		No = 0, Yes = 1
Market	Categorical		
PACs	Categorical		
Others, middlemen	Categorical		
Rice selling prices at different places	Continuous	INR/kilogram	
Market	Continuous		
PACs	Continuous		
Rice production has changed or not over last 20-30 years	Categorical		No = 0, Yes = 1
If rice production has changed, then in which direction	Categorical		Increased = 1, Decreased = 2
Amount of NPK used in rice production	Continuous	Kilogram/acre	
No. of agricultural labourers hired for rice production	Continuous	Nos./acre	
Wheat irrigated area	Continuous	Acres	
Wheat unirrigated area	Continuous	Acres	
Total amount of wheat produced	Continuous	Kilogram	
Amount of wheat saved for self-consumption	Continuous	Kilogram	
Amount of wheat sold	Continuous	Kilogram	
Wheat selling places	Categorical		No = 0, Yes = 1
Market	Categorical		
PACs	Categorical		
Others, middlemen	Categorical		
Wheat selling market price	Continuous	INR/kilogram	

Variable	Type of variable	Units (if continuous)	Variable code (if categorical)
Wheat production has changed or not over last 20-30 years	Categorical		No = 0, Yes = 1
If wheat production has changed, then in which direction	Categorical		Increased = 1, Decreased = 2
Amount of NPK used in wheat' production	Continuous	Kilogram/acre	
No. of agricultural labourers hired for wheat production	Continuous	Nos./acre	
Utilisation of machinery	Continuous	Minutes/ acre	
Sprayer/duster	Continuous		
Diesel pump sets	Continuous		
Electric pump sets	Continuous		
Power tiller	Continuous		
Tractor	Continuous		
Rotavator	Continuous		
Rice transplanter	Continuous		
Ownership status of machinery	Categorical		Own = 1, Rented = 2, Other like borrowed from neighbours = 3
Sprayer/duster	Categorical		
Diesel pump sets	Categorical		
Electric pump sets	Categorical		
Power tiller	Categorical		
Tractor	Categorical		
Rotavator	Categorical		
Rice transplanter	Categorical		
Can access credit under *kisan credit card* (KCC) or not	Categorical		No = 0, Yes = 1
Credit amount taken under *kisan credit card* (KCC)	Continuous	INR	
Used to get fund under PM-*Kisan* or not	Categorical		No = 0, Yes = 1
Amount of fund received under PM-*Kisan*	Continuous	INR	
Used to take loan or not	Categorical		No = 0, Yes = 1
Reasons for not taking loans	Categorical		No = 0, Yes = 1
Capable enough to manage on their own	Categorical		
Credits/ funds get from *Kisan Credit Card*	Categorical		

Variable	Type of variable	Units (if continuous)	Variable code (if categorical)
(KCC) and PM-*Kisan* is enough			
Not available for small farmers	Categorical		
Not available without own land	Categorical		
Excessive paperwork	Categorical		
No guidance for filling online application	Categorical		
Sources of loans	Categorical		No = 0, Yes = 1
Gramin banks	Categorical		
Co-operative societies	Categorical		
Money lenders	Categorical		
Gram panchayat	Categorical		
Insurance companies	Categorical		
NGOs	Categorical		
JEEViKA	Categorical		
Landlords	Categorical		
Neighbours, relatives, and friends	Categorical		
Political parties	Categorical		
Others	Categorical		
Amount of loan taken in current year	Continuous	INR	
Amount of loan taken in last 3 years	Continuous	INR	
Could repay your loan taken in last 3 years or not	Categorical		Yes = 1, No = 2, Still repaying = 3
Having crop insurance or not	Categorical		No = 0, Yes = 1
Faced post-harvest loss or not	Categorical		No = 0, Yes = 1
Reasons for post-harvest loss – Rank wise	Categorical		Injury from agricultural machinery = 1, Environmental hazards = 2, Water logging = 3, Human or Animal Damages = 4, Others like low market price = 5
At Rank 1	Categorical		
At Rank 2	Categorical		
At Rank 3	Categorical		
At Rank 4	Categorical		
Different types of reasons for post-harvest loss	Categorical		No = 0, Yes = 1
Injury from agricultural machinery	Categorical		
Environmental hazards	Categorical		
Water logging	Categorical		

Variable	Type of variable	Units (if continuous)	Variable code (if categorical)
Human or animal damages	Categorical		
Others like low market price	Categorical		
If the reason behind post-harvest loss is environmental hazards, then types of environmental hazards	Categorical		No = 0, Yes = 1
Drought	Categorical		
Heavy rainfall	Categorical		
Flood	Categorical		
Hailstorm	Categorical		
higher no. of hot temperate days	Categorical		
Change in wind direction	Categorical		
Excessive hot wind/loo	Categorical		
Excessive cold wind	Categorical		
Faced crop loss in last 2 years (in 2019 and 2018) or not	Categorical		No = 0, Yes = 1
Faced rice loss in 2019 or not	Categorical		No = 0, Yes = 1
Faced wheat loss in 2019 or not	Categorical		No = 0, Yes = 1
Percentage crop loss in 2019	Continuous	Per cent	
Reasons for crop loss in 2019	Categorical		No = 0, Yes = 1
Injury from agricultural machinery	Categorical		
Environmental hazards	Categorical		
Water logging	Categorical		
Human or animal damages	Categorical		
If the reason behind 2019 crop loss is environmental hazards, then types of environmental hazards	Categorical		No = 0, Yes = 1
Drought	Categorical		
Heavy rainfall	Categorical		
Flood	Categorical		
Hailstorm	Categorical		
Higher no. of hot temperate days	Categorical		
Change in wind direction	Categorical		
Excessive hot wind/ loo	Categorical		

Variable	Type of variable	Units (if continuous)	Variable code (if categorical)
Excessive cold wind	Categorical		
Received compensation or not in 2019	Categorical		No = 0, Yes = 1
Compensation source for 2019 crop loss	Categorical		No = 0, Yes = 1
Gramin banks	Categorical		
Co-operative societies	Categorical		
Money lenders	Categorical		
Gram panchayat	Categorical		
Insurance companies	Categorical		
NGOs	Categorical		
Landlords	Categorical		
Neighbours, relatives, and friends	Categorical		
Political parties	Categorical		
JEEViKA	Categorical		
Others	Categorical		
Amount of compensation received for 2019 crop loss	Continuous	INR	
Compensation received is enough or not in 2019	Categorical		No = 0, Yes = 1
Faced rice loss in 2018 or not	Categorical		No = 0, Yes = 1
Faced wheat loss in 2018 or not	Categorical		No = 0, Yes = 1
Percentage crop loss in 2018	Continuous	Per cent	
Reasons for crop loss in 2018	Categorical		No = 0, Yes = 1
Injury from agricultural machinery	Categorical		
Environmental hazards	Categorical		
Water logging	Categorical		
Human or animal damages	Categorical		
If the reason behind 2018 crop loss is environmental hazards, then types of environmental hazards	Categorical		No = 0, Yes = 1
Drought	Categorical		
Heavy rainfall	Categorical		
Flood	Categorical		
Hailstorm	Categorical		
Higher no. of hot temperate days	Categorical		

Variable	Type of variable	Units (if continuous)	Variable code (if categorical)
Change in wind direction	Categorical		
Excessive hot wind/ loo	Categorical		
Excessive cold wind	Categorical		
Received compensation or not in 2018	Categorical		No = 0, Yes = 1
Compensation source for 2018 crop loss	Categorical		No = 0, Yes = 1
Gramin banks	Categorical		
Co-operative societies	Categorical		
Money lenders	Categorical		
Gram panchayat	Categorical		
Insurance companies	Categorical		
NGOs	Categorical		
Landlords	Categorical		
Neighbours, relatives, and friends	Categorical		
Political parties	Categorical		
JEEViKA	Categorical		
Others	Categorical		
Amount of compensation received for 2018 crop loss	Continuous	INR	
Compensation received is enough or not in 2018	Categorical		No = 0, Yes = 1

Table 8: Data on climate characteristics and trends

Variable	Type of variable	Variable code
District	Categorical	Gaya = 0, Purnia = 1
Characteristics of climatic variables today	Categorical	Much More than Required/ Usual = 1, Somewhat More than Required/ Usual = 2, Same as Required/ Usual = 3, Somewhat Less than Required/ Usual = 4, Much Less than Required/ Usual = 5
Rainfall	Categorical	
Temperature	Categorical	
Wind speed	Categorical	
Heavy rainfall	Categorical	
Flood	Categorical	
More hot temperate days	Categorical	
Drought	Categorical	
Hailstorm	Categorical	

Variable	**Type of variable**	**Variable code**
Excessive loo	Categorical	
Excessive cold wind	Categorical	
Characteristics of climatic variables during last 5-10 years	Categorical	Much Higher than Present = 1, Higher than Present = 2, Almost Similar to Present = 3, Lesser than Present = 4, Much Lesser than Present = 5
Rainfall	Categorical	
Temperature	Categorical	
Wind speed	Categorical	
Heavy rainfall	Categorical	
Flood	Categorical	
More hot temperate days	Categorical	
Drought	Categorical	
Hailstorm	Categorical	
Excessive loo	Categorical	
Excessive cold wind	Categorical	
Characteristics of climatic variables during last 20-30 years	Categorical	Much Higher than Present = 1, Higher than present = 2, Almost similar to present = 3, Lesser than present = 4, Much lesser than present = 5
Rainfall	Categorical	
Temperature	Categorical	
Wind speed	Categorical	
Heavy rainfall	Categorical	
Flood	Categorical	
More hot temperate days	Categorical	
Drought	Categorical	
Hailstorm	Categorical	
Excessive loo	Categorical	
Excessive cold wind	Categorical	
Perception about climate change over 20-30 years, i.e., climate is changing or not	Categorical	No = 0, Yes = 1
Perception of change in temperature patterns in the last 5-10 years	Categorical	No = 0, Yes = 1
Higher no. of hot temperate days	Categorical	
Higher intensity of hotter temperature over fewer number of days	Categorical	

Variable	Type of variable	Variable code
Perception of change in rainfall pattern in Last 5-10 Years	Categorical	No = 0, Yes = 1
More rainy days	Categorical	
Higher intensity of rainfall over fewer number of days	Categorical	
Monsoon rainfall shifting – getting advanced	Categorical	
Monsoon rainfall shifting – getting delayed	Categorical	
Perception of change in wind pattern in last 5-10 years	Categorical	No = 0, Yes = 1
Change in monsoon wind direction	Categorical	
More loo days	Categorical	
More excessive cold wind days	Categorical	
Higher intensity of loo over fewer number of days	Categorical	
Higher intensity of cold wind over fewer number of days	Categorical	
Monsoon wind shifting – getting advanced	Categorical	
Monsoon wind shifting – getting delayed	Categorical	
Perception of change in temperature pattern in last 20-30 years	Categorical	No = 0, Yes = 1
Higher no. of hot temperate days	Categorical	
Higher intensity of hotter temperature over fewer number of days	Categorical	
Perception of change in rainfall pattern in last 20-30 years	Categorical	No = 0, Yes = 1
More rainy days	Categorical	
Higher intensity of rainfall over fewer number of days	Categorical	
Monsoon rainfall shifting – getting advanced	Categorical	
Monsoon rainfall shifting – getting delayed	Categorical	
Perception of change in wind pattern in last 20-30 years	Categorical	No = 0, Yes = 1
Change in monsoon wind direction	Categorical	
More loo days	Categorical	

Variable	Type of variable	Variable code
More excessive cold wind days	Categorical	
Higher intensity of loo over fewer number of days	Categorical	
Higher intensity of cold wind over fewer number of days	Categorical	
Monsoon wind shifting -- getting advanced	Categorical	
Monsoon wind shifting – getting delayed	Categorical	

Table 9: Characteristics of agricultural adaptation

Variables	Type of variable	Unit (if continuous)	Variable code (if categorical)
District	Categorical		Gaya = 0, Purnia = 1
Production decision affected or not due to climate change (CC)	Categorical		No = 0, Yes = 1
Changing production decision due to CC – Rank wise			Change in crop sowing and harvesting time = 1, Change in cropping pattern = 2, Shifting land from more to less water intensive crops = 3, Use new tech. and agri. equipment = 4, Use high quality inputs = 5, Change in choice of crops = 6, Use of new climate resilient seeds = 7, Others = 8
At Rank 1	Categorical		
At Rank 2	Categorical		
At Rank 3	Categorical		
At Rank 4	Categorical		
Changing production decision towards	Categorical		No = 0, Yes = 1
Change in crop sowing and harvesting time	Categorical		
Change in crop pattern like multi-cropping/inter-cropping	Categorical		

Variables	Type of variable	Unit (if continuous)	Variable code (if categorical)
Shifting land from more water intensive to less water intensive crops	Categorical		
Use of new technologies and agricultural equipment	Categorical		
Use of high-quality inputs like seeds, pesticides, insecticides, etc.	Categorical		
Changing choice of crops	Categorical		
Use of new climate resilient seeds	Categorical		
If 3, i.e., shifting land from more water intensive crop towards less water intensive crop – Rank wise	Categorical		Maize = 1, Millet = 2, *Bajra* = 3, *Jowar* = 4, *Moong* = 5, *Masoor* = 6, *Arhar* = 7, *Chana* = 8, *Matar* = 9, Other Pulses = 10, Vegetables = 11, Potato = 12, Onion = 13, Fruits = 14, Other = 15
At Rank 1	Categorical		
At Rank 2	Categorical		
At Rank 3	Categorical		
At Rank 4	Categorical		
Shifting land towards less water intensive crops, like,	Categorical		No = 0, Yes = 1
Maize	Categorical		
Millet	Categorical		
Bajra	Categorical		
Jowar	Categorical		
Moong	Categorical		
Masoor	Categorical		
Arhar	Categorical		
Chana	Categorical		
Matar/Pea dal	Categorical		
Other pulses	Categorical		
Vegetables	Categorical		
Potato	Categorical		
Onion	Categorical		
Fruits	Categorical		
Any Other Crop	Categorical		
Have trusted relationships with	Categorical		No = 0, Yes = 1
Relatives	Categorical		
Neighbours	Categorical		
Friends	Categorical		
Landlords	Categorical		
Big farmers	Categorical		
Panchayat members	Categorical		

Variables	Type of variable	Unit (if continuous)	Variable code (if categorical)
JEEViKA	Categorical		
Social workers	Categorical		
Co-operative society members	Categorical		
Government officials	Categorical		
Getting information for consumable inputs from	Categorical		No = 0, Yes = 1
Media like newspaper, radio, TV	Categorical		
Neighbours, relatives and friends	Categorical		
Local people like, big farmers, ***panchayat*** members, political party members	Categorical		
Extension services like, KCC, KVKs, SMS, farmers' portal	Categorical		
Government/ Non-Government organisations like agriculture extension offices, research institutes, government. agencies	Categorical		
Local traders	Categorical		
JEEViKA	Categorical		
Getting information on capital inputs from	Categorical		No = 0, Yes = 1
Media like newspaper, radio, TV	Categorical		
Neighbours, relatives & friends	Categorical		
Local people like big farmers, ***panchayat*** members, political party members	Categorical		
Extension services like, KCC, KVKs, SMS, farmers' portal	Categorical		
Government/ Non-Government organisations like agriculture extension offices, research institutes, government agencies	Categorical		
Local traders	Categorical		
JEEViKA	Categorical		
Traditional knowledge is required or not along with information on new technologies	Categorical		No = 0, Yes = 1
Used to attend government workshops or not	Categorical		No = 0, Yes = 1
Workshops are helpful or not	Categorical		No = 0, Yes = 1
Reasons behind workshops not being helpful	Categorical		No = 0, Yes = 1
Very expensive	Categorical		
Unavailability of time	Categorical		
Low quality service	Categorical		

Variables	Type of variable	Unit (if continuous)	Variable code (if categorical)
Not enough number of interactions	Categorical		
Held too far to go and attend	Categorical		
Others	Categorical		
Other reasons, specifically	Categorical		
Know of farmers' clubs (FCs) or not	Categorical		No = 0, Yes = 1
Member of FCs or not	Categorical		No = 0, Yes = 1
Know of farmers' field schools (FFSs) or not	Categorical		No = 0, Yes = 1
Member of FFSs or not	Categorical		No = 0, Yes = 1
Know of *krishi vigyan kendras* (KVKs) or not	Categorical		No = 0, Yes = 1
Member of KVKs or not	Categorical		No = 0, Yes = 1
Know of SHGs or not	Categorical		No = 0, Yes = 1
Member of SHGs or not	Categorical		No = 0, Yes = 1
SHGs have membership fee or not	Categorical		No = 0, Yes = 1
SHG member fee amount	Continuous	INR	
SHGs have service fee or not	Categorical		No = 0, Yes = 1
SHG service fee amount	Continuous	INR	
No. of SHG formal meets	Continuous	Nos.	
No. of SHG informal meets	Continuous	Nos.	
Know Agricultural Technology Management Agency (ATMA) or not	Categorical		No = 0, Yes = 1
Member of ATMA or not	Categorical		No = 0, Yes = 1
Know of co-operative societies or not	Categorical		No = 0, Yes = 1
Member of co-operative societies or not	Categorical		No = 0, Yes = 1
Want to be a member of any such social groups or not	Categorical		No = 0, Yes = 1
Reasons for not wanting to be a member of such social groups	Categorical		No = 0, Yes = 1
Very expensive	Categorical		
Unavailability of time	Categorical		
Low quality service	Categorical		
Not enough no. of interactions	Categorical		
Poor feedback from others	Categorical		
Too far to go and attend meetings	Categorical		
Other	Categorical		
Other reasons, specifically	Categorical		
Carry ancestral/ traditional knowledge (TK) or not	Categorical		No = 0, Yes = 1

Variables	Type of variable	Unit (if continuous)	Variable code (if categorical)
Rank of carrying TK	Categorical		Lesser effectiveness = 1, Less effectiveness = 2, Medium effectiveness = 3, High effectiveness = 4, Higher effectiveness = 5
Ancestral knowledge/TK is helpful or not	Categorical		No = 0, Yes = 1
Rank for TK helpful or not	Categorical		Lesser effectiveness = 1, Less effectiveness = 2, Medium effectiveness = 3, High effectiveness = 4, Higher effectiveness = 5
Technical assistance (TA) is helpful or not	Categorical		No = 0, Yes = 1
Rank of TA	Categorical		Lesser effectiveness = 1, Less effectiveness = 2, Medium effectiveness = 3, High effectiveness = 4, Higher effectiveness = 5
Informal community network (ICN) is helpful or not	Categorical		No = 0, Yes = 1
Rank of ICN	Categorical		Lesser effectiveness = 1, Less effectiveness = 2, Medium effectiveness = 3, High effectiveness = 4, Higher effectiveness = 5
Formal community network (FCN) is helpful or not	Categorical		No = 0, Yes = 1
Rank of FCN	Categorical		Lesser effectiveness = 1, Less effectiveness = 2, Medium effectiveness = 3, High effectiveness = 4, Higher effectiveness = 5
Most helpful adaptation channels for farming decisions	Categorical		No = 0, Yes = 1
Only TK	Categorical		
Only TA	Categorical		
Only ICN	Categorical		
Only FCN	Categorical		
Combination of TK and TA	Categorical		
Combination of TK and ICN	Categorical		
Combination of TK and FCN	Categorical		
Combination of TA and ICN	Categorical		
Combination of TA and FCN	Categorical		
Combination of TK, TA, and ICN	Categorical		

Variables	Type of variable	Unit (if continuous)	Variable code (if categorical)
Combination of TK, TA, and FCN	Categorical		
Combination of TK, TA, ICN, and FCN	Categorical		
Rank of most helpful adaptation channels of farming decisions	Categorical		Lesser effectiveness = 1, Less effectiveness = 2, Medium effectiveness = 3, High effectiveness = 4, Higher effectiveness = 5
Only TK	Categorical		
Only TA	Categorical		
Only ICN	Categorical		
Only FCN	Categorical		
Combination of TK and TA	Categorical		
Combination of TK and ICN	Categorical		
Combination of TK and FCN	Categorical		
Combination of TA and ICN	Categorical		
Combination of TA and FCN	Categorical		
Combination of TK, TA, and ICN	Categorical		
Combination of TK, TA, and FCN	Categorical		
Combination of TK, TA, ICN, and FCN	Categorical		

4. Secondary data estimation results

For deriving answers to our key research questions listed in Section 3.1, both secondary and primary data analyses have been attempted. Utilising secondary data for all the 38 districts in Bihar for the period spanning 1990-2019, we have attempted different panel estimation models to regress rice and wheat yields separately on all the regressors mentioned in the last section (Alternative specifications of production growth rates for both the crops as a dependent variable were also carried out to check for the robustness of our results. These are discussed later in this chapter).

Recall that, for all of the above specifications, the regressors include community networks, climate, and education indices estimated using PCA. Additionally, the extracted values of (unobservable) inherent ability, for which space-state modelling based on Kalman filtering has been used, is also included as an important regressor. We start examining the order in which different models were estimated for rice yields.

4.1. Panel regressions for rice yields

Overview of models estimated for rice yields

At the outset, plotting the time series of rice and wheat yields for individual districts revealed that there is an underlying time trend in both the series for most districts. Thus, the estimations of rice and wheat yields are carried out by considering the time trend variables. The flow of analyses was as follows.

Both FE (district FE) and RE models were estimated including time trend (at level and its square); the Hausman test for both rice and wheat estimations showed that the prob.>chi^2 value is equal to 0.000, which was less than 0.05, so the null H_0: RE over FE, was rejected. Accordingly, FE (with district FE and no time FE) was found to be preferred over RE at 5 per cent level of significance.

The analysis was further extended to check for cross-sectional dependence, heteroscedasticity and autocorrelation problems in the FE model. Friedman's and Pesaran's tests for cross-sectional independence were run, and the presence of contemporaneous correlation was found. Further, a modified Wald test was carried out as a check for group wise heteroscedasticity in the FE regression model, and the presence of heteroscedasticity was not ruled out. Finally, the Woolridge test for serial correlation was run, and the errors were found to be auto correlated. For all these tests, the probability values were found to be less than 0.05, confirming the presence of cross-sectional dependence, heteroscedasticity and autocorrelation. Thus, FGLS and PCSE models were estimated.

Detailed results of tests for heteroscedasticity, autocorrelation, cross-sectional dependence, etc. for rice regression models have been presented in Table 23 in Appendix B.

One more notable exercise was to check the inherent ability variable for its correlation with the residuals for all specifications that have time trend variables, namely, FE, RE, FGLS and PCSE. Here, ability was found to be uncorrelated with the residuals, implying that it is a valid instrument. Recall that inherent ability is the "unobservable" variable that was extracted from the state-space model for rice yields using Kalman filtering. The correlation between inherent ability and residuals of different model specifications are given in Table 24 in Annexure B.

A summary of the key results for the select models for rice yields regressions are given below (

Table 10). Here, a comparison of pooled, fixed effects (district FE alone and district and time FE together), RE, FGLS and PCSE regression estimates in the individual columns have been presented. The model results in Columns 1, 2, 4, 5, and 6incorporate the time trend as well as its square term as regressors, whereas those in Column 3do not include time trend since time-FE (TFE) include time as FE (by specification), thus obviating the need to repeat time trends in the regression equation.

Table 10: Summary of panel regressions for rice yields using different panel estimation models

Regressors	Pooled	FE (District FE)	FE (District + Time FE)	RE	FGLS	PCSE
	Col. (1)	Col. (2)	Col. (3)	Col. (4)	Col. (5)	Col. (6)
Irrigated Area	.9201808***	.6055852***	.3635372**	.814458***	.8198316***	.8291788***
	(12.78)	(4.44)	(2.96)	(8.42)	(25.03)	(7.88)
Ground Water Depth	-.0363354**	-.0664657***	-.0298003*	-.0456266**	-.0402197***	-.042906*
	(-2.35)	(-3.84)	(-1.88)	(-2.72)	(-9.85)	(-1.96)
Cultivated Area Under HYV	-.3751714***	-.8539477***	-.6036259***	-.7160966***	-.4625536***	-.4900429***
	(-3.92)	(-7.92)	(-6.36)	(-7.06)	(-13.36)	(-3.34)
Pump Sets	-7.44e-06***	.0000109*	.0000115**	-4.99e-06*	-4.35e-06**	-5.65e-06*
	(-3.34)	(1.98)	(2.41)	(-1.55)	(-2.55)	(-1.98)
Tractors	.0000468**	-.0000936**	-.0000997***	.0000141	.0000206*	.0000366*
	(2.97)	(-2.66)	(-3.29)	(0.62)	(1.57)	(1.62)
Power Tillers	.0000168	-.0000649	-.0000679	.0000695	-4.77e-07	-9.36e-07
	(0.29)	(-0.75)	(-0.91)	(0.99)	(-0.01)	(-0.01)
NPK Usage	8.20e-07	2.85e-06*	-1.07e-06	2.08e-06	2.71e-06***	3.41e-06*
	(0.61)	(1.67)	(-0.68)	(1.32)	(4.55)	(1.48)
Soil Quality Index (SQI)	-1.17878***	-3.078408***	-2.904921***	-1.750523***	-.9178221***	-1.055092**
	(-3.16)	(-4.97)	(-5.45)	(-3.37)	(-3.65)	(-2.08)
Main Agricultural Labour	-8.93e-07***	-8.26e-07**	-4.57e-07	-1.29e-06***	-8.62e-07***	-1.02e-06***
	(-4.24)	(-2.01)	(-1.29)	(-4.68)	(-6.86)	(-3.21)
Household Size	.1755074***	-.1694697*	-.1629917**	.1988561***	.2289904***	.2209191***
	(3.98)	(-1.95)	(-2.16)	(3.36)	(6.34)	(3.58)
Sex Ratio	-.0004453	-.0080952***	-.0074753***	-.0029552**	-.0005237	-.0007593
	(-0.57)	(-4.41)	(-4.68)	(-2.66)	(-0.88)	(-0.55)
Literacy Rate	-.0099198	-.0327009***	-.0283732***	-.0275281***	-.0038441	-.0007971
	(-1.32)	(-3.28)	(-3.26)	(-3.40)	(-1.03)	(-0.07)
Education Index	.8150408***	1.418244***	1.191741***	1.035664***	.4110923**	.508144
	(3.09)	(3.63)	(3.49)	(3.51)	(2.99)	(1.21)
Climate Index	1.065851***	1.567198***	1.395353	1.18777***	.6580686***	.5364168
	(4.10)	(4.81)	(4.50)	(4.03)	(5.01)	(1.13)
Avg. Annual Temperature	4.73438***	5.455872***	6.033238***	4.924747***	4.773653***	4.281417**
	(3.82)	(4.13)	(5.13)	(3.99)	(8.31)	(2.25)
Avg. Annual Temperature Squared	-.0955561***	-.1101375***	-.1211018***	-.0997407***	-.096603***	-.0869989**
	(-3.99)	(-4.29)	(-5.30)	(-4.18)	(-8.68)	(-2.35)
Avg. Annual Rainy Days	.1724728*	.3551972***	.1912009**	.2811397**	.4065267***	.4030259***
	(1.61)	(3.64)	(2.10)	(2.80)	(17.75)	(3.49)
Avg. Annual Rainy Days Squared	-.0019645	-.0195719*	-.0160101*	-.011957	-.0282345***	-.0267182**
	(-0.15)	(-1.65)	(-1.46)	(-0.98)	(-10.37)	(-2.00)
Avg. Monsoon Rainfall	.002441***	.001824**	.0020042***	.0019529**	.00235***	.0025245***
	(3.20)	(2.68)	(3.22)	(2.77)	(15.80)	(3.01)
Avg. Monsoon Rainfall Squared	-3.57e-06***	-3.30e-06***	-2.99e-06***	-3.29e-06**	-3.92e-06***	-4.08e-06***
	(-3.00)	(-3.12)	(-3.13)	(-2.99)	(-17.77)	(-3.29)
Annual Frequency of Highest Maximum Temperature (HMAX)	-.0031668***	-.0027138*	-.0018267*	-.0052263***	-.0036748***	-.0042484**
	(-3.02)	(-1.95)	(-1.51)	(-4.28)	(-7.34)	(-2.79)
Annual Frequency of Lowest Minimum Temperature (LMIN)	.0046234***	.0049042**	.0048761***	.007151***	.0072369***	.0072979***
	(3.06)	(2.76)	(3.14)	(4.41)	(8.75)	(3.04)
Annual Frequency of Heaviest Rainfall in Last 24 Hours (HVYRF)	-.0039567***	-.0035041***	-.0011275*	-.0044743***	-.0031089***	-.0030029**
	(-5.17)	(-4.18)	(-1.46)	(-5.53)	(-9.02)	(-2.23)
Community Network Index (CNI)	6.574617***	6.435696***	5.534437***	3.946501**	5.421213***	6.237156**
	(3.88)	(3.37)	(3.27)	(2.25)	(8.12)	(2.53)
Inherent Ability (IA) (Extracted from Kalman Filtering)	-.0914182	-.0119686	.0891327	-.0692829	-.0429565*	-.0365633
	(-0.67)	(-0.10)	(0.83)	(-0.55)	(-1.60)	(-0.27)

Regressors	Pooled	FE (District FE)	FE (District + Time FE)	RE	FGLS	PCSE
	Col. (1)	Col. (2)	Col. (3)	Col. (4)	Col. (5)	Col. (6)
Adaptation Variable 1 (CNI * IA)	-3.037641***	-3.178993***	-3.393589***	-2.899497***	-2.225362***	-2.262593**
	(-3.55)	(-4.26)	(-5.15)	(-3.73)	(-13.33)	(-2.95)
Adaptation Variable 2 (IA * Literacy Rate)	.0271658***	.0271027***	.0218448***	.0267388***	.0216128***	.0218859***
	(7.12)	(8.16)	(7.30)	(7.71)	(26.84)	(5.43)
Adaptation Variable 3 (CNI * Literacy Rate)	-.0582557**	-.0524562**	-.0395851*	-.0162943	-.046941***	-.0598966*
	(-2.67)	(-2.12)	(-1.74)	(-0.72)	(-4.46)	(-1.58)
Time Trend	-.0444328***	.0073494	NA	.0006297	-.0250404**	-.0324058
	(-3.05)	(0.40)		(0.04)	(-2.44)	(-1.05)
Time Trend Squared	.0027758***	.002108***	NA	.0020449***	.0021601***	.0023524**
	(8.20)	(6.20)		(6.08)	(7.81)	(2.70)
Constant	-59.93241***	-58.93848***	-66.62334***	-59.13089***	-60.91449***	-54.37983**
	(-3.73)	(-3.55)	(-4.49)	(-3.72)	(-8.14)	(-2.22)
Year Dummy			x			
Overall Model Significance	1%	1%	1%	1%	1%	1%

Figures in parentheses refer to the value of the t-statistic
Coefficients in '***', '**', '*' are statistically significant at 1%, 5%, and 10% level respectively.

Signs and significance of coefficients for rice yields – with special focus on the role of community networks and inherent ability

It is interesting to note that the signs and statistical significance of the coefficients estimated for most regressors are found to be plausible or intuitive. For instance, the coefficient of proportion of area irrigated is found to be positive for all the models, implying that as the share of cultivable land area that is under some form of irrigation (surface or groundwater) rises, rice yields are enhanced. It is also found to be statistically significant for almost all the regressions. Additionally, it is plausible that with rice being a water-intensive crop, groundwater depth (associated with depleting water tables and scarcity of groundwater resources), entails a negative and significant effect for rice yields across all the models.

