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An agenda for spatial economic research in Rwanda

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1. Executive Summary

This paper aims to illustrate the potential that spatial economics has to reveal policy-relevant insights in Rwanda. For six thematic policy areas, we make the case for the policy relevance of spatial economic analysis, present existing data and analysis on Rwanda, highlight interesting examples of international research, and suggest ideas for further research that may have policy relevance.

The field of empirical spatial economics involves the analysis of spatially disaggregated variables, including i) secondary and administrative survey data where it is available at sufficient spatial granularity; and ii) remote sensing data derived by algorithm from satellite imagery. This field is far newer than the field of empirical economics in general, but there is already a rich international literature illustrating fascinating research possibilities that could be applied in Rwanda. In their review of applications of satellite data in economics, Donaldson and Storeygard (2016) write:

> *"A revolution has taken place in remote sensing and allied fields such as computer science, engineering, and geography. Petabytes of satellite imagery have become publicly accessible at increasing resolution, many algorithms for extracting meaningful social science information from these images are now routine, and modern cloud-based processing power allows these algorithms to be run at global scale." (p171)*

Rwanda has a strong aspiration to use technology and innovation to drive economic growth. Vision 2050 aspires to a knowledge-intensive economy,[1] and spatial data and analysis is seen as an instrumental tool to achieve that. This is evidenced by the prominence of spatial data and analysis across different government institutions. The Rwanda Space Agency seeks to "develop Rwanda's space sector towards socio-economic development" and use analysis of satellite imagery in ways that promote growth.[2] It has already supported soil moisture analysis and satellite data-based land use surveys and crop yield estimates, and has used satellite imagery of the 2021 eruption of Mount Nyiragongo to inform decision-makers and first responders of events in Rubavu and Goma.[3] Rwanda's Ministry of ICT has a ICT Hub Strategy (2019) to work towards a knowledge-based economy, and the country has a Smart City Master Plan (2017) and a Smart Rwanda Master Plan (2015). The Ministry of

[1] Government of Rwanda (2020) Rwanda Vision 2050: Abridged Version. Kigali.
[2] http://space.gov.rw/about
[3] https://www.newtimes.co.rw/opinions/rwanda-space-agency-creating-opportunity-emerging-space-economy

Environment and Rwanda Land Management and Use Authority also launched the long-awaited National Spatial Data Infrastructure platform in 2021.[4] Other entities such as Environmental Systems Research Institute (ESRI) have geoportals that relate to Rwanda. University of Rwanda also has a Centre for Geographic Information Systems and Remote Sensing, which already has an impressive legacy of spatial literature from its staff and students from which we draw in this study.

To fulfil Rwanda's ambitions for the use of technology and data for socioeconomic development, creative and innovative approaches are needed that take advantage of methodologies that have been applied in other contexts. A range of GIS specialists exist who are in Rwanda or focus on Rwanda, but rarely connect their work to the field of economics, and those in the field of economics could benefit more by leveraging spatial analysis. Therefore, this paper is an attempt to link the fields of GIS and remote sensing and economics, and highlight the possibilities that the marriage of the two fields - as well as a more spatial approach to non-GIS data - can afford. We do not comment on data governance and infrastructure issues - which, whilst important, are beyond the scope of the paper - except to emphasise the importance of open data for a productive policy research environment.

Spatial data is of relevance to a range of thematic policy areas. As noted, for this paper we select six areas that are both of national policy importance in Rwanda, and that are especially amenable to spatial analysis. These areas are:

- Tracking economic activity and welfare
- Agriculture
- Land use and natural resources
- Air pollution
- Climate change adaptation and emergency management
- Urbanisation and infrastructure

This is not an exhaustive list of policy areas in which spatial economics can contribute, but covers a wide scope of major topics. Our goal in covering these themes is not to give a comprehensive update of all literature in the theme, but to cite some major examples and most importantly, to spur some useful and creative ideas for further research.

Table 1 summarises the ideas for further research that we find in our paper. An important caveat is due: some of the research ideas we suggest involve data that exist but are not available without permission from the Government of Rwanda (such as the building footprints behind the 2022 Census or mobile phone data), or must be purchased. However, data are publicly downloadable for other research ideas, and it is our hope that these ideas - which are described in more detail in the main paper - lead to or inspire further policy-relevant research to be conducted.

[4] https://www.ktpress.rw/2021/11/rwanda-launches-cost-effective-geographical-data-platform/

Table 1: Our ideas for further research split by policy theme

Theme	**Idea for further research**
Tracking economic activity and welfare	Estimate sub-national GDP for Rwanda
	Update the Multidimensional Poverty Index to track poverty at fine spatial and temporal scale
	Use mobile phone data to estimate spatial patterns of wealth, money flows and migration patterns
	Update the Economic Geography of Rwanda study
Agriculture	Extract insights on crop trends from periodic satellite-based crop maps
	Analyse drivers of differences in crop performance between Districts
	Predict crop yields as an input into index-based insurance
	Conduct land suitability analysis to aim to improve crop land allocation
	Other agronomic applications such as crop detection, crop disease detection, and climate risk maps for individual crops
Land use and natural resources	Monitor land use cover
	Monitor deforestation
	Analyse the spatial form of Rwanda's cities as they expand their land footprint
	Monitor illegal mining
	Monitor water resources
Air pollution	Replicate the Dasgupta et al. (2020) Dar es Salaam study to find the areas of Rwanda's cities vulnerable to the worst air pollution
	Analyse the impact on air pollution of no-idling zones outside schools
	Analyse the impact of air pollution on productivity and cognition
Emergency management and climate change adaptation	Create or contribute to a digital platform to inform emergency and disaster management
	Analyse exposure to climate hazards and disasters
	Track the implementation of NDC adaptation measures in rural areas
	Analyse the inclusiveness of climate adaptation measures such as flood defences
	Analyse the impact of irrigation on crop production, and explore other

	research possibilities relating to irrigation
	Identify housing built in areas at risk of landslides
Urbanisation and Infrastructure	Create a housing suitability index and other urban applications using the Suitability tool, to inform urban planning and the placement of social housing
	Track urban spatial growth, compactness and relative growth of formal housing
	Conduct a nationwide property valuation
	Assess the impact of roads on economic activity and assets
	Conduct transport analysis and updated accessibility analysis for Rwanda's cities
	Use restaurants, roofs or other unconventional data sources to estimate economic activity or assets in Rwanda's cities at detailed spatial scale

2. Tracking economic activity and welfare

2.1. Policy Relevance

Vision 2050 aims to set a development path for Rwanda to be an upper middle income country by 2035 and a high income country by 2050; this goal is focused on a single measure, Gross Domestic Product (GDP) per capita. The National Strategy for Transformation 1 also aims to eradicate extreme poverty by 2024, which stood at 16% in 2017 according to EICV 5, and Rwanda's poverty statistics are of keen political and economic interest. However, GDP per capita is a single figure that focuses on the entire economy and does not consider local differences in economic activity; the same applies to poverty reduction.

However, Rwanda does have spatially relevant development plans. Rwanda counts urbanisation and agriculture as drivers of growth, has a Spatial Development Framework, a Local Economic Development Plan, a National Land Use and Development Master Plan and a series of urban master plans for Kigali, the secondary cities and soon, the satellite cities. Rwanda is keen to promote industrial parks and formal businesses across the country, as well as cross-border trade with its neighbours to take advantage of the opportunities afforded by its geographic position in the region.

Moreover, the characteristics of Rwanda's economy, as well as the shocks to which it is subjected, are distributed unequally across its landmass; for example, as the climate changes, rainfall - and thus flooding and landslides - are predicted to increase in the west and drought is predicted to increase in the east. It will thus be of increasing policy relevance to the Government to understand how these major national-level indicators tracking the economy as a whole, and other indicators of economic activity, distribute across the country spatially.

2.2. Existing data and analysis for Rwanda

In this section, we identify different datasets which could be utilised for projects in Rwanda to track economic activity and welfare spatially, and highlight spatial analysis that has already been done on the topic that focuses on Rwanda.

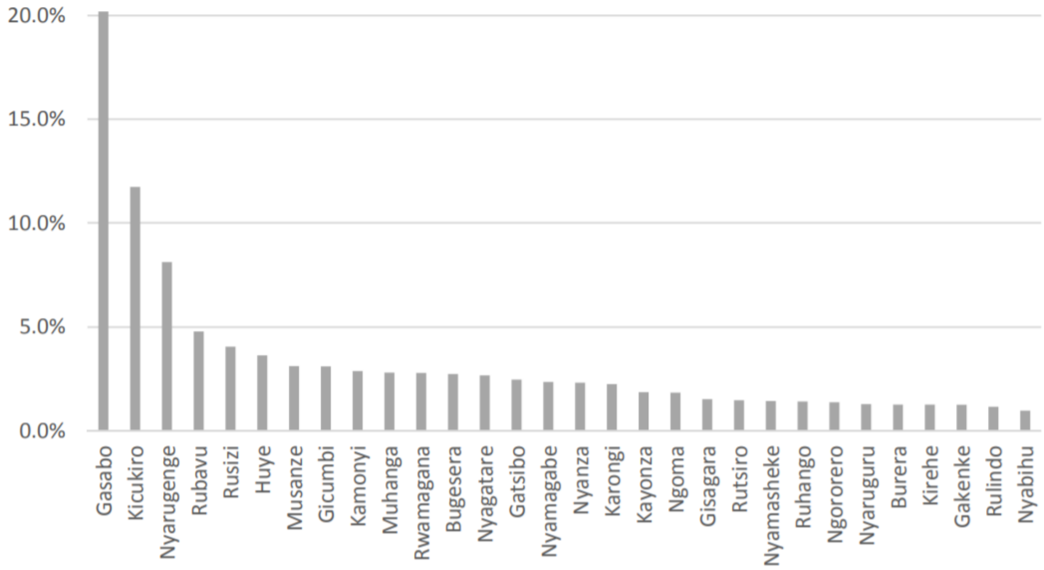
Table 1: Spatial datasets related to tracking economic activity and welfare

Data	**Description**	**Source**
NTL	Night-time lights	NASA
Population	Population distributions	WorldPop
Cell towers	Mobile infrastructure	OpenCelliD
Distances	Distances to key locations	OpenStreetMap
Mobile	Mobile ownership	Mobile Network Operators
Mobile calls	Mobile usage	Mobile Network Operators
Mobile transactions	Mobile payments	Mobile Network Operators

Many satellite systems are now providing data through different portals that serve to facilitate the extraction of data for a specific administrative boundary and time span. In addition, mobile network operators (MNO) have data on mobile calls and usage, the use of which for research is tightly regulated by Rwanda Utilities Regulatory Authority (RURA).