Contrary to common belief, the adoption of HYV seeds in Bihar has not boosted rice yields, and the coefficient is found to be mostly negative and significant for almost all the models. Even though the Bihar government has provided subsidised HYV rice seeds to the farming communities, these have not translated into significant gains for farmers. Due to lack of awareness and adaptability, its diffusion has been low, leaving Bihar farmers to use a mix of HYV, hybrid, and traditional varieties for sowing rice. Among items of agricultural machinery, the use of tractors (in most cases) increase rice yields and that of power tiller declines rice yields in almost all the regressions, with varying degrees of statistical significance. In particular, the FGLS and PCSE estimates are found to be statistically significant and positive for usage of tractors on rice yields. Higher usage of pump sets is indicative of greater reliance on underground water for irrigation, and this is usually associated with lower rice yields, and the coefficients are also found to be statistically significant in most such cases. The exceptions in this case are the FE models (with only district fixed effect and with district and time fixed effect) that exhibit a positive sign of the coefficient, indicating that higher usage of pump sets supports higher rice yields. The usage of NPK fertilisers is found to have a positive effect on rice yields along with the negative and significant impact of soil quality index (SQI). The effect of NPK is found to be significant for the FE (with district FE), FGLS and PCSE models. Controlling for other variables, rice yields are found to be especially sensitive to this input. Finally, with a rise in the number of main agricultural workers, there is a statistically significant fall in agricultural yields for most specifications. This could be attributed to the pressure of too many labourers on limited land resources, depressing the marginal productivity of the agricultural labour force.[13]

In the case of demographic characteristics, household size positively influences yields in general, and all the positive coefficients are also statistically significant. This supports the fact that larger families

[13] Note that the dependent variable is yields and not aggregate output.

have greater stakes in agriculture, and this helps improve yields. A higher sex ratio (female to male proportion) is found to affect rice yields negatively across all models. This is found to be statistically significant in the case of panel regressions, but not significant for FGLS and PCSE cases. Relative to some other crops, rice cultivation is a more labour-intensive operation, and with the number of men in farming communities migrating to urban areas to seek alternative income opportunities, women's labour has been fulfilling the labour demand-supply gap in rice production. While evidence elsewhere might have supported that women's participation in rice cultivation has resulted in higher land productivity and improved technical efficiency, in the case of Bihar, this is not borne out by the secondary dataset for rice yields. Literacy rate has an ambiguous impact on rice yields –it has a negative and significant impact on rice productivity. But this is found to be statistically insignificant in the case of FGLS and PCSE. This is understandable, as higher literacy rates might be associated with out-migration of the farming population to non-agricultural or professional occupations in rural or urban areas, which might work toward less focus on agricultural activities. Interestingly, however, across all models, the education index has a positive influence on farm productivity. Higher education (across all levels) causes higher yields, and this is statistically significant for all the specifications, as one would expect.

As for the effect of climate variables, higher values of the climate index, which capture the influence of factors other than temperature and rainfall (that is, wind speed, cloud cover, evapotranspiration, and diurnal temperature range) cause rise of rice yields, as one would expect, across all specifications. These are also found to be statistically significant. More importantly, higher average annual temperature and rainfall levels tend to boost rice productivity and both these variables display threshold effects evident from the negative signs of the squared values of these two variables. That is, there exists a non-monotonic relationship between rice yields and average temperature and average monsoon rainfall. Up to the threshold level, both promote productivity, but beyond it, yields fall for the rice crop. These results tie in well with those of studies done by the IPCC and World Bank on this subject. The remaining climate variable, namely, average annual rainy days (and its squared value) mostly display a positive influence on rice productivity, although some threshold effects (with negative signs for the squared terms) can be seen for the annual rainy days. Thus, as one would expect, a higher number of rainy days are not conducive for rice yields beyond a threshold level.

The impact of extreme weather events on crop yields are also prominent. As the number of days with highest maximum temperature (HMAX) increases, rice yields decline for all the specifications. However, the number of days with lowest minimum temperature (LMIN) has a positive effect on rice yields. While a higher number of days with heavy rainfall in the last 24 hours (HVYRF) has significant negative effects on both rice yields across all specifications. Notably, all these impacts of extreme climate events on rice yields are statistically significant for most of the specifications.

Given the focus of the research, some very interesting results on the role of community networks and inherent ability (or traditional knowledge/learning-by-doing) channels of agricultural adaptation have been derived. It is evident that the community network index (CNI) has a positive and statistically significant influence on rice yields in Bihar, while inherent ability (IA) influence rice productivity negatively though statistically insignificant. Thus, between the twin channels – community networks– allow rice farmers to adapt agricultural productivity in the face of climate change and weather shocks, but inherent ability has an opposite impact though statistically insignificant for most of the model specifications. This is the direct influence of these two channels. When, in fact, the two variables are interacted, that is, CNI*IA, it is found that the coefficient has a negative sign and is mostly statistically significant for all the models. This points to the fact that the two channels of community networks and ability (traditional knowledge/ learning-by-doing) tend to substitute for each other. Furthermore, on the one hand, the interaction of inherent ability with literacy rate, or, IA*Literacy Rate, has a positive influence on rice yields, implying that higher literacy rate makes ability more effective in boosting rice yields, or, the two complement each other. On the other hand, the interaction of community network index with literacy rate, that is, CNI*Literacy Rate, yields the opposite result. This implies that community network index and literacy rate substitute for each other, meaning that a higher literacy level tends to weaken the positive effect of community networks on rice yields, as social and local ties may loosen with farming communities attaining higher literacy levels, often with out-migration, and transition to nuclear families and urbanisation. These are important sociological implications of the analysis.

Finally, the inclusion of the time trend variable (that captures a range of exogenous influences relating to changes in governance, institutional mechanisms, policies, political regimes, and technology) point towards reducing overall rice yields, although a positive coefficient of the time trend squared variable displays threshold effects, which implies that yields tend to rise after a phase of downward movement.

On overall, all the models are statistically significant at 1 per cent level of, implying that the models provide an overall good fit to the underlying data. Some robustness tests for alternative model estimates are now presented.

Robustness checks for rice crop regressions

The signs and significance of the coefficients worked out for different models is now compared for a robustness check by extending the analysis to include growth of rice production as an alternate dependent variable. It must be borne in mind that we feel that yields are a more precise indicator of long-run productivity change in agriculture than the rate of growth of production. This is because yields have been normalised by area cultivated, which is limited, and this imposes a binding constraint on yields.

The summary of all these outcomes is presented below (Table 11). Notably, although the signs and significance of all the regression models in the table are presented, the focus of the discussion will be on Columns (7) to (10), since FGLS and PCSE estimates are the ones that have finally been identified as most accurate for the secondary data set.

Table 11: Robustness checks for rice crop

Regressors	Rice Yields						Rice Production		Remarks based on Col. (5) & (7)
	Pooled	FE (District FE)	FE (District + Time FE)	RE	PCSE	PCSE (Time FE)	PCSE	PCSE (Time FE)	
	Col. (1)	Col. (2)	Col. (3)	Col. (4)	Col. (5)	Col. (6)	Col. (7)	Col. (8)	Col. (9)
Irrigated Area	.9201808***	.6055852***	.3635372**	.814458***	.8291788***	.6852649***	93080.5***	88158.87***	+
	(12.78)	(4.44)	(2.96)	(8.42)	(7.88)	(7.67)	(5.84)	(5.74)	
Ground Water Depth	-.0363354**	-.0664657***	-.0298003*	-.0456266**	-.042906*	-.0190226	-6562.876**	-4982.77*	-
	(-2.35)	(-3.84)	(-1.88)	(-2.72)	(-1.96)	(-1.10)	(-2.41)	(-1.90)	
Cultivated Area Under HYV	-.3751714***	-.8539477***	-.6036259***	-.7160966***	-.4900429***	-.2098979*	-132371.2***	-105542.5***	-
	(-3.92)	(-7.92)	(-6.36)	(-7.06)	(-3.34)	(-1.60)	(-7.05)	(-5.58)	
Pump Sets	-7.44e-06***	.0000109*	.0000115**	-4.99e-06*	-5.65e-06*	-5.80e-06**	-.24309	-.1585957	-
	(-3.34)	(1.98)	(2.41)	(-1.55)	(-1.98)	(-2.22)	(-0.41)	(-0.27)	
Tractors	.0000468**	-.0000936**	-.0000997***	.0000141	.0000366*	.0000307	33.66392***	33.83261***	+
	(2.97)	(-2.66)	(-3.29)	(0.62)	(1.62)	(1.44)	(7.44)	(7.82)	
Power Tillers	.0000168	-.0000649	-.0000679	.0000695	-9.36e-07	.0000117	-8.093709	-10.35276	-
	(0.29)	(-0.75)	(-0.91)	(0.99)	(-0.01)	(0.15)	(-0.44)	(-0.58)	
NPK Usage	8.20e-07	2.85e-06*	-1.07e-06	2.08e-06	3.41e-06*	-7.06e-07	1.171829***	.8573473**	+
	(0.61)	(1.67)	(-0.68)	(1.32)	(1.48)	(-0.43)	(3.35)	(2.81)	
Soil Quality Index (SQI)	-1.17878***	-3.078408***	-2.904921***	-1.750523***	-1.055092**	-1.217053**	-183117**	-202982.4***	-

Regressors	Rice Yields						Rice Production		Remarks based on Col. (5) & (7)
	Pooled	FE (District FE)	FE (District + Time FE)	RE	PCSE	PCSE (Time FE)	PCSE	PCSE (Time FE)	
	Col. (1)	Col. (2)	Col. (3)	Col. (4)	Col. (5)	Col. (6)	Col. (7)	Col. (8)	Col. (9)
	(-3.16)	(-4.97)	(-5.45)	(-3.37)	(-2.08)	(-2.42)	(-2.82)	(-3.19)	
Main Agricultural Labour	-8.93e-07***	-8.26e-07**	-4.57e-07	-1.29e-06***	-1.02e-06***	-4.38e-07*	.1262579**	.1720638***	+/-
	(-4.24)	(-2.01)	(-1.29)	(-4.68)	(-3.21)	(-1.70)	(2.07)	(3.06)	
Household Size	.1755074***	-.1694697*	-.1629917**	.1988561***	.2209191***	.163834**	40866.47***	32842.2***	+
	(3.98)	(-1.95)	(-2.16)	(3.36)	(3.58)	(2.97)	(4.28)	(3.59)	
Sex Ratio	-.0004453	-.0080952***	-.0074753***	-.0029552**	-.0007593	-.0006171	-220.8989	-210.2279	-
	(-0.57)	(-4.41)	(-4.68)	(-2.66)	(-0.55)	(-0.54)	(-1.16)	(-1.25)	
Literacy Rate	-.0099198	-.0327009***	-.0283732***	-.0275281***	-.0007971	-.00001	2325.381	2759.051*	+/-
	(-1.32)	(-3.28)	(-3.26)	(-3.40)	(-0.07)	(-0.00)	(1.28)	(1.66)	
Education Index	.8150408***	1.418244***	1.191741***	1.035664***	.508144	.356107	-41696	-54590.28	+/-
	(3.09)	(3.63)	(3.49)	(3.51)	(1.21)	(1.06)	(-0.65)	(-0.89)	
Climate Index	1.065851***	1.567198***	1.395353	1.18777***	.5364168	.8545807**	12048.36	61748.08	+
	(4.10)	(4.81)	(4.50)	(4.03)	(1.13)	(2.29)	(0.21)	(1.11)	
Avg. Annual Temperature	4.73438***	5.455872***	6.033238***	4.924747***	4.281417**	4.888781**	375369.3**	284950.8*	+
	(3.82)	(4.13)	(5.13)	(3.99)	(2.25)	(2.90)	(2.25)	(1.58)	
Avg. Annual Temperature Squared	-.0955561***	-.1101375***	-.1211018***	-.0997407***	-.0869989**	-.0991987***	-7634.979**	-5905.97*	-
	(-3.99)	(-4.29)	(-5.30)	(-4.18)	(-2.35)	(-3.02)	(-2.34)	(-1.67)	
Avg. Annual Rainy Days	.1724728*	.3551972***	.1912009**	.2811397**	.4030259***	.1698001*	30224.17**	7959.411	+
	(1.61)	(3.64)	(2.10)	(2.80)	(3.49)	(1.77)	(2.48)	(0.65)	
Avg. Annual Rainy Days Squared	-.0019645	-.0195719*	-.0160101*	-.011957	-.0267182**	-.0119427	-1656.062	-229.4101	-
	(-0.15)	(-1.65)	(-1.46)	(-0.98)	(-2.00)	(-1.06)	(-1.20)	(-0.17)	
Avg. Monsoon Rainfall	.002441***	.001824**	.0020042***	.0019529**	.0025245***	.001656**	338.8254***	266.0876**	+
	(3.20)	(2.68)	(3.22)	(2.77)	(3.01)	(2.38)	(3.63)	(2.82)	
Avg. Monsoon Rainfall Squared	-3.57e-06***	-3.30e-06***	-2.99e-06***	-3.29e-06**	-4.08e-06***	-2.50e-06**	-.5453409***	-.4011566**	-
	(-3.00)	(-3.12)	(-3.13)	(-2.99)	(-3.29)	(-2.32)	(-3.63)	(-2.69)	
HMAX	-.0031668***	-.0027138*	-.0018267*	-.0052263***	-.0042484**	-.0030241**	-697.1149***	-638.0077***	-
	(-3.02)	(-1.95)	(-1.51)	(-4.28)	(-2.79)	(-2.33)	(-3.38)	(-3.16)	
LMIN	.0046234***	.0049042**	.0048761***	.007151***	.0072979***	.0067965***	1599.819***	1613.654***	+
	(3.06)	(2.76)	(3.14)	(4.41)	(3.04)	(3.23)	(4.10)	(4.17)	
HVYRF	-.0039567***	-.0035041***	-.0011275*	-.0044743***	-.0030029**	-.0016942*	-588.879***	-533.8104***	-
	(-5.17)	(-4.18)	(-1.46)	(-5.53)	(-2.23)	(-1.60)	(-3.86)	(-3.48)	
Community Network Index (CNI)	6.574617***	6.435696***	5.534437***	3.946501**	6.237156**	4.571638**	470658.3	424115.4	+

Regressors	Rice Yields						Rice Production		Remarks based on Col. (5) & (7)
	Pooled	FE (District FE)	FE (District + Time FE)	RE	PCSE	PCSE (Time FE)	PCSE	PCSE (Time FE)	
	Col. (1)	Col. (2)	Col. (3)	Col. (4)	Col. (5)	Col. (6)	Col. (7)	Col. (8)	Col. (9)
	(3.88)	(3.37)	(3.27)	(2.25)	(2.53)	(2.35)	(1.31)	(1.35)	
Inherent Ability (IA) (Extracted from Kalman Filtering)	-.0914182	-.0119686	.0891327	-.0692829	-.0365633	-.0315796	-431.8175	-1306.542	-
	(-0.67)	(-0.10)	(0.83)	(-0.55)	(-0.27)	(-0.30)	(-0.03)	(-0.09)	
Adaptation Variable 1 (CNI * IA)	-3.037641 ***	-3.178993 ***	-3.393589 ***	-2.899497 ***	-2.262593 **	-2.355548 ***	-49983.43	-37099.98	-
	(-3.55)	(-4.26)	(-5.15)	(-3.73)	(-2.95)	(-3.46)	(-0.59)	(-0.45)	
Adaptation Variable 2 (IA * Literacy Rate)	.0271658 ***	.0271027 ***	.0218448 ***	.0267388 ***	.0218859 ***	.0189028	983.6495 **	699.2737 *	+
	(7.12)	(8.16)	(7.30)	(7.71)	(5.43)	(5.91)	(2.54)	(1.83)	
Adaptation Variable 3 (CNI * Literacy Rate)	-.0582557 **	-.0524562 **	-.0395851 *	-.0162943	-.0598966 *	-.033708	-7844.023	-7819.781 *	-
	(-2.67)	(-2.12)	(-1.74)	(-0.72)	(-1.58)	(-1.17)	(-1.33)	(-1.47)	
Time Trend	-.0444328 ***	.0073494	NA	.0006297	-.0324058		-7776.444 *	-3487769 *	-
	(-3.05)	(0.40)		(0.04)	(-1.05)		(-1.98)	(-1.51)	
Time Trend Squared	.0027758 ***	.002108***	NA	.0020449 ***	.0023524 **		166.3703 *		+
	(8.20)	(6.20)		(6.08)	(2.70)		(1.79)		
Constant	-59.93241 ***	-58.93848 ***	-66.62334 ***	-59.13089 ***	-54.37983 **	-60.98507 **	-4746853 **		-
	(-3.73)	(-3.55)	(-4.49)	(-3.72)	(-2.22)	(-2.81)	(-2.23)		
Year Dummy			x			x		x	
Overall Model Significance	1%	1%	1%	1%	1%	1%	1%	1%	

Figures in parentheses refer to the value of the t-statistic
Coefficients in '***', '**', '*' are statistically significant at 1%, 5%, and 10% level respectively.

Here, for the purpose of comparison, Columns (5) and (6) use rice yields as the dependent variable and Columns (7) and (8) use growth of rice production as the alternative dependent variable. As can be seen, among the basic resources and technology variables, the sign of the coefficients of proportion of area irrigated and use of power tillers is positive, implying both increase rice yields and growth of rice production. Similarly, the influence of ground water depth, area under HYV technology and pump sets is toward reducing both – rice yields and growth of rice output – across all the regressions. The usage of tractors boosts rice yields and is statistically significant.

Among other consumable inputs, the use of NPK fertilisers bolsters growth of rice production as well as rice yields. While the soil quality index, in general, tends to have a declining impact on rice yields as well as production growth. Agricultural labour input displays negative marginal productivity for rice yields and positive one for rice production growth.

Next, household/family size and sex ratio (female/ male population) have a positive and negative effect respectively, and uniformly on both rice yields and growth rate of rice output. While the overall literacy rate lowers rice yields, it tends to increase the growth rate of output. In comparison, the education index is found to increase rice yields and lower production growth rates.

Higher values of the climate index (comprising of variables other than temperature and rainfall) tend to improve yields and production growth alike. Further, the effect of temperature (average annual levels and its squared term) rainfall (average monsoon levels and its squared term) and rainy days (average annual days, and its squared value) are mostly found to be qualitatively similar on rice yields and growth rates of rice production. The variables pertaining to extreme weather events, such as annual frequency of highest maximum temperature (HMAX) and annual frequency of heaviest rainfall in last 24 hours (HVYRF) have similar negative effects on rice yield and production growth, while the effect of annual frequency of lowest minimum temperature (LMIN) is positive for both rice yield and production growth.

One of the adaptation channels, namely, community/ social networks (CNI), always improve rice yields and rice production growth rates. While inherent ability (IA), embodying traditional knowledge and learning-by-doing effects, tends to dampen both rice yields and production growth, though the effects are statistically insignificant. Again, similar to earlier results, CNI and IA tend to weaken the effect of each other (that is, they substitute for each other), as captured by the negative sign of the coefficient of their interaction, CNI*IA. Interestingly, however, while literacy rate bolsters or reinforces (complements) the positive effect of IA on rice yields. The opposite is true for its effect on CNI. Higher literacy rates tend to substitute for the CNI channel in terms of the influence on rice yields as well as its production growth.

The overall specification provides a good fit, as all the different models are overall significant at 1% level of significance. Besides, most of the key results are consistent, or else, when they are different, the outcomes can be plausibly explained or rationalised. The other general takeaway from the robustness checks is that for most regressors, the sign of the coefficient is similar.

4.2. Panel regressions for wheat yields

Overview of models estimated for wheat yields

As in the case for rice yields, there is a time trend in the data series on wheat for most districts of Bihar over 1990-2019. Thus, for the purpose of estimations, models with the time trend variables have been used. The set of models estimated for wheat yields is also similar to that for rice yields.

The analyses begin with estimating pooled regressions with time trend. Next both FE (district FE) and FE (district & Time FE), and RE models were estimated, and the Hausman test showed that the prob.>chi^2 value was less than 0.05. This implied rejection of H_0, or preference of FE (with district FE and no time FE) over RE at 5 per cent level of significance.

The analysis was extended to check for the presence of heteroscedasticity, cross-sectional independence, and serial correlation. Like in case of rice yields, Modified Wald test for group-wise heteroscedasticity was carried out and the prob.> chi^2 was found to be less than 0.05, indicating the presence of group-wise heteroscedasticity in the FE model estimation. The Woolridge test for serial correlation was done and, again, the prob. value was found to be less than 0.05, pointing to the presence of first-order autocorrelation. The Friedman's/ Pesaran's test of cross-sectional independence was carried out and, the prob. value was found to be less than 0.05, indicating the presence of contemporaneous correlation. Thus, both FGLS and PCSE models were also run for wheat yields estimations to overcome these problems.

Additionally, all the above models were estimated again with a time trend and its squared value included as a regressor for wheat yields. As in the case of the other models for wheat yields, the Hausman test favoured use of FE over RE estimates. Moreover, the Modified Wald test exhibited the presence of group-wise heteroscedasticity, the Woolridge test pointed toward first-order serial correlation, and the Friedman's/ Pesaran's test indicated for presence of cross-sectional dependence, requiring correction through FGLS and PCSE estimates. All these test results are presented in Table 23 in Annexure B.

Another promising result was that when the role of inherent ability for wheat yield estimations with time trend was checked for, wherein ability is the "latent" filtered out variable from the state-space modelling exercise, and it was correlated with the residuals for all the models – FE, RE, FGLS, and PCSE – it was found to be uncorrelated with them in all cases, implying that it is a valid instrument. The correlation between inherent ability and residuals of different model specifications are given in Table 24 in Annexure B.

In what follows immediately, a summary of the key results for select models for wheat yields regressions are tabulated (Table 12). As earlier, a comparison of results for pooled, fixed effects (district FE alone and district and time FE together), RE, FGLS and PCSE regressions is presented in the individual columns. The model results in Columns 1, 2, 4, 5, and 6 include time trend and time trend squared variables as regressors, whereas those in Column 3 does not include time trend since Time-FE already include time as FE, obviating the need to repeat time trends in the regression equation.

Table 12: Summary of panel regressions for wheat yields using different panel estimation models

Regressors	Pooled	FE (District FE)	FE (District + Time FE)	RE	FGLS	PCSE
	Col. (1)	Col. (2)	Col. (3)	Col. (4)	Col. (5)	Col. (6)
Irrigated Area	1.135014***	.8828794***	.8190708***	1.009763***	1.116953***	1.099239***
	(9.30)	(5.05)	(5.03)	(6.45)	(41.87)	(6.87)
Ground Water Depth	.0667415***	.0992563***	.0478291**	.0942947***	.0777335***	.0790101***
	(5.31)	(5.98)	(2.91)	(6.21)	(30.65)	(4.79)
Cultivated Area Under HYV	.1742799*	.026951	.1271253	.0212627	.0730325***	.0704061
	(1.72)	(0.23)	(1.20)	(0.20)	(3.16)	(0.51)
Pump Sets	-5.28e-06**	7.22e-06	7.13e-06	-5.09e-06*	-6.13e-06***	-5.87e-06**
	(-2.62)	(1.33)	(1.42)	(-1.61)	(-6.58)	(-2.27)
Tractors	-4.20e-06	-.0000731**	-.0000711**	-.0000169	-.0000103*	-7.04e-06
	(-0.29)	(-2.13)	(-2.25)	(-0.77)	(-1.70)	(-0.41)
Power Tillers	.0000523	.0000128	-.0000198	.0000603	.0000908***	.0000777
	(0.95)	(0.15)	(-0.26)	(0.89)	(4.36)	(1.14)
NPK Usage	4.27e-06***	5.09e-06***	1.42e-06	5.35e-06***	5.44e-06***	5.56e-06**
	(3.38)	(3.02)	(0.87)	(3.51)	(15.75)	(2.78)
Soil Quality Index (SQI)	-.3079494	-1.204567*	-1.296128**	-.4606878	-.3379089*	-.3018062
	(-0.90)	(-1.94)	(-2.27)	(-0.91)	(-1.54)	(-0.70)
Main Agricultural Labour	-9.98e-07***	-1.25e-06***	-1.18e-06***	-1.42e-06***	-9.08e-07***	-9.34e-07**
	(-5.22)	(-3.09)	(-3.17)	(-5.20)	(-7.24)	(-2.92)
Household Size	.1370264***	-.0886663	-.1186022*	.1026183*	.0931952***	.1112478**
	(3.66)	(-1.03)	(-1.49)	(1.89)	(5.88)	(2.02)
Sex Ratio	-.0028572***	-.000299	-.0001881	-.0020438*	-.0019284***	-.0020009*
	(-4.25)	(-0.16)	(-0.11)	(-1.94)	(-5.67)	(-1.90)
Literacy Rate	-.0122669	-.0157606	-.0064575	-.0169769*	-.0014065	-.0002016
	(-1.29)	(-1.38)	(-0.60)	(-1.71)	(-0.56)	(-0.02)
Education Index	1.193629***	2.478827***	2.6997***	1.862994***	.9743658***	.9669547**
	(5.29)	(6.50)	(7.59)	(6.64)	(11.35)	(2.31)
Climate Index	.1627561	.2269376	-.1234642	.0692276	.4812526***	.4656686
	(0.67)	(0.75)	(-0.41)	(0.25)	(7.13)	(1.20)
Avg. Annual Temperature	-.2235504	-2.351597*	-2.200445*	-1.233986	-.7683208***	-.5954725
	(-0.20)	(-1.81)	(-1.78)	(-1.05)	(-3.14)	(-0.43)
Avg. Annual Temperature Squared	.0067785	.047232*	.0436683*	.0256388	.0165075***	.0130477
	(0.31)	(1.87)	(1.82)	(1.12)	(3.45)	(0.49)
Avg. Annual Rainy Days	.1590209*	.0798168	.1030713	.0960191	.2550477***	.2549196**
	(1.61)	(0.83)	(1.07)	(1.01)	(19.49)	(2.35)
Avg. Annual Rainy Days Squared	-.0103763	.0031365	-.008003	-.0001616	-.0209659***	-.020366*
	(-0.88)	(0.27)	(-0.69)	(-0.01)	(-12.91)	(-1.60)
Avg. Monsoon Rainfall	-.0002899	-.000546	.0003025	-.0005017	.0000922	-.0000609
	(-0.41)	(-0.81)	(0.46)	(-0.74)	(0.91)	(-0.08)
Avg. Monsoon Rainfall Squared	5.95e-07	9.56e-07	-1.25e-07	8.87e-07	1.10e-08	3.24e-07
	(0.54)	(0.91)	(-0.12)	(0.85)	(0.07)	(0.28)
Annual Frequency of Highest Maximum Temperature (HMAX)	-.0001294	-.0003192	-.0004954	-.000984	.0003676*	.0002442
	(-0.13)	(-0.23)	(-0.39)	(-0.83)	(1.46)	(0.20)
Annual Frequency of Lowest Minimum Temperature (LMIN)	-.0009394	-.005283***	-.0045124**	-.0024873*	-.0012653**	-.0016351
	(-0.67)	(-3.02)	(-2.77)	(-1.59)	(-2.86)	(-0.89)
	-.0017594**	-.0017186**	-.0004109	-.0020483**	-.0016575***	-.001814*

Regressors	Pooled	FE (District FE)	FE (District + Time FE)	RE	FGLS	PCSE
	Col. (1)	Col. (2)	Col. (3)	Col. (4)	Col. (5)	Col. (6)
Annual Frequency of Heaviest Rainfall in Last 24 Hours (HVYRF)	(-2.49)	(-2.09)	(-0.50)	(-2.64)	(-9.57)	(-1.74)
Community Network Index (CNI)	4.273466**	6.667857***	6.26325***	5.690747***	3.945909***	4.381562*
	(2.39)	(3.21)	(3.18)	(3.04)	(5.26)	(1.81)
Inherent Ability (IA) (Extracted from Kalman Filtering)	.9379194***	.8708831***	1.022844***	.8864121***	1.197933***	1.215984***
	(3.56)	(3.56)	(4.22)	(3.60)	(31.33)	(3.93)
Adaptation Variable 1 (CNI * IA)	-1.121603	-1.308117	-1.706023*	-1.29687	-.6264582***	-.4985538
	(-0.95)	(-1.20)	(-1.66)	(-1.18)	(-3.93)	(-0.49)
Adaptation Variable 2 (IA * Literacy Rate)	.0187711**	.0210662***	.0126403**	.0207799***	.0105335***	.0098208*
	(2.67)	(3.21)	(2.03)	(3.15)	(11.35)	(1.46)
Adaptation Variable 3 (CNI * Literacy Rate)	-.0487831**	-.0870282***	-.0816637***	-.0688535***	-.0436006***	-.0497647*
	(-2.51)	(-3.58)	(-3.42)	(-3.24)	(-3.92)	(-1.49)
Time Trend	-.0337656**	-.0414799**	NA	-.0282666*	-.0340483***	-.0309737
	(-2.55)	(-2.29)		(-1.81)	(-6.06)	(-1.34)
Time Trend Squared	.0016195***	.0018415***	NA	.0016654***	.001388***	.0012667*
	(5.28)	(5.53)		(5.31)	(8.28)	(1.88)
Constant	1.945866	29.40346*	28.03111*	15.30736	8.09353**	5.816281
	(0.13)	(1.81)	(1.80)	(1.01)	(2.59)	(0.32)
Year Dummy			x			
Overall Model Significance	**1%**	**1%**	**1%**	**1%**	**1%**	**1%**

Figures in parentheses refer to the value of the t-statistic
Coefficients in '***', '**', '*' are statistically significant at 1%, 5%, and 10% level respectively.

Signs and significance of coefficients for wheat yields – with special reference to the role of community networks and inherent ability

Notably, for wheat yields as the dependent variable, the signs and statistical significance of the coefficients worked out for most regressors need closer scrutiny and discussion. The coefficients associated with irrigated area are found to be positive in all estimations. One of the reasons for this could be the greater dependence of wheat cultivation on rainfall in Bihar. Reliance on rain-fed agriculture would also help in explaining the effect of groundwater depth (the level of underground water tables) on wheat yields. The coefficients here are found to be mostly positive and statistically significant.

For agricultural technology and input variables, the following results emerge. As one would expect, the adoption of HYV seeds for wheat is found to enhance yields, and the coefficient is found to be positive but insignificant in almost all the models. In the case of agricultural implements, while the use of tractors is found to have a negative influence on wheat yields, that of power tillers is found to be positive in most of the models. The only exception here is FE estimates (District & Time FE) that display a negative but statistically insignificant sign. Higher usage of pump sets is indicative of greater reliance on groundwater irrigation, and this is found to have a negative association with wheat yields. The level and mix of NPK fertilisers are found to have a positive effect on wheat yields along with a negative effect of soil quality index (SQI)for all the model specifications. As for the input of main agricultural workers, as in the case of rice yields, there is a fall in agricultural yields uniformly for all specifications. The negative sign may be ascribed to increasing pressure on limited cultivable land, causing negative marginal labour productivity in the case of wheat yields.

Among the demographic characteristics, household size is found to generally positively impact wheat yields, except for FE regressions. Thus, a larger family size helps improve wheat yields. As in the case of rice yields, a higher female to male population proportion is found to have a negative influence on wheat yields across all models and is also found to be statistically significant for FGLS and PCSE models. The reasons may be similar to those for the rice crop. As men from farming households out-migrate to urban areas to alternative occupations, women's labour has been filling in. In the case of Bihar, this has seemingly not worked in favour of enhancing wheat yields. –While literacy rate is found to generally have a negative impact on wheat yields though insignificant, education index is found to have a positive and significant impact on wheat yields for all model specifications. The negative effect of literacy rate is understandable, as higher literacy rate might be driving out erstwhile farming population to non-farming activities as well as out-migration, leading to a lower focus on agricultural productivity, and greater reliance on hired labour, beset with incentive problems.

Next, among the climate variables, it is found that higher values of climate index (reflective of the influence of wind speed, cloud cover, evapotranspiration, and diurnal temperature range) cause an increase in wheat yields uniformly across most of the model specifications, although all are found to have very poor statistical significance. The influence of temperature regimes is similar to that for rice yields. A higher average annual temperature tends to dampen wheat productivity, even though the statistical significance is very weak. Moreover, when average annual temperature squared is also included as a separate regressor, the threshold effects are evident, in that there is a positive sign estimated for the coefficient of this variable. That is, there exists a non-linear relationship between wheat yields and average temperature. Up to a certain level, higher temperatures declines wheat productivity, but beyond it, yields begin to boost for the wheat crop. This is exactly opposite to the results for rice crop. However, the difference in the effects of increase in annual temperature is understandable, as the two crops are cultivated in varied seasons, rice is a kharif (summer) crop and wheat is a rabi (winter) crop. Given that wheat is a less water-intensive crop, higher average monsoon rainfall levels are found to lower yields, and the square of this variable is also found to have a positive effect. The coefficients across all models for all these four regressors are found to be mostly statistically insignificant. The remaining climate variable, namely, average annual rainy days (and its squared value), display a positive influence on wheat productivity, although some threshold effects (with negative signs for the squared terms for all the models for all these variables) are observable. Thus, beyond a certain limit, a greater level of monsoon rains is beneficial, but higher number of rainy days is not beneficial for wheat yields. However, most of these results are found to be statistically insignificant.

As similar to the rice yields, a higher number of days with heavy rainfall in the last 24 hours (HVYRF) has significant negative effects on wheat yields across all specifications. However, the number of days with lowest minimum temperature (LMIN) has a negative effect on wheat yields. The impact of higher number of days with highest maximum temperature (HMAX) varies across specifications. It has negative effect on wheat yields for pooled, FE, and RE models, while it tends to increase wheat yields for FGLS and PCSE models. Notably, all these impacts of extreme climate events on wheat yields are statistically significant for most of the specifications, except HMAX.

What occupies centre-stage in the analysis is how community networks and inherent ability (learning-by-doing/ ancestral knowledge) help farmers adapt agriculture to climate change. From the signs of the coefficients, it can be seen that the twin channels of autonomous adaptation – community/ social networks index (CNI) and inherent ability (IA) – both has a positive influence on wheat yields in Bihar districts. Both these effects are found to be statistically significant across all estimations. In addition to these direct effects, an attempt has been made to capture how these interact with each other and, individually, with the literacy rate. As in the case of rice yields, it has been found that the coefficient of CNI*IA has a negative sign and is statistically insignificant in all cases. The negative sign implies that the two channels of community networks and ability (traditional knowledge or learning-by-doing) tend to offset or weaken each other in terms of their impact on wheat yields. Furthermore, in conformity with the results for rice yields, the interaction of inherent ability with literacy rate, or, IA*Literacy Rate, generates a positive reinforcing effect on wheat yields, implying that the two complement each other in boosting yields. Contrary to this, the interactive term of community network index and literacy rate, that is, CNI*Literacy Rate, yields a negative sign, which says that community network index and literacy rate tend to substitute for each other, or, a higher literacy weakens the positive effect of community networks on wheat yields. This could be due to social and local ties waning as members of farmer households attain higher literacy levels. These are interesting sociological takeaways from the research, also found in case of rice yields estimates.

Lastly, the incorporation of the time trend (that reflects the influence of a gamut of exogenous factors such as governance, institutions, policy regimes, political systems, and technology) indicate declining yields over time. However, the positive coefficient of the time trend squared variable indicates threshold effects, which implies that yields tend to fall at first and then rise after a period of time.

On overall, all the models are statistically significant at 1 per cent level of, implying that the models provide an overall good fit to the underlying data. The results of some robustness checks for alternative models are discussed next.

Robustness checks for wheat crop regressions

As for the rice crop, robustness checks have been carried out for wheat yields regressions by comparing the signs and significance of the coefficients worked out for different models. The analysis is again extended to include the growth rate of wheat production as an alternate dependent variable. We reiterate the fact that, even though we consider the case of an alternative regressand, we believe that yields are a more accurate measure of long-run productivity change in agriculture than the rate of growth of production for reasons discussed earlier.

The review of all the regression outcomes is tabulated below (

Table 13). The focus of discussion on the signs and significance will be on Columns (5) to (8) as PCSE regression method is the ones that are recognised as most accurate for secondary data estimations.

Table 13: Robustness check for wheat crop

Regressors	Wheat Yields						Wheat Production		Remarks based on Col. (5) & (7)
	Pooled	FE (District FE)	FE (District + Time FE)	RE	PCSE	PCSE (Time FE)	PCSE	PCSE (Time FE)	
	Col. (1)	Col. (2)	Col. (3)	Col. (4)	Col. (5)	Col. (6)	Col. (7)	Col. (8)	Col. (9)
Irrigated Area	1.135014 ***	.8828794 ***	.8190708 ***	1.009763 ***	1.099239	1.015186 ***	54956.41 ***	58377.28 ***	+
	(9.30)	(5.05)	(5.03)	(6.45)	(6.87)	(6.71)	(4.28)	(4.60)	
Ground Water Depth	.0667415 ***	.0992563 ***	.0478291 **	.0942947 ***	.0790101	.0443828 ***	2356.625 *	-418.4086	+
	(5.31)	(5.98)	(2.91)	(6.21)	(4.79)	(3.31)	(1.74)	(-0.34)	
Cultivated Area Under HYV	.1742799 *	.026951	.1271253	.0212627	.0704061	.097576	-97229.27 ***	-93325.58 ***	+/-
	(1.72)	(0.23)	(1.20)	(0.20)	(0.51)	(0.74)	(-8.04)	(-7.79)	
Pump Sets	-5.28e-06**	7.22e-06	7.13e-06	-5.09e-06*	-5.87e-06	-6.63e-06**	-2.242533 ***	-2.252734 ***	-
	(-2.62)	(1.33)	(1.42)	(-1.61)	(-2.27)	(-2.76)	(-6.61)	(-6.63)	
Tractors	-4.20e-06	-.0000731 **	-.0000711 **	-.0000169	-7.04e-06	-5.71e-06	21.87066 ***	21.89819 ***	+/-
	(-0.29)	(-2.13)	(-2.25)	(-0.77)	(-0.41)	(-0.36)	(6.89)	(7.02)	
Power Tillers	.0000523	.0000128	-.0000198	.0000603	.0000777	.0000723	43.18629 ***	42.03615 ***	+
	(0.95)	(0.15)	(-0.26)	(0.89)	(1.14)	(1.12)	(5.45)	(5.38)	
NPK Usage	4.27e-06***	5.09e-06***	1.42e-06	5.35e-06***	5.56e-06	4.15e-06**	.6214763 ***	.5571802 ***	+
	(3.38)	(3.02)	(0.87)	(3.51)	(2.78)	(2.50)	(3.17)	(3.40)	
Soil Quality Index (SQI)	-.3079494	-1.204567 *	-1.296128 **	-.4606878	-.3018062	-.3336286	-27412.4	-25299.96	-

Regressors	Wheat Yields						Wheat Production		Remarks based on Col. (5) & (7)
	Pooled	FE (District FE)	FE (District + Time FE)	RE	PCSE	PCSE (Time FE)	PCSE	PCSE (Time FE)	
	Col. (1)	Col. (2)	Col. (3)	Col. (4)	Col. (5)	Col. (6)	Col. (7)	Col. (8)	Col. (9)
	(-0.90)	(-1.94)	(-2.27)	(-0.91)	(-0.70)	(-0.83)	(-0.76)	(-0.74)	
Main Agricultural Labour	-9.98e-07***	-1.25e-06***	-1.18e-06***	-1.42e-06***	-9.34e-07	-8.27e-07**	.0165109	.0166972	+/-
	(-5.22)	(-3.09)	(-3.17)	(-5.20)	(-2.92)	(-2.89)	(0.47)	(0.51)	
Household Size	.1370264***	-.0886663	-.1186022*	.1026183*	.1112478	.10817**	36098.35***	34522.86***	+
	(3.66)	(-1.03)	(-1.49)	(1.89)	(2.02)	(2.00)	(5.80)	(5.75)	
Sex Ratio	-.0028572***	-.000299	-.0001881	-.0020438*	-.0020009	-.0020938**	150.6587	127.9821	+/-
	(-4.25)	(-0.16)	(-0.11)	(-1.94)	(-1.90)	(-2.16)	(1.40)	(1.21)	
Literacy Rate	-.0122669	-.0157606	-.0064575	-.0169769*	-.0002016	.0028653	511.8197	587.8635	+/-
	(-1.29)	(-1.38)	(-0.60)	(-1.71)	(-0.02)	(0.26)	(0.47)	(0.58)	
Education Index	1.193629***	2.478827***	2.6997***	1.862994***	.9669547	1.20946***	183939.6***	200861.4***	+
	(5.29)	(6.50)	(7.59)	(6.64)	(2.31)	(3.06)	(5.09)	(6.09)	
Climate Index	.1627561	.2269376	-.1234642	.0692276	.4656686	.2782036	21143.51	30878.87	+
	(0.67)	(0.75)	(-0.41)	(0.25)	(1.20)	(0.82)	(0.64)	(1.05)	
Avg. Annual Temperature	-.2235504	-2.351597*	-2.200445*	-1.233986	-.5954725	-.9279498	-68758.45	-83613.01	-
	(-0.20)	(-1.81)	(-1.78)	(-1.05)	(-0.43)	(-0.77)	(-0.68)	(-0.78)	
Avg. Annual Temperature Squared	.0067785	.047232*	.0436683*	.0256388	.0130477	.0191063	1443.236	1680.74	+
	(0.31)	(1.87)	(1.82)	(1.12)	(0.49)	(0.82)	(0.73)	(0.80)	
Avg. Annual Rainy Days	.1590209*	.0798168	.1030713	.0960191	.2549196	.1983009**	8746.806	3846.754	+
	(1.61)	(0.83)	(1.07)	(1.01)	(2.35)	(2.20)	(1.10)	(0.51)	
Avg. Annual Rainy Days Squared	-.0103763	.0031365	-.008003	-.0001616	-.020366	-.0220251**	-501.7105	-484.1901	-
	(-0.88)	(0.27)	(-0.69)	(-0.01)	(-1.60)	(-2.05)	(-0.56)	(-0.56)	
Avg. Monsoon Rainfall	-.0002899	-.000546	.0003025	-.0005017	-.0000609	.0007193	23.13187	83.45343*	+/-
	(-0.41)	(-0.81)	(0.46)	(-0.74)	(-0.08)	(1.07)	(0.43)	(1.54)	
Avg. Monsoon Rainfall Squared	5.95e-07	9.56e-07	-1.25e-07	8.87e-07	3.24e-07	-7.20e-07	.0210765	-.0635123	+
	(0.54)	(0.91)	(-0.12)	(0.85)	(0.28)	(-0.68)	(0.25)	(-0.79)	
HMAX	-.0001294	-.0003192	-.0004954	-.000984	.0002442	-.0001425	-34.84264	-37.83147	+/-
	(-0.13)	(-0.23)	(-0.39)	(-0.83)	(0.20)	(-0.13)	(-0.29)	(-0.31)	
LMIN	-.0009394	-.005283***	-.0045124**	-.0024873*	-.0016351	-.0010516	261.5595*	289.9368*	+/-
	(-0.67)	(-3.02)	(-2.77)	(-1.59)	(-0.89)	(-0.60)	(1.48)	(1.69)	
HVYRF	-.0017594**	-.0017186**	-.0004109	-.0020483**	-.001814	-.0007962	-299.068***	-290.3139***	-
	(-2.49)	(-2.09)	(-0.50)	(-2.64)	(-1.74)	(-0.94)	(-3.26)	(-3.25)	
Community Network Index (CNI)	4.273466**	6.667857***	6.26325***	5.690747***	4.381562	3.497007*	234956.8	177567.4	+
	(2.39)	(3.21)	(3.18)	(3.04)	(1.81)	(1.53)	(0.91)	(0.71)	

Regressors	Wheat Yields						Wheat Production		Remarks based on Col. (5) & (7)
	Pooled	FE (District FE)	FE (District + Time FE)	RE	PCSE	PCSE (Time FE)	PCSE	PCSE (Time FE)	
	Col. (1)	Col. (2)	Col. (3)	Col. (4)	Col. (5)	Col. (6)	Col. (7)	Col. (8)	Col. (9)
Inherent Ability (IA) (Extracted from Kalman Filtering)	.9379194 ***	.8708831 ***	1.022844 ***	.8864121 ***	1.215984	1.385813 ***	31657.4*	36052.13 *	+
	(3.56)	(3.56)	(4.22)	(3.60)	(3.93)	(5.34)	(1.58)	(1.94)	
Adaptation Variable 1 (CNI * IA)	-1.121603	-1.308117	-1.706023 *	-1.29687	-.4985538	-1.316521 *	254266.7 **	219647.2 **	+/-
	(-0.95)	(-1.20)	(-1.66)	(-1.18)	(-0.49)	(-1.47)	(2.88)	(2.60)	
Adaptation Variable 2 (IA * Literacy Rate)	.0187711 **	.0210662 ***	.0126403 **	.0207799 ***	.0098208	.0046587	-255.8902	-471.5452	+/-
	(2.67)	(3.21)	(2.03)	(3.15)	(1.46)	(0.78)	(-0.62)	(-1.17)	
Adaptation Variable 3 (CNI * Literacy Rate)	-.0487831 **	-.0870282 ***	-.0816637 ***	-.0688535 ***	-.0497647	-.0347381	-5138.984	-4358.398	-
	(-2.51)	(-3.58)	(-3.42)	(-3.24)	(-1.49)	(-1.11)	(-1.36)	(-1.20)	
Time Trend	-.0337656 **	-.0414799 **	NA	-.0282666 *	-.0309737	NA	-1264.11	NA	-
	(-2.55)	(-2.29)		(-1.81)	(-1.34)		(-0.65)		
Time Trend Squared	.0016195 ***	.0018415 ***	NA	.0016654 ***	.0012667	NA	11.03689	NA	+
	(5.28)	(5.53)		(5.31)	(1.88)		(0.20)		
Constant	1.945866	29.40346 *	28.03111 *	15.30736	5.816281	10.8356	392817.8	664494.4	+
	(0.13)	(1.81)	(1.80)	(1.01)	(0.32)	(0.69)	(0.30)	(0.48)	
Year Dummy			x			x		x	
Overall Model Significance	1%	1%	1%	1%	1%	1%	1%	1%	

Figures in parentheses refer to the value of the t-statistic
Coefficients in '***', '**', '*' are statistically significant at 1%, 5%, and 10% level respectively.

In the above table, Columns (5) and (6) use wheat yields as the dependent variable and Columns (7) and (8) use the rate of growth of wheat production as the alternative dependent variable. Evidently, among the basic resource and technology variables, the sign of the coefficients of the proportion of area irrigated, ground water depth, and use of power tillers is estimated to be positive, implying that all three boost both – wheat yields and rate of growth of wheat output – across most of the models. Contrarily, the influence of pump sets tends to dampen wheat yields. . The proportion of cultivated area under HYV technology and usage of tractors give mixed results. The proportion of cultivated area under HYV technology seemingly boosts wheat yields and this is also statistically significant, while it tends to lower the rate of growth of wheat production. While higher usage of tractors tends to dampen wheat yield, but raises the production growth.

Among other inputs, use of NPK fertiliser usage encourages both wheat yields and growth of production along with the negative impact of soil quality index (SQI). Agricultural labour continues to impede wheat yields, while it tends to improve production growth, although in this case, the coefficients are not statistically significant for production growth models.

Next, household size has a positive effect uniformly on both wheat yields and growth of wheat output, but the sex ratio (female/ male population) has a negative effect only on wheat yields but a positive influence on the growth rate of wheat production while the overall literacy rate lowers wheat yields and growth rate of output. In comparison, the education index is found to always rise wheat yields as well as production growth rates.

As regards climate variables, the impacts are very mixed. Higher values of climate index (comprising variables other than temperature and rainfall) always encourage yields and production growth rates, similar to the rice regressions. Higher average temperature tends to lower both yields and the growth rate of output, while the threshold effects due to its squared term turn it around the other way, that is, these tend to raise yields and the output growth rates. The effect of average monsoon rainfall encourages yields and growth rates of output for wheat specifically in case of PCSE models, but the squared term of rainfall tends to reinforce the negative effect on yield while it offsets the positive one on growth rate of production. A higher number of annual rainy days boosts yields as well as the growth rate of output, while threshold effects caused by its squared term counter these effects.

Among the extreme weather event variables, a higher number of days with heavy rainfall in the last 24 hours (HVYRF) has significant negative effects on wheat yields and production growth rates. A higher number of days with highest maximum temperature (HMAX) has a negative effect on wheat yields and production growth while the impact of the number of days with lowest minimum temperature (LMIN) is mixed. It has negative effect on wheat yields and positive effect on wheat production growth rates.

The twin autonomous adaptation channels of community networks (CNI) and inherent ability (IA) always improves yields and growth rate of output of wheat. All these results are more significant for wheat yields as compared to its production growth rates. Like all our earlier results, CNI and IA tend to weaken the effect of each other (that is, they substitute for each other) for wheat yield, as indicated by the negative sign of the coefficient of their interaction variable, CNI*IA, but complement each other in case of wheat production growth. Interestingly, however, while literacy rate always reinforces (complements) the positive effect of IA on wheat yields, it weakens each other effect on output growth rates. While higher literacy rates tend to substitute for positive CNI effects on wheat yields as also on wheat production growth rates.

The overall specification provides a good fit for production growth rates, as PCSE models are significant at 1 per cent level of significance for both wheat yields and production growth rates.

4.3. Final selected results with FGLS and PCSE estimations for rice and wheat yields

In what follows, the finally selected panel regression results for both rice and wheat yields, after correcting for cross-sectional dependence, heteroscedasticity and serial correlation, are presented and discussed. That is, we have chosen the results based on FGLS and PCSE methods only. Further, a number of climate variables that were found to be statistically weak explanatory variables of both types of crop yields have been dropped from these estimations. Given the underlying trend in the dependent variable, the time trend and its squared term have been included in the regressions. The estimated FGLS and PCSE models for rice yields are presented in Columns (1) and (2) and those for wheat yields are presented in Columns (3) and (4) below.

Table 14: Results of finally selected crop yields regression estimations

Regressors	Rice Yield		Wheat Yield	
	FGLS	PCSE	FGLS	PCSE
	Col. (1)	Col. (2)	Col. (3)	Col. (4)
Irrigated Area	.8198316***	.8291788***	1.116953***	1.099239***
	(25.03)	(7.88)	(41.87)	(6.87)
Ground Water Depth	-.0402197***	-.042906*	.0777335***	.0790101***
	(-9.85)	(-1.96)	(30.65)	(4.79)
Cultivated Area Under HYV	-.4625536***	-.4900429***	.0730325***	.0704061
	(-13.36)	(-3.34)	(3.16)	(0.51)
Pump Sets	-4.35e-06**	-5.65e-06*	-6.13e-06***	-5.87e-06**
	(-2.55)	(-1.98)	(-6.58)	(-2.27)
Tractors	.0000206*	.0000366*	-.0000103*	-7.04e-06
	(1.57)	(1.62)	(-1.70)	(-0.41)
Power Tillers	-4.77e-07	-9.36e-07	.0000908***	.0000777
	(-0.01)	(-0.01)	(4.36)	(1.14)
NPK Usage	2.71e-06***	3.41e-06*	5.44e-06***	5.56e-06**
	(4.55)	(1.48)	(15.75)	(2.78)
Soil Quality Index (SQI)	-.9178221***	-1.055092**	-.3379089*	-.3018062

Regressors	Rice Yield		Wheat Yield	
	FGLS	PCSE	FGLS	PCSE
	Col. (1)	Col. (2)	Col. (3)	Col. (4)
	(-3.65)	(-2.08)	(-1.54)	(-0.70)
Main Agricultural Labour	-8.62e-07***	-1.02e-06***	-9.08e-07***	-9.34e-07**
	(-6.86)	(-3.21)	(-7.24)	(-2.92)
Household Size	.2289904***	.2209191***	.0931952***	.1112478**
	(6.34)	(3.58)	(5.88)	(2.02)
Sex Ratio	-.0005237	-.0007593	-.0019284***	-.0020009*
	(-0.88)	(-0.55)	(-5.67)	(-1.90)
Literacy Rate	-.0038441	-.0007971	-.0014065	-.0002016
	(-1.03)	(-0.07)	(-0.56)	(-0.02)
Education Index	.4110923**	.508144	.9743658***	.9669547**
	(2.99)	(1.21)	(11.35)	(2.31)
Climate Index	.6580686***	.5364168	.4812526***	.4656686
	(5.01)	(1.13)	(7.13)	(1.20)
Average Annual Temperature	4.773653***	4.281417**	-.7683208***	-.5954725
	(8.31)	(2.25)	(-3.14)	(-0.43)
Average Annual Temperature Squared	-.096603***	-.0869989**	.0165075***	.0130477
	(-8.68)	(-2.35)	(3.45)	(0.49)
Average Annual Rainy Days	.4065267***	.4030259***	.2550477***	.2549196**
	(17.75)	(3.49)	(19.49)	(2.35)
Average Annual Rainy Days Squared	-.0282345***	-.0267182**	-.0209659***	-.020366*
	(-10.37)	(-2.00)	(-12.91)	(-1.60)
Average Monsoon Rainfall	.00235***	.0025245***	.0000922	-.0000609
	(15.80)	(3.01)	(0.91)	(-0.08)
Average Monsoon Rainfall Squared	-3.92e-06***	-4.08e-06***	1.10e-08	3.24e-07
	(-17.77)	(-3.29)	(0.07)	(0.28)
Annual Frequency of Highest Maximum Temperature (HMAX)	-.0036748***	-.0042484**	.0003676*	.0002442
	(-7.34)	(-2.79)	(1.46)	(0.20)
Annual Frequency of Lowest Minimum Temperature (LMIN)	.0072369***	.0072979***	-.0012653**	-.0016351
	(8.75)	(3.04)	(-2.86)	(-0.89)
Annual Frequency of Heaviest Rainfall in Last 24 Hours (HVYRF)	-.0031089***	-.0030029**	-.0016575***	-.001814*
	(-9.02)	(-2.23)	(-9.57)	(-1.74)
Community Network Index (CNI)	5.421213***	6.237156**	3.945909***	4.381562*
	(8.12)	(2.53)	(5.26)	(1.81)
Inherent Ability (IA)	-.0429565*	-.0365633	1.197933***	1.215984***
	(-1.60)	(-0.27)	(31.33)	(3.93)
Adaptation Variable 1 (CNI*IA)	-2.225362***	-2.262593**	-.6264582***	-.4985538
	(-13.33)	(-2.95)	(-3.93)	(-0.49)
Adaptation Variable 2 (IA* Literacy Rate)	.0216128***	.0218859***	.0105335***	.0098208*
	(26.84)	(5.43)	(11.35)	(1.46)
Adaptation Variable 3 (CNI*Literacy Rate)	-.046941***	-.0598966*	-.0436006***	-.0497647*
	(-4.46)	(-1.58)	(-3.92)	(-1.49)
Time Trend	-.0250404**	-.0324058	-.0340483***	-.0309737
	(-2.44)	(-1.05)	(-6.06)	(-1.34)
Time Trend Squared	.0021601***	.0023524**	.001388***	.0012667*
	(7.81)	(2.70)	(8.28)	(1.88)
Constant	-60.91449***	-54.37983**	8.09353**	5.816281
	(-8.14)	(-2.22)	(2.59)	(0.32)
Wald-chi^2	12950.86	539.42	41436.78	791.36
R^2		0.5619		0.5486
Constant	0.0000	0.0000	0.0000	0.0000
Model Significance	1%	1%	1%	1%

Figures in parentheses refer to the value of the t-statistic
Coefficients in '***', '**', '*' are statistically significant at 1%, 5%, and 10% level respectively.

Some important points to be noted and the results derived above are now discussed.

In case of both the methods, since time trend and time trend squared variables were both included as explanatory variables, it precluded simultaneous incorporation of time fixed effects in any of these models. Further, according to the Hausman test for both rice and wheat yield regressions, the FE model was found to work better than the RE model. This has also been discussed earlier.

Additionally, as also discussed earlier, in case of both rice and wheat yields regressions, problems of contemporaneous correlation, heteroscedasticity and autocorrelation were present. Hence, we had to make use of FGLS and PCSE models.

For both the regressions, we can see that the t-statistics of the FGLS are much higher than that of the PCSE model for both the rice and wheat yield regressions. These higher t-statistics values may be because of the under-estimation of the standard errors of the estimated coefficients as mentioned by Beck and Katz (Beck and Katz 1995). Thus, PCSE results are preferred over the FGLS model results for both rice and wheat yields, although both models are significant at 1 per cent level of significance.

As discussed earlier, both FGLS and PCSE estimations show that the share of cultivated area under irrigation improves rice and wheat yields significantly. The effect of groundwater table on rice yields is significantly negative and even though this is found to be positive for wheat

Contrary to expectations, the adoption of HYV technology has not boosted rice yields in Bihar, and this is evident from the coefficients, which are found to be both negative and significant. Even though the Bihar government has provided subsidised HYV rice seeds, these have not led to marked productivity gains for farmers, perhaps due to lack of full awareness of their use and inability to adapt to this new technology. Interestingly, however, both FGLS and PCSE estimations show that deployment of HYV technology has improved wheat yields, and the result is statistically significant for FGLS model. Higher use of irrigation pump sets (diesel and electric) is found to dampen both rice and wheat yields. Clearly, the negative result for usage of pump sets is counterintuitive, especially since ground water depth has been controlled for. However, note that this unexpected effect is realised on yields and not the level of production. The negative outcome may be due to the composition of rain-fed versus irrigated mix, and on account of the mix of underground versus surface irrigation, both of which have not been controlled for in the analysis due to paucity of data. A higher reliance on the other two agricultural equipment, namely, tractors is found to improve both rice yields, but it tends to have a negative influence on wheat yields, while power tillers have exactly opposite influence. It dampens rice yields but improves wheat yields.

Amongst consumable inputs, a higher usage of NPK fertilisers is assessed to have a positive effect on both rice and wheat yields across all regressions along with the negative impact of soil quality index (SQI), while agricultural labour input is found to uniformly lower yields for both crops, implying excessive labour pressure on limited land. As one would expect, a larger household size is found to raise productivity of both crops, while a larger female to male population ratio tends to dampen productivity in the case of both crops. As stated earlier, this may be ascribed to the men of the farming households migrating to urban areas to seek alternative non-agricultural occupations, leaving women or even hired agricultural labour to fill the supply gap. The use of hired labour may be subject to incentives issues. In Bihar, in general, this has not worked in favour of enhancing yields. Interestingly, a higher overall literacy rate works toward dampening both the crop yields of rice, but education index improves both the crop yields.

As for the important climate variables, a higher value of the climate index (reflective of the impact of wind speed, cloud cover, evapotranspiration processes, and diurnal (day versus night) temperature range) result in an increase in both rice and wheat yields, and the coefficients are highly statistically significant for FGLS models. The effects of temperature and rainfall variables are also plausible. Higher average annual temperature levels tend to boost rice yields, but it dampens wheat yields across both the models, but for both, there are threshold effects. That is, the temperature squared variable is found to have a negative and significant coefficient for rice yields and positive coefficients for wheat yields. This implies that higher temperatures will boost crop yields but after a point yields are lowered with further increases in temperature for rice yields and exactly opposite for wheat yields. Similar effects are borne out with regard to average monsoon days (along with its squared values). Thus, excessively high temperature or monsoon rainfall tends to dampen rice yields and improve wheat yields. While exactly opposite effects are borne out to average annual rainy days (and its squared values).

The impact of extreme weather events on crop yields are also prominent. As the number of days with highest maximum temperature (HMAX) increases, rice yields decline while wheat yields improve. However, the number of days with lowest minimum temperature (LMIN) has a positive effect on rice yields, but negative for wheat. These differing effects may be due to the seasonality of the crop cycle, as rice tends to be grown during the summer/ monsoon (kharif) season while wheat is grown in the winter (rabi) season. While a higher number of days with heavy rainfall in the last 24 hours has significant negative effects on both rice and wheat yields.

The role of community networks and inherent ability in terms of its impact on rice and wheat yields – the focus of the analysis – throws up some very insightful results. Community network index works toward boosting rice and wheat yields. Inherent ability is also found to work in favour of wheat yields, but it adversely affects rice yields although statistically insignificant. For both rice and wheat yields, the coefficient of the interactive variable, CNI*IA, is estimated to be negative: it is statistically significant for both rice and wheat regressions. The negative sign signifies that the two channels – community networks and ability (traditional knowledge or learning-by-doing) – work to counter each other or weaken each other in terms of their impact on both rice and wheat yields. Furthermore, uniformly for both rice and wheat yields, the interaction of inherent ability with literacy rate, or IA*Literacy Rate has a positive reinforcing effect, implying that the two tend to supplement each other in boosting yields. Unlike this, the interactive variable comprising community network index and literacy rate, that is, CNI*Literacy Rate, yields a negative sign, which implies that community network index and literacy rate tend to substitute for each other, or a higher literacy weakens the positive effect of community networks on both rice and wheat yields, and mostly significant. This result may be because of the weakening of social and local ties as members of farming households attain higher literacy levels and move away or migrate to other locations for alternative work opportunities and indicate the interesting sociological significance of the research.

Lastly, the incorporation of the time trend (that encompasses the influence of an array of exogenous features such as governance, institutions, policy regimes, political systems, and technology) indicates falling yields for both rice and wheat over time. However, a positive coefficient of time trend squared variable for rice as well as wheat yields displays threshold effects, which indicates that yields tend to rise for both the crops after reaching a threshold level.

This completes our interpretation and discussion of secondary data analyses.

5. Primary data estimation results

5.1 Mixed method results based on perception survey approach

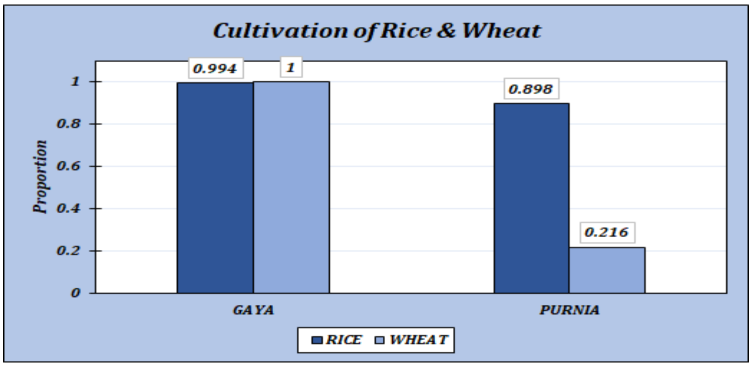
Mixed research approaches have been used to analyse primary data, both quantitative and qualitative (perception, rankings), obtained from the respondents. The perception survey analysis consists of econometric approaches such as basic and descriptive statistics of both categorical and continuous variables and normal QQ plots for continuous variables. The descriptive statistics of some of the key outcomes are represented in Table 25 in Annexure C for the two surveyed districts – Gaya and Purnia, separately.

Farmer households' characteristics

Table 25, Schedule A shows the descriptive statistics for household characteristics of 411 surveyed farming households. All households in this sample are primarily engaged in cultivation, with a majority (75 per cent in Gaya and 69 per cent in Purnia) being marginal and small farmers.

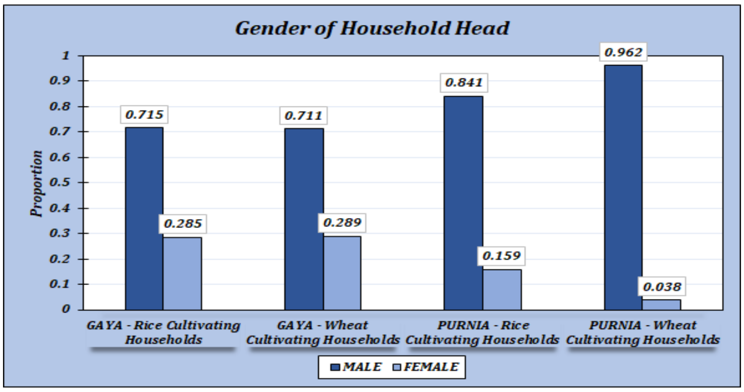
In the sample, almost all households in Gaya cultivate both rice and wheat. In Purnia, around 90 per cent of the households cultivate rice but only around 21.6 per cent of households cultivate wheat (Figure 3).

Figure 3: Cultivating households with different crop type



In both Gaya and Purnia, a majority of the households is headed by a male. The proportion of male headed households is higher for Purnia as compared to Gaya. In Gaya, since almost all households cultivate both rice and wheat, the proportion of male headed households is almost similar for rice and wheat cultivating households. In comparison, in Purnia, the proportion of male headed households is higher for wheat cultivating households as compared to rice cultivating ones (Figure 4).