Bundervoet et al. (2015) estimate GDP at the subnational level in Rwanda and Kenya. The study estimates GDP in Rwanda's 30 districts, as shown in Figure 1 below. The authors estimate that the three Kigali districts of Gasabo, Kicukiro and Nyarugenge comprise fully 40% of Rwanda's total GDP in 2013, whilst containing 10% of the country's population.

Figure 1: District-level contribution to overall GDP



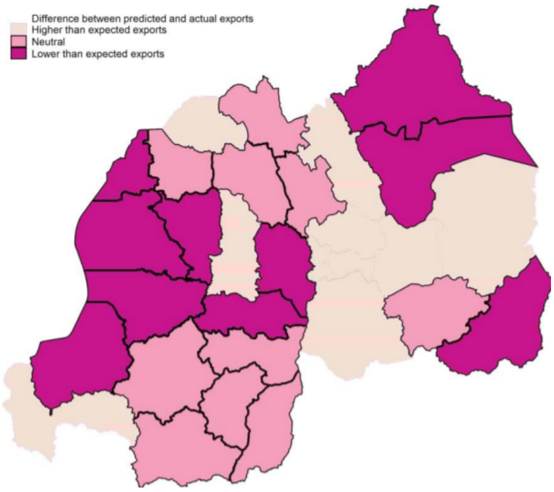
Source: Bundervoet, Tom; Maiyo, Laban; Sanghi, Apurva. 2015. Bright Lights, Big Cities : Measuring National and Subnational Economic Growth in Africa from Outer Space, with an Application to Kenya and Rwanda. Policy Research Working Paper;No. 7461. World Bank, Washington, DC. © World Bank. p22

Laterite authors Rajashekar et al. (2019) published a significant study commissioned by IGC, "The economic geography of Rwanda," which contains a rich collection of analyses and insights. It does not use satellite data but makes thorough use of secondary and administrative data including from electronic billing machines, Population and Housing Census, Establishment Census, WorldPop, POPGRID, Rwanda's 2017 household survey EICV 5, and the Labour Force Survey. The study covers spatial population and migration patterns, the geography of firms, structural transformation and economic complexity, internal trade (including a gravity model) and infrastructure. Figure 2 shows the result from a gravity model of internal trade which predicts internal trade between Rwanda's districts, based on their sizes and the distance between them.

Njuguna & McSharry (2017) predicted a multidimensional poverty index (MPI) at the sector level in Rwanda with a cross-validated correlation of 88 percent using night-time lights, population density, mobile ownership and mobile calls. Figure 4 shows the prediction at the sector level, which is a more disaggregated level than poverty statistics have previously been available. One strength of this model is that night lights, population density, mobile phone ownership and mobile call data are available for each month, and this MPI could readily be constructed monthly, in contrast to EICV poverty data which is only available every three to four years.

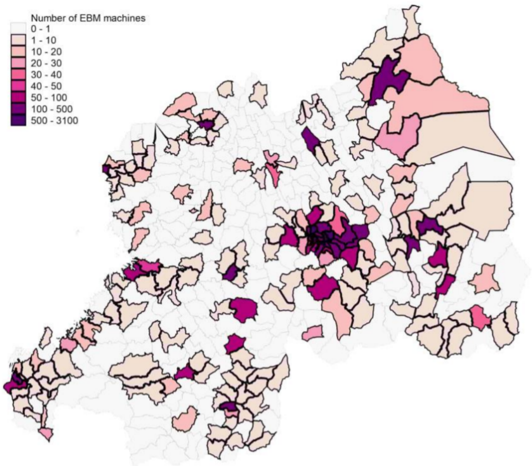
Joshua Blumenstock has written several interesting papers using mobile phone data in Rwanda, including "A method for estimating the relationship between phone use and wealth" with Shen & Eagle (2009), "Risk and reciprocity over the mobile phone network" with Eagle & Fafchamps (2011), "Mobile divides: gender, socioeconomic status, and mobile

Figure 2: The difference between expected and actual internal (EBM) exports as predicted by a gravity model of internal trade



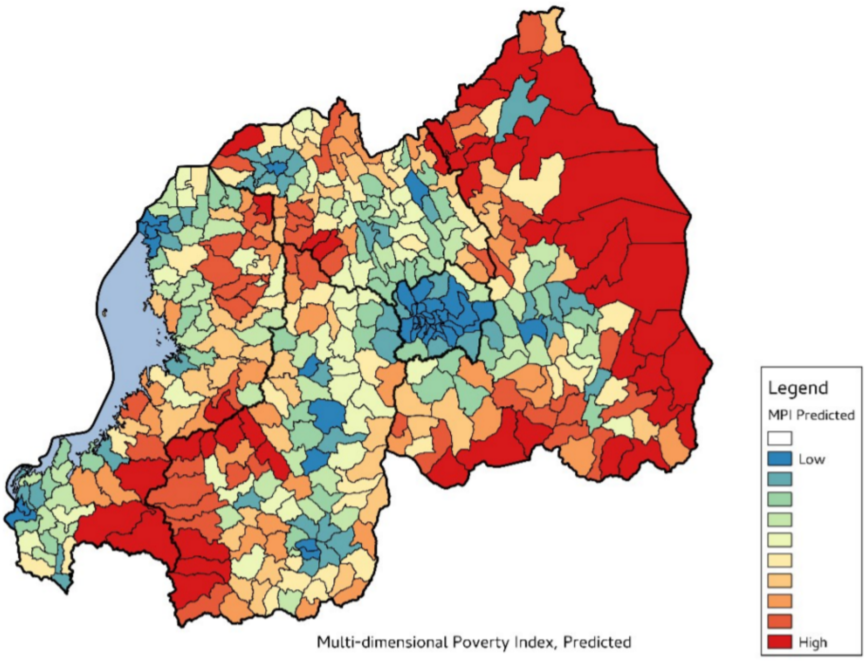
Source: Rajashekar, A., Stoelinga, D., & Richards, M. (2019). The economic geography of Rwanda's cities. Laterite, commissioned by International Growth Centre. https://www.theigc.org/wp-content/uploads/2019/08/Rajashekar-2019-Final-report.pdf , p76

Figure 3: The location of EBM machines in Rwanda in 2018



Source: Rajashekar, A., Stoelinga, D., & Richards, M. (2019). The economic geography of Rwanda's cities. Laterite, commissioned by International Growth Centre. https://www.theigc.org/wp-content/uploads/2019/08/Rajashekar-2019-Final-report.pdf , p33

Figure 4: Multidimensional Poverty Index



Njuguna, Christopher and McSharry, Patrick E. (2017), Constructing Spatiotemporal Poverty Indices From Big Data. Journal of Business Research, 70: 318-327. , Available at SSRN: https://ssrn.com/abstract=2852722 p14

phone use in Rwanda" with Eagle (2009), "Inferring patterns of internal migration from mobile phone call records" in 2011 and "Divided we call: disparities in access and use of mobile phones in Rwanda" in 2012.

The Government of Rwanda & World Bank's (2019) "Future Drivers of Growth" report contains spatial economic analysis relating to the urbanisation and agglomeration-themed chapter,[5] but this could usefully be extended to other themes.

2.3. International research

The international literature has estimated economic activity and welfare in interesting ways both at the national and sub-national level, as well as across multiple countries. Night-time lights[6] have been used to estimate subnational income per capita (Ebener et al., 2005), the size of the informal economy and remittances in Mexico in comparison to official GDP figures (Ghosh et al., 2010), the global incidence of poverty (Elvidge et al., 2009), and economic growth (Henderson, et al., 2012). Table 2 contains a range of papers.

Other studies also discuss individual and household behaviours linking remote sensing data to urbanisation. Bruederle and Hodler (2018) find strong correlation between nighttime lights and human development proxies, which include indicators of local household wealth, education, and health collected from geo-referenced Demographic and Health Surveys (DHS) from 29 African countries. Jean et al. (2016) estimate consumption expenditure and asset wealth by applying a machine learning method (convolutional neural network) to high-resolution satellite imagery in five African countries. They show that a convolutional neural network can be trained to identify image features, which could further explain up to 75% of the variation in local-level economic outcomes. Dingel, Miscio, and Davis (2019) characterise the spatial distributions of human capitals/skills in three large developing countries, Brazil, China, and India, by using the lights-based metropolitan areas which aggregates finer geographic units on the basis of contiguous areas of light in nighttime satellite images, without sticking to administrative boundaries. Michaels et al. (2018) use a range of remotely sensed imagery to measure urbanisation in Tanzania.