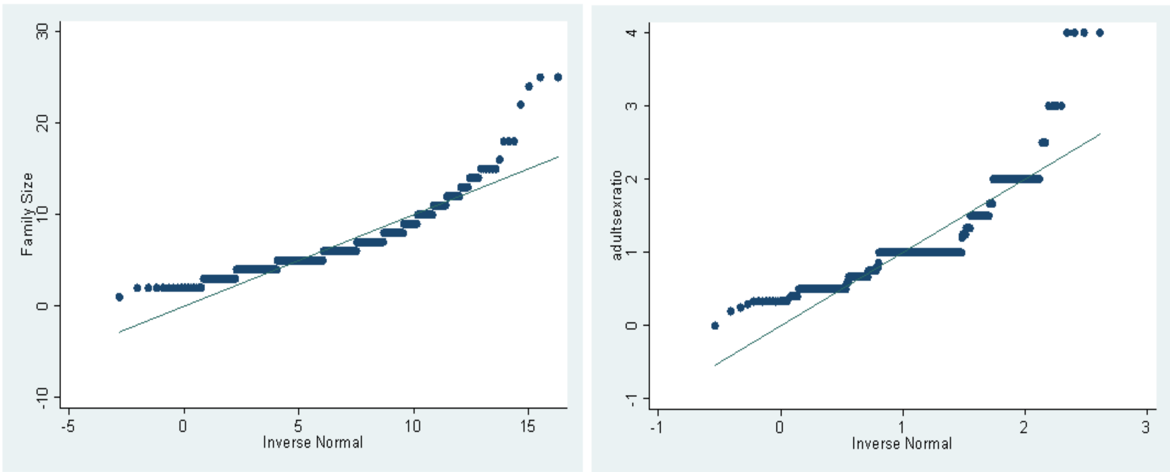
Figure 4: Gender of household head



Households in the two districts do not differ much with regard to their demographic and socio-economic profiles (that is, along the lines of caste, religious, origin[14], family type, family size, and educational attainment, etc.), which validates the choice of districts as mentioned in the survey design and primary data collection section in Chapter 3. A vast majority, above 99 per cent of households, in both the districts are Hindus and a major proportion of households belong to backward castes (98.2 per cent in Gaya and 96 per cent in Purnia). Further, a very large proportion of households in the two districts are also native to the place, but, in relative terms, the proportion of natives is much higher in Gaya (around 95.8 per cent) as compared to Purnia (around 82 per cent).

At present, a majority of the families are nuclear families (73.5 per cent in Gaya and 78.4 per cent in Purnia) but in the past, there was a greater preponderance of joint families (76 per cent in Gaya and 77.1 per cent in Purnia). Although a majority of families are nuclear in nature, the average family size is around 6-7 in both districts with almost no outliers and with low average number of earning members (around 2 per household) in both the districts. This reflects high dependency ratios and consumption pressure in most families as the family size is generally high with fewer earning members and low adult sex ratio in average and few outliers. The distributions of family size and adult sex ratio are depicted in Figure 5.

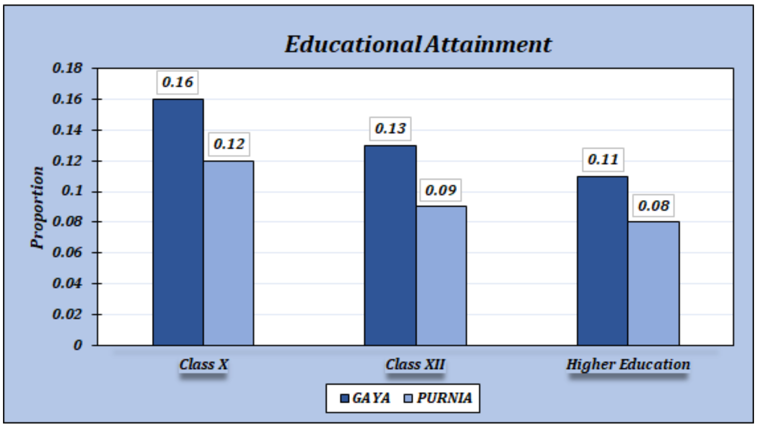
Figure 5: Distributions of family size and adult sex ratio



The distribution of educational attainment of family members is poor or low in both districts, as a majority of family members attain education only up to class/grade X, though the scenario is better in Gaya than in Purnia, mainly on account of its proximity to urban centres. The figure below (Figure 6) shows the proportion of family members attaining a particular level of education. On an average, only 16 per cent of household members in Gaya have completed class X, 13 per cent have completed class XII and only 11 per cent have attained higher education. The numbers for Purnia are 12 per cent, 9 per cent and 8 per cent respectively.

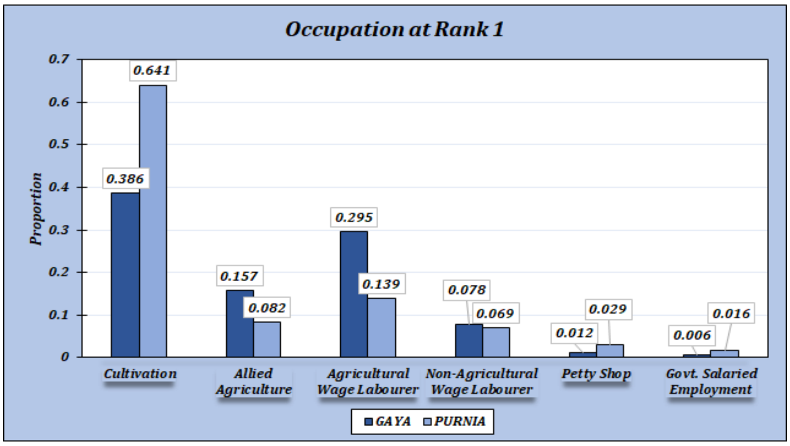
Figure 6: Distribution of educational attainment of household members

[14] Origin defines whether the household is a native of the districts or has in-migrated from somewhere else.



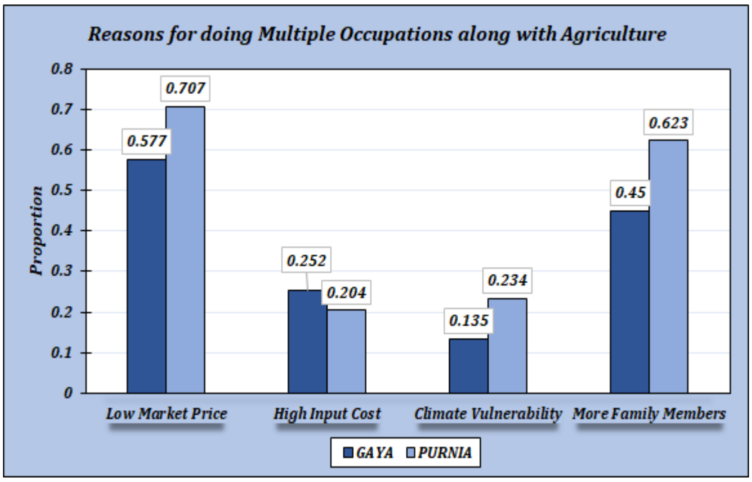
Respondents in both Gaya and Purnia engage in other occupations along with cultivation. Although cultivation is commonly believed to be the primary occupation, it is not even the main occupation for a majority of the farmer respondents in Gaya. From the figure below (Figure 7), one can see that less than 40 per cent of the respondents in Gaya stated cultivation as their main occupation. Around 30 per cent stated agricultural wage labour as their main occupation followed by activities allied to agriculture at around 15 per cent. In Purnia, cultivation remains the main occupation for a majority of the respondents. Around 65 per cent of the respondents said cultivation is their main occupation followed by agricultural wage labour (14 per cent) and allied agricultural activities (8 per cent).

Figure 7: Different occupations of households at rank 1



It seems that the reason why respondents are engaged in other occupations along with agriculture is that income from agriculture is not sufficient for the household. The two main reasons given by respondents in both districts for being engaged in other occupations along with agriculture is low market price of agricultural produce and large family size. As can be seen in **Error! Reference source not found.**, around 58 per cent farmers in Gaya and 71 per cent farmers in Purnia said that the reason for engaging in multiple occupations is low market prices for agricultural produce, and around 45 per cent respondents in Gaya and 62 per cent of the respondents in Purnia cited large family size as the reason (Figure 8).

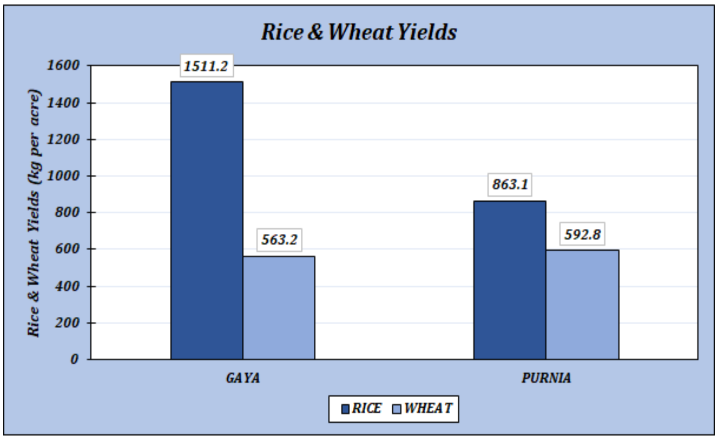
Figure 8: Reasons for insufficient agricultural income and engaging in multiple occupations along with agriculture



Agricultural technology and inputs and associated survey observations

With a higher proportion of surveyed rice and wheat cultivating households in Gaya (99.4 per cent for rice and 100 per cent for wheat) as compared to Purnia (89.8 per cent for rice and 21.6 per cent for wheat), rice yields are higher in Gaya than Purnia, and wheat yields are almost the same for the two districts (although slightly higher in Purnia) (see Figure 9).

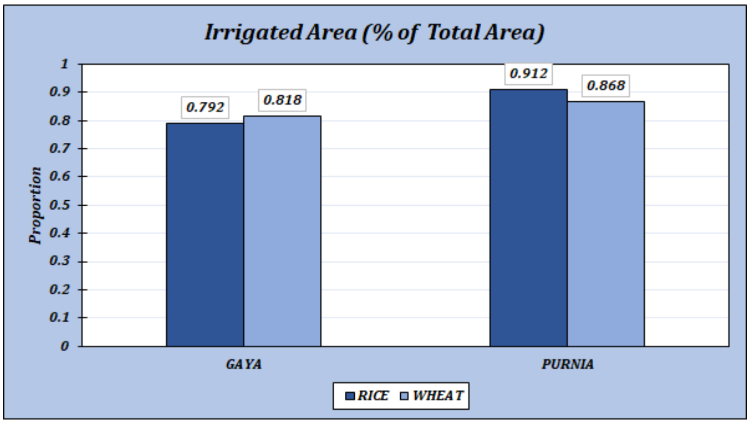
Figure 9: Crop yields



There appears to have been a significant change in the cropping pattern in both districts over the last 10-20 years. In Purnia, the proportion of households cultivating maize has increased by 68 per cent, while the proportion of rice cultivating households has risen by only 11 per cent. Further, there has been a decline in wheat cultivating households by 25 per cent over the past 10-20 years. This indicates that in Purnia, the cropping pattern has changed from more water intensive crops towards less water intensive ones. Responses from households in Gaya also indicate a significant change in cropping pattern, where the numbers of rice and wheat cultivating households have increased over the past 10-20 years from 50 per cent to 87 per cent for rice and 45 per cent to 89 per cent for wheat. While the changes in cropping pattern could be attributed to changes in farming decisions in response to climate change, given the higher water intensity of both wheat and rice cultivation in comparison with maize, the fact that Purnia is a high rainfall region makes the findings somewhat unlikely. The changes over the past 10-20 years could be due to institutional factors such as the low market price of rice and wheat as compared to maize. In fact, the reason for the change in cropping pattern being institutional factors has been pointed out by some farmers in the survey in Purnia.

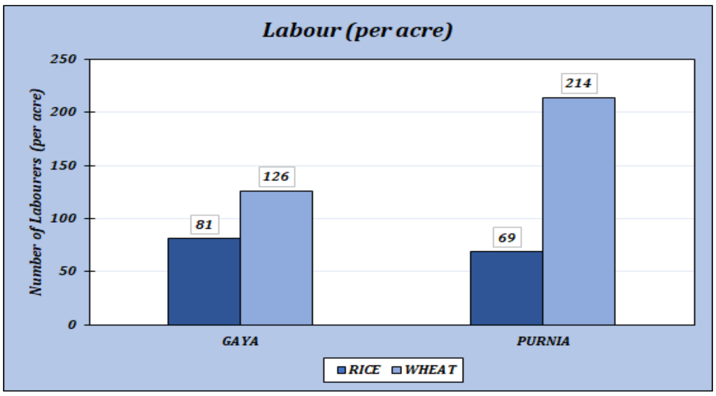
The three main factors on which crop production depends are climatic variations, available natural resources and agricultural inputs. The first two factors, i.e., climatic variations and local natural resources, are out of human control; the last one, viz., inputs, such as irrigation infrastructure, labour, machinery, seeds, fertilisers, pesticides, credit, etc., is human regulated. In what follows, the focus will be on these inputs. The graph below (Figure 10) shows the proportion of irrigated area for rice and wheat production in the two districts. It is clear from the graph that a higher proportion of area is irrigated in Purnia as compared to Gaya in the case of both crops. This is noteworthy as Purnia receives higher rainfall than Gaya, and Purnia is also richer in groundwater as well as surface water resources. Another interesting thing is that the proportion of irrigated area is higher for wheat production than rice production in Gaya, even though rice cultivation is more water intensive than wheat cultivation. This may be because irrigation during the *kharif* season is a little difficult in Gaya due to the low ground water table and rice is a *kharif* crop. But it is feasible for wheat, which is a *rabi* crop grown after the monsoon season, when ground water recharge has taken place. In Purnia, the proportion of irrigated area is slightly higher for rice as compared to wheat, which is obvious as irrigation is feasible perennially due to higher availability of ground water resources in Purnia.

Figure 10: Irrigated area as an input for crop production



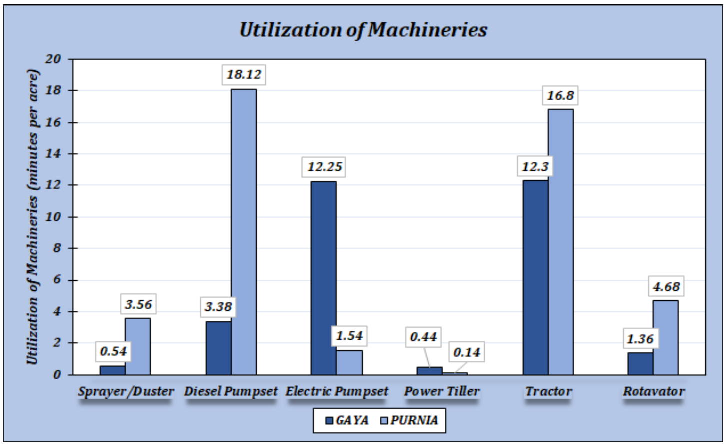
As can be seen in Figure 11, the number of labourers used per acre is slightly higher for Gaya (81 in Gaya as compared to 69 in Purnia per cropping season) for rice production, while it is much higher in Purnia for wheat production (214 in Purnia as compared to 126 in Gaya per cropping cycle). It is also much higher for wheat production than for rice production, in general, maybe because rice production is more mechanised than wheat production.

Figure 11: Labour inputs for crop production



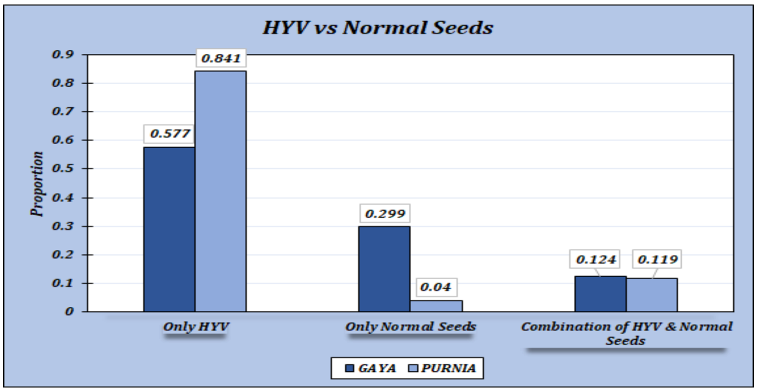
From **Error! Reference source not found.** 12, it can be seen that in Gaya, the machinery and equipment used most intensively are electric pump sets and tractors; both are used for around 12 minutes per acre, followed by diesel pump sets (3 minutes per acre). In Purnia, the most intensively used machine is the diesel pump set (18 minutes per acre), followed by tractors (17 minutes per acre) and rotavator (5 minutes per acre). Thus, the two most important pieces of machinery used for crop production are tractors and pump sets, either electric or diesel, depending on the availability of electricity in the region. Further, it has been observed that around 60 per cent or more of the households in Purnia own low-priced machinery like pump sets. But the case is the opposite in Gaya. Around 60 per cent households in Gaya rented small machinery and equipment. Around 90 per cent of the households rented high-priced machinery like tractors and rotavators in both districts. This may be because of a large proportion of households in both districts belonging to the marginal and small farmer category.

Figure 12: Utilisation of machinery and equipment as inputs for crop production



In both Gaya and Purnia, a majority of the households use only HYV seeds (see **Error! Reference source not found.** 13). The proportion of households using only HYV seeds in Purnia is 84.1 and in Gaya it is 57.7 per cent. The proportion of households using only normal seeds is 29.9 per cent in Gaya and 4 per cent in Purnia. The remaining 12.4 per cent of the households in Gaya and 11.9 per cent in Purnia use both HYV and normal seeds.

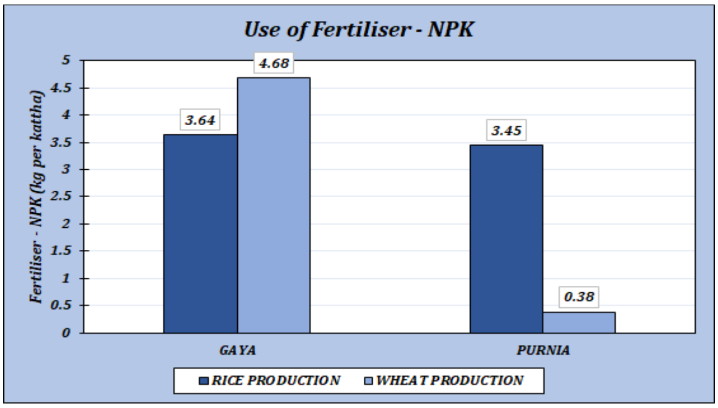
Figure 13: Seeds as an input for crop production



NPK fertilisers are used more intensively in Gaya than in Purnia for both rice and wheat production (see Figure 14). The difference is marginal in the case of rice production, but very large in the case of wheat. For rice, 3.6 kg of NPK is used per *kattha*[15] in Gaya as compared to 3.4 kg per *kattha* in Purnia while the usage is 4.68 kg per *kattha* in Gaya and just 0.38 kg per *kattha* in Purnia for wheat. In general, households in Gaya use more fertilisers than in Purnia.

[15] 32 *katthas* = 1 acre.

Figure 14: Use of NPK for crop production

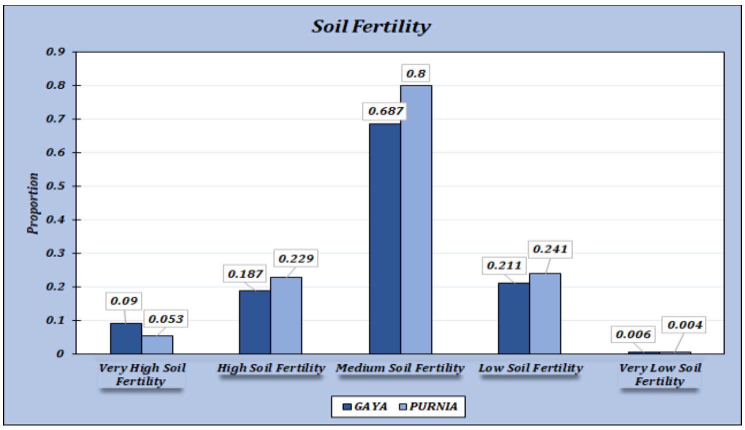


Pesticides is another major input used in crop production in both districts. More than 50 per cent of the households in the two districts adopt pest control with the proportion being higher in Purnia, at around 85 per cent. This could be attributed to the more frequent outbreak of pest and disease in Purnia (see Appendix A).

Another important input for crop production is credit. A majority, around 53 per cent, of households, in Gaya do not take any loans, while a majority, around 67 per cent, of households in Purnia take loans. The key reason reported by the respondents for not taking loans is that they do not need loans (this is around 84 per cent of the respondents among those who do not take loans in the two districts).

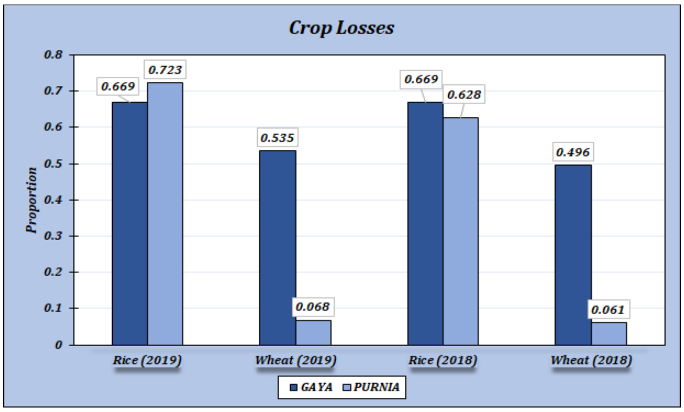
Farmers' responses to questions about the fertility of the soil are given in the graph below (Figure 15). Some households have multiple landholdings with varying soil fertility; therefore, the total proportion for a district may exceed 1, as is the case here. A majority, around 69 per cent in Gaya and 80 per cent in Purnia, have land with medium soil fertility. The proportion of households having land with low soil fertility was found to be 21 per cent in Gaya and 24 per cent in Purnia. The proportion of households having ownership of high soil fertility land is only slightly lower – at 19 per cent in Gaya and 23 per cent in Purnia. There are also some households who own land with very high soil fertility, with Gaya having a greater proportion of such households than Purnia. The proportion of households owning very low soil fertility land is close to negligible for both districts. Overall, the proportion of households having land with very high and high soil fertility is higher than that with low and very low soil fertility land in both districts.

Figure 15: Soil fertility



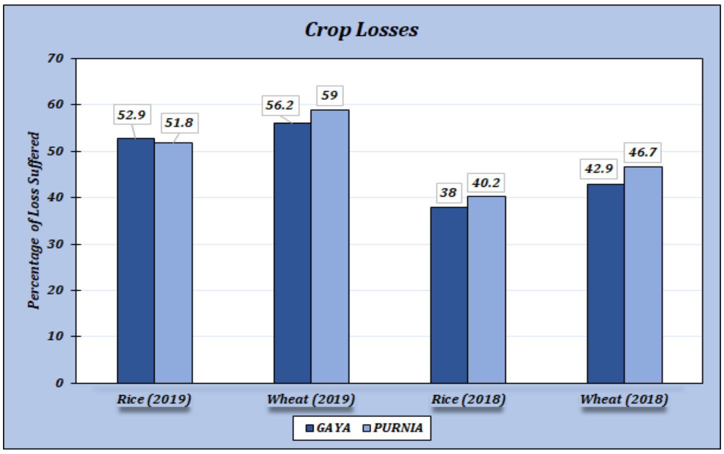
Based on input use, as described above, farming is fairly modernised in our sample of households, especially in Gaya. Together with the information on soil quality, one would expect farming to be reasonably profitable or at least not unprofitable for a majority of the households. However, losses are not uncommon in both Gaya and Purnia. The graph below Figure 16) shows the proportion of households reporting losses for rice and wheat for the years 2018 and 2019. More than 50 per cent of households in Gaya incurred losses on rice and wheat cultivation in both years. In the case of rice, 67 per cent of households in Gaya incurred losses in both 2018 and 2019, while in the case of wheat, 50 per cent of households in 2018 and 54 per cent in 2019 faced losses. In Purnia, 63 per cent of households in 2018 and 72 per cent of households in 2019 incurred losses in the case of rice. The proportion of households incurring losses for wheat is quite low in Purnia, with 6 per cent of households in 2018 and 7 per cent in 2019. More households reported having incurred losses in 2019 for both rice and wheat as compared to 2018.

Figure 16: Households suffering crop losses in the years 2018 and 2019



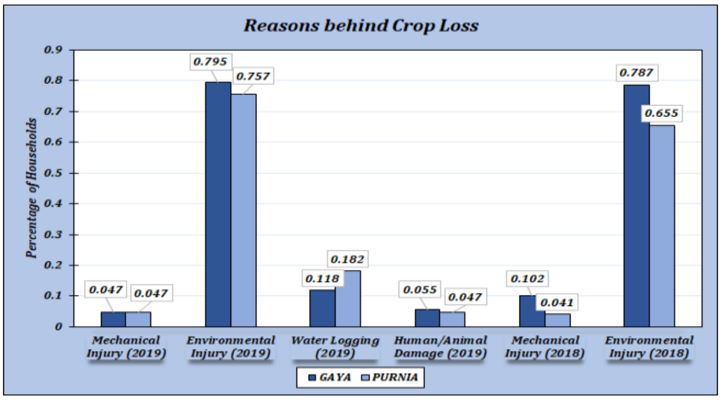
The percentage of loss suffered is also quite high for both rice and wheat in the two districts (see Figure 17). It was higher in 2019 than it was in 2018 and was reported to be higher for wheat than rice; moreover, it was higher in Purnia than in Gaya, except in the case of rice in 2019, although the difference was small. This indicates that the percentage of crop loss is increasing over time, and Purnia is more vulnerable to crop loss than Gaya, and wheat is more vulnerable than rice. From Figure 14, one can see that, for rice, households in Gaya suffered on an average 38 per cent loss in 2018 and 53 per cent in 2019. The corresponding figures for Purnia were 40 per cent and 52 per cent. For wheat production, households in Gaya suffered an average loss of 43 per cent in 2018 and 56 per cent in 2019. The corresponding figures for Purnia were 47 per cent and 59 per cent.

Figure 17: Average crop loss in percentage



The main reason for crop loss cited by respondents in both districts is environmental hazards (see Figure 18). In Gaya, 79 per cent and 80 per cent of respondents attributed crop losses in 2018 and 2019 respectively to environmental hazards. The corresponding figures for Purnia were 66 per cent and 76 per cent respectively. The proportion of respondents citing other reasons for crop losses was quite small for both districts for 2018 and 2019.

Figure 18: Reasons behind crop loss



Under environmental hazards, the main contributors identified by respondents were extreme events, such as heavy rain and drought in Gaya, and heavy rain and floods in Purnia in both years – 2018 and 2019. As can be seen from Figure 19 and Figure 20, in Gaya, 35 per cent of the respondents in 2018 and 57 per cent in 2019 mentioned heavy rain as the main contributor of crop loss, and 52 per cent in 2018 and 37 per cent in 2019 indicated drought as the main reason for this loss. In Purnia, the major contributor was heavy rain followed by floods, with 75 per cent of the respondents in 2018 and 74 per cent in 2019 mentioning heavy rain, and 37 per cent in 2018 and 41 per cent in 2019 mentioning floods.

Figure 19: Different types of environmental hazards as the reason for crop loss in 2018

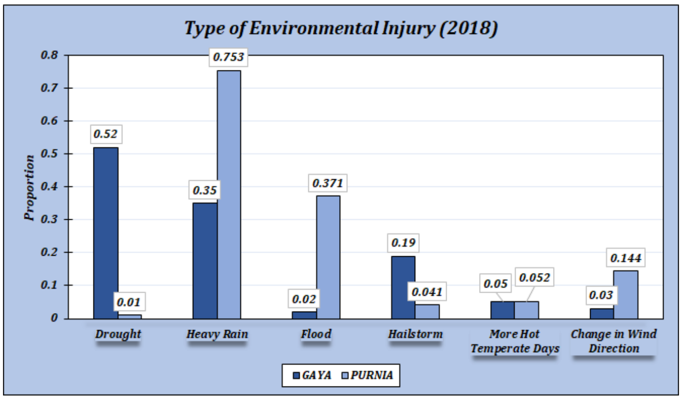
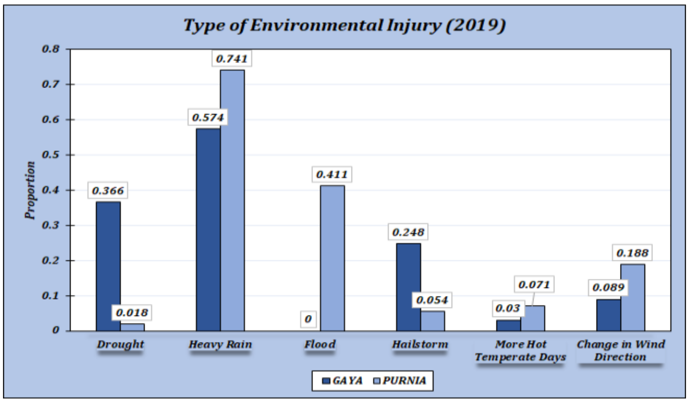


Figure 20: Different types of environmental hazards as a reason for crop loss in 2019



Unfortunately, households do not get enough compensation to cope with crop losses. Even when they receive compensation, the amount is not sufficient to cover the loss. Figure 21 and Figure 22 show the proportion of households receiving compensation and the amount of compensation received by households for the years 2018 and 2019 respectively in the two districts. Figure 21 indicates that the proportion of households who received compensation is well below 10 per cent. The exceptions are in the case of the wheat crop in Purnia, where the proportion of households receiving compensation for losses was 11 per cent in 2018 and 30 per cent in 2019. The average amount of compensation received by households was below INR 8000 for the two crops in both years for both districts (see Figure 22). The compensation received was higher in Purnia than it was in Gaya, not surprising as Purnia faced a higher percentage of crop loss in both 2018 and 2019 in the case of both rice and wheat.