Table 2: Summary of research on using alternative data sources to measure economic activity

Author	**Title**	**Primary data sources**	**Spatial coverage**	**Measure**
Ebener et al. (2005)	From wealth to health: modelling the distribution of income per capita at the sub-national level using night-time light imagery	Night-time lights	Multi country	GDP
Henderson et al. (2012)	Measuring Economic Growth from Outer Space	Night-time lights	Multi country	Growth of GDP

[5] World Bank Group; Government of Rwanda. 2020. Future Drivers of Growth in Rwanda : Innovation, Integration, Agglomeration, and Competition. Washington, DC: World Bank. © World Bank. https://openknowledge.worldbank.org/handle/10986/30732
[6] The Defense Meteorological Satellite Program (DMSP) night-time light data measured by NASA offers a means of estimating economic activity.

Elvidge et al. (2009)	A global poverty map derived from satellite data	Night-time lights	Global & national	International poverty line ($2 per day)
Gosh et al. (2010)	Estimation of Mexico's Informal Economy and Remittances Using Nighttime Imagery	Night-time lights	Mexico	Informal economy & remittances
Njuguna & McSharry (2017)	Prediction of subnational multidimensional poverty in Rwanda	Night-time lights; mobile CDR	Rwanda	Multidimensional poverty
Bruederle & Hodler (2017)	Nighttime Lights as a Proxy for Human Development at the Local Level	Night-time lights	29 African countries	Household wealth, education and health
Islam & Alam (2021)	Nighttime Light Intensity and Child Health Outcomes in Bangladesh	Night-time lights	Bangladesh	Child health outcomes
Soto et al. (2011)	Prediction of Socioeconomic Levels using Cell Phone Records	Mobile CDR	City level	Socioeconomic levels
Smith-Clarke et al. (2014)	Poverty on the Cheap: Estimating Poverty Maps Using Aggregated Mobile Communication Networks	Mobile CDR	Cote d'Ivoire	IMF poverty rate estimates

2.4. Ideas for further research

Estimate sub-national GDP for Rwanda

Sub-national GDP at the district or even sector level for Rwanda could be estimated at different points in time based on nightlights and other available spatial correlates, enabling a picture of how Rwanda's economy is developing spatially over time, and which districts are growing fastest. However, caution should be exercised at smaller-scale spatial resolutions - the smaller the scale, the less accurate nightlight-based estimates of economic activity tend to be. Cloud cover may also be an issue for intra-annual satellite measurements and this should be investigated for Rwanda.

Update the Multidimensional Poverty Index to track poverty at fine spatial and temporal scale

As mentioned above, Njuguna & McSharry (2017) predicted a multidimensional poverty index (MPI) at the sector level in Rwanda with a cross-validated correlation of 88 percent using four night-time lights, population density from the 2012 Census, mobile ownership and mobile calls. As calculating the MPI requires an expensive survey, it would be possible to use the machine learning model to estimate MPI on a quarterly basis. Since in Rwanda the next population census will be in 2022 and results taking time to be published, future studies may choose to use the DHS composite wealth index as an alternative ground truth even though it has a lower resolution being calculated at the district level. Having such a spatio-temporal measure of poverty would help to design interventions and both monitor and evaluate their impact. The real-time MPI could be visualised using a dashboard which could be driven by API access to the required input datasets.

Use mobile phone data to estimate spatial patterns of wealth, money flows and migration
A decade on, if the relevant mobile phone data could be made available, whichever of Blumenstock's studies on Rwanda is of most interest, could be replicated. Blumenstock estimated the relationship between phone use and wealth, which implies that a study could provide a spatially disaggregated picture of wealth in Rwanda. Blumenstock was able to estimate migration patterns from mobile phone call records - tracking patterns of internal migration might be especially interesting during the COVID-19 period. He also analysed how the 2008 Lake Kivu earthquake in Rwanda affected patterns of mobile airtime sharing, which he conceptualises as a proxy for mobile money and a way of sharing risk; if mobile money data were accessible an improved version of this study could be done, for instance to understand how people coped with the Mount Nyiragongo volcano eruption.

Update the Economic Geography of Rwanda study
The Rajashekar et. al (2019) study "The economic geography of Rwanda", draws on data ranging from 2011 to 2018. After the 2022 census and sixth household survey have been published, an update to this study, or updates to any of the major themes of population density and urbanisation, firms, economic activity and economic complexity, internal trade, could be done. Another option is to take one of these themes and produce a digestible report at regular intervals, for example annually, publish and distribute this to MINECOFIN, BNR, BRD, MINICOM, NIRDA and any other interested parties. This should coordinate with the economic indicators dashboard currently being developed by the National Bank of Rwanda in partnership with IGC.

3. Agriculture

3.1. Policy Relevance

The agriculture sector contributes 26% of Rwanda's GDP but 62% of its labour force (WDI, 2020), so plays an outsized role in the economic welfare of the country. Rwanda's Vision 2050 emphasises the importance of more technology-intensive agriculture and agro-processing. The National Strategy for Transformation 1 (NST 1) seeks to "increase crop and livestock quality, productivity, and production by modernising agriculture and increasing resilience to climate change" (Government of Rwanda, 2018, p7), and the agriculture sector contributes to targets poverty reduction, food security, health, and social protection in the Social Transformation Pillar of NST 1. Rwanda's Agriculture Policy (2018) has four major policy objectives: increased contribution to wealth creation; economic opportunities and prosperity - jobs and poverty alleviation; improved food security and nutrition; and increased resilience and sustainability.

Rwanda's Crop Intensification Program (CIP), which started in 2007, conducts the following activities according to the Ministry of Agriculture: improving seed and fertiliser use, providing a proximity extension service, marketing agricultural products, encouraging good farming practises amongst farmers, promoting an agro-inputs dealers' network, stimulating reliable private sector input and output markets through electronic fertiliser auctions, establishing food sufficiency and sovereignty of Rwanda.[7]

Another pillar of the CIP is land use consolidation, a systematic plan for growing specific crops grown in selected areas (Muhinda & Dusengemungu, 2015). Spatially, agricultural land is fragmented into many small plots, and land use consolidation seeks to improve the productivity of agricultural land through economies of scale. There are almost certainly advantages to taking a spatial data-driven approach to crop selection under the CIP, especially given the need to understand and manage climate risks and reduce economic losses from adverse weather patterns. Thus spatial data support future decision-making about both crop selection and resource allocation when implementing agricultural policy and the planned measures in Rwanda's Nationally Determined Contribution, its plan to mitigate and adapt to climate change.

3.2. Existing data and analysis in Rwanda

In this section, we identify different datasets which could be utilised for projects in Rwanda to track agriculture spatially, and highlight spatial analysis that has already been done on the topic that focuses on Rwanda.

Table 3: Spatial datasets related to agriculture

Data	**Description**	**Source**
Crops	Crops	Rwanda Agriculture Board
NDVI	Greenness indices	Copernicus
Weather	Weather	Rwanda Meteorological Agency
Weather	Precipitation & vegetation	FAO-GIEWS

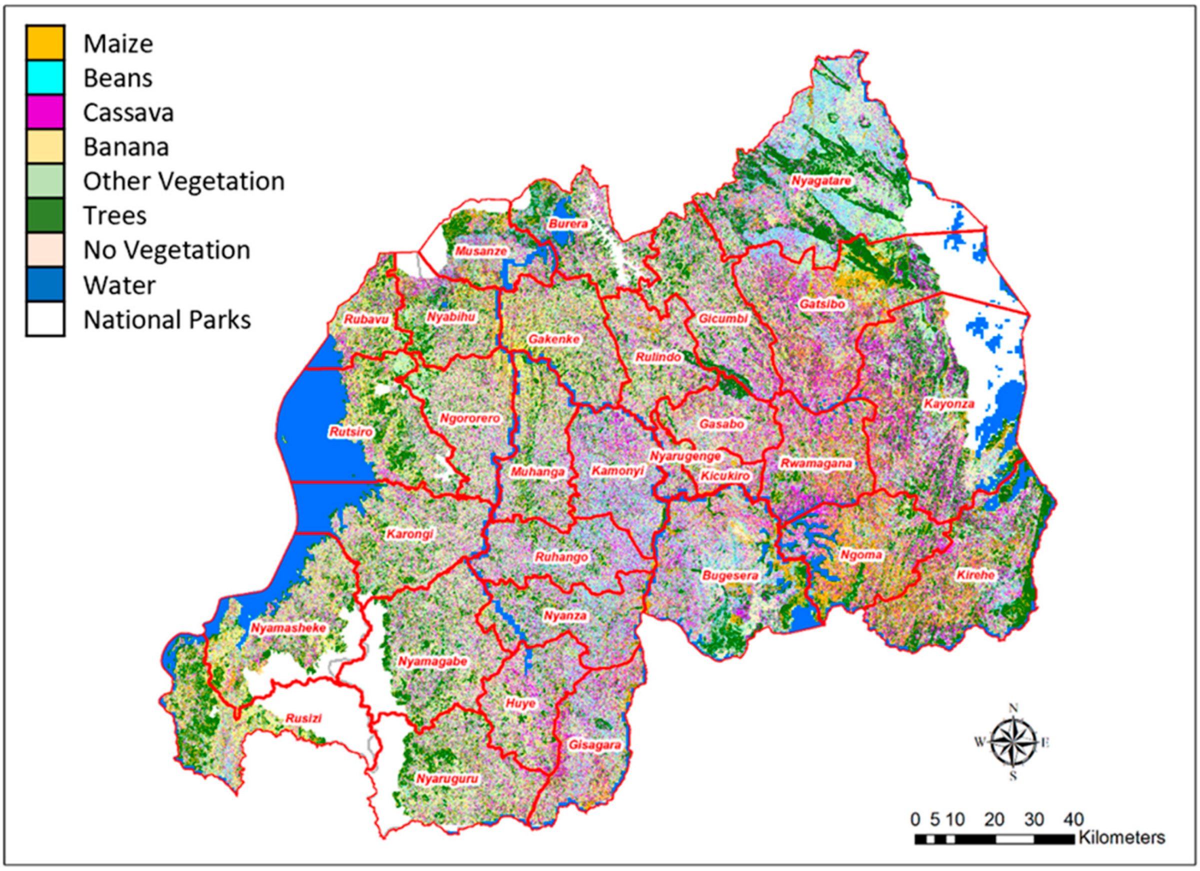
[7] https://rab.gov.rw/index.php?id=188

Weather	Rainfall & vegetation	[ClimateSERV]
Weather	Climate and hydrology	[ClimateEngine]
Soil	Soil type	[Ambee]
Land Cover	Land use classification	[ESA]