Figure 21: Proportion of households receiving compensation for crop loss

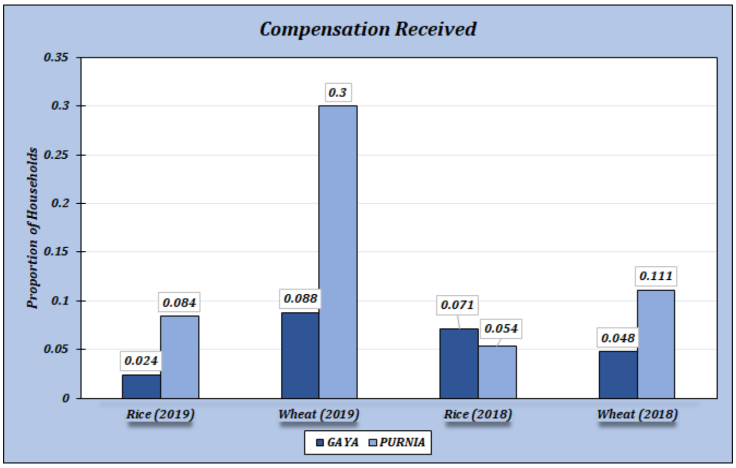
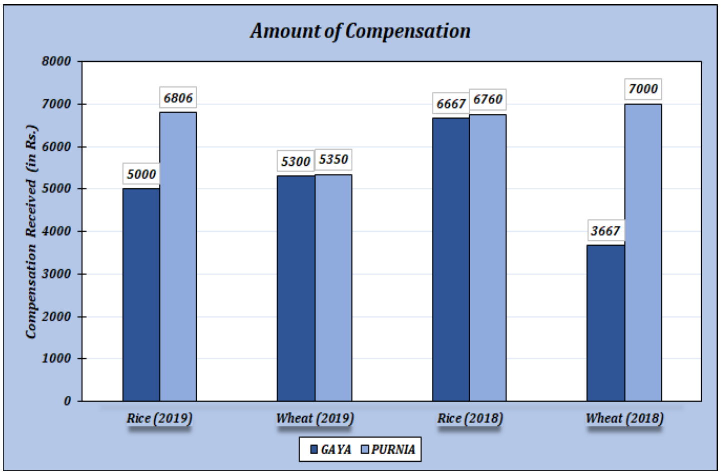


Figure 22: Average compensation amount received for crop loss

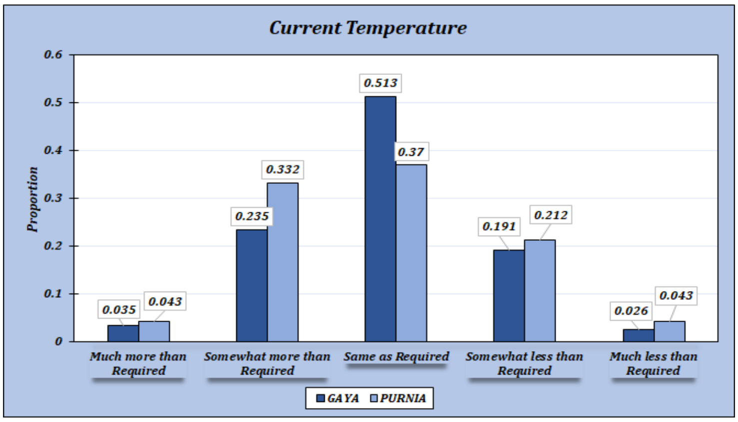


Farmers' perception about climate change and agriculture

The survey also sought the opinions of farmers on climate change, such as temperature regimes, rainfall pattern, wind pattern, heavy rainfall, drought, flood, excessive cold/hot winds, hot temperate days, etc. Nearly 64.2 per cent of the respondents in Gaya and 63.1 per cent in Purnia believe that, in general, climate change is happening, and this response was neutral with regard to the respondent's gender. Thus, slow and persistent climate change occurrences have been noted by a significant number of respondents.

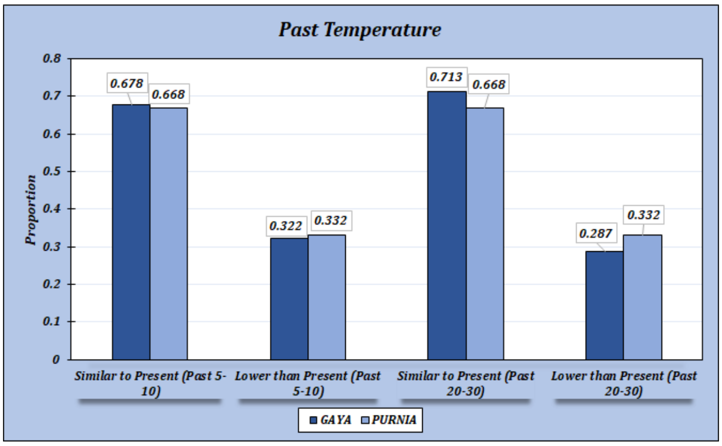
As can be seen in Figure 23, around 51.3 per cent of the respondents in Gaya and 37 per cent in Purnia perceive that the present temperature patterns are optimal or as they would require these to be for cultivation purposes. However, another significant proportion, around 20 per cent in Gaya and 20 to above 30 per cent in Purnia, also said that the prevailing temperature patterns are somewhat more than required or somewhat less than required.

Figure 23: Perception about current temperature regimes



Some of these opinions also carry over to comparisons with past trends. For instance, around 67.8 per cent of the respondents in Gaya and 66.8 per cent in Purnia feel that temperatures in the past 5-10 years were almost similar to the present, while an overwhelming proportion of respondents – 71.3 per cent in Gaya and 66.8 per cent in Purnia – felt that the temperature regimes over the past 20-30 years have been similar to those prevailing currently (see Figure 24).

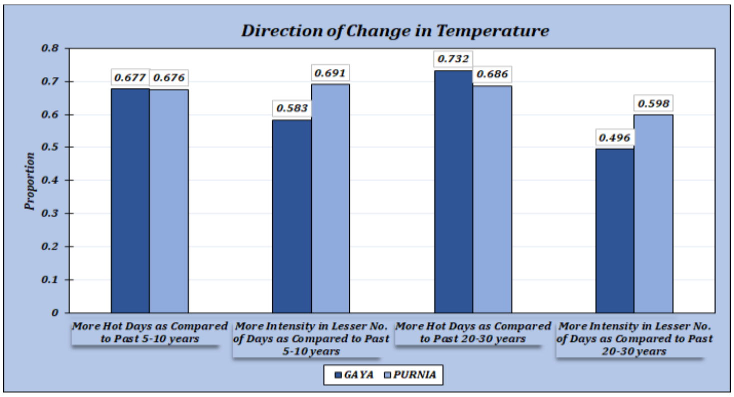
Figure 24: Perceptions about changes in temperature pattern over time



Perceptions on change in temperature over the past 5-10 years and 20-30 years were sought in terms of two specific indicators – a greater number of hot temperate days and a greater intensity of hotter temperatures over a fewer number of days. A higher proportion of respondents perceive that there has been a change towards a greater number of hot temperate days (nearly 67.7 per cent in Gaya and 67.6 per cent in Purnia over the past 5-10 years, and around 73.2 per cent in Gaya and 68.6 per cent in Purnia for the past 20-30 years) as compared to those who felt that there has been a change towards a greater intensity of hot days over a shorter span of days (58.3 per cent in Gaya and 69.1 per cent in Purnia for the previous 5-10 years, and 49.6 per cent in Gaya and 59.8 per cent in Purnia for the past 20-30 years) (see Figure 25).

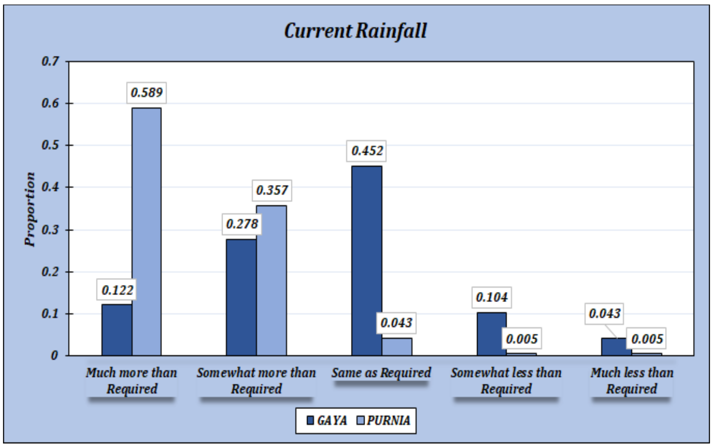
Between the two indicators of change in temperature pattern, a larger number of respondents in both districts felt that the changing trend of a higher number of hot temperate days has happened over the past 20-30 years, whereas a larger proportion in both the districts perceive the higher intensity of hot days spread over a fewer number of days as a phenomenon of the past 5-10 years. This indicates that more hot temperate days is more of a longer gradual climate change phenomenon while higher intensity of hot temperatures over fewer days is a more recent climate change trend (Figure 25).

Figure 25: Perceptions about changing temperature regimes over medium- and long-time frames



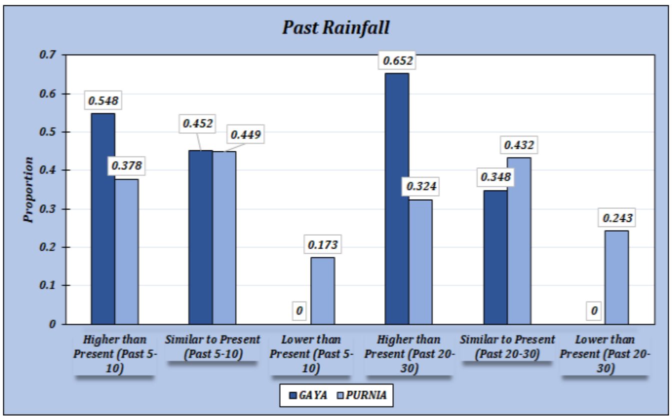
Next, as can be seen in the graph below, a significant proportion (around 45.2 per cent) of respondents in Gaya felt that the prevailing volume of rainfall is as needed, but a significant percentage (58.9 per cent) of respondents in Purnia think that current rainfall levels are much higher than required or optimal for cultivation (Figure 26).

Figure 26: Perceptions about current rainfall levels



In comparison with historical trends, respondents in Gaya believe that rainfall in the past was higher than it is now – 54.8 per cent and 65.2 per cent of the respondents believed so based on their recall of both 5-10 years and 20-30 years ago respectively. In comparison, in Purnia, nearly 44.9 per cent and 43.2 per cent of respondents felt that rainfall was almost similar to the present for both the past time periods – 5-10 years and 20-30 years (see Figure 27 below).

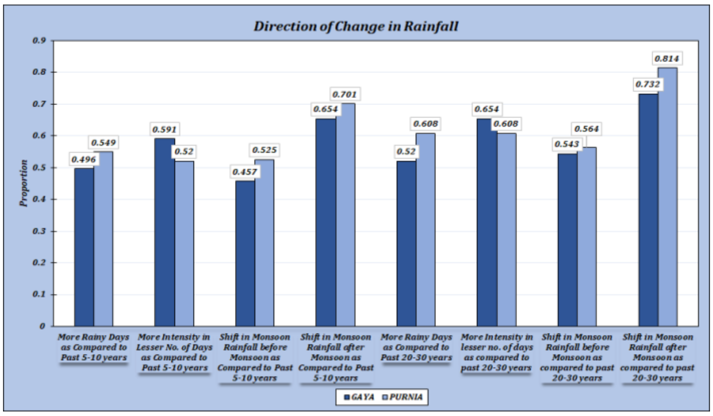
Figure 27: Perceptions about changes in rainfall pattern over time



Thus, these observations seem to indicate that there is a perception of decline in rainfall levels over time in Gaya, since a significant proportion of the farmers surveyed perceive that rainfall in the past 20-30 years was much higher than it was in the past 5-10 years and further, that it was higher in the past 5-10 years than it is at present. In case of Purnia, rainfall levels are generally believed to be higher than required. Thus, incidence of heavy/extreme rainfall is more common in Purnia than in Gaya. In Gaya, only 30 per cent of respondents stated that the occurrence of extreme rainfall events is as one would normally expect, and occurrence of floods is less than it was earlier. In case of Purnia, around half of the surveyed population, nearly 50.5 per cent of respondents, reported experiencing somewhat more than usual extreme rainfall events. But, only 34 per cent of respondents reported experiencing somewhat more than usual instances of flood events.

A large proportion of respondents in the two districts (between 45 to over 80 per cent) feel that the rainfall pattern has changed in many different ways – that is, there is now a greater number of rainy days, more intense rainfall concentrated over a fewer number of days, shifting of monsoon rainfall in terms of both early or delayed arrival, etc. A high proportion of respondents in both districts perceive that there has been a shift towards delayed monsoons. Nearly 65.4 per cent of respondents in Gaya and around 70.1 per cent in Purnia felt that this has happened over the past 5-10 years. An even higher proportion of respondents, an overwhelming 73.2 per cent in Gaya and 81.4 per cent in Purnia, believe that this delay has happened over the past 20-30 years. In fact, another insight is that this pattern of delayed arrival of monsoons is followed by more intense rainfall spread over a fewer number of days (a perception of 59.1 per cent of respondents in Gaya and 51.9 per cent in Purnia over the past 5-10 years, and even higher at 65.4 per cent in Gaya and 60.8 per cent in Purnia over the past 20-30 years) (Figure 28). This view is also supported by the findings of scientists and climatologists.

Figure 28: Perceptions about changing rainfall patterns over medium and long-time frames



Optimal temperature along with declining rainfall levels over the years in Gaya should have resulted in a higher perception of the incidence of droughts. However, only 11 per cent of respondents stated that there is increased incidence of droughts at present compared to the past and a significant proportion of respondents, around 30 to 37 per cent, feel droughts to be as one would normally expect or somewhat less frequent than earlier. In Purnia, drought incidence should be less because of its higher rainfall than Gaya. Around 39.7 per cent of respondents feel drought to be somewhat less frequent than usual. The perception of lower incidence of drought could be due to improved irrigation and water supply infrastructure in the villages as compared to that in the past.

With regard to other indicators of climatic change and extreme events, several additional opinions were expressed.

Nearly 54.4 per cent of respondents in Gaya and nearly 50 per cent in Purnia said that the prevailing wind speeds are as they would expect them to be. Moreover, an overwhelming proportion (more than 80 per cent in both Gaya and Purnia) felt that wind speeds in the past 5-10 years as well as past 20-30 years were the same as it is at present. Thus, there is observably no significant change in wind speeds over the past 20-30 years.

Changes in additional features of wind are also significant. A significant proportion of respondents in the two districts feel that wind intensity has changed towards excessively hot winds/loo (around 65.4 per cent in Gaya and 64.7 per cent in Purnia have felt this to be the case over the past 5-10 years, and nearly 75.6 per cent in Gaya and 64.7 per cent in Purnia have believed this to have happened over the past 20-30 years). Nearly half of the surveyed population in the two districts believe that such hot weather incidents (called loo) as an extreme weather event has been as expected and it has been more or less unchanged over the past 20-30 years. It was also felt that hot winds were spread more intensely over a fewer number of days (53.5 per cent in Gaya and 60.3 per cent in Purnia over the past 5-10 years, and 43.3 per cent in Gaya and 52.4 per cent in Purnia over the past 20-30 years). There is also a perceived change in wind directions – the proportion of respondents that think there has been a change is 49.6 per cent of respondents in Gaya and 52.4 per cent in Purnia in the past 5-10 years, and 54.3 per cent in Gaya and 52.9 per cent in Purnia in the past 20-30 years. Although a very small proportion of respondents feel that the wind pattern has changed towards excessively cold winds (around 16 to 28 per cent in the two districts), a significant proportion of respondents (around 52.6 per cent in Gaya and 47 per cent in Purnia) believe cold waves to be as expected, and nearly 70 per cent felt these were almost the same as in the past 20-30 years in both districts.

The nature of adaptation to cope with climate change impacts is discussed below.

Agricultural adaptation to climate change by farmers

The survey threw light on some very perceptive responses of farmers on the linkage between climate change and agriculture, clearly bringing out the role of various planned and autonomous adaptation routes.

Importantly, a high proportion of farmer respondents in the two districts felt that there has been continuous climate change, and this affects their production decisions. This was felt by 62 per cent of the respondents in Gaya and 68.2 per cent in Purnia and was neutral with respect to the respondent's gender. The overall ordering of adaptation measures (due to gradually changing climate) relied upon by them has been found to be as follows: (i) shifting of production decisions toward changing crop sowing and harvesting time (adopted by 62.6 per cent in Gaya and 70.1 per cent in Purnia), (ii) changing cropping patterns like crop-mix, multi-cropping/inter-cropping (27.3 per cent) and re-allocation of land from more to less water intensive crops (22.2 per cent) in case of Gaya, and (iii) use of new technologies and agricultural equipment (32.3 per cent), and use of new climate resilient seeds (13.2 per cent) in Purnia. This indicates efforts towards climate change adaptation by farmers. The ordering of choices (ii) and (iii) got reversed between Gaya and Purnia with respect to the respondent's gender; however, it remained the same for option (i) irrespective of the gender.

Furthermore, even though Purnia farmers have not indicated shifting of land from more to less water intensive crops (perhaps because Purnia is not water deficient) as a farming adaptation decision due to climate change, we have seen earlier in the section on agricultural technology and inputs and the related survey observation that maize has replaced both rice and wheat as a crop to some extent in Purnia. Respondents in Gaya clearly stated that they had shifted land from more to less water intensive crops as a farming adaptation decision due to climate change, and this was placed at rank 3 as a choice. It is also possible that the shift from more to less water intensive crops in Purnia was in response to government policy incentives as some other studies indicate. In terms of the specific crop-wise transitions, around 50 per cent of farming households in Gaya reported that they had shifted their rice/wheat land to cultivate less water intensive crops like *masoor* dal,[16] followed by *chana*[17] (36.4 per cent) and potato (22.7 per cent). In Purnia, most respondents indicated having shifted their rice/wheat land to cultivate crops such as vegetables (76.9 per cent), followed by maize (46.2 per cent) and potato (30.8 per cent).

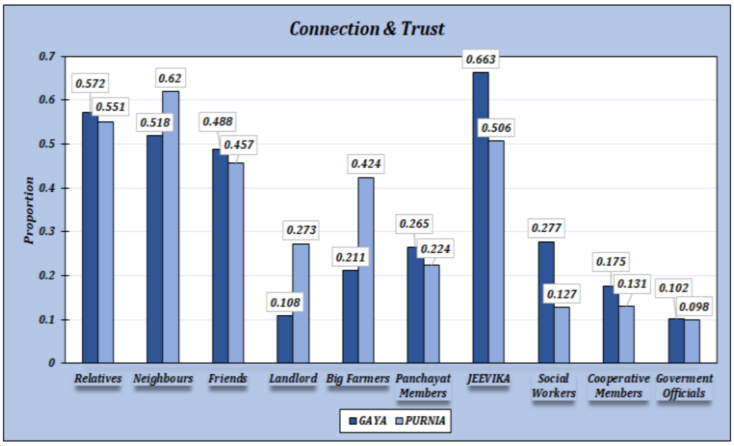
A very promising finding of the study was that, in Gaya, respondent households display trust and reliance (for their farming decisions) on the advice and help received from JEEViKA; this was their

[16] Lentil

[17] Chickpea

top choice (as many as 66.3 per cent reported this to be the case), followed by suggestions/advice from relatives (57.2 per cent), from neighbours (51.8 per cent) and from friends (48.8 per cent). In comparison, a higher proportion of Purnia households said that they trusted the advice on farming decisions from neighbours (62 per cent), followed by relatives (55.1 per cent), JEEViKA (50.6 per cent) and friends (45.7 per cent). Thus, a large proportion of households in both districts affirmed their trust and reliance on advice either from JEEViKA, which is a formal community network (FCN) type of organisation, or from neighbours, relatives, and friends, which is an informal community network (ICN) institution (Figure 29).

Figure 29: Farmer's perceptions on the intensity of connections and trust in informal and formal community networks



These results are more pronounced for Purnia when the gender of the household head is taken into account. For instance, and very importantly, the pattern of trust by women headed households in Purnia was found to be qualitatively similar to that in Gaya, but with much higher proportions – 73.7 per cent of such households trusted support from JEEViKA and relatives, followed by neighbours (at 71.1 per cent).

As for the use of consumable inputs such as fertilisers, pesticides, seeds, etc., respondents in Gaya reported that they get most of their information from neighbours, relatives, and friends put together (around 57.2 per cent), followed by JEEViKA (35.5 per cent) or media (35.5 per cent) (newspaper, radio, and television) and local connections (23.5 per cent) (big farmers, *gram panchayat* members, and sometimes political party members). In Purnia, respondents derive most of their information on usage of agricultural inputs from local traders/suppliers (75.9 per cent), followed by neighbours, relatives, and friends as a group (51.4 per cent), and local connections (44.9 per cent) (big farmers, *gram panchayat* members, and political party members). Once we include the gender perspective, proxied by the gender of the household head, the results vary with respect to this factor for Gaya households, whereas responses for Purnia households are neutral with regard to gender as a factor. A significant proportion of male headed households receive information on consumable inputs from neighbours, relatives, and friends (54.2 per cent), followed by media (33.9 per cent) and JEEViKA (30.5 per cent), whereas more female headed households obtain information from neighbours, relatives, and friends put together (64.6 per cent), followed by JEEViKA (47.9 per cent) and media (39.6 per cent). This points to the significance of JEEViKA as a channel for dissemination of new information. Importantly, it indicates that female headed households have greater social connections and tend to rely more on these.

For capital inputs, most respondents in Gaya derive information from neighbours, relatives, and friends as a group (62 per cent), followed by local community connections (30.7 per cent) (big farmers, *gram panchayat* members, and political party members) and media (30.1 per cent) (newspaper, radio, and television), while in Purnia, the order is as follows – neighbours, relatives, and friends put together (53.5 per cent), local traders (53.1 per cent), media (16.2 per cent) or extension services (16.3 per cent) (*kisan call centres* (KCCs), *krishi vigyan kendras* (KVKs), short message services (SMSs), farmers' portal. The results are gender neutral.

Thus, in general, it can be inferred that as far as sourcing information on agricultural consumables and capital inputs in concerned, the role of ICT/ICT-enabled extension services (KCCs, KVKs, SMS, farmers' portal) as a part of climate smart agriculture (CSA) initiatives is somewhat less prevalent or less effective in both districts. Hence, the role of autonomous adaptation comes into play.

Most respondents believe that traditional/ ancestral knowledge is required along with information and diffusion of new technologies in both districts (an overwhelming 84.9 per cent in Gaya and almost the entire sample, 99.2 per cent, in Purnia).

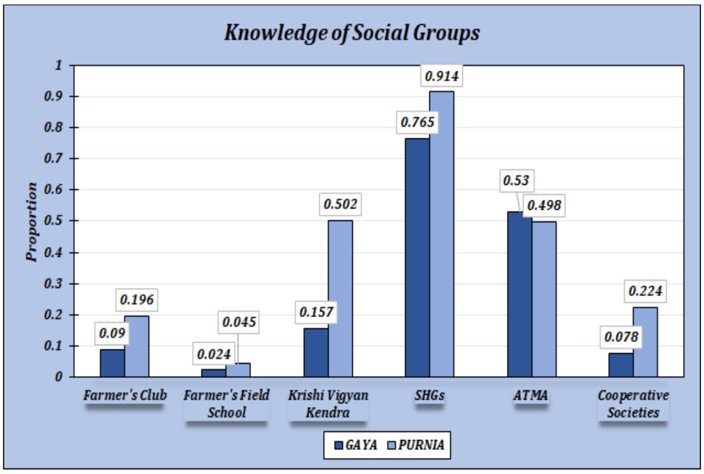
According to the survey responses, a very small proportion of households in the two districts have been attending government-run workshops and training sessions (16.9 per cent in Gaya and 37.9 per cent in Purnia). Among households attending these workshops, around 60.7 per cent of the respondents in Gaya believe that these are beneficial, and a bulk, around 87.1 per cent, find them effective in Purnia. This indicates that although access to workshops is low, its effectiveness is perceived to be very high, making it important to organise more such public-run dissemination and training activities. The government could extend more widespread support to farmers in various formal ways, which is perceived as being very useful by a significant majority of farmers. Households in Purnia were found to be more inclined and receptive toward this kind of formal community networking opportunities.

Analysis based on gender indicates that a larger number of male-headed households attend these government run workshops in both districts, with a comparatively higher proportion in Purnia. Thus, social and cultural factors affect the participation of women in such workshops. Almost all female headed households in Gaya found attending these workshops useful, while in Purnia a greater proportion of male headed households felt that these are effective. Perhaps this is on account of the proximity of Gaya to the urban centres and greater awareness of the workshops, irrespective of gender.

Among the respondents in Gaya who do not attend workshops the following reasons were offered: lack of information about the events (43.5 per cent), lack of time to attend (17.4 per cent), too expensive to attend (16.7 per cent) and long distance to the venue (13 per cent). In Purnia, the reasons mentioned were lack of information on the organisation of such events (60.5 per cent), too far away to attend (18.4 per cent) and lack of time (10.5 per cent). Thus, the key reason for the low effectiveness of and participation in such workshops is lack of access to announcements, costs, and location. This indicates that government policies and initiatives should focus not only on the number of workshops being organised, but also on adequate prior announcement, reduction in registration/travel costs, flow of information and dissemination, and more regular interaction with the farmers.

A significant proportion of respondents have indicated awareness or knowledge of SHGs in both districts (around 76.5 per cent in Gaya and 91.4 per cent in Purnia), followed by either ATMA (53 per cent in Gaya and 50 per cent in Purnia) or KVKs (15.7 per cent in Gaya and 50.2 per cent in Purnia) (Figure 30).

Figure 30: Farmers' knowledge/awareness about social groups and networks



Within specific categories of social groups, the following findings are revealing. Gaya displays a higher proportion of households with knowledge of SHGs who have opted for their membership (72.4 per cent), while the percentage of such households, who are aware of SHGs and have sought their membership, is lower at 45.5 per cent in Purnia. Thus, even when a larger number of respondents in Purnia were aware of SHGs as compared to those in Gaya (76.5 per cent in Gaya and 91.4 per cent in Purnia), more households in Gaya are members of SHGs as compared to households in Purnia. Linkages with urban centres could be the reason for this behaviour.

In both districts, a higher proportion of women (92 per cent in Gaya and 100 per cent in Purnia) are aware of SHGs as compared to men (63.7 per cent in Gaya and 88.3 per cent in Purnia), and further, a higher proportion of female headed households in both districts (90.5 per cent in Gaya and 92.1 per cent in Purnia) have availed membership of SHGs than male headed households (63.5 per cent in Gaya and 36 per cent in Purnia). This indicates that women are more socially connected and ought to be encouraged to take up a more significant role in decision making and stewarding adaptation efforts in agriculture, especially those that benefit from community networking. Thus, more structured and institutionalised opportunities should be provided to them.

A noticeable proportion of households in the two districts said that there is no SHG membership fee (58.7 per cent in Gaya and 63.7 per cent in Purnia) and/or service fee (97.8 per cent in Gaya and 95.1 per cent in Purnia). Among those who are members and are paying fees, the perception was that the mean yearly membership fees prevailing currently (of INR 314.50 in Gaya and INR 202.30 in Purnia) are rather high. Further, the average number of meetings in a month – both formal and informal ones – is higher in Gaya than in Purnia: formal ones being 3.89 in Gaya and 3.47 in Purnia, and informal ones being 1.141 in Gaya and 0.205 in Purnia on average. Awareness and linkages with urban centres could be the reason for this.

Even though a larger number of respondents in Gaya (around 53 per cent) know of the existence of ATMA as compared to Purnia (49.8 per cent), most households are not members of ATMA (98.8 per cent in Gaya and 87.7 per cent in Purnia). Again, a higher proportion of female respondents (62.7 per cent in Gaya and 53.8 per cent in Purnia) know about ATMA than male respondents (45.1 per cent in Gaya and 48.3 per cent in Purnia).

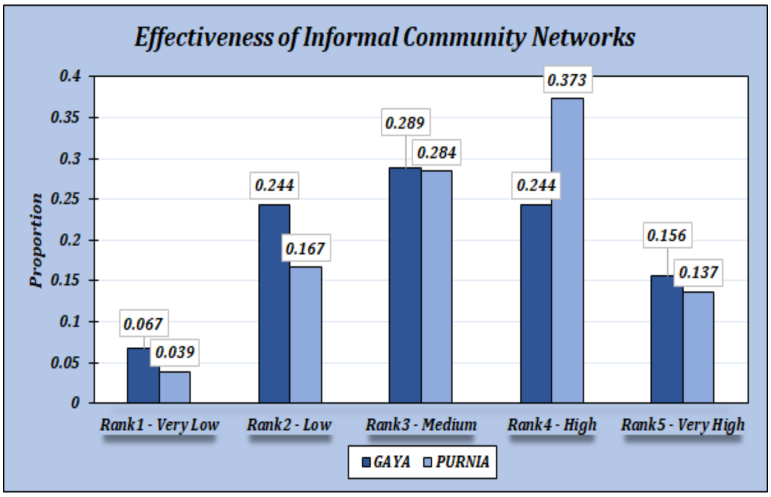
A larger proportion of Purnia households (50.2 per cent) know about KVKs; in Gaya, 46.4 per cent of the respondents were unaware of the actual functioning of KVKs. But all respondents in the two districts were members of KVKs. Within each district, among the respondents who know about KVKs, more male respondents (20.9 per cent in Gaya and 57.8 per cent in Purnia) know of KVKs than female respondents (9.3 per cent in Gaya and 29.2 per cent in Purnia).

A predominant proportion in both the districts want to be a member of such social groups (50.8 per cent in Gaya and 73.6 per cent in Purnia). Clearly, the proportion is higher in Purnia, among which most were male respondents (round 76.5 per cent). Among those respondents who did not want to seek membership of such social groups, lack of time (51.6 per cent) followed by geographical distance (22.6 per cent) were the major reasons given in Gaya. In comparison, in Purnia, a marked proportion of respondents expressed unwillingness to become members citing reasons such as lack of time (44.8 per cent) followed by 'other' reasons (20.7 per cent). Of the latter, reasons such as ill health (33.3 per cent) and lack of information about such social groups (33.3 per cent) were noted. All the respondents were males. The reasons for women abstaining from membership of social groups appears to be different from that stated by male respondents. About half the female respondents in Gaya were unwilling to become members due to the low quality of the concerned service (50 per cent), followed by insufficient interaction (25 per cent). In Purnia, 40 per cent of female respondents expressed unwillingness because of lack of time, followed by the expense involved (20 per cent) or distance (20 per cent) or insufficient interaction (20 per cent).

Next, as can be seen in Figure 28, a significant percentage of respondents in both districts perceive informal community networks (ICN) to be very helpful (around 61.4 per cent in Gaya and 66.9 per cent in Purnia). On a scale of one to five,[18] where the higher the number, the higher the effectiveness of the network, respondents in Gaya ranked ICN at number 3 (around 28.9 per cent), which indicates medium effectiveness, while in Purnia, respondents rank ICN at number 4 (at 37.3 per cent), which indicates high effectiveness. This implies that a larger percentage of respondents in Purnia think that ICN is effective, and the intensity of this perception is also stronger as compared to respondents in Gaya.

A larger proportion of women in Gaya (65.3 per cent) think that ICNs are beneficial while in Purnia, a larger proportion of men (69 per cent) perceive this to be the case. The analysis of gender perspective showed that even as a high enough proportion of respondents perceive that ICN is beneficial, the proportion is higher for women in Gaya than males in Purnia. Regarding the intensity of this perception, captured through the ranking mechanism, in Gaya, a significant proportion of male respondents rank ICN at number 2 (32.1 per cent), while a significant proportion of female respondents rank it at number 3 (41.2 per cent); a fairly large proportion of both male (32.9 per cent) and female (52.2 per cent) respondents rank ICN at number 4 in Purnia (Figure 31).

Figure 31: Farmers' perception on the effectiveness of informal community networks

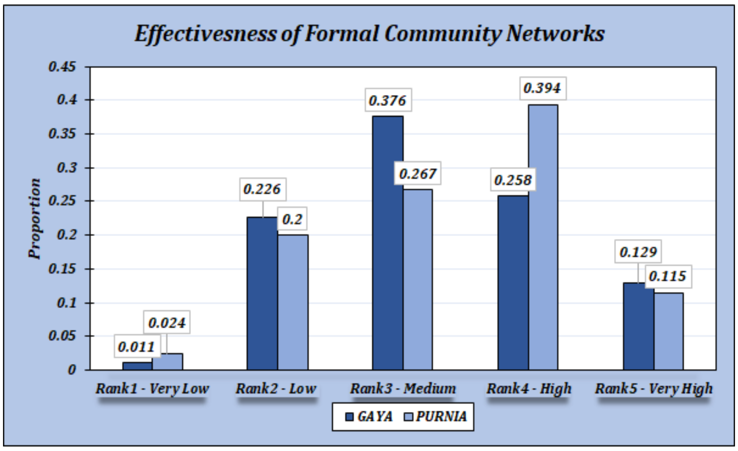


As for formal community networks (FCNs), it can be seen from Figure 32 below that a much lower share of responding households in both districts believe that FCNs are effective (28.9 per cent in Gaya and 47.7 per cent in Purnia), with a comparatively higher proportion in Purnia. Nearly 37.6 per cent of

[18] Respondents were asked to rate the effectiveness of formal and informal community networks on a scale of one to five with a ranking of one indicating the least effectiveness, 2 indicating low effectiveness, 3 indicating medium effectiveness, 4 indicating high effectiveness and 5 indicating very high effectiveness.

respondents in Gaya have ranked FCN at 3 (medium effectiveness), while a slightly larger proportion in Purnia have ranked FCN at 4 (around 39.4 per cent), indicating higher effectiveness. This implies that respondents in Purnia were generally found to be more favourably inclined toward FCN as compared to those in Gaya. Gender wise, a larger proportion of female respondents in Purnia feel that FCN is helpful as compared to those who think otherwise, while a lower share of female respondents in Gaya perceives it to be helpful. Although the proportion of female respondents in Gaya who perceive FCN as useful is higher than the proportion of male respondents, it is lower than the proportion of female respondents in Purnia. A significant proportion of male respondents in Gaya (38.5 per cent) ranked FCN at 3, while a slightly larger percentage of female respondents (39 per cent) ranked it at 4. In Purnia, both male (39.2 per cent) and female (40 per cent) respondents have ranked FCN at 4, indicating high effectiveness.