Crop data is available from the Rwanda Agricultural Board (RDB) and the National Institute of Statistics in Rwanda (NISR). Weather data is available from the Rwanda Meteorology Agency (RMA). In addition, it is possible to access weather information from several satellite products as seen in Table 3.

Hegarty-Craver et al. (2020) apply machine learning to satellite data to generate crop maps for Rwanda. They train the machine learning algorithm to be used on satellite data, on a high-fidelity ground-truth dataset using imagery from unmanned aerial vehicles (drone footage). This included examples of large mono-cropped fields, small intercropped fields, and natural vegetation. They were thus able to generate a map of the different crops grown across the entire country, shown in Figure 5.

Figure 5: Crop map for 2019 Season A in Rwanda, based on satellite imagery



Uwizera & McSharry (2017) investigate the role of rainfall for facilitating forecasting, monitoring and dynamic allocation of maize in Rwanda; while this study focuses on maize, much of the analysis is also relevant for other crops. A quantitative approach developed simple models for forecasting and monitoring the performance of the maize crop while taking account of local rainfall estimated by satellite imagery. Rainfall is found to be a statistically significant determinant of crop yield. The selected model captures the influence of rainfall during different months of the year, following the crop calendar published by the Food and Agriculture Organisation (FAO).

Also on maize, Bucagu et al. (2020) use spatial data to study the determinants of maize yield (tonnes per hectare) in Nyakiliba sector and Gashora sector located in Birunga and Central Bugesera, and to estimate maize yield gaps and their impact on food security. The Normalised Difference Vegetation Index (NDVI) correlated strongly with both maize yield and soil fertility indicators. The study estimated positive and significant responses of maize yield to the use of nitrogen and phosphorus fertilisers.

Ngwijabagabo et al. (2021) use spatial data to find areas of land that are suitable for agroforestry in Musanze District, based on rainfall, temperature, soil pH, altitude, and land use, and found that 24% of the District was classed as “very suitable” for agroforestry. They suggest that GIS could be used far more widely to facilitate site selection for agroforestry projects.[8]

McSharry, Swartz & Spray (2016) use multiple satellite-based measures to predict tea productivity at several tea factories in Rwanda, using applied machine learning techniques. Using crop specific models identified by machine learning, it would be possible to predict future contributions to GDP in Rwanda from key commodities such as tea and coffee.

3.3. International research

The literature on the spatial analysis of agriculture is vast, so our review is necessarily partial; we show examples of studies or summary papers in some important thematic areas within agriculture.

Basic informative spatial layers relevant to agriculture
Remote sensing and GIS can be used to generate layers that may be relevant to agriculture in a range of ways including flood plain mapping, hydrological modelling, rainfall, land use cover, land use changes, crop growth monitoring, stress detection (Kingra et al., 2016).

Agronomic uses of remote sensing data
The Normalised Difference Vegetation Index provides a means of assessing whether or not the target spatial area being observed contains live green vegetation. It is the most commonly used vegetation index, but has been followed by a range of others including the Soil Adjusted Vegetation Index, Vegetation Condition Index, Temperature Crop Index and

[8] https://www.ajol.info/index.php/rjeste/article/view/221044

others. Shanmugapriya et al. (2019) outline a range of agronomic uses that relate to crop condition assessment, nutrient and water status, weed identification and management, pest and disease infestation, and precision agriculture - for example site-specific nitrogen fertiliser management.

Determinants of crop yields and agricultural productivity

One branch of the literature studies the impact of geographic attributes on crop yields, such as temperature (Schlenker and Roberts, 2009; Calzadilla et al., 2013; Burke et al., 2015; Zhao et al., 2017), heat indices (Zai et al., 2019), rainfall (Jayachandran, 2006; Levine and Yang, 2014), land quality (Cassman, 1999; Wiebe et al., 2003; Wiebe, 2003), topography (Kravchenko and Bullock, 2000), and more generally, climate change (Ward et al., 2014).

Remote sensing data have been widely used to predict agricultural output or measure agricultural productivity. For example, Wójtowicz et al. (2016) reviewed various remote sensing methods designed to optimise profitability of agricultural crop production and protect the environment. Adamopoulos and Restuccia (2021) used high-resolution micro-geography data and a spatial accounting framework to quantify the role of geography and land quality for agricultural productivity differences across countries. They find that low agricultural land productivity is not due to unfavourable geographic endowments, but due to the irrational choice of crop production.

Crop choices

Another category of studies investigates crop choices and agricultural land use. For example, Scott (2014) investigates how US agricultural policy alters dynamic incentives for the preparation of land for crop agriculture. They do this by using the USDA's Cropland Data Layer, which classifies 30-metre pixels throughout the US into crop-specific categories. Holmes and Lee (2012) used similar data to estimate the factors determining specialisation of crop choice at the level of individual fields, distinguishing between the role of natural advantage (soil characteristics) and economies of density (scale economies achieved when farmers plant neighbouring fields with the same crop).

Other innovative applications

The increasing availability of satellite data at higher spatial, temporal, and spectral resolutions is enabling new applications in agricultural production, including agricultural insurance or agricultural risk management. Benami et al. (2021) provided a review on approaches of using lower-cost techniques, including weather and satellite data, to estimate agricultural losses for index insurance, which is a way to manage risk by helping people avoid the most severe possible consequences of bad weather and build confidence to invest in additional income-generating opportunities. Ozdogan et al. (2010) summarised opportunities and challenges of remote sensing in irrigated agriculture.

3.4. Ideas for further research

Extract insights on crop trends from periodic satellite-based crop maps

Hegarty-Craver et al. (2020) generated a crop map for the entire country of Rwanda for Season A in 2019, but were focused on pioneering the methodology rather than extracting insights on crop map patterns. The map they generated, if replicated for multiple crop seasons, could be used to extract important descriptive statistics about crop growth in Rwanda. In doing so, it could supplement Rwanda's Seasonal Agricultural Survey and find which crops have expanded or reduced, in which areas of the country, and in which topographies. These data could also be used in innovative ways to track the impact of climate change or of a particularly wet or dry season on crop choice. Hegarty-Craver et al. recommend increasing the size of the UAV-based ground-truthing dataset, adding categories to the limited categories the authors worked with.

Analyse drivers of differences in crop performance between Districts

Understanding the threat of greater variability in weather patterns due to climate change requires an analysis of the impact of local weather conditions on local crop yield. Using machine learning (ML) approaches such as those introduced in Uwizera & McSharry (2017), the performance of a crop can be assessed in a specific area. As the variation in rainfall is explicitly taken into account, it is possible to infer if the performance of the crop in a particular district is worse or greater than expected in relation to the amount of the rainfall that occurred. Uwizera & McSharry show that the reported performance of maize in some districts varies over time and is often underestimated or overestimated by the model. Further research is necessary to assess the causes of this variability and to ensure that the districts that underperformed can learn from the districts that overperformed at that particular time.

Predict crop yields as an input into index-based insurance

Traditionally, mechanistic crop models have been constructed to derive mathematical relationships between productivity and a wide range of explanatory variables. With increasing volumes of data becoming available, it is now possible to use machine learning to identify predictive models and to adapt to local conditions. Along with the location of the cultivated land (latitude, longitude, altitude), soil conditions and local weather conditions, crop productivity depends on the availability of key inputs such as fertiliser, pesticide and of course management practises. Ground level data for these last three variables would need to be collected to better understand their effect on yield. Nevertheless, the existing literature and previous studies in Rwanda suggest that satellite imagery offers a means of developing accurate predictions of crop yield.

The normalised difference vegetation index (NDVI) provides a means of assessing whether or not the target spatial area being observed contains live green vegetation. Such greenness indices and weather variables from satellite products were used to predict agricultural yield (McSharry, Swartz & Spray, 2016). This study also demonstrated the considerable potential for using remote sensing to develop a parametric insurance product known as index-based insurance. The accuracy, availability and spatial coverage of satellite data may offer a means of creating innovative products for the agriculture sector.