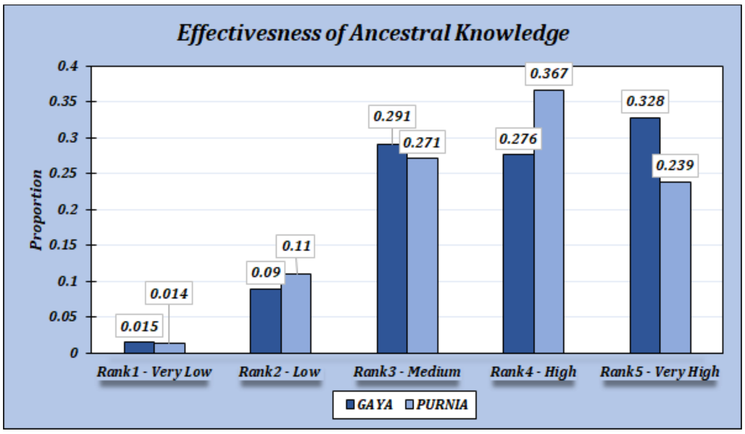
Figure 32: Farmers' perceptions on the effectiveness of formal community networks



An overwhelming proportion of respondents in both districts believe that they have ancestral/traditional knowledge (TK) (86.7 per cent in Gaya and 93.5 per cent in Purnia), and that it is helpful in making or modifying their farming decisions (93.1 per cent in Gaya and 95.2 per cent in Purnia); the perception was slightly higher in Purnia for all cases. Although a larger share of Purnia respondent households think that TK is helpful, its ranking differs across districts as well as across gender. A significant proportion of respondent households in Gaya has ranked TK at 5 (32.8 per cent) (highest effectiveness). In Purnia, around 36.7 per cent (largest share) ranked TK at 4, which implies high, but not the highest, level of perceived effectiveness (Figure 33).

Gender wise, the survey found that a higher proportion of female respondents in both districts think that they have TK, a large chunk of male respondents in Gaya (93.4 per cent) felt it is helpful, and a large share of women respondents in Purnia (96.8 per cent) felt that it is helpful. Ranking TK across districts and respondent's gender differs; a significant share of male respondents in Gaya (36.6 per cent) ranked it at number 5 (highest effectiveness), while 33.3 per cent of women respondents in Gaya rank it at 3 (medium effectiveness). In comparison, in Purnia, both male (34.8 per cent) and female (41.7 per cent) respondents ranked it at 4 (high effectiveness). This indicates that there is a significant difference in the ranking of its effectiveness between males and females in Gaya whereas in Purnia, the responses were more or less the same for both males and females.

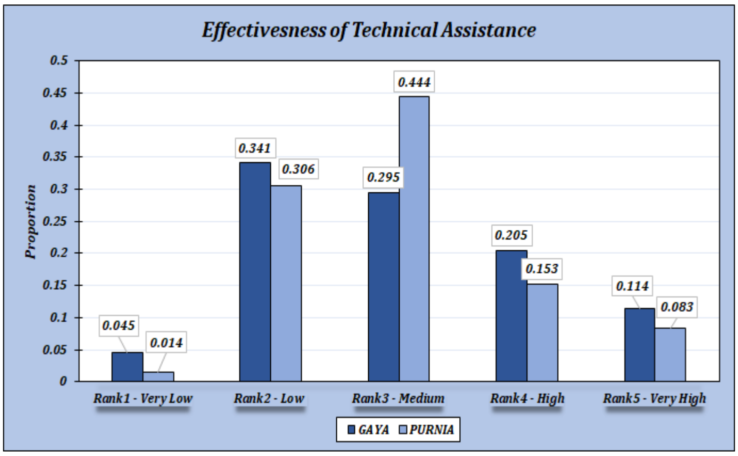
Figure 33: Farmers' perceptions on the effectiveness of ancestral knowledge



A relatively smaller fraction of respondents in the two districts perceive that technical assistance (TA) is helpful for farming decisions (26.5 per cent in Gaya and 29.4 per cent in Purnia) as compared to ICN, FCN, and TK. A significant share of respondents in Gaya ranked TA at 2 (34.1 per cent), which indicates that the effectiveness of TA is perceived to be low, while a relatively larger fraction of respondents in Purnia ranked it at 3 (around 44.4 per cent), which indicates medium effectiveness (see Figure 34 below).

Although a small proportion of respondents found TA useful, more male respondents (32.9 per cent in Gaya and 36.1 per cent in Purnia) found it so as compared to female respondents (18.7 per cent in Gaya and 10.8 per cent in Purnia). In terms of relative effectiveness, 40 per cent of male respondents in Gaya gave a ranking of 3 for TA. About half the female respondents in the district ranked it even higher at 4 (high effectiveness). In Purnia, male respondents (46.2 per cent) rank TA at 3 while it was ranked 2 and 3 by an equal proportion of female respondents (28.6 per cent).

Figure 34: Farmers' perceptions on the effectiveness of technical assistance

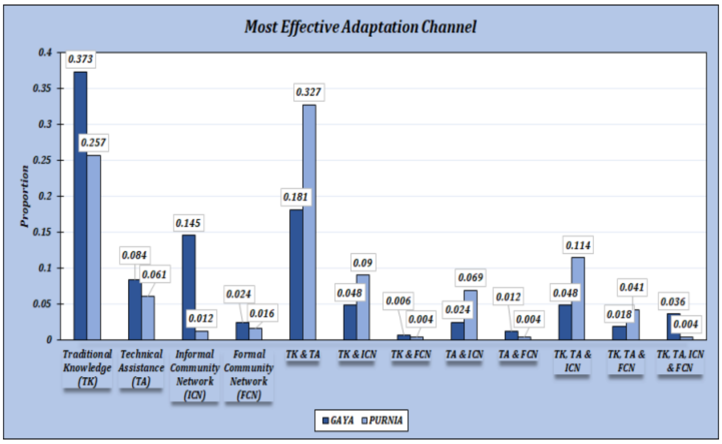


Overall, across all adaptation channels referred to above, a large section of respondents in Gaya preferred only TK (37.3 per cent), followed by a combination of TK and TA (18.1 per cent), and only ICN (14.5 per cent). In comparison, in Purnia, respondents preferred a combination of TK and TA (32.7 per cent), followed by only TK (25.7 per cent), and a combination of TK, TA and ICN (11.4 per cent). Thus, there is a clear preponderance of reliance on the three channels – TK, TA and ICN (see Figure 35 below).

A higher proportion of respondents in Gaya ranked TK and the combination of TK and TA at 4 and only ICN at 2. As compared to this, a large percentage of respondents in Purnia ranked the combination of TK and TA, and only TK at 5, and ranked the combination of TK, TA and ICN at 4. Since respondents in Gaya ranked their first three choices at 4, 4 and 2 and respondents in Purnia ranked their preferences at 5, 5 and 4, one can say that respondents in Purnia perceived the effectiveness of these adaptation channels to be higher.

The analysis of gender differentiated results are qualitatively similar, except in the case of female respondents in Purnia, among whom the largest proportion preferred only TK (32.3 per cent) and a combination of TK and TA (32.3 per cent), followed by a mix of TK and ICN (around 12.3 per cent); this is different from the overall preference ordering of a combination of TK and TA, followed by only TK, and a combination of TK, TA and ICN (which was preferred by only 6.2 per cent in this case).

Figure 35: Farmers' perceptions on the most effective adaptation channels for farming decisions



This completes the discussion of the results of the primary survey using the mixed methods approach. Most of these results are a corroboration of what was found regarding the role of inherent ability and community network channels of adaptation based on secondary data. The insights provided by gender distinguished responses are interesting.

In what follows, the survey econometric regression results are examined.

5.2 Survey econometric estimation results

Using the perception survey responses from farmers in the chosen villages and blocks in Gaya and Purnia, econometric regression specific to survey analysis have been used by correcting the standard errors of the regression by taking into account the sampling technique, that is, stratified random sampling and sample size to check for the dependence of rice and wheat yields on availability of natural resources, farm inputs, farming technology, household characteristics, climate variables, ability (ancestral knowledge) and community networks for each of the crops – rice and wheat – separately.

Primary survey regression estimates for rice yields

The result of the regression estimates for rice are given in Table 15 below.

Table 15: Survey regression results for rice yields using primary survey data

Regressors	Gaya	Purnia	Combined
Agricultural labour hired	-1.133704 (-1.56)	-1.598756 (-0.75)	-1.426621* (-1.64)
Usage of NPK fertiliser	-.0923154 (-0.08)	-1.095557 (-0.71)	-.2206359 (-0.27)
No. of times of pest control adoption	-2.789529** (-2.92)	-6.983547 (-0.85)	-4.504561** (-2.44)
Use of HYV seeds	-21.0405 (-0.14)	372.1415 (0.91)	52.68053 (0.36)
Utilisation of sprayer/ duster	.3134596 (0.85)	-.3378848 (-1.31)	-.2067754 (-1.25)

Regressors		Gaya	Purnia	Combined
Utilisation of diesel pumps		.2027943 (1.39)	.2318821 (0.75)	.1363532 (1.04)
Utilisation of electric pumps		-.2304976 (-1.26)	.4284223 (1.13)	-.0028804 (-0.02)
Utilisation of power tiller		-.4197021*** (-3.94)	1.997138 (1.03)	-.3308049** (-2.17)
Utilisation of tractor		-.1072002 (-0.85)	-.3339376** (-2.66)	-.1548883* (-1.96)
Utilisation of rotavator		1.167169 (1.56)	-.1584092 (-0.58)	.1269766 (0.61)
Utilisation of rice transplanter		1.057375*** (4.32)	0	.8907887*** (3.29)
Loan amount		.000712 (0.27)	.0004871 (0.75)	.0000938 (0.17)
Farmer type		140.0524 (1.02)	371.9186** (2.32)	278.6802* (1.68)
Own land		-13.9749 (-0.07)	371.833* (1.95)	171.1946 (0.98)
Family type		-136.6627 (-0.92)	283.884 (1.17)	-86.60279 (-0.76)
Family size		-44.23523* (-1.87)	26.1989 (0.95)	-19.16648 (-0.83)
Adult sex ratio		27.64359 (0.26)	1201.867 (1.35)	389.6131 (1.06)
Gender of household head		55.28988 (0.41)	67.34533 (0.26)	18.10488 (0.15)
Proportion of earning members		28.64179 (0.05)	977.101 (1.32)	360.0026 (0.77)
Soil fertility		24.22225 (0.16)	-6.272942 (-0.03)	39.232 (0.28)
Temperature		-211.9139 (-1.28)	-386.8144 (-1.29)	-175.277 (-1.02)
Rainfall		90.21121 (0.51)	-193.9134 (-0.76)	282.4566** (2.01)
Wind speed		-90.02956 (-0.50)	28.20079 (0.15)	-78.55913 (-0.55)
Proportion of family member passed class X		291.4206 (0.81)	1538.115* (1.74)	265.1127 (1.04)
Proportion of family member passed class XII		201.3724 (0.73)	-535.4516 (-0.81)	388.8895* (1.82)
Proportion of family member attended higher education		989.7109** (2.00)	209.4903 (0.37)	648.7404* (1.98)
Experience level		27.71532 (0.21)	-123.6693 (-0.87)	-117.2846 (-0.96)
Ancestral knowledge	**Less effective**	499.422 (1.56)	-108.4505 (-0.29)	432.6002* (1.70)
	High effective	277.8238* (1.61)	-271.257 (-1.25)	203.8577 (1.25)
Technical assistance	**Less effective**	-585.7634*** (-3.34)	-414.3462 (-1.25)	-557.7453*** (-3.74)
	High effective	230.6137 (1.16)	-26.18491 (-0.13)	70.58666 (0.47)
Informal community networks	**Less effective**	202.4416 (0.66)	-549.8704 (-1.45)	-124.6175 (-0.52)
	High effective	-402.9222** (-2.36)	-414.0915 (-1.17)	-196.8671 (-1.10)
Formal community networks	**Less effective**	119.3274 (0.37)	962.5281* (1.66)	692.5305* (1.95)
	High effective	-55.316 (-0.30)	435.2034** (2.36)	87.47429 (0.86)
Trusted networks with relatives, neighbours & friends		43.42912 (0.29)	-469.8408 (-0.96)	-225.48 (-0.93)
Trusted network with JEEViKA		313.0585**	126.2124	304.0016

Regressors	Gaya	Purnia	Combined
	(2.19)	(0.70)	(1.49)
Attending government-run workshops	172.9173 (0.92)	105.1514 (0.61)	-49.62593 (-0.43)
Constant	601.8339 (0.98)	-953.3114 (-0.70)	-45.38372 (-0.06)
District Dummy	NA	NA	-320.5673* (-1.75)
Block, Panchayat, Village	x	x	x
Prob.>F	0.0000	0.5540	0.0000
R^2	0.3693	0.2686	0.1821
No. of Observations	135	196	331
Type of Standard Error (S.E.)	Linearised	Linearised	Linearised
Model Significance	1 per cent		1 per cent

Note: Figures in parentheses refer to the value of the t-statistic.
Coefficients in '***', '**', '*' are statistically significant at 1%, 5%, and 10% level respectively.
'0' represents dropped variables by the regression estimation.
'NA' indicates not included in the regression estimation.

From Table 15, one can see that *Prob.>F*-values are highly significant at 1 per cent level except for rice yields for Purnia, and the R^2 values are moderate for rice yields. Thus, one can say that rice models are fitted well.

As is evident from the estimations (Table 15), labour used per acre is found to have a negative impact on rice yields in both Gaya and Purnia, although it is significant only for Gaya. For the two districts combined, it is negative and significant. This corroborates the earlier results from the analysis of secondary data and suggests that the pressure of too many labourers on limited land resources is depressing the marginal productivity of the agricultural labour force.

Among agricultural machinery and equipment, only a few have a positive impact on rice yields, while the rest display more than optimal use of machinery and equipment. While the use of sprayers and dusters has a positive and significant impact on rice yields in Gaya, its impact is negative in Purnia, even though it is statistically insignificant. The negative impact may be because of the presence of a threshold effect of the use of sprayers and dusters for pest control. Pest control helps to protect the crop up to a point, but it causes reduction in crop yields due to excessive usage/application. In both the districts, the frequency of usage of pest control is excessive as the coefficients are negative and statistically significant except for Purnia. The use of diesel pump sets increases rice yields in both Gaya and Purnia, as rice is a water-intensive crop. However, the coefficients are insignificant. The use of electric pump sets depresses yields in Gaya but improves yields in Purnia. The use of power tillers reduces rice yields in Gaya and the impact is significant, while in Purnia its impact is positive though insignificant. The use of tractors, surprisingly, leads to a reduction in rice yields and the impacts are significant on overall and in Purnia. The use of rotavators increases yields in Gaya and decreases it in Purnia; however, the coefficient is significant only for Gaya. Finally, the use of rice transplanters has a positive and significant impact on rice yields in Gaya. No household in Purnia in the sample reported the use of a rice transplanter; therefore, it is omitted from the regression.

The loans/credit variable includes the total credit availed by a farming household from all sources for agricultural purposes. The coefficient of this variable is quite low and insignificant even though it is positive. This would be reasonable if households do not avail much credit and have their own resources to meet the costs of cultivation.

HYV is a dummy variable that takes the value 1 if the household uses HYV seeds and 0 otherwise. Its impact is positive for rice yields in case of Purnia, while the impact is negative in Gaya. Secondary data analysis showed a negative impact of HYV seeds on rice yields indicating lack of awareness among farmers regarding the use of HYV seeds. The primary data result, however, seems to suggest that farmers in Purnia have become more aware of the use of HYV seeds lately, and use it to their advantage as compared to Gaya. The usage of NPK fertilisers has a negative impact in both the districts, Gaya and Purnia, corroborating results from secondary data and providing further evidence of the improper and unbalanced use of fertilisers in Indian agriculture.

To account for gender wise differences, a dummy has been used with the variable 'gender of the household head' taking the value 1 if the household head is a female and 0 if it is a male. The coefficient of this variable is positive for both Gaya and Purnia, indicating that female headed households are better at managing agriculture than male headed households. While adult sex ratio has a positive effect on rice yields in both Gaya and Purnia, it is found to be statistically insignificant. This is the opposite of what was found from secondary data estimates, perhaps because the regressor used there is different from that used in primary data analysis and referred to the overall female to male population ratio. This is a very interesting result from the primary data analysis. Further, a higher proportion of earning members present in a family tends to boost rice yields in both Gaya and Purnia, though again it is statistically insignificant.

Family size has a negative and significant impact on rice yields in Gaya; in Purnia, it is positive but insignificant. Although larger families have a greater stake in agriculture, higher family expenses constrain resource availability for agricultural activity, reducing yields. The variable 'family type' takes a value 1 if the family is a joint family or an extended family and 0 if it is a nuclear family. The impact of family type is negative for Gaya and positive for Purnia. Both are insignificant.

The variable 'own land' takes the value 1 if the land where cultivation takes place is owned by the household and 0 otherwise. Its impact on rice yields is positive and significant for Purnia. For Gaya, it is negative but insignificant. The variable 'farmer type' takes the value 1 if the landholding is small/marginal; otherwise, it takes the value 0. Its impact on rice yields is positive for both Gaya and Purnia and significant for Purnia.

'Soil fertility' is a dummy that takes the value 1 if soil fertility is medium, high, or very high and 0 if it is low or very low. Its impact on rice yields is negative in Purnia and positive in Gaya. Both are statistically insignificant.

The variables 'temperature' and 'wind speed' are also dummy variables that take the value 1 if temperature and wind speed are perceived to be as required or somewhat more than required for cultivation and 0 otherwise. The impact of temperature on rice yields is negative and insignificant for both Gaya and Purnia. This means that the normally prevailing temperatures in Gaya and Purnia are above the threshold where an increase in average temperature would lead to lowered rice yields. Wind speed affects rice yield adversely in Gaya and improves it in Purnia though the impacts are statistically insignificant. Since more than half of the surveyed households in both Gaya and Purnia have perceived that wind speed is as would be required for cultivation, the varied impacts of wind speed across the two districts either display inconsistency in the responses or the presence of threshold effects as wind speed is much higher in Gaya as compared to Purnia (see Table 22 in Annexure A).

'Rainfall' is also a dummy variable like other climate variables but defined differently for the two districts. The variable 'rainfall' takes the value 1 if rainfall is as will be required for cultivation or somewhat more than required and 0 otherwise for Gaya, and for Purnia, it takes value 1 if rainfall is somewhat or much more than required for cultivation and 0 otherwise. We make this difference in the formation of the rainfall dummy since a majority of the Gaya households perceive that rainfall in Gaya is just as will be required or somewhat more than required for cultivation. In comparison, in Purnia, a majority of the households perceive that rainfall is somewhat and much more than required for cultivation (see Table 25, Schedule C in Annexure C). However, the variable 'rainfall' takes the value 1 if rainfall is as required or somewhat or much more than required and 0 otherwise for the two districts' combined estimation. The impact of rainfall on rice yields is positive in Gaya and negative in Purnia. Both are insignificant. This result is not surprising as Purnia is an area with heavy rainfall and Gaya is an area with low rainfall.

Among the planned adaptation channels, education is found to improve crop yields in general. Nonetheless, the educational scenario is very poor in both Gaya and Purnia in our sample (see Figure 6 and Table 25, Schedule A in Annexure C). The regression analysis depicts that a higher proportion of family members who have passed grade/class X, class XII and attained higher education has a positive effect on increases yields in Gaya. The coefficient is only significant for higher education. In Purnia, yields only rise for grade/class X education attainment and higher education attainment, for grade/ class XII, yields tend to fall even though the coefficient is insignificant. This may be because educated members either migrate or transition to other occupations and focus less on agricultural activities in their native places. Another planned adaptation channel, technical assistance, shows adverse and significant effects on rice yields for both the districts if it is perceived by the farmers to be less effective, that is, ranking with very low and low effectiveness one a scale of 1 to 5. However, it depicts a mixed-effect on rice yields, positive for Gaya and negative for Purnia if it is highly effective, that is, ranking of medium, high, and very high on a scale of 1 to 5; these effects are found to be statistically insignificant.

The main focus of this research is on the role of inherent ability and community networks. Inherent ability is captured by the variables 'experience level' and 'effectiveness of ancestral knowledge', informal network (reflecting community network spill-overs) is captured by 'effectiveness of informal community networks' and 'trusted networks with relatives, neighbours and friends', and formal network is captured by 'effectiveness of formal community networks', 'trusted network with JEEViKA' (institutional support for adaptation and technological progress in agriculture) and 'attendance in government-run workshops'. When the ancestral knowledge is perceived to be less effective, that is, ranking as very low and low in effectiveness on a scale of 1 to 5, it mostly lowers rice yields for Purnia and raises them for Gaya, though it is insignificant. However, ancestral knowledge with perceived high effectiveness, that is, ranking with medium to very high on a scale of 1 to 5, exhibits positive impacts on rice yields in Gaya and negative impacts in Purnia, though it is only significant for Gaya.

Another way to capture inherent ability, which is derived from learning-by-doing, is captured by the experience level. This is defined as a dummy variable that takes value 1 if the age of the respondent farmer is equals to or more than the average age of surveyed respondents of a particular district and 0 otherwise, where the average age differs across the two districts (the average age of respondents is 43 years in Gaya and 47 years in Purnia as can be seen in Table 25, Schedule A in Annexure C) and for the combined estimation, the variable 'experience level' is defined as a dummy variable that takes value 1 if the age of the respondent is equal to or more than the average age of all surveyed respondents, which is 45 years and 0 otherwise. The experience level also found to have a positive effect on rice yields in Gaya and negative impact in Purnia. These adverse effects of both ancestral knowledge and experience level in Purnia may be because of higher climate vulnerability of Purnia than Gaya and hence, the inherent ability (that is derived from the ancestral knowledge and past experience) fails to work as effectively in Purnia.

Another pertinent autonomous adaptation channel is the informal community networks. Whenever informal community network is believed to be less effective, that is, ranking of very low and low effectiveness on a scale of 1 to 5, it tends to dampen rice yields. In comparison, the effect is negative for rice yields for both the districts, and it is significant for Gaya under the high effectiveness case, that is, ranking of medium to very high effectiveness on a scale of 1 to 5, of informal community networks. On the contrary, the trusted connection of Gaya farmers with their relatives, neighbours, and friends, which represents another form of informal network channel, displays a positive impact on rice yields though it is statistically insignificant. However, its impact in Purnia is negative. Here the variable 'trusted network with relatives, neighbours, and friends' is also a dummy variable that takes value 1 if the farmers are closely connected with their relatives, neighbours, and friends and can trust them for their farming decisions and it takes a value 0 otherwise. Hence, one can infer that higher the informal networks higher will be the crop yields for both the districts. But in Purnia, it is an exceptional for rice yields, since both the coefficients of the variables 'informal community networks' and 'trusted connections of farmer with their relatives, neighbours, and friends' are found to be negative, though these are statistically insignificant.

Furthermore, formal community network, which is another relevant planned adaptation channel besides educational attainment and technical assistance, has been promoted along with the informal community network. Although the knowledge/ awareness about such formal community network groups/ platforms is very low, as indicated by the farmers' responses (see Table 25, Schedule D in Annexure C), it tends to boost rice yields in both the districts no matter whatever its perceived effectiveness – low or high. However, the impacts of formal community networks are significant only for rice yields in Purnia. The exception is its impact on rice yields in Gaya for its high effectiveness level; the effect is negative though it is statistically insignificant. Apart from formal community networks, the trusted connections of farmers with JEEViKA members, which is yet another indicator of formal networks, displays significant positive impacts on rice yields in both Gaya and Purnia. Here, the variable 'trusted network with JEEViKA' is a dummy variable that takes value 1 if the farmers are close to JEEViKA members and place trust on them for their farming decisions and 0 otherwise.

Another platform of formal network where ICT-enabled extension services have been promoted is the government-run workshops. The variable 'attending government-run workshops' takes value 1 if farming households have been attended these workshops and 0 otherwise. Higher attendance in such government-run workshops is found to improve rice yields in both Gaya and Purnia.

Finally, the variable 'district' takes the value 1 if the household is in Purnia and 0 if it is in Gaya. The value of the coefficient is negative implying that rice yields in Purnia are lower than in Gaya, other things held constant.

All these regressions have controlled for the blocks, *panchayats*, and villages so that characteristics specific to these could be controlled similar to the fixed effects; notably, these variables are included as categorical ones.

We now discuss the results of primary survey regressions for wheat yields (Table 16).

Primary survey regression estimates for wheat yields

Table 16: Survey regression results for wheat yields using primary data

Regressors	Gaya	Purnia	Combined
Agricultural labour hired	.0852663 (0.95)	-.1241608*** (-3.17)	.0737796 (1.42)
Usage of NPK fertiliser	.0566472 (0.07)	-109.6251* (-1.89)	-.1051093 (-0.14)
No. of times of pest control adoption	.5100849 (0.51)	-20.57368 (-0.94)	.2163288 (0.24)
Use of HYV seeds	326.686** (2.36)	0	277.214** (2.11)
Utilisation of sprayer/ duster	-.036421 (-0.09)	NA	-.095112 (-0.38)
Utilisation of diesel pumps	-.0563076 (-0.61)	-.0659763 (-0.49)	-.0755724 (-1.05)
Utilisation of electric pumps	.1642393* (1.61)	-.8061606*** (-3.07)	.1699779** (2.11)
Utilisation of power tiller	-.0064488 (-0. 09)	0	-.0250611 (-0.35)
Utilisation of tractor	.0359705 (0.42)	.2006047** (2.01)	.0563033 (0.80)
Utilisation of rotavator	-.3363113 (-0.60)	-.7432649*** (-5.14)	-.2573416 (-1.05)
Utilisation of rice transplanter	NA	NA	NA
Loan amount	.0085624*** (3.30)	-.0073441*** (-3.79)	.0069391*** (3.65)
Farmer type	-212.701 (-1.56)	512.7186*** (4.60)	-194.1285* (-1.99)
Own land	-47.97443 (-0.28)	0	-21.22257 (-0.12)
Family type	-335.6262** (-2.93)	192.3817** (2.05)	-251.935** (-2.39)
Family size	-24.4771	204.5104***	-27.25637*

Regressors		Gaya	Purnia	Combined
		(-1.32)	(6.88)	(-1.84)
Adult sex ratio		-196.8861 (-1.49)	-740.7835*** (-4.93)	-166.6214 (-1.53)
Gender of household head		223.2239* (1.89)	NA	194.2035* (1.71)
Proportion of earning members		-402.1519 (-0.93)	846.5795* (1.74)	-490.2328 (-1.35)
Soil fertility		215.3089* (1.92)	-1325.092*** (-5.56)	222.7273** (2.23)
Temperature		84.91913 (0.52)	-8.43962 (-0.05)	84.13787 (0.65)
Rainfall		120.262 (0.97)	0	109.4194 (0.88)
Wind speed		-125.1438 (-0.98)	NA	-109.6145 (-1.16)
Proportion of family member passed class X		-138.9309 (-0.58)	-2043.743** (-2.88)	-155.0319 (-0.64)
Proportion of family member passed class XII		560.9705* (1.82)	NA	445.3458* (1.95)
Proportion of family member attended higher education		687.8865 (1.36)	NA	557.7386* (1.78)
Experience level		145.3553 (1.23)	-217.131** (-2.31)	133.6598 (1.46)
Ancestral knowledge	-356.6184* (-1.80)	NA	-305.9935* (-1.67)	
	103.0643 (0.74)	-128.0714 (-0.90)	122.0419 (1.15)	
Technical assistance	-27.63094 (-0.14)	NA	-65.83279 (-0.43)	
	-283.2053* (-1.62)	NA	-255.9562* (-1.70)	
Informal community networks	-153.5447 (-0.69)	NA	-144.944 (-0.90)	
	157.1359 (1.02)	NA	132.2122 (1.04)	
Formal community networks	81.2989 (0.41)	NA	99.12294 (0.66)	
	46.92334 (0.42)	NA	109.1535 (1.12)	
Trusted networks with relatives, neighbours & friends		13.55059 (0.14)	350.8134** (2.64)	31.40645 (0.40)
Trusted network with JEEViKA		-179.2044 (-0.80)	294.769* (1.68)	-149.5868 (-0.93)
Attending government-run workshops		-249.1216* (-1.69)	577.6744*** (5.14)	-151.6215 (-1.29)
Constant		822.6316 (1.55)	322.9124 (1.04)	756.7425* (1.74)
District Dummy		NA	NA	-374.0538** (-2.27)
Block, Panchayat, Village		x	x	x
Prob.>F		0.0000	0.0227	0.0000
R^2		0.5302	0.9558	0.4699
No. of Observations		77	27	104
Type of Standard Error (S.E.)		Linearised	Linearised	Linearised
Model Significance		1 per cent	5 per cent	1 per cent

Note: Figures in parentheses refer to the value of the t-statistic.
Coefficients in '***', '**', '*' are statistically significant at 1%, 5%, and 10% level respectively.
'0' represents dropped variables by the regression estimation.
'NA' indicates not included in the regression estimation.

From Table 16, one can see that *Prob.>F*-values are highly significant at 1 per cent and 5 per cent level, and the R^2 values are quite high for wheat yields. Thus, similar to the rice yields models, wheat yield models are also well fitted.

For wheat yields, labour used per acre has a positive impact in Gaya though statistically insignificant. Here, the increased use of labour does not put pressure on limited land resources to depress the marginal productivity of labour. In Purnia, an increase in the use of labour is found to have a negative and significant impact on wheat yields.

As in the case of rice yields, only a few agricultural machinery and equipment have a positive impact on wheat yields. The use of sprayers and dusters has a negative impact in Gaya Again, the negative impact may be due to an increase in pest infestations. The use of diesel pump sets has a negative impact on wheat yields in both Gaya and Purnia, although it is insignificant. In contrary. use of electric pump sets has an exactly opposite effect to that of diesel pump sets in Gaya and similar negative effect in Purnia. Recall that while Gaya is a water scarce district, Purnia has a wetter climate. Power tillers are used only in Gaya for wheat production and its impact on yields is negative. Again, the use of tractors has a positive impact on wheat yields in both Gaya and Purnia. Similarly, the use of rotavators has a negative impact on yields in both Gaya and Purnia. However, the impact of both tractors and rotavators are insignificant, except in the case of Purnia.

The impact of loans/credit availed on wheat yields is positive in Gaya and negative in Purnia, and the coefficients are significant.

The use of HYV seeds has a positive impact on wheat yields in Gaya as expected. The use of NPK fertilisers has a positive but insignificant impact on wheat yields in Gaya. It has a negative and significant impact on wheat yields in Purnia, perhaps implying improper or sub-optimal application of fertilisers. Similar district-specific impacts have been observed is case of use of pest control.

Female headed households have a positive impact on wheat yields in Gaya again, suggesting that female headed households manage agriculture better than male headed households. Family size has a positive impact on wheat yields in Purnia but negative impact in Gaya, although this negative impact is insignificant. This implies that the positive effect associated with family size outweighs the negative effect. The impact of 'joint family' on wheat yields is negative for Gaya and positive for Purnia. A higher proportion of earning members tends to improve wheat yields in Purnia but dampen it in Gaya, although the negative effect is insignificant.