Conduct land suitability analysis to improve crop land allocation
There is considerable potential for improving the current system of crop land allocation by district in Rwanda by relying more on data-driven predictive analytics. In addition to the Ngwijabagabo et al. (2021) study on land suitability for agroforestry in Musanze, papers focused on many countries use spatial analysis to predict land suitability for various crops. There is thus scope to expand the Musanze analysis to use spatial datasets on soil type, topography, weather, distance to roads and other variables to generate a map of land suitability for agroforestry as well as the various major crops. This could inform crop land allocation decisions and irrigation location decisions. An extension to this might be to model how climate change affects land suitability, due to increased drought, rainfall or temperatures in certain locations as predicted by the Global Climate Models.

Other agronomic applications
The future potential contribution of spatial data to the agriculture sector relies on research and development and the operationalization of applications using machine learning in a number of areas. These include: (1) crop detection using classification models; (2) crop disease detection using drones and satellite; (3) yield forecasting; and (4) climate risk maps for individual crops generated by combining yield models with climate scenarios. This would be in tandem with and completing the seasonal agricultural survey that is regularly conducted by the National Institute of Statistics(NISR).

4. Land use and natural resources

4.1. Policy Relevance

Rwanda's NST 1 has an Economic Transformation Pillar that promotes the "Sustainable Management of Natural Resources and Environment to Transition Rwanda towards a Green Economy". Rwanda has an Environment Policy, Land Policy, Biodiversity Policy, Water and Sanitation Policy, and an Energy Policy. Rwanda is also a signatory to the Bonn Challenge which aims to restore 350 million hectares of deforested and degraded landscape by 2030 in order to increase resilience towards climate change. The country met its target in 2019 when afforestation efforts increased forest coverage to 30% of the total country area, but efforts are ongoing to ensure this remains the case.

The country has also conducted the natural capital accounts (NCA) of different natural resources such as land, water, mineral resources and ecosystem services in a bid to integrate them into the national account (Nishimwe et al., 2020). All sectoral NCAs highlight the need for better quality and frequent spatial data to get a better picture of natural resources and model future trends to inform policy making. The NCAs adopted the System of Environmental Economic Accounting (SEEA) developed by the United Nations Statistics Division. The SEEA calls for the use of geospatial data and techniques to understand spatial and temporal variability in natural resources (FAO, OECD and WB, 2014). Thus, spatial data and techniques will be crucial to enable regular, robust, and internationally comparable natural resource accounts in Rwanda.

4.2. Existing data and analysis in Rwanda

In this section, we identify different datasets which could be utilised for projects in Rwanda to track land use and natural resources spatially, and highlight spatial analysis that has already been done on the topic that focuses on Rwanda.

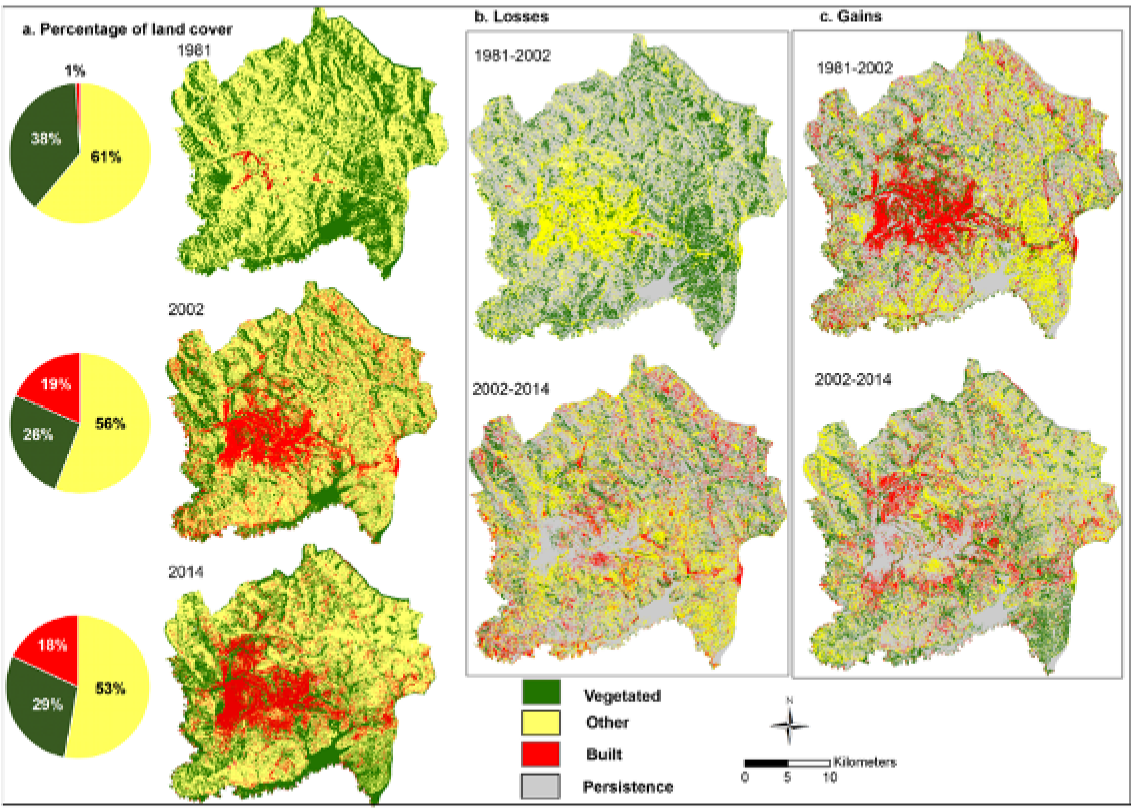
Table 4: Spatial datasets related to land use and natural resources

Data	Description	Source
World View satellite images	Countrywide 25 cm high-resolution satellite images.	NISR
Land Administration Information System (LAIS)	A comprehensive compendium of countrywide land parcels and their characteristics (size, location and use).	RLMUA
ESRI 2020 land cover	A global classification map of land covers	ESRI
Water Network spatial data	Shapefile data on urban, peri-urban and rural water networks (pipelines, water sources and reservoirs)	WASAC
RLMUA Land Use Cover	2019 countrywide land use cover based on high resolution satellite images	RLMUA
Mining Concession Data	Shapefile data on areas given as mining concessions	RMB
NDVI	Greenness indices	Copernicus
Weather	Precipitation & vegetation	FAO-GIEWS
Weather	Rainfall & vegetation	ClimateSERV
Weather	Climate and hydrology	ClimateEngine
Soil	Soil conditions	Ambee
Land Cover	Land use classification	ESA

The land use sector in Rwanda has benefited from ample use of spatial data. For instance, the groundbreaking land tenure regularisation was done with the use of aerial photography and satellite imagery (Ngoga, 2019). The national land use master plan was done based on various geo-spatial analysis to understand the settlements patterns, size, and density. The Kigali and secondary city master plans produced considerable high resolution geospatial analysis of features such as slope, land cover and use, presence of amenities and infrastructure. Moreover, the Spatial Development Framework (SDF) done by UN-HABITAT and MININFRA performed a spatial multi-criteria evaluation using the various spatial and non-spatial data to produce a spatial structure of Rwanda. This sparked an interest to map settlements more dynamically in Rwanda hence the ongoing project to produce urban dynamic maps.

On land use cover, Mugiraneza, Ban and Haas, (2019) analysed land cover change in Kigali from 1984 to 2016 using multi-temporal Landsat satellite images and estimated a loss of ecosystem services worth 69 million US dollars as a result of cropland degradation in favour of urban areas. Mugiraneza, Nascetti and Ban, (2020) used Landsat images with Google Earth Engine to estimate land use changes in urban Kigali and found that impervious surfaces have been increasing by an average of 3.7% annually from 1990 to 2019. High resolution satellite images were also used to detect and monitor not just land cover but also precise land use such as informal settlements in Kigali (Mugiraneza, Nascetti and Ban, 2019). Akinyemi, Pontius and Braimoh, (2017) also used spatial data combined with intensity analysis to estimate changes in land cover in Kigali between 1981 and 2014. Akinyemi, (2017) demonstrated that spatial analysis can be used to track forest coverage in the rural parts of Rwanda, as shown in Figure 6.

Figure 6: Kigali land cover changes (1981, 2020, 2014)



Source: Akinyemi,Pontius and Braimoh (2017)

A study conducted by the Stockholm Environmental Institute (SEI) across 3 different districts found that the national ambitions in natural resource management were not effectively translated into local district development plans owing to spatial variability across districts (Johnson et al., 2018). This underscores the need for fit-to purpose tools that can capture that spatial variability and dynamicity. spatial analysis and remote sensing tools can play that role.

In the water sector, Mukanyandwi et al. (2019) study the spatial distribution of water quality in springs used for drinking water in Rwanda in 2017. Their analysis indicated that pollutants are more easily transported into water bodies during the rainy season than during the dry season.[9] Umwali et al. (2021) examine how the spatial and seasonal variation of water quality on Lake Muhazi is influenced by land use and land cover, and use their findings to recommend "the establishment and safeguarding [of] protection belts in the lake vicinity".[10] Deltares (2021) conducted detailed hydrological modelling for flood-prone areas of Kigali, predicting which areas of the city will be affected by flood events of varying extremes and degrees of probability, from one-in-two years to one-in-fifty years.[11]

Soil erosion which is a particularly thorny issue in Rwanda given its topography and has been subject to various studies using spatial analysis techniques. Kulimushi et al., (2021) used remote sensing to classify sub-watersheds in Nyabarongo catchment area by the erosion risk and proposed priority areas for conservation efforts. Nambajimana et al., (2019) used the RUSLE (Revised Universal Soil Loss Equation) model in GIS to assess soil erosion in Rwanda finding that annual soil loss has reduced from 110 to 89 million tons from 2000 to 2015 and that soil loss was strongly correlated to extreme poverty in the area. This downward trend in soil erosion was confirmed on a smaller scale in Nyamasheke district using similar methodology (Niyonsenga, Mugabowindekwe and Mupenzi, 2021).