Ownership of land has a negative but insignificant impact in Gaya. All households in Purnia in our sample own land, therefore, this variable is omitted for Purnia. Higher the number of households with small/marginal landholdings, higher is the wheat yields in Purnia but lower it is in Gaya, though it is statistically insignificant. The rise in crop yield for a higher proportion of small/ marginal landholding is in accordance with the principal-agent theory.

The impact of soil fertility is negative for Purnia but positive for Gaya. This may be the case because of richer soil quality in Gaya as compared to Purnia (see soil texture and erosion in Table 22 in Annexure A).

The impact of both climatic variables, temperature and rainfall on wheat yields is positive for Gaya. This means that the prevailing climatic conditions in Gaya and Purnia are above the threshold, such that further increases in temperature or rainfall will lead to an increase in wheat yields. The rainfall variable is dropped by the regression estimation for wheat yield in Purnia. However, we have tried to capture the effect of rainfall on wheat yield in Purnia through different combinations of rainfall variable wherein its definition is varied (see Table 26 in Annexure C for more details). Table 26 lists three model specifications: the first one is the same as in Table 16, that is, the variable for rainfall takes value 1 if rainfall is somewhat or much more than required for cultivation and 0 otherwise; the second one considers the rainfall dummy value taken as in case of the combined districts' estimations, that is, it takes value 1 if rainfall is as required or somewhat or much more than required and 0 otherwise; and the third one considers the rainfall dummy value to be similar to the case for Gaya, that is, it takes value 1 if rainfall is as required or somewhat more than required and 0 otherwise. Like in case of model 1, the rainfall variable gets dropped in model 2 as well. Model 3 estimates the rainfall impact on wheat yield in Purnia, and it displays a positive effect. So, we infer that, in general, rainfall improves wheat yields in Purnia. Further, wind speed affects wheat yield in Gaya adversely although it is statistically insignificant.

A higher proportion of family members who have passed grade/class XII and attained higher education leads to gains in yields in case of both Gaya and Purnia. For class X education attainment, there is a negative effect on yields in both Gaya and Purnia. Technical assistance tends to lower wheat yield for Gaya and, in general, for the combined districts' estimations. It is significant only when it is perceived as highly effectiveness, that is, ranking with medium to very high effectiveness on a scale of 1 to 5, indicating the need for more technical assistance to boost crop yields. The variable 'technical assistance' has not been included in the wheat yield estimations for Purnia due to the degrees of freedom problem in a small sample size.

Ancestral knowledge dampens wheat yields in Gaya significantly when it is perceived to be less effective. Since there are no such observations for less effective influence of ancestral knowledge under wheat yield in Purnia, it is not included in the regression analysis. However, ancestral knowledge with high deemed effectiveness displays a positive impact on wheat yields in Gaya and negative impact in Purnia, though the latter is insignificant. Thus, the significant negative impact of ancestral knowledge for wheat yield in Gaya may be due to its less perceived effectiveness since the effect turns to positive as the deemed effectiveness of ancestral knowledge gets higher. Further, the experience level also a represents positive impact on wheat yields in Gaya and a negative one in Purnia, and the impact is found to be significant only for Purnia. These adverse effects of both ancestral knowledge and experience level in Purnia may be because of more climate-vulnerability of Purnia than Gaya and, hence, the inherent ability (that is derived from the ancestral knowledge and past experience) having a weaker effect or failing to work effectively in Purnia.

Informal community networks have also not been included in the wheat yield regression for Purnia (this is similar to 'technical assistance' as a regressor), due to the degrees of freedom problem in a small sample size. Whenever informal community network is perceived to be less effective, it tends to dampen wheat yields, in general as well as in Gaya. In comparison, the impact is positive for wheat yields under the perceived high effectiveness case. In addition, the personal connection of farmers with their relatives, neighbours, and friends and their trust on them tends to improve wheat yield in both the districts, and it is significant in Purnia. Hence, one can infer that higher the informal networks higher will be wheat yields for both the districts.

In addition to informal community networks, formal community networks work well, especially where ICT-enabled extension services are present. Although the knowledge/ awareness of formal community network groups/ platforms is somewhat poor, according to farmers' responses (see Table 8, Schedule D in Appendix), these tend to boost wheat yield in both the districts no matter whatever is its effectiveness – low or high – perceived by the farmers. The variable 'formal community network' has also not been included in the wheat yield estimation for Purnia due to the degrees of freedom problem in a small sample size; this again similar to the variable 'technical assistance' and 'informal community networks'. Apart from the formal community networks, trusted connections of farmers with JEEViKA members displays a significant positive impact on wheat yield in Purnia but a negative one in Gaya, though the latter effect is insignificant.

Further, higher attendance in 'government-run workshops', which is yet another formal platform where ICT-enabled extension services are promoted, raises wheat yields significantly in Purnia. While the involvement in government-run workshops should improve crop yields, in general, an increase in attendance in such government-run workshops tends to dampen wheat yield significantly in Gaya. This contradictory result may be because a very small percentage of farming households in Gaya, only around 17 per cent, reported that they attend these workshops and, thus, these are not too effective (see Table 25, Schedule D in Annexure C).

Finally, the coefficient of the district dummy is negative implying that wheat yields are higher in Gaya than in Purnia.

Similar to rice estimation, blocks, *panchayats*, and villages have been controlled in all wheat yields regressions.

This completes the discussion of results. In what follows, we summarise the key takeaways of the analyses and derive policy implications. We also attempt to draw up a menu of policies that could be used to operationalise policy recommendations for climate adaptation and transition to climate smart agricultural practices.

6. Summary of findings and policy recommendations

6.1. Background and main findings from primary and secondary data analyses

The phenomenon of climate change refers to alterations that go beyond common atmospheric conditions, leading to a rise in mean global temperature, often called "global warming". Global warming has been proven to cause not simply changes in average temperature and precipitation regimes, but also a rise in the frequency and intensity of extreme events, such as floods, droughts, heat waves, and storms, all of which are a consequence of the changes in temperature and precipitation configurations. These changes could have significant adverse consequences for the food and farming sectors, and grave implications for livelihoods in emerging economies such as India.

The measures to cope with global warming and climate change can broadly be classified into two: mitigation measures that focus on reducing and absorbing greenhouse gases and adaptation options that help countries and societies mitigate the adverse effects of climate change. The thrust of most approaches so far has been on mitigating greenhouse gas emissions. However, in the case of agriculture in particular, there is an increasing shift in favour of adaptation measures based on the assessment of vulnerability and risk posed by climate change for agricultural productivity and living standards of agriculture-dependent communities. These include, inter alia, changes in crop mix and inter-cropping, modifications at the time of sowing and harvesting, greater reliance on more climate resilient varieties, etc.

Changes in climate regimes pose serious concerns for India. Average temperatures in India have displayed a rising trend and precipitation patterns have become more uncertain. By 2050, annual average temperatures in India are projected to rise 1 to 2^0 Celsius under the climate-sensitive scenario (RCP 4.5) and 1.5 to 3^0 Celsius under the carbon-intensive scenario (RCP 8.5) (Mani, et al. 2018). In the specific context of the state of Bihar, which is the focus of this study, climatic patterns have shown notable variations over a shorter period – the last three to four decades. The Bihar State Action Plan on Climate Change notes a minimum temperature rise of 0.6 to 1.5^0 Celsius during December-January and a maximum temperature decline of -3.0^0 (Southwest) to -1.4^0 Celsius (Northeast) during April-May over the period 1971-2000 in different parts of Bihar. Besides, based on trends during the period 1984-2012, heavy rainfall frequency has been found to be more pronounced in the month of July in Patna while Purnia displays a heavier rainfall occurrence as compared to Patna during the months of June to September.

Consequently, rising mean temperatures, variations in seasonal rainfall patterns and climate extremes have already been found to have a grave impact on agriculture in India and more so for the heavily agriculture dependent economy of Bihar. As per a study by experts at the Central University of South Bihar, Gaya (CUSB), alterations in surface temperature over the state of Bihar pose critical new challenges – with increased uncertainty – for cropping patterns, with critical implications for farming and availability of water resources (S. Kumar 2020).

It is important to distinguish between planned adaptation and autonomous adaptation. According to IPCC's Third Assessment Report (IPCC, Climate Change 2001. Synthesis Report 2001) , planned adaptation to climate change is a result of deliberate policy decisions, derived from the knowledge that background conditions have changed or are likely to change and, therefore, action is needed to return, to maintain, or to achieve a desired state of nature. In comparison, autonomous adaptation, also commonly called as spontaneous adaptation, is not an intentional response to climatic stimuli, but is triggered by ecological changes in natural systems and by market or welfare changes in human systems (IPCC, Climate Change 2001. Synthesis Report 2001). In light of the growing importance and absence of rigorous analyses of autonomous adaptation, this study has focused on identifying the ongoing process of such channels of adaptation to climate change in Bihar agriculture. The study attempts to delineate the contribution of farmers' ability (traditional/ ancestral knowledge and experience) and knowledge spill-overs among farming communities towards climate adaptation measures in Bihar.

The methods of analyses involve quantitative methods to delineate the role of ability and community networks, based on secondary data as well as a primary survey of two districts of Bihar, while controlling for other factors, namely, social, economic, technological, availability of resources, climate, etc. in adapting to climate change. One part of the quantitative analysis is based on secondary data. Since climate change is a long-term phenomenon and its impact on different agro-climatic zones differs, panel econometric analysis of secondary data at the district-level, spanning the 30-year period of 1990-2019, for all the 38 districts of Bihar have been relied on. The dependent variables are taken to be rice and wheat yields.

Another important component of the quantitative analysis has been the primary field survey that has helped to complement the panel regression estimations based on secondary data. For the primary survey, two districts of Bihar – Gaya and Purnia – were selected, which are fairly similar with regard to their socio-economic characteristics, but belong to two distinct agro-climatic zones, to capture the role of climatic factors in agricultural decisions. This allows us to capture the differences in the roles of ability and community networking channels of climate adaptation.

In what follows, the key findings of this study are presented.

The research finds that farming communities are discerning about climate change. Nearly 64.2 per cent of the farming households in Gaya and 63.1 per cent in Purnia believe that there is climate change. From a broader perspective, it is perceived that temperature, rainfall, wind speed, heavy rainfall, number of hot temperate days, drought, excessive hot dry winds (loo), excessive cold winds, and other climate events are more or less similar or changing gradually over the past 5-10 or 20-30 years. The only exception to this was the perception of rainfall in Gaya, where a majority of the farmer respondents stated that rainfall in the past was much higher than it is at present. This indicates that farmers do perceive slow and persistent changes in climate patterns. The perception of climate change is also consistent across gender. However, the responses to more specific questions on climate change were more revealing.

For instance, it was felt by farmers that there has been a change towards a greater number of hot temperate days as compared to a greater intensity of hot days over a shorter time span. Moreover, the changing trend towards a greater number of hot temperate days has happened in relation to the past 20-30 years, whereas higher intensity of hot days spread over a fewer number of days has been a phenomenon of the past 5-10 years. This indicates that more hot temperate days is more of a long-run and gradual climate change phenomenon, while higher intensity of hot temperatures over fewer days is a more recent climate change trend.

There has been a change in rainfall towards delayed monsoon rainfall, followed by more intense rainfall spread over a fewer number of days. Moreover, a significant (50 to even over 80 per cent) of respondents in both districts feel that rainfall pattern has changed in several ways, that is, a greater number of rainy days, heavier rainfall concentrated over a fewer number of days, and shifting of monsoon rainfall in terms of both early and delayed arrival in comparison to the past 20-30 years. This is in line with changes expected from long-run climate change.

Over the past 20-30 years, it was revealed that there have been changes in wind patterns in terms of alterations in wind direction, excessive loo, and delayed timing of monsoon winds while, over the shorter time frame of 5-10 years, wind patterns are perceived to have changed in terms of more intense loo over a fewer number of days and shifting of monsoon winds to an earlier time as compared to monsoon days prevalent in the past. A small but significant proportion of respondents also perceive that wind patterns have changed towards excessively cold winds and toward more intense colder winds spread over a fewer number of days.

This change in climate, as perceived by farming households, is not without its impact on agriculture. Secondary data estimation results show that higher average annual temperature levels tend to boost rice yields and decline wheat yields, but for both, there are threshold effects. That is, higher temperatures will boost (dampen) rice (wheat) yields but only up to a point, after which, yields fall (rise) with further increases in temperature. Similar effects are borne out with regard to average annual rainy days and average monsoon rainfall as well. Thus, excessively high temperature, monsoon rainfall or annual rainy days tend to dampen (improve) rice (wheat) yields, except for average annual rainy days for wheat.

Primary survey data estimation results also corroborate the above climate related impact on yields. Evidently, both temperature and rainfall regimes seem to have surpassed their respective thresholds for wheat yield gains, while for rice yield, temperature seems to be crossed its threshold but rainfall fall short of the threshold level, pointing to the scope for potential gain.

Other than temperature and precipitation, wind speed, cloud cover, evapotranspiration processes, and diurnal (day versus night) temperature range also have a combined impact on yields (captured through climate index). Secondary analysis shows that an increase in the combination of these variables tends to boost both rice and wheat yields.

Furthermore, the impact of extreme weather events on crop yields are also prominent. As the number of days with highest maximum temperature increases, rice yields decline while wheat yields improve. However, the number of days with lowest minimum temperature has a positive effect on rice yields, but negative for wheat. These differing effects may be due to the seasonality of the crop cycle, as rice tends to be grown during the summer/ monsoon (kharif) season while wheat is grown in the winter (rabi) season. A higher number of days with heavy rainfall in the last 24 hours has a significant negative effect on both rice and wheat yields.

Primary survey data also revealed that environmental hazards are perceived to be the most significant contributor to crop losses incurred by farmers, with the major environmental hazards perceived to be heavy rainfall followed by drought in Gaya and flood in Purnia. Farmers faced more wheat than rice losses, both in 2018 and 2019, indicating that wheat output is more vulnerable to environmental hazards than rice. However, since climate regimes have seemingly crossed the threshold levels for rice yield gains, but not for wheat, rice could also be more vulnerable to long-run climatic variations than wheat.

Furthermore, most of the time, the compensation that they receive for crop losses is not adequate.

Gender wise analysis indicates that female headed households are better at managing agriculture than male headed households in both Gaya and Purnia. This is exactly the opposite of the findings from estimates based on secondary data, which indicated that a higher female to male population ratio tends to dampen productivity in the case of both crops. As mentioned earlier, this may be because men from farming households migrate to urban areas to seek alternative non-agricultural occupations, leaving women or even hired labour to handle agricultural operations. Further, secondary data analysis considers a broader dimension of gender through an overall female to male population ratio at the district level, which might be a weaker indicator of the role of women in agriculture.

Changes in climate result in farmers taking various adaptation measures through both planned and autonomous adaptation strategies to cope. A high proportion of the respondents of our primary survey felt that there has been continuous climate change and this influences their production decisions. This perception did not vary with the gender of the respondents.

The effectiveness of planned adaptation channels to cope with climate change is found to be rather weak in both the surveyed districts -- Gaya and Purnia – as knowledge spread and capacity building through ICT-enabled extension services, government workshops, agriculture related formal social groups such as farmers' clubs (FCs), farmer's field schools (FFSs), *krishi vigyan kendras* (KVKs), etc., are quite low. This is compounded by lower levels of acquired education and awareness of such formal social groups and forums. The only exceptions were the role of self-help groups (SHGs) and JEEViKA. Bihar's farming households are coping with climate change mainly through autonomous adaptation channels, such as traditional knowledge of farmers (affecting their ability) and informal community networks.

For the analysis, an attempt has been made to examine the role played by inherent ability (intrinsic to ancestral knowledge and learning-by-doing) and community networks (knowledge spill-over from friends, family, relatives, neighbours, KVKs, government/ block officials, FFSs and FCs). The following specific results were derived from the research.

Secondary and primary data regression analyses have shown that inherent ability/ancestral knowledge has a positive impact on rice and wheat yields (an exception is rice yields in secondary data analysis where it shows a negative impact[19]). This general positive result is strengthened by the households' responses on the effectiveness of ancestral knowledge. A majority of the respondents in the primary survey ranked the effectiveness of ancestral knowledge between and medium and very high. Furthermore, the impact of the inherent ability channel is reinforced or supplemented by increases in literacy rate.

In fact, a higher fraction of respondents, mostly women (in the primary survey) in both districts believe that they rely on ancestral/ traditional knowledge and practices in making cultivation decisions.

Secondary data regressions show that community networks, in general, have a positive impact on both rice and wheat yields. This result is supported by household responses on the effectiveness of formal and informal community networks, with a majority of responses ranking them as being of medium to very high effectiveness. The impact of community networks declines with an increase in literacy rate. This result may reflect the weakening of social and local ties as members of farming households attain higher literacy levels and move away or migrate to other locations for alternative opportunities. However, survey econometric analysis shows that informal community networks (captured through households' responses regarding the effectiveness of informal community networks and trusted connections with relatives, neighbours and friends) tend to dampen rice yields and boost wheat yields. The reason behind this asymmetric influence of informal community networks between rice and wheat yields could be because of two facts: one is the out-migration effect of more educated family members in search of better job opportunities in urban areas or other states resulting in these farming household members losing their social and local ties with other farming families in their native villages, and this negative effect could be higher for rice yields as the process of rice production is more difficult/strenuous and labour-intensive than wheat. Another could be that that rice cultivators are more experimental in nature, while wheat cultivators mostly rely on knowledge gathered from informal community networks, for example, neighbours' experience, which is also found by Munshi (2004). These are important sociological implications of our research that require more in-depth analysis.

Within community networks, whenever informal community networks (such as connections with neighbours, relatives, friends, big farmers, landlords, etc.) show a negative impact for rice yield and a positive impact for wheat yield, the role of JEEViKA as a formal community network (these are organised networks such as co-operatives, non-governmental organisations (NGOs), FFSs, FCs, etc.) shows a positive impact for both rice and wheat yields in the primary survey data regression analysis. This may be because of the education factor. Wherever the impact of basic education (that is, class X education) on crop yields is found to be positive (negative), informal community networks are found to affect crop yields negatively (positively) while formal community networks affect yields positively (negatively). This result on the role of informal community networks derived from the primary data analysis ties in well with the one derived from the secondary data analysis, which points toward the dampening effect of community networks with a rise in overall literacy, while that of formal community network, represented by JEEViKA, gets reinforced due to increasing basic class X education. These results indicate that higher acquired knowledge dampens the role of informal community networks but promotes the role of formal community networks and vice-versa. This is as one would expect it to be. Farming households trust and rely more on informal community networks, such as friends, relatives, and neighbours than formal community networks, like government/ block officials, *gram panchayat* members, co-operative members, NGO members, etc., in taking farming

[19] We believe that the quality of data could be responsible for some results.

decisions. The only exception to this is the trust and reliance on JEEViKA for farming decisions, which is comparable to or even more than that of informal community networks. The responses as regards the role of JEEViKA are extremely promising almost across the board. Participation in government workshops is low, even though they are stated to be beneficial, which may be due to access and cost related factors. Attendance is also higher among male headed households than female headed ones, seemingly associated with social and cultural factors.

Awareness and consequently, membership, of social groups like FCs, FFSs, KVKs, agricultural technology management agency (ATMA), co-operative societies, etc., is generally very low. The only social groups that a majority of people are aware of and are members of are SHGs. Awareness and membership of SHGs are higher among female headed households than male headed households, implying higher social connectedness among women.

An important result of the study is that inherent ability and community networks substitute each other. The higher the influence of community networks in agricultural adaptation, the lower is the impact of inherent ability and vice-versa. Furthermore, regression estimates show that a higher literacy rate makes ability more effective in boosting crop yields, that is, the two complement each other. Community network index and literacy rate substitute for each other. This may be due to social and local ties loosening with farming communities attaining higher literacy levels, often leading to out-migration, transition to nuclear families and urbanisation. These are important sociological implications of the analysis that require more analysis.

6.2. Specific adaptation actions for sustainable agriculture and menu of policies

In light of the unprecedented levels of global warming and climate change, and the much researched and inextricable agriculture-climate relationship from a scientific standpoint, this study aimed to bring in the social and economic perspectives to bear on this link. Several very interesting findings have been derived, that have been summarised in the preceding section.

In what follows, a suggested menu of policies, based on the findings of the research that could help promote a move toward sustainable climate-resilient and resource conserving agriculture. In this regard, some specific adaptation measures or actions that need emphasis in the context of the study area and site, that is the state of Bihar, are suggested in Table 17.

Table 17: Types of specific adaptation actions/measures for climate resilient and resource conserving agriculture

Type of adaptation measure	Focus on	State and study specific examples emanating from our research
Hard adaptation	Infrastructure and technology	• Large network of weather monitoring stations and early warning systems to predict climate variations and extreme weather events • Building climate smart agriculture (CSA) infrastructure under climate resilient agriculture • Establishing ICT-enabled extension services for climate risk alerts and for knowledge dissemination for optimal use of inputs, machinery and equipment, namely, organic fertilisers, pesticides, HYV seeds, new climate resilient seeds, irrigation practices, etc. • Wider extension and follow up of soil health card (SHC) services • Building financial institutions at village-level to provide credit • Building knowledge dissemination institutions at village-level to promote informal community networking along with higher education or skills training • Formation of formal social groups like, FCs, FFSs, ATMA, co-operatives, KVKs, etc., at village-level for agricultural information flow • Organising more government-run workshops and training programmes at the village-level, and making them affordable

Type of adaptation measure	Focus on	State and study specific examples emanating from our research
		• Building communication facilities for both in-person and virtual information dissemination • Agricultural universities with laboratories for more agriculture-focused research • Climate resilient irrigation infrastructure (e.g., drip irrigation, sprinkler irrigation, use of renewable energy for pumping, etc.) • Diversifying occupation options to reduce pressure on land • Improving access to government regulated APMCs and input *bhandars* like seed *bhandars* with access at the village-level
Soft adaptation	Information access, capacity building, policies, behavioural and institutional change	• ICT-enabled extension services for climate risk alerts and knowledge diffusion of best practices for optimal use of inputs and machinery, specifically organic fertilisers, pesticides, HYV seeds, new climate-resilient seeds, utilisation of irrigation pump sets (run on clean energy) • Capacity building, knowledge sharing and co-operation through village-level formal social groups (e.g., FCs, FFSs, ATMA, co-operatives, etc.) and government held workshops, e.g., like those run by SHGs and JEEVIKA, more actively at the village-level • Dissemination of soil related information like optimal use of inputs according to soil quality by promoting soil health cards (SHCs) • Risk insurance coverage (e.g., insurance, compensation, etc.) • Promoting government regulated APMCs (e.g., PACs) and input *bhandars* (e.g., seed *bhandars*) to enhance avenues for raising farmers' net income • Promotional government policies and private incentives to incentivise autonomous adaptation (e.g., shifting sowing and harvesting time, shifting land from more to less water intensive crops, etc.), and planned adaptation (e.g., optimal utilisation of inputs, adopting climate-smart agriculture, climate-resilient irrigation system, ICT-enabled extension services, conservation farming, precision farming, organic farming, etc.) by PPPs • Behavioural and institutional changes (e.g., access to credits, KCCs, PM-*kisan* funds, access to crop insurance), especially for women
Nature or Ecosystem-Based Adaptation	Harnessing nature's capacity to protect against climate impacts/risks	• Preservation of groundwater and surface water • Restoration of soil quality and preservation from soil degradation through greater reliance on organic inputs • Restoration and renaturation for flood plains • Establishment of diverse and climate-resilient agriculture systems

Source: Authors' compilation

As a follow up to the above, some general and specific policy menu options incorporating adaptation measures listed in Table 17 can be prescribed; these are compiled in Table 18.

Table 18: Policy menu in general for climate resilient and resource conserving agriculture

	Regulatory measures for environmental protection and resource conservation	Creating markets to get prices right for environment and natural resources	Green fiscal incentives and support	Greening support from the banking and financial system – including development and institutional finance
Climate Resilient and Resource Conserving Agriculture	Secure land and water rights to enable investments in sustainable land and water management Land management regulations and practices (e.g., controlled grazing of animals that can	Environmental tax reform – on inputs or outputs – to discourage harmful farming methods, such as intensive application of fertilisers/pesticides or groundwater extraction, resource intensive cropping mix, etc.	Budgetary and other public allocation of finance to pilot, demonstrate and scale up climate-resilient agriculture (e.g., investment in research, extension and infrastructure in institutions and universities)	Concessional finance to farming households to adopt climate-resilient agricultural practices – solar water pumps, drip and sprinkler irrigation Low-interest bearing loans on sustainable investment in

	Regulatory measures for environmental protection and resource conservation	Creating markets to get prices right for environment and natural resources	Green fiscal incentives and support	Greening support from the banking and financial system – including development and institutional finance
	protect stream-beds or erosion control) Temporary ban on use of select insecticides/pesticide, ban on crop residue or stubble burning	Subsidies to stimulate green transitions, such as organic farming, climate resilient crop varieties, shifting land from more to less water intensive crops Rationalise energy subsidies for agriculture Payment for ecosystem or environmental services (PES) to provide incentives to adopt climate-smart agricultural practices Developing market linkages and integration for climate-resilient crops	Tax relief or credit/ subsidy provision to private sector to venture into climate resilient agricultural technologies and practices Conditional insurance or social protection cover for vulnerable farming households, due to risk of adopting new methods, which otherwise pose a barrier to investments in climate-resilient agriculture	agricultural production Concessional finance for greenfield investments by private sector or PPPs

Source: (Keswani Mehra and Sarkar 2021)

6.3. Practical policy recommendations for climate-resilient agriculture in Bihar:

- Mainstream autonomous adaptation for successful climate resilient agriculture into NAPCC, SAPCCs, and sectoral development plans and programmes
- Promote climate-smart agriculture (CSA) and ICT-enabled extension services at local/ village-level
- Rationalise inefficient government input price and subsidy regimes to reward and incentivise climate resilient agriculture
- Provide support for indigenous farming practices derived from traditional knowledge as well as natural farming and sustainable agriculture practices
- Design social groups for formal networking and incentivise knowledge sharing by both formal and informal networking
- Invest in public education systems to reinforce and disseminate the positive effects of community networks on grain yield along with proper education/acquired knowledge
- Promote outreach, training, re-skilling and agri-business centres of excellence to spread awareness and build capacities for climate-resilient agriculture
- Make government-owned farmlands and agricultural laboratories and universities available as incubators for testing innovative climate-resilient farming
- Behavioural and institutional changes (e.g., access to credit, *kisan credit cards*, PM-*kisan* funds, access to crop insurance, etc.), especially for women/female headed households as they are often found to bolster crop yields more as compared to male-headed households
- Green investment or concessional finance for risks and costs related to the adoption of new climate resilient technologies or services, with focus on more vulnerable groups (e.g., female headed households) to facilitate climate-resilient agriculture and sustainability of the local environment.

This foregoing discussion puts forward a compendium of strategies and policy menus drawn from a rigorous analysis of primary and secondary data on the interface between climate change and agriculture in Bihar. It is hoped that this will facilitate design and discussion of policy options for planned and autonomous channels of adaptation of Bihar (and more generally Indian) agriculture to climate change through greener and more climate resilient agricultural practices. Notably, adequate thought will have to be given to choosing the correct mix of such policies, as often time – trade-offs or conflicts encountered among goals of equity, efficiency, fiscal sustainability, political acceptability, administrative feasibility and commitment towards international trade and environmental agreements need to be settled efficaciously while designing policies. This aspect remains the subject matter of future research.

In what follows, we conclude this research.

Conclusions

This research examines climate change adaptation processes as these would have unfolded in the rice and wheat growing districts in the state of Bihar. Bihar is located in the Eastern part of India. The research is an attempt to tease out the role of farmers' ability (traditional knowledge and learning-by-doing) and local community networks on agricultural productivity to understand adaptation strategies at the sub-national/ district level. Quantitative as well as mixed method approaches were used to delineate the role of ability and community networks, based on secondary data as well as a primary survey of two districts, while controlling for the underlying driving factors (social, economic, technological, resources' availability, climate etc.) in adaptation of agriculture to climate change.

The research finds that higher average annual temperature levels tend to boost rice yields and decline wheat yields, but for both, there are threshold effects. That is, higher temperatures will boost (dampen) rice (wheat) yields but only up to a point, after which, yields are lowered with further increases in temperature. Similar effects are borne out with regard to average annual rainy days and average monsoon days as well. Thus, excessively high temperature, monsoon rainfall or rainy days tend to dampen rice yields, while for wheat yields, excessively high temperature and monsoon rainfall tend to improve it but excessive rainy days tend to lower wheat yields. Farming communities are discerning about this change in climate patterns and its impact on agriculture, taking various adaptation measures to cope with it through both planned and autonomous adaptation strategies. The effectiveness of planned adaptation to cope with climate change is somewhat weak in Bihar, in general, as knowledge spread and capacity building through ICT-enabled extension services, government workshops, agriculture related formal social groups such as FCs, FFSs, KVKs, etc., are quite low, except with regard to SHGs and JEEViKA. Attendance at workshops and membership of social groups is lower in female headed households as compared to the male headed ones. Notwithstanding this, female headed households have shown better management capability in agriculture in Bihar than the male headed ones. Despite the lower effectiveness of the planned adaptation channel, Bihar's farming households are adapting to climate change, which is often found to be driven by autonomous adaptation channels. For the analysis, an attempt has been made to examine the role played by two autonomous channels – inherent ability (intrinsic to ancestral knowledge and learning-by-doing) and community networks (knowledge spill-over from friends, family, relatives, neighbours, JEEViKA, etc.). Both secondary and primary data analyses have shown that inherent ability/ancestral knowledge has a positive impact on both rice and wheat yields. The impact of inherent ability is reinforced or supplemented by increases in basic acquired education or literacy rate. Furthermore, community networks have a positive impact on both rice and wheat yields. These twin adaptation channels – inherent ability and community network – weaken each other effect on crop yields. However, the impact of community networks dampen crop yields with an increase in basic acquired education or literacy rate. This result may be because of the weakening of social and local ties as members of farming households attain higher literacy levels and move away or out-migrate to other locations for alternative work opportunities.

The adoption of climate-resilient strategies is an impending need for agriculture in India, and more so for the state of Bihar, to attain sustainable agriculture, food security and livelihoods. To promote a judicious move towards sustainable climate-resilient and resource-conserving agriculture, the study indicates the need for specific adaptation policies. These include infrastructure for early warning systems to predict climate variations and extreme weather events, ICT-enabled extension services for climate risk alerts and knowledge dissemination, formation of formal social groups at the village-level to strengthen formal community networks, knowledge imparting institutions at the village-level to strengthen informal community networks, innovating new climate-resilient technologies, financial institutions at village-level to promote green credit systems as hard adaptation measures; adoption of natural and organic farming, promotion of indigenous farming practices, adoption of ICT-enabled extension services, capacity building and knowledge sharing through formal social groups along with informal community networks as soft adaptation measures; and preserving natural resources, such as groundwater, soil quality, etc., under other options.

Thus, in future, one can focus on attaining sustainable agriculture through innovation of new climate-resilient technologies, incentives for natural and organic farming, climate-smart and sustainable agriculture, incentives for active involvement of farmers in formal social groups and government held workshops, capacity building and knowledge sharing, indigenous farming practices, incentives for preserving natural resources, incentives for adoption of clean energy, etc., by maintaining effective functioning of ICT-enabled extension services, formal social groups, green credit support, and imparting knowledge and training in skills while strengthening both informal and formal community networks. Further, one needs to focus on the cost-benefit analyses of adaptation strategies across hard and soft adaptation strategies.

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Annexure A

Figure 36: District map of Gaya based on block divisions

Figure 37: District map of Purnia based on block divisions

Table 19: Agro-climatic zones of Bihar

Agro-climatic zones	Districts
Agro-climatic zone I (Northern West)	West Champaran, East Champaran, Siwan, Saran, Sitamarhi, Sheohar, Muzaffarpur, Vaishali, Madhubani, Darbhanga, Samastipur, Gopalganj, Begusarai
Agro-climatic Zone II (Northern East)	Purnia, Katihar, Saharsa, Supaul, Madhepura, Khagaria, Araria, Kishanganj.
Agro-climatic zone IIIA (Southern East)	Sheikhpura, Munger, Jamui, Lakhisarai, Bhagalpur & Banka.
Agro-climatic zone IIIB (Southern West)	Rohtas, Bhojpur, Buxar, Bhabhua, Arwal, Patna, Nalanda, Nawada, Jehanabad, Aurangabad, Gaya.