4.3. International research

Land-use classification and change monitoring

Remote sensing data and Geographical Information Systems have been used to detect land-use and land-cover changes in many regions. For example, Wang et al. (2020) implemented this analysis in one of the world's most vulnerable and rapidly growing cities — Kathmandu in Nepal. Tadese et al. (2020) analysed the long-run dynamics and underlying causes of land-use changes in the Awash River Basin to find the underlying causes, as a way to help the design of sustainable environmental management strategies and practises to ensure the sustainability of the ecosystem and natural resources.

Some recent studies utilise more general information such as atmosphere, geographical characteristics, and surface reflection from satellite images to define land use for developing countries. Liu et al. (2018) developed the multi-temporal global urban land maps based on

[9] https://link.springer.com/article/10.1007/s10661-019-7757-9
[10] https://pubmed.ncbi.nlm.nih.gov/34462606/
[11] Deltares (2021) "Storm Water and Wetland Management Model for the delineated flood prone areas in Kigali City: Flood model and hazard assessment report". Unpublished report commissioned by the World Bank.

Landsat images. They construct Normalised Urban Areas Composite Index (NUACI) combining from the satellite images and utilise the Google Earth Engine to facilitate the global urban land classifications.

Carbon credits

Carbon credits can provide a sustainable flow of income to developing countries in return for offsetting and reducing carbon emissions. Carbon credits are a financial instrument used to mitigate the growth in concentrations of Greenhouse Gases (GHG). A carbon credit is equal to one tonne of carbon equivalents. Carbon markets already exist to allow entities to trade carbon and this activity has helped to develop innovative projects for solar, biomass, reforestation and improvements in land use. A UN taskforce was set up to investigate the potential for a global voluntary carbon market (IIF, 2020). The taskforce recommended a number of actions, one of which is increasing the availability of remote sensing data to improve and digitise the monitoring, reporting and verification (MRV) process. By streamlining the certification of carbon projects via faster, cheaper and less bureaucratic MRV, it will be easier to scale up this important activity to address climate change. Projects are already underway in the coffee sector in Nicaragua (Porras et al., 2015).

Quantifying natural resources

In studies related to natural resources, researchers use the data collected from different types of satellites to record and track changes to the surface area covered by these resources. An early example of quantification of deforestation using satellite data is Skole and Tucker (1993). In their book “Remote sensing of natural resources”, Wang and Weng (2013) reviewed applications of remote sensing related to land cover classification, natural landscape and forestry assessing, vegetarian biomass and carbon cycle modelling, and classification and monitoring of wetland, soils, and minerals.

Innovative analysis using remote sensing of deforestation

Foster and Rosenzweig (2003), an interesting early example of a study aiming to find the economic determinants of natural resource cover, use three decades of satellite data to attempt to understand the rise in forest cover in India since the late 1950s, and their analysis shows that forest growth is driven by the demand for forest products due to income growth, rather than by supply side factors (cited in Donaldson & Storeygard, 2016).

Burgess et al. (2012) use satellite data that tracks annual deforestation in Indonesia to examine how local officials’ incentives affect deforestation, and find that each additional district created in a province induces an 8.2 percent increase in the province’s deforestation rate, consistent with an economic concept known as Cournot equilibrium taking place between the districts. Burgess, Costa, and Olken (2019) investigate the impact of Brazil’s 2006 anti-deforestation policy on land use choices there. BenYishay et al. (2017) utilise satellite-based forest cover data to measure the effect of indigenous communities' land rights on the rate of deforestation in Brazil, finding that they had no effect on satellite-based greenness measures.

Jayachandran, de Laat, Lambin, and Stanton (2017) deploy a randomised controlled trial in combination with satellite images and algorithms that can detect farmers' individual trees in Uganda, and find a strong impact of a payment-for-ecosystem services programme on reducing deforestation.

Land suitability for afforestation and reforestation for climate change mitigation
Zomer et al. (2008) conduct a global spatial analysis of land suitability for reforestation and afforestation for the purpose of climate change mitigation, finding that 27% of the global area suitable for this purpose is in Sub-Saharan Africa. The majority of the suitable land on the continent was found to be shrubland, grassland or savanna.

Tracking legal and illegal mining activity
The different stages of mining activities, from the exploration phase to the extraction phase, lead to natural landscape alteration that is detectable in satellite imagery. Ngom et al. (2020) pioneer a methodology for tracking artisanal and small-scale gold mining in a study area in the south east of Senegal, including legal and illegal mining activity, in a bid to provide a useful input to help to monitor and regulate the activity. Forkuor et al. (2020) use remote sensing to map and monitor illegal mining activity in South-Western Ghana between 2015 and 2019, finding a significantly decreasing trend in response to successful government policy.

Tourism and natural resources
Donaldson and Storeygard (2016) state that remote sensing can hint at the impacts of tourism, citing Faber and Gaubert (2017) who estimate that tourism and beach quality are highly correlated in Mexico, and that tourism has positive effects on non-tourism sectors in the same municipality.

Detecting the impact of human settlements on natural resources
Brei et al. (2016) use nighttime light data to investigate the effect of coastal light pollution on the sea turtle population in the Caribbean. They find that nighttime light significantly reduces the number of sea turtle nests, worth up to $288 million.

4.4. Ideas for further research

Monitor land use cover
As noted in the "existing data and analysis in Rwanda" section, a number of studies have monitored land use cover. However similar studies of land use cover could be regularly updated. Land use patterns could also be overlaid with the Kigali and secondary city master plans, or the National Land Use Master Plan, to understand how spatial land use change is responding (or not responding) to land use planning.[12]

[12] With this analysis it will be possible to make statements such as "the land zoned for formal housing in District X has in fact been used for the expansion of informal settlements, whereas in District Y formal housing zones have largely been built as formal housing", or "the land zoned for forestry has seen increased forest cover".

Monitor deforestation
Forest coverage is a dynamic feature that needs robust monitoring to ensure that forest harvesting and planting are balanced, and that Rwanda meets its Bonn Challenge target of 30% deforestation. To this end, geospatial data analysis and techniques can be appropriate tools. There may also be a need to monitor illegal deforestation if this can be well-defined spatially.

Analyse the spatial form of Rwanda's cities as they expand
It will be of policy interest to learn how cities expand from urban centres to sub-urban areas and further to peripheral areas, to understand whether cities are expanding in a densifying or a sprawling way with respect to population density, and to understand which parts of Rwanda's cities are developing the fastest. Following the literature, we can measure city expansion using either night light intensity (Zhou et al., 2015) or daytime satellite imagery (Pesaresi et al., 2016; Channan et al., 2014). It is also possible to measure the compactness of Rwanda's cities as in Harari (2020). Compact city shape is related to faster population growth, higher agglomeration economies and lower carbon footprints.

Monitor illegal mining
The application of remote sensing in the natural resources sector holds huge potential in Rwanda, for instance, in the mining sector artisanal mining is still prevalent and susceptible to illegal mining (NISR, 2019a). Analysis of satellite images could help to monitor and track mining activities as an input into policy on the regulation of illegal mining.

Monitor water resources
In the water sector, Rwanda is still considered as 'a non-stressed country," however, there is a spatial variability to this with the southern and eastern part of the country being more vulnerable to drought (NISR, 2019b). There is, therefore, a need to further research focusing on spatially disaggregated stocks and flows of water resources and their modelling especially in tandem with demographic dynamics.

5. Air pollution

5.1. Policy Relevance

A focus on air pollution alongside such broad themes in this paper as urbanisation and agriculture, requires justification. We include it here both because of its relevance for human health, the economy and policy, and because it lends itself to research with a spatial dimension. Air pollution can cause cardiovascular and respiratory diseases, lung cancer and strokes (Schraufnagel et al., 2019). It is thus an obvious public health issue related to urbanisation, and the health hazards can have a considerable economic cost. In 2013 the World Bank indicated that air pollution led to $5.11 trillion in welfare losses, and $225 billion in lost labour income globally (World Bank and Institute for Health Metrics and Evaluation, 2016). Research from 2018 identifying the sources of air pollution showed that the transport sector and wood & charcoal burning are the key sources of air pollution in Rwanda (Kalisa et al., 2018), and research from 2021 confirmed this, placing the proportions at approximately 40% each for transport and wood & charcoal burning, with 20% coming from industry.[13] Moreover, Rwanda's cities are set to grow rapidly, increasing the policy salience of air pollution.

On air pollution policy, Rwanda has a 2016 "Law Governing the Preservation of Air Quality and Prevention of Air Pollution in Rwanda", and a 2018 "Ministerial Order Ministerial Order Relating to Air Pollutants Emission". The country is seeking to cut charcoal use for cooking from 83% to 42% by 2030[14], has an Electric Mobility Strategy to promote the use of electric motorbikes and buses,[15] and has been one of the first African countries to introduce Euro 4 standards for imported vehicles.

Weather is relevant to air pollution levels so we also include a minor focus on it. Rwanda's Meteorological Service, known as Meteo Rwanda, aims to "provide accurate, timely weather and climate information and products", using meteorological stations across the country, to provide advance warning on extreme weather events, and to advance meteorological training, science and advocacy.[16]

5.2. Existing data and analysis in Rwanda

In this section, we identify different datasets which could be utilised for projects in Rwanda to track air pollution and weather spatially, and highlight spatial analysis that has already been done on the topic that focuses on Rwanda.