Source: (BAPCC 2015)

Table 20: Important physiographic features of agro-climatic zones

Agro-climatic zones	Soil	pH	Organic Matters (%)	Available Nitrogen (kilogram/hectare)	Available Phosphorus (Kilogram/hectare)	Available Potash (Kilogram/hectare)
Agro-climatic zone I (Northern West)	Sandy loam, loam	6.5–8.4	0.2-1.0	150-350	5-50	100-300
Agro-climatic Zone II (Northern East)	Sandy loam, Clay loam	6.5–7.8	0.2-1.0	150-300	10-35	150-250
Agro-climatic zone III (Southern East & West)	Sandy loam, Clay loam, loam, Clay	6.8–8.0	0.5-1.0	200-400	10-100	150-350

Source: (BAPCC 2015)

Table 21: Basic characteristics of agro-climatic zones

Agro-climatic zones	Soil types	Total rainfall (Millimetres)	Temperature (Degree Celsius)	
			Max.	Min.
Agro-climatic zone I (Northern West)	Sandy loam, loam	1040 – 1450 (1245.00)	36.6	7.7
Agro-climatic Zone II (Northern East)	Sandy loam, Clay loam	1200 – 1700 (1450.00)	33.8	8.8
Agro-climatic zone III (Southern East & West)	Sandy loam, Clay loam, loam, Clay	990 – 1240 (1115.00)	37.1	7.8

Source: (BAPCC 2015)

Table 22: Comparison between districts in regards to climatic variations, extreme weather events, soil texture, soil erosion, and crop yields

Characteristics	Gaya	Purnia	Kishanganj
Average Temperature (in Degree Celsius)	25.47	25.14	25.19
Diurnal Temperature Range (in Degree Celsius)	12.58	12.14	11.79
Average Annual Rainfall (in Millimetres)	72.98	135.47	162.92

Characteristics	Gaya	Purnia	Kishanganj
Average Annual Rainy Days (in No.)	3.72	5.24	5.63
Average Monsoon Rainfall (in Millimetres)	208.93	328.27	416.71
Average Monsoon Rainy Days (in No.)	9.86	11.39	12.33
Drought as Extreme Events	Regular	Occasional	Occasional
Flood as extreme Events	None	Regular	Regular
Heat Waves as Extreme Events	Regular	Regular	Occasional
Cold Waves as Extreme Events	None	Regular	Occasional
Pests and Disease as Extreme Events	None	Regular	Regular
Fine Soil Texture (in %)	79.71	37.18	52.86
Medium Soil Texture (in %)	4.88	23.05	35.89
Coarse Soil Texture (in %)	3.27	22.52	5.72
Rocky Soil Texture and Water bodies (in %)	12.15	17.25	5.53
Slight Soil Erosion (in %)	57.25	88.28	54.96
Moderate Soil Erosion (in %)	33.82	8.52	41.06
Severe Soil Erosion (in %)	7.65		
Very Severe Soil Erosion (in %)	1.27	3.2	3.98
Rice Yield (in Metric Tons/Hectare)	1.9	1.46	1.33
Wheat Yield (in Metric Tons/Hectare)	1.53	1.53	1.53

Source: DE&S, India Water Portal, KVK Portal-ICAR, and IMD

Annexure B

Table23: Tests for crop yield regressions with time trend

Tests	Rice Yields		Wheat Yields	
	Prob. value	Remarks	Prob. value	Remarks
Hausman test H_0: RE over FE	0.0000***	FE preferred over RE	0.0013***	FE preferred over RE
Friedman's test of cross-sectional independence	0.0000***	Presence of contemporaneous correlation	0.0000***	Presence of contemporaneous correlation
Pesaran's test of cross-sectional independence	0.0000***	Presence of contemporaneous correlation	0.0000***	Presence of contemporaneous correlation
Modified Wald test for group wise heteroscedasticity in FE models	0.0000***	Presence of heteroscedasticity	0.0000***	Presence of heteroscedasticity
Wooldridge test for autocorrelation	0.0001***	Presence of 1st order autocorrelation	0.0000***	Presence of 1st order autocorrelation

Table 24: Correlation between ability and residuals of different panel models

Models	Correlation between ability and residuals of models			
	Rice		Wheat	
	Value	Remarks	Value	Remarks
Pooled Model for Crop Yields	0.0000	Uncorrelated	-0.0000	Uncorrelated
FE with district fixed effect for crop yields	-0.0372	Uncorrelated	-0.0086	Uncorrelated
FE with district and time fixed effect for crop yields	-0.0372	Uncorrelated	-0.0118	Uncorrelated
RE for crop yields	-0.0309	Uncorrelated	-0.0031	Uncorrelated
FGLS model for crop yields	0.0153	Uncorrelated	0.0131	Uncorrelated
PCSE model for crop yields	0.0075	Uncorrelated	0.0068	Uncorrelated
PCSE model with time fixed effect for crop yields	-0.0268	Uncorrelated	-0.0317	Uncorrelated
PCSE model for crop production	-0.0162	Uncorrelated	-0.0121	Uncorrelated
PCSE model with time fixed effect for crop production	-0.0356	Uncorrelated	-0.0446	Uncorrelated

Coefficients in bold and '**' represent significance at 5% level of significance.

Annexure C

Table 25: Descriptive Statistics of Survey Data

Variables	Type	Unit	Descriptive Statistics Gaya	Descriptive Statistics Purnia
A. Household Characteristics				
Rice cultivating households	Categorical		99.4	89.8
Wheat cultivating households	Categorical		100	21.6
Cultivation as an occupation at rank 1	Categorical		38.6	64.1
Allied Agriculture as an occupation at rank 1	Categorical		15.7	8.2
Agricultural wage labourers as an occupation at rank 1	Categorical		29.5	13.9
Non-agricultural wage labourers as an occupation at rank 1	Categorical		7.8	6.9
Petty shop as an occupation at rank 1	Categorical		1.2	2.9
Govt. salaried employment as an occupation at rank 1	Categorical		0.6	1.6
Low market price of agricultural products as a reason for engaging in multiple occupations along with cultivation	Categorical		57.7	70.7
High input cost as a reason for engaging in multiple occupations along with cultivation	Categorical		25.2	20.4
Climate vulnerability as a reason for engaging in multiple occupations along with cultivation	Categorical		13.5	23.4
More no. of family members as a reason for engaging in multiple occupations along with cultivation	Categorical		45	62.3
Marginal and small farmers	Categorical		75.3	69.4
Medium and large farmers	Categorical		24.7	30.6
Gender of household head – Male	Categorical		71.1	84.5
Gender of household head – Female	Categorical		28.9	15.5
Religion – Muslim	Categorical		0.6	11.4
Religion – Hindu	Categorical		99.4	88.6
Caste – Backward	Categorical		98.2	95.9
Caste – Forward	Categorical		1.8	4.1
Origin – Native	Categorical		95.8	82
Origin – Migrated	Categorical		4.2	18
Family type – Nuclear	Categorical		73.5	78.4
Family type – Joint	Categorical		26.5	21.6
Family size	Continuous	No.	7	6
Adult sex ratio	Continuous	Ratio	1.04	1.04
No. of earning members	Continuous	No.	1.9	1.7
Age of respondent	Continuous	Years	43.3	47.6
Mean of household members passed class X	Continuous	No.	0.17	0.14
Mean of household members passed class XII	Continuous	No.	0.14	0.09
Mean of household members attained higher education	Continuous	No.	0.1	0.08

Variables	Type	Unit	Descriptive Statistics	
			Gaya	Purnia
B. Agriculture-Related Information				
Average rice yield	Continuous	Kg/ acre	1511.2	863.1
Average wheat yield	Continuous	Kg/ acre	563.2	592.8
Land ownership status – Own land	Categorical		87.3	87.3
Land ownership status – Own land and leased out	Categorical		5.5	4.7
Land ownership status – Do not own land and leased in	Categorical		95.2	93.5
Sown status – Once	Categorical		17.4	17.1
Sown status – Twice	Categorical		82.5	93.1
Sown status – More than twice	Categorical		12	9
Soil fertility – Very high	Categorical		9	5.3
Soil fertility – High	Categorical		18.7	22.9
Soil fertility – Medium	Categorical		68.7	80
Soil fertility – Low	Categorical		21.1	24.1
Soil fertility – Very low	Categorical		0.6	0.4
Soil degradation is happening	Categorical		52.4	51.8
Reason for soil degradation – Soil erosion	Categorical		17.7	18.8
Reason for soil degradation – Nutrient depletion	Categorical		79	83.5
Reason for soil degradation – Water logging	Categorical		9.7	24.7
Reason for soil degradation – Salinity or acidity	Categorical		0	5.9
Households adopted pest control	Categorical		45.8	84.9
Usage of pest control in a year	Continuous	No.	8.8	7.5
Usage of NPK for rice production	Continuous	Kg./ acre	3.64	3.45
Usage of NPK for wheat production	Continuous	Kg./ acre	4.68	0.38
Usage of sprayer/duster	Continuous	Minutes/ acre	0.54	3.56
Usage of diesel pumps	Continuous	Minutes/ acre	3.38	18.12
Usage of electric pumps	Continuous	Minutes/ acre	12.25	1.54
Usage of power tiller	Continuous	Minutes/ acre	0.44	0.14
Usage of tractor	Continuous	Minutes/ acre	12.3	16.8
Usage of rotavator	Continuous	Minutes/ acre	1.36	4.68
No. of labour hired for rice production	Continuous	No./ acre	81	69
No. of labour hired for wheat production	Continuous	No./ acre	126	214
Households use HYV seeds	Categorical		54.4	92.2
Average amount of loan	Continuous	INR	12228	39728
Households practice multi-cropping	Categorical		31.9	15.9
Rice production has increased over 20-30 years	Categorical		67.4	74.3
Rice production has decreased over 20-30 years	Categorical		32.6	25.7
Wheat production has increased over 20-30 years	Categorical		62.2	52.6
Wheat production has decreased over 20-30 years	Categorical		37.8	47.4
Households faced crop loss in 2018 in rice	Categorical		66.9	62.8

Variables	Type	Unit	Descriptive Statistics	
			Gaya	Purnia
Households faced crop loss in 2018 in wheat	Categorical		49.6	6.1
Households faced crop loss in 2019 in rice	Categorical		66.9	72.3
Households faced crop loss in 2019 in wheat	Categorical		53.5	6.8
Reason for crop loss in 2018 – Mechanical injury	Categorical		10.2	4.1
Reason for crop loss in 2018 – Environmental Hazards	Categorical		78.7	65.5
Reason for crop loss in 2018 – Water logging	Categorical		9.4	14.9
Reason for crop loss in 2018– Human or animal damage	Categorical		7.1	8.8
Reason for crop loss in 2019 – Mechanical injury	Categorical		4.7	4.7
Reason for crop loss in 2019 – Environmental Hazards	Categorical		79.5	75.7
Reason for crop loss in 2019 – Water logging	Categorical		11.8	18.2
Reason for crop loss in 2019 – Human or animal damage	Categorical		5.5	4.7
Type of environmental hazards in 2018 – Drought	Categorical		52	1
Type of environmental hazards in 2018 – Heavy rainfall	Categorical		35	75.3
Type of environmental hazards in 2018 – Flood	Categorical		2	37.1
Type of environmental hazards in 2018 – Hailstorm	Categorical		19	4.1
Type of environmental hazards in 2018 – More no. of hot temperate days	Categorical		5	5.2
Type of environmental hazards in 2018 – Change in wind direction	Categorical		3	14.4
Type of environmental hazards in 2019 – Drought	Categorical		36.6	1.8
Type of environmental hazards in 2019 – Heavy rainfall	Categorical		57.4	74.1
Type of environmental hazards in 2019 – Flood	Categorical		0	41.1
Type of environmental hazards in 2019 – Hailstorm	Categorical		24.8	5.4
Type of environmental hazards in 2019 – More no. of hot temperate days	Categorical		3	7.1
Type of environmental hazards in 2019 – Change in wind direction	Categorical		8.9	18.8
Households received compensation for rice loss in 2018	Categorical		7.1	5.4
Households received compensation for wheat loss in 2018	Categorical		4.8	11.1
Households received compensation for rice loss in 2019	Categorical		2.4	8.4

Variables	Type	Unit	Descriptive Statistics	
			Gaya	Purnia
Households received compensation for wheat loss in 2019	Categorical		8.8	30
C. Climate Conditions				
Households perceived changing climate	Categorical		64.2	63.1
Temperature is much more than required at present	Categorical		5.3	3.6
Temperature is somewhat more than required at present	Categorical		21.7	33
Temperature is same as required at present	Categorical		55.3	37.9
Temperature is somewhat less than required at present	Categorical		15.8	21
Temperature is much less than required at present	Categorical		2	4.5
Temperature regime has changed over past 5-10 years towards – Higher no. of hot temperate days	Categorical		67.7	67.6
Temperature regime has changed over past 5-10 years towards – Higher temperature intensity in lesser no. of days	Categorical		58.3	69.1
Temperature regime has changed over past 20-30 years towards – Higher no. of hot temperate days	Categorical		73.2	68.6
Temperature regime has changed over past 20-30 years towards – Higher temperature intensity in lesser no. of days	Categorical		49.6	59.8
Rainfall is much more than required at present	Categorical		12.5	57.8
Rainfall is somewhat more than required at present	Categorical		27	36
Rainfall is same as required at present	Categorical		46.1	5.3
Rainfall is somewhat less than required at present	Categorical		9.2	0.4
Rainfall is much less than required at present	Categorical		5.3	0.4
Rainfall pattern has changed over past 5-10 years towards – Higher no. of rainy days	Categorical		49.6	54.9
Rainfall pattern has changed over past 5-10 years towards – Higher rainfall intensity in lesser no. of days	Categorical		59.1	52
Rainfall pattern has changed over past 5-10 years towards – Shift in monsoon rainfall before monsoon	Categorical		45.7	52.5
Rainfall pattern has changed over past 5-10 years towards – Shift in monsoon rainfall after monsoon	Categorical		65.4	70.1
Rainfall pattern has changed over past 20-30 years towards – Higher no. of rainy days	Categorical		52	60.8

Variables	Type	Unit	Descriptive Statistics	
			Gaya	Purnia
Rainfall pattern has changed over past 20-30 years towards – Higher rainfall intensity in lesser no. of days	Categorical		65.4	60.8
Rainfall pattern has changed over past 20-30 years towards – Shift in monsoon rainfall before monsoon	Categorical		54.3	56.4
Rainfall pattern has changed over past 20-30 years towards – Shift in monsoon rainfall after monsoon	Categorical		73.2	81.4
Wind speed is much more than required at present	Categorical		2.6	5.4
Wind speed is somewhat more than required at present	Categorical		19.9	28.6
Wind speed is same as required at present	Categorical		53	50.4
Wind speed is somewhat less than required at present	Categorical		21.8	13.4
Wind speed is much less than required at present	Categorical		2.6	2.2
Wind pattern has changed over past 5-10 years towards – Change in monsoon wind direction	Categorical		49.6	52.5
Wind pattern has changed over past 5-10 years towards – Excessive hot winds or loo	Categorical		65.4	64.7
Wind pattern has changed over past 5-10 years towards – Excessive cold winds	Categorical		23.6	28.4
Wind pattern has changed over past 5-10 years towards – Higher hot wind intensity in lesser no. of days	Categorical		53.5	60.3
Wind pattern has changed over past 5-10 years towards – Higher cold wind intensity in lesser no. of days	Categorical		30.7	30.3
Wind pattern has changed over past 5-10 years towards – Shift in monsoon wind before monsoon	Categorical		25.2	23
Wind pattern has changed over past 5-10 years towards – Shift in monsoon wind after monsoon	Categorical		17.3	25
Wind pattern has changed over past 20-30 years towards – Change in monsoon wind direction	Categorical		54.3	52.9
Wind pattern has changed over past 20-30 years towards – Excessive hot winds or loo	Categorical		75.6	64.7
Wind pattern has changed over past 20-30 years towards – Excessive cold winds	Categorical		27.6	16.2
Wind pattern has changed over past 20-30 years towards – Higher hot wind intensity in lesser no. of days	Categorical		43.3	52.4

Variables	Type	Unit	Descriptive Statistics	
			Gaya	Purnia
Wind pattern has changed over past 20-30 years towards – Higher cold wind intensity in lesser no. of days	Categorical		33.1	27.4
Wind pattern has changed over past 20-30 years towards – Shift in monsoon wind before monsoon	Categorical		22.8	14.2
Wind pattern has changed over past 20-30 years towards – Shift in monsoon wind after monsoon	Categorical		21.2	27.9
Heavy rainfall as extreme weather events over past 5-10 years – Higher than present	Categorical		0	6.5
Heavy rainfall as extreme weather events over past 5-10 years – Almost similar to present	Categorical		78.3	63
Heavy rainfall as extreme weather events over past 5-10 years – Lesser than present	Categorical		21.7	30.4
Flood as extreme weather events over past 5-10 years – Higher than present	Categorical		2.7	23.5
Flood as extreme weather events over past 5-10 years – Almost similar to present	Categorical		48.2	60.1
Flood as extreme weather events over past 5-10 years – Lesser than present	Categorical		49.1	16.4
Higher no. of hot temperate days as extreme weather events over past 5-10 years – Higher than present	Categorical		7.8	9.3
Higher no. of hot temperate days as extreme weather events over past 5-10 years – Almost similar to present	Categorical		58.3	55.2
Higher no. of hot temperate days as extreme weather events over past 5-10 years – Lesser than present	Categorical		33.9	35.5
Drought as extreme weather events over past 5-10 years – Higher than present	Categorical		4.3	0
Drought as extreme weather events over past 5-10 years – Almost similar to present	Categorical		63.5	89.1
Drought as extreme weather events over past 5-10 years – Lesser than present	Categorical		32.2	10.9
Hailstorm as extreme weather events over past 5-10 years – Higher than present	Categorical		0	0
Hailstorm as extreme weather events over past 5-10 years – Almost similar to present	Categorical		78.3	84.7
Hailstorm as extreme weather events over past 5-10 years – Lesser than present	Categorical		21.7	15.3
Excessive hot waves as extreme weather events over past 5-10 years – Higher than present	Categorical		20	11.4
Excessive hot waves as extreme weather events over past 5-10 years – Almost similar to present	Categorical		64.3	64.9

Variables	Type	Unit	Descriptive Statistics	
			Gaya	Purnia
Excessive hot waves as extreme weather events over past 5-10 years – Lesser than present	Categorical		15.6	23.8
Excessive cold waves as extreme weather events over past 5-10 years – Higher than present	Categorical		14	10.8
Excessive cold waves as extreme weather events over past 5-10 years – Almost similar to present	Categorical		75.4	75.7
Excessive cold waves as extreme weather events over past 5-10 years – Lesser than present	Categorical		10.5	13.5
Heavy rainfall as extreme weather events over past 20-30 years – Higher than present	Categorical		0	12
Heavy rainfall as extreme weather events over past 20-30 years – Almost similar to present	Categorical		65.2	63
Heavy rainfall as extreme weather events over past 20-30 years – Lesser than present	Categorical		34.8	25
Flood as extreme weather events over past 20-30 years – Higher than present	Categorical		0	25.1
Flood as extreme weather events over past 20-30 years – Almost similar to present	Categorical		58.9	57.9
Flood as extreme weather events over past 20-30 years – Lesser than present	Categorical		41.1	16.9
Higher no. of hot temperate days as extreme weather events over past 20-30 years – Higher than present	Categorical		4.3	6.6
Higher no. of hot temperate days as extreme weather events over past 20-30 years – Almost similar to present	Categorical		53.9	59
Higher no. of hot temperate days as extreme weather events over past 20-30 years – Lesser than present	Categorical		41.7	34.4
Drought as extreme weather events over past 20-30 years – Higher than present	Categorical		7.8	0
Drought as extreme weather events over past 20-30 years – Almost similar to present	Categorical		51.3	87.5
Drought as extreme weather events over past 20-30 years – Lesser than present	Categorical		40.9	12.5
Hailstorm as extreme weather events over past 20-30 years – Higher than present	Categorical		0	0
Hailstorm as extreme weather events over past 20-30 years – Almost similar to present	Categorical		78.3	82.5
Hailstorm as extreme weather events over past 20-30 years – Lesser than present	Categorical		21.7	17.5
Excessive hot waves as extreme weather events over past 20-30 years – Higher than present	Categorical		21.7	10.3

Variables	Type	Unit	Descriptive Statistics	
			Gaya	Purnia
Excessive hot waves as extreme weather events over past 20-30 years – Almost similar to present	Categorical		55.6	68.6
Excessive hot waves as extreme weather events over past 20-30 years – Lesser than present	Categorical		22.6	21.1
Excessive cold waves as extreme weather events over past 20-30 years – Higher than present	Categorical		15.8	10.3
Excessive cold waves as extreme weather events over past 20-30 years – Almost similar to present	Categorical		68.4	72.4
Excessive cold waves as extreme weather events over past 20-30 years – Lesser than present	Categorical		15.8	17.3
D. Farmers' Adaptation Strategies				
Farmers perceiving that climate change is happening and it is affecting farming decisions	Categorical		62	68.2
Change in farming decisions at rank 1 – Change in sowing and harvesting time	Categorical		55.6	65.9
Change in farming decisions at rank 1 – Change in cropping pattern to crop-mix, multi-cropping, etc.	Categorical		16.2	7.2
Change in farming decisions at rank 1 – Shift to less water-intensive crops	Categorical		17.2	2.4
Change in farming decisions at rank 1 – Use of new technologies and agricultural equipment	Categorical		7.1	14.4
Change in farming decisions at rank 1 – Use of high-quality consumable inputs	Categorical		1	3.6
Change in farming decisions at rank 1 – Change in choice of crops	Categorical		0	4.2
Change in farming decisions at rank 1 – Use of new climate-resilient seeds	Categorical		2	2.4
Information flows for consumable inputs through – Media	Categorical		35.5	21.6
Information flows for consumable inputs through – Relatives, neighbours, friends	Categorical		57.2	51.4
Information flows for consumable inputs through – Local people	Categorical		23.5	44.9
Information flows for consumable inputs through – ICT-enabled extension services	Categorical		9	15.9
Information flows for consumable inputs through – Govt. or non-govt. organisations	Categorical		13.9	18.8
Information flows for consumable inputs through – Local traders	Categorical		22.3	75.9

Variables	Type	Unit	Descriptive Statistics	
			Gaya	Purnia
Information flows for consumable inputs through – JEEViKA	Categorical		35.5	11.4
Information flows for capital inputs through – Media	Categorical		30.1	16.3
Information flows for capital inputs through – Relatives, neighbours, friends	Categorical		62	53.5
Information flows for capital inputs through – Local people	Categorical		30.7	50.2
Information flows for capital inputs through – ICT-enabled extension services	Categorical		7.2	16.3
Information flows for capital inputs through – Govt. or non-govt. organisations	Categorical		9.6	13.9
Information flows for capital inputs through – Local traders	Categorical		16.3	53.1
Information flows for capital inputs through – JEEViKA	Categorical		28.3	9.4
Households aware about farmers' clubs (FCs)	Categorical		9	19.6
Households aware about farmers' field schools (FFSs)	Categorical		2.4	4.5
Households aware about *krishi vigyan kendras* (KVKs)	Categorical		15.7	50.2
Households aware about self-help groups (SHGs)	Categorical		76.5	91.4
Households aware about agricultural technology management agency (ATMA)	Categorical		53	49.8
Households aware about cooperative societies	Categorical		7.8	22.4
Households attend govt.-run workshops	Categorical		16.9	38
Reason for not attending govt.-run workshops – Very costly	Categorical		16.7	5.9
Reason for not attending govt.-run workshops – Unavailability of time	Categorical		17.4	10.5
Reason for not attending govt.-run workshops – Low quality service	Categorical		3	3.3
Reason for not attending govt.-run workshops – Not enough interactions	Categorical		10.1	6.6
Reason for not attending govt.-run workshops – Poor feedback from other farmers	Categorical		0.7	7.2
Reason for not attending govt.-run workshops – Too far	Categorical		13	18.4
Reason for not attending govt.-run workshops – Getting no such information	Categorical		42.8	60.5
Reason for not attending govt.-run workshops – Workshop not held	Categorical		0.7	0
Farmers' trusted connections with – Relatives	Categorical		57.2	55.1

Variables	Type	Unit	Descriptive Statistics	
			Gaya	Purnia
Farmers' trusted connections with – Neighbours	Categorical		51.8	62
Farmers' trusted connections with – Friends	Categorical		48.8	45.7
Farmers' trusted connections with – Landlords	Categorical		10.8	27.3
Farmers' trusted connections with – Big farmers	Categorical		21.1	42.4
Farmers' trusted connections with – Gram panchayat members	Categorical		26.5	22.4
Farmers' trusted connections with – JEEViKA members	Categorical		66.3	50.6
Farmers' trusted connections with – Social workers	Categorical		27.7	12.7
Farmers' trusted connections with – Cooperative society members	Categorical		17.5	13.1
Farmers' trusted connections with – Block or govt. officials	Categorical		10.2	9.8
Farmers believe that they are carrying ancestral knowledge	Categorical		86.7	93.5
Ancestral knowledge (AK) is helpful for farming decisions	Categorical		93.1	95.2
Technical assistance (TA) is helpful for farming decisions	Categorical		26.5	29.4
Informal community networks (ICNs) is helpful for farming decisions	Categorical		61.4	66.9
Formal community network (FCNs) is helpful for farming decisions	Categorical		28.9	47.8
Effectiveness of ancestral knowledge (AK) – Very low	Categorical		1.5	1.4
Effectiveness of ancestral knowledge (AK) – Low	Categorical		9	11
Effectiveness of ancestral knowledge (AK) – Medium	Categorical		29.1	27.1
Effectiveness of ancestral knowledge (AK) – High	Categorical		27.6	36.7
Effectiveness of ancestral knowledge (AK) – Very high	Categorical		32.8	23.9
Effectiveness of technical assistance (TA) – Very low	Categorical		4.5	1.4
Effectiveness of technical assistance (TA) – Low	Categorical		34.1	30.6
Effectiveness of technical assistance (TA) – Medium	Categorical		29.5	44.4
Effectiveness of technical assistance (TA) – High	Categorical		20.4	15.3
Effectiveness of technical assistance (TA) – Very high	Categorical		11.4	8.3

Variables	Type	Unit	Descriptive Statistics	
			Gaya	Purnia
Effectiveness of informal community networks (ICNs) – Very low	Categorical		6.7	3.9
Effectiveness of informal community networks (ICNs) – Low	Categorical		24.4	16.7
Effectiveness of informal community networks (ICNs) – Medium	Categorical		28.9	28.4
Effectiveness of informal community networks (ICNs) – High	Categorical		24.4	37.3
Effectiveness of informal community networks (ICNs) – Very high	Categorical		15.6	13.7
Effectiveness of formal community networks (FCNs) – Very low	Categorical		1.1	2.4
Effectiveness of formal community networks (FCNs) – Low	Categorical		22.6	20
Effectiveness of formal community networks (FCNs) – Medium	Categorical		37.6	26.7
Effectiveness of formal community networks (FCNs) – High	Categorical		25.8	39.4
Effectiveness of formal community networks (FCNs) – Very high	Categorical		12.9	11.5
Most helpful adaptation strategy for farming decisions – Only AK	Categorical		37.3	25.7
Most helpful adaptation strategy for farming decisions – Only TA	Categorical		8.4	6.1
Most helpful adaptation strategy for farming decisions – Only ICN	Categorical		14.4	1.2
Most helpful adaptation strategy for farming decisions – Only FCN	Categorical		2.4	1.6
Most helpful adaptation strategy for farming decisions – AK & TA	Categorical		18.1	32.7
Most helpful adaptation strategy for farming decisions – AK & ICN	Categorical		4.8	9
Most helpful adaptation strategy for farming decisions – AK & FCN	Categorical		0.6	0.4
Most helpful adaptation strategy for farming decisions – TA & ICN	Categorical		2.4	6.9
Most helpful adaptation strategy for farming decisions – TA & FCN	Categorical		1.2	0.4
Most helpful adaptation strategy for farming decisions – AK & TA & ICN	Categorical		4.8	11.4
Most helpful adaptation strategy for farming decisions – AK & TA & FCN	Categorical		1.8	4.1
Most helpful adaptation strategy for farming decisions – AK& TA & ICN & FCN	Categorical		3.6	0.4

Table 26: Different model specifications of wheat yield for Purnia based on primary survey

Regressors		Model 1	Model 2	Model 3
Agricultural Labour Hired		-.1241608*** (-3.17)	-.1241608*** (-3.17)	-.032347 (-0.77)
Usage of NPK Fertiliser		-109.6251* (-1.89)	-109.6251* (-1.89)	-72.80799 (-1.54)
No. of Times of Pest Control Adoption		-20.57368 (-0.94)	-20.57368 (-0.94)	33.52014* (1.92)
Use of HYV Seeds		0	0	0
Utilisation of Diesel Pumps		-.0659763 (-0.49)	-.0659763 (-0.49)	-.1597295 (-1.53)
Utilisation of Electric Pumps		-.8061606*** (-3.07)	-.8061606*** (-3.07)	-.3344296 (-1.39)
Utilisation of Power Tiller		0	0	0
Utilisation of Tractor		.2006047** (2.01)	.2006047** (2.01)	.3590735*** (3.55)
Utilisation of Rotavator		-.7432649*** (-5.14)	-.7432649*** (-5.14)	-.9570001*** (-5.96)
Loan Amount		-.0073441*** (-3.79)	-.0073441*** (-3.79)	-.0065688*** (-6.06)
Farmer Type		512.7186*** (4.60)	512.7186*** (4.60)	253.6537** (2.46)
Own Land		0	0	0
Family Type		192.3817** (2.05)	192.3817** (2.05)	-54.85922 (-0.63)
Family Size		204.5104*** (6.88)	204.5104*** (6.88)	227.2772*** (8.92)
Adult Sex Ratio		-740.7835*** (-4.93)	-740.7835*** (-4.93)	-885.0269*** (-8.99)
Proportion of Earning Members		846.5795* (1.74)	846.5795* (1.74)	NA
Soil Fertility		-1325.092*** (-5.56)	-1325.092*** (-5.56)	-1809.108*** (-6.46)
Temperature		-8.43962 (-0.05)	-8.43962 (-0.05)	587.6434** (2.62)
Rainfall		0	0	364.1329** (2.72)
Proportion of Family Member Passed Class X		-2043.743** (-2.88)	-2043.743** (-2.88)	-3526.782*** (-5.92)
Experience Level		-217.131** (-2.31)	-217.131** (-2.31)	-474.0688*** (-4.93)
Ancestral Knowledge	**Less Effective**	NA	NA	NA
	High Effective	-128.0714 (-0.90)	-128.0714 (-0.90)	-257.6451* (-1.83)
Trusted Networks with Relatives-Neighbours-Friends		350.8134** (2.64)	350.8134** (2.64)	398.8269*** (3.31)
Trusted Network with JEEViKA		294.769* (1.68)	294.769* (1.68)	594.5296*** (3.46)
Attending Govt.-Run Workshops		577.6744*** (5.14)	577.6744*** (5.14)	468.0327*** (5.45)
Constant		322.9124	322.9124	710.376**

Regressors	Model 1	Model 2	Model 3
	(1.04)	(1.04)	(2.65)
Block, Panchayat, Village	x	x	x
Prob.>F	0.0227	0.0227	0.0000
R^2	0.9558	0.9558	0.9653
No. of Observations	27	27	27
Type of Standard Error (S.E.)	Linearised	Linearised	Linearised
Model Significance	5 per cent	5 per cent	1 per cent

Note: Figures in parentheses refer to the value of the t-statistic.
Coefficients in '***', '**', '*' are statistically significant at 1%, 5%, and 10% level respectively.
'0' represents dropped variables by the regression estimation.

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