Table 5: Spatial datasets related to climate change, weather and air pollution

Data	**Description**	**Source**
Air quality	Air quality in several cities across Africa	AfriqAir
Air quality	World-wide air quality information	Aqicn
EarthData	CO2	EarthData
Weather	Weather variables	Rwanda Meteorology Agency

[13] Bahati, Moise, (2021), Vehicles, firewood contribute 80 percent air pollutants in Rwanda, April 28, 2021, https://www.newtimes.co.rw/news/vehicles-firewood-contribute-80-percent-air-pollutants-rwanda
[14] https://www.newtimes.co.rw/news/rwanda-needs-137bn-reduce-charcoal-use-half
[15] https://www.ktpress.rw/2021/09/rwanda-engages-the-private-sector-in-combating-air-pollution/
[16] https://www.meteorwanda.gov.rw/index.php?id=14

Weather	Reconstructed temperature and rainfall data	ENACTS
Weather	Precipitation & vegetation	FAO-GIEWS
Weather	Weather variables	Weather Underground
Weather	Rainfall & vegetation	ClimateSERV
Weather	Climate and hydrology	ClimateEngine

A range of data sources for weather, climate and air quality are available for Rwanda from international agencies, and national government institutions. For example, on its Air Quality Monitoring System, Rwanda Environmental Management Authority tracks a range of indicators of air quality in real time on a dashboard hosted at a public web site.[17] Academic research projects such as AfriqAir also collect air quality information from a number of sites across the City of Kigali.

Siebert et al. (2019) provide an excellent summary of the available weather and climate information for Rwanda. There were a large number of active meteorological stations in Rwanda prior to the mid-1990s and since around 2010. To address temporal and spatial gaps in meteorological observation in several African nations (including Rwanda), the ENACTS (Enhancing National Climate Services) initiative reconstructs rainfall and temperature data by combining station data with satellite rainfall estimates, and with reanalysis products for temperature.

Subramanian et al. (2020) track a range of air quality indicators between March 2017 and July 2018 and find little spatial variation across Kigali. Kalisa et al. (2021) track the impact of car free days and the COVID-19 lockdown on air pollution levels in Kigali. They find that that car free days reduce PM2.5 by 15%, the full 2020 COVID lockdown, which greatly reduced road transport, reduced air pollution by 33% and the partial 2020 COVID lockdown reduced air pollution by 21%; these results confirm the importance of the transport sector for urban air pollution.[18] However, forthcoming analysis by Kalisa in 2021 will use mobile air quality monitors to track the spatial distribution of air quality across the city. Kalisa also focuses on the impact of car idling during school pickups on air pollution in classrooms; this topic may have scope for a spatial focus.[19]

Whilst it is possible to map pollution, it is much more difficult to map greenhouse gas emissions. Rwanda has a national-level greenhouse gas inventory in its Biennial Update (REMA, 2021)[20]; GGGI has also supported secondary cities to produce city-level greenhouse

[17] https://aq.rema.gov.rw/
[18] https://www.theigc.org/wp-content/uploads/2021/08/Kalisa-et-al-June-2021-Policy-Brief.pdf
[19] https://twitter.com/EgideKALISA/status/1396242373143896068
[20] https://unfccc.int/sites/default/files/resource/Rwanda%20First%20Biennial%20Update%20Report_Final_V.pdf

gas inventories. However, these are too complex and aggregated to be readily reproducible in map form for Rwanda.

5.3. International research

Monitoring air pollution levels using remote sensing
The traditional measures of air pollution in terms of particle and gaseous concentrations are based on data collected from ground monitoring sites, which are usually limited in the spatial coverage. One way to overcome the drawback of ground monitoring sites is to utilise remote sensing data. Chudnovsky (2021) reviewed the complexity of air pollution monitoring from space and discussed the fundamental considerations when transforming from satellite imagery into particulate matter concentration estimations at the ground level and per pixel.

Analysing the impact of weather on air pollution
Dasgupta et al. (2020) examine the determinants of variation in air pollution, using satellite images to analyse the spatial dynamics of vehicle traffic, air pollution, and exposure of vulnerable residents in Dar es Salaam, Tanzania. They find that temperature, humidity, and wind-speed factors have a significant impact on the intensity and spatial distribution of air pollution; for example, they find that during days in which weather conditions facilitate the highest levels of pollution, areas on the wind path of major highways experience the worst exposure.[21]

Analysing the response of air pollution to policy
Air pollution from remote sensing data has been widely used in environmental economics studies for policy evaluations. In the US context, Zou (2021) uses 13 years of satellite observations to document how geographical areas respond to a cyclical, once-every-six-day air quality monitoring schedule under the federal Clean Air Act. He finds that air quality is significantly worse on days unmonitored by authorities than on days that are monitored, writing that this is explained by “short-term suppression of pollution on monitored days, especially during high-pollution periods when the city’s noncompliance risk is high”.

Gutiérrez and Teshima (2018) explored the impact of import competition induced by free-trade agreements on factories’ outcomes related to energy use and pollution emission. Specifically, using the satellite data, they found that tariff decreases lead to more air pollution around plants' location by increasing energy efficiency.

Economic, social and health impacts of air pollution
Jayachandran (2009) estimates the impact of air pollution (measured by particulate matter) resulting from Indonesia’s devastating late-1997 forest fire on infant and foetal mortality by using daily satellite sensor readings about airborne smoke and dust. Jbaily et al. (2022) examine PM2.5 levels - the most widely used measure of harmful air pollution - in US zip

[21] https://documents1.worldbank.org/curated/en/960861584126320950/pdf/Traffic-Air-Pollution-and-Distributional-Impacts-in-Dar-es-Salaam-A-Spatial-Analysis-with-New-Satellite-Data.pdf

codes, alongside demographic data on ethnic composition, between 2001 and 2016. They find that spatially, low-income populations have been consistently exposed to higher average PM2.5 levels than high-income populations, and that this difference also applies on racial lines: areas with higher-than-average Black, Asian, Hispanic or Latino populations have been exposed to higher PM2.5 levels than areas with higher-than-average White and Native American populations. However, they do not examine the drivers of these correlations.[22]

In an innovative paper for OECD, Dechezleprêtre et al. (2019) combine satellite-based measures of air pollution with statistics on regional economic activity at the local level across the European Union from 2000-2015. They use an instrumental variables approach and find that a 1 $\mu g/m^3$ increase in PM2.5 concentration causes a reduction in GDP of 0.8% the same year, which is large compared to the change in PM2.5. Most of that impact is due to reductions in output per worker from reduced labour productivity or absenteeism at work. This suggests high economic returns to abatement of air pollution in a European context.

5.4. Ideas for further research

Replicate the Dasgupta et al. (2020) Dar es Salaam study, to find the areas of Rwanda's cities vulnerable to the worst air pollution

As mentioned above, Dasgupta et. al (2020) examine the determinants of variation in air pollution, using satellite images to analyse the spatial dynamics of vehicle traffic, air pollution, and exposure of vulnerable residents in Dar es Salaam, Tanzania. This study is entirely replicable using openly available data for Kigali or any secondary city and could identify the areas of the city that are most vulnerable to air pollution on the days with the highest pollution levels. This, along with other existing data on air pollution and location in Rwanda, could inform the location of zones in which the government might target the most effort to keep air pollution levels low.

Analyse the impact on air pollution of no-idling zones outside schools

Air pollution scientist Dr Egide Kalisa researches and raises awareness of the air quality effects of cars idling during school pickups in Rwanda. Cars idling during school pickups is common but can increase children's exposure to pollution and exacerbate respiratory diseases.[23] In order both to inform transport policy and initiatives, and to track progress on air pollution, further data-gathering and analysis are warranted to buttress the limited literature so far on this. Beyond measuring the impact of car idling on air quality in schools, one potential idea is to use mobile air quality sensors to track the impact of a ban on car idling within a certain perimeter of a range of schools across a city, on air quality in those schools.

Analyse the impact of air pollution on productivity and cognition

[22] https://www.nature.com/articles/s41586-021-04190-y

[23] Ashimwe, Edwin, (2020), Students and air pollution: The effects, December 23, 2020, https://www.newtimes.co.rw/lifestyle/students-and-air-pollution-effects

As noted above, Dechezleprêtre et al. (2019) combine satellite-based measures of air pollution with statistics on regional economic activity at the local level across the European Union from 2000-2015. If a spatially and temporally granular measure of productivity or cognition could be found in Rwanda, this could be combined with air pollution data and other relevant covariates and the impact of air pollution on productivity or cognition could be analysed. One possible measure of cognition is school examination results; Lee Crawfurd raised the idea of combining these with air pollution data in 2021.

6. Climate change adaptation and emergency management

6.1. Policy Relevance

Rwanda's climate is changing. Temperatures in Rwanda are likely to increase significantly over coming decades, and there will be a considerable increase in extreme heat and the number of hot days. Rainfall patterns will also change, with increasing intensity of heavy rainfall, as well as shifts in annual and seasonal levels of rainfall. As a result, Rwanda will be increasingly exposed to a range of disasters related to weather and climate change such as storms, droughts, floods and landslides (usually after heavy rainfall) (World Bank, 2021).

Rwanda is also exposed to non-climate-related disasters such as earthquakes and volcanic eruptions. These disasters have human and economic consequences; they also lend themselves to mapping and analysis with a spatial component. The damages caused by disasters were considerable; for instance in 2020 alone, disasters caused 298 deaths while 8,098 houses and 4,661 hectares of crops were destroyed (MINEMA, 2020), along with uncounted negative economic, social and health impacts to the affected population.

Rwanda has an ambitious policy agenda to address climate change which is led by the Ministry of Environment. The Green Growth and Climate Resilience Strategy (2011) includes 14 programmes of action covering mitigation and adaptation. Rwanda's Environment and Climate Change Policy (2019) articulates its strong aspirations to mitigate and adapt to climate change, and the country's updated Nationally Determined Contribution, which was submitted to the United Nations Framework Convention on Climate Change in 2020, contains an allocation of 5.3 billion USD allocated for adaptation, split into a range of measures across the water, agriculture, land and forestry, human settlement, health, transport and mining sectors. We do not focus here on climate change mitigation in this section.

Led by the Ministry of Emergency Management (MINEMA), Rwanda has a National Disaster Risk Management Policy from 2012 and a National Disaster Risk Management Plan from 2013. MINEMA published National Contingency Plans in 2018 and 2019 covering flooding & landslides, drought, storms, earthquakes, volcanic eruption, and other disasters including fire incidences, terrorism and “population influx”. The national flood and landslide contingency plan proposes the identification and mapping of all hazard-prone areas (MINEMA, 2018) while earthquake risk contingency suggests to put in place mechanisms for earth observation and holistic research for seismic activity that in order to regularly monitor seismic activity and disseminate real-time earthquake related information(MINEMA, 2019). More recently, the post-disaster needs assessment (PDNA) for the Nyiragongo Volcanic eruption in 2021 recommended the establishment of a real-time monitoring system for ash and gases to understand spatial variation of air quality especially in the city of Rubavu and Musanze.

The National Risk Atlas of Rwanda (Government of Rwanda, 2015) profiles disasters and proneness of various areas to those disasters in order to inform development decisions in Rwanda. Its conception was made possible through extensive geospatial data analysis. However, the atlas is a static snapshot and does not reflect the dynamic changes in proneness especially those due to anthropogenic reasons. Disaster mapping in Rwanda would therefore be enriched by more advanced and integrated spatial techniques that more accurately and dynamically reflect disaster risks.

6.2. Existing data and analysis in Rwanda

In this section, we identify different datasets which could be utilised for projects in Rwanda to track climate change adaptation and emergency management spatially, and highlight spatial analysis that has already been done on the topic that focuses on Rwanda.

Table 6: Spatial datasets related to disaster management

Data	Description	Source
Meteorological data	Daily rainfall, maxima and minima temperatures, longitudes, latitudes and elevation from 14 meteorological stations located in all four provinces and Kigali City for 14 years (from 2000 to 2013).	Rwanda Meteorological Agency
The Soil Map of Rwanda (2003)	A map of soil type, depth and geology	MINAGRI
Rainfall data	Daily rainfall for the period from as early as 1930. Available data are broken down by station and over 130 stations spread all over the country are listed.	FEWSNET

Data on rainfall and evapotranspiration	Shapefile data on rainfall and evapotranspiration	World Food Program (WFP)
EM-DAT	International database on over 22,000 disasters, 1900-present	EM-DAT
Water Network spatial data	Shapefile data on urban, peri-urban and rural water networks (pipelines, water sources, reservoirs)	WASAC
RLMUA Land Use Cover	2019 countrywide land use cover based on high resolution satellite images	RLMUA

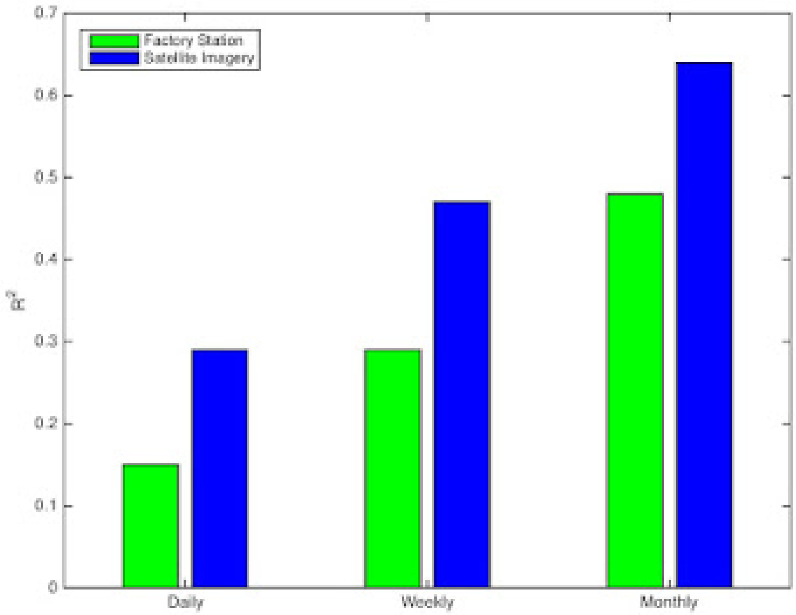
McSharry et al. (2016) investigate the availability of weather data for Rwanda and its potential for constructing an index insurance product for the tea sector. While 220 ground weather stations were identified, during the period 2010 to 2014, there were many inactive stations and many missing values, with measurements available for 36% of the time. If we only consider the weather stations for which data was available at some point during our period of interest, the average availability is 59%. These relatively low availability figures serve to emphasise a serious challenge for using ground weather stations for constructing and assessing index insurance products and other data driven projects. By coarsening the spatial resolution to the level of a district it is possible to obtain a weather database with reasonable data quality. For the thirty districts in Rwanda, it was possible to extract a consistent dataset with measurements available for 92% of the time. This data issue serves to highlight the challenge of assessing the impacts of climate using ground stations.

An alternative source of weather and environmental data can be extracted from satellite imagery. While providing a relatively consistent set of observations, there are issues with cloud cover. The evaluation of different sources of information for the tea sector provides some insights into the efficacy of these datasets. Monthly forecasts based on satellite imagery explained 64% of the variability in tea productivity on average. Satellite imagery outperforms local ground weather stations located at the tea factory by 33%. Satellite imagery has great potential for climate change adaptation studies. However it is best to calibrate with ground weather stations, such as those at airports which tend to offer high quality observations over a long historical period.

A follow-on study used climate scenarios and the established relationships between weather and tea productivity to quantify the potential economic impact on the tea sector. A detailed climate risk map was produced to provide recommendations on where tea could be safely grown in the future. Rwanda has an advantage of being able to adapt to global warming by growing tea at higher altitudes which both serves to produce high quality tea and to offset the increase in temperature. The study produced a climate risk map for the Ministry of

Environment to promote evidence-based adaptation which was supported by the Green Climate Fund (2018). Later the UK Government used this map to justify and support a climate proof investment in tea and provided a GBP 7 million accountable grant. This case

Figure 7: Performance of tea productivity forecasts using weather information at the factory station and satellite imagery. The performance improves with temporal aggregation and the satellite information provides superior performance.



study shows the importance of data to improve understanding, establish evidence based policy and motivate strategic partnerships.

An analysis of Rwanda's climatology using this new ENACTS data set for 1981–2016, indicated that the rainfall climatology of Rwanda exhibits a clear seasonal bimodality typical of the East Africa region (Siebert et al., 2019). Topography has a significant effect with the more mountainous, higher-elevation western part of the country being consistently cooler and wetter than the lower, flatter eastern region. The World Bank's Climate Risk Country Profile on Rwanda gives a useful overview of key climate trends in Rwanda to date as well as climate projections for the country based on the 32 Global Climate Models.[24]

A range of papers exist that model flood patterns in parts of Rwanda. A Master's thesis, "Diagnostic Assessment on Urban Floods Using Satellite Data and Hydrologic Models in Kigali" maps flooding in the Nyabugogo catchment (Manyifika, 2015), and a published paper by Umugwaneza et al. (2021) analyses the impact of climate change on the water balance in the Nyabugogo catchment using 10 global climate models. Their conclusion was that:

> *"Climate change is expected to have an impact on the components of the hydrological cycle (such as streamflow and surface runoff). This situation may, therefore, lead to an increase in water stress, calling for the integrated management of available water resources in order to match the increasing water demand in the study area. This study's*

[24] https://climateknowledgeportal.worldbank.org/sites/default/files/2021-09/15970-WB_Rwanda%20Country%20Profile-WEB.pdf

findings could be useful for the establishment of adaptation plans to climate change, managing water resources, and water engineering." (Umugwaneza et al., 2021)

A paper named "Integrated Geospatial Analysis and Hydrological Modeling for Peak Flow and Volume Simulation in Rwanda" by Mind'je et al (2021) develops a "hydrological modelling system" for the Nyabarongo River catchment in Rwanda that analyses its hydrological response to rainfall events through "discharged flow and volume simulation".

In a 2020 paper titled "Impacts of Climate Change on the Potential Productivity of Eleven Staple Crops in Rwanda", Austin et al. (2020) estimate the potential responses of 11 staple crop yields to predicted changes in temperature and rainfall in Rwanda. To do so, they use a cross sectional model based on yield data collected from over 14,000 villages.

Ndayisaba et al. (2017) analyse annual trends in vegetation greenness in Rwanda from 2000-2015 and estimate "the relationship between these dynamics and climate factors by means of MODIS NDVI, air temperature, SOI and precipitation datasets". Li et al. (2021) estimate how climate change will affect land use and land use cover (LULC) in Rwanda and describe their method as follows: "based on LULC analyses of Rwanda in 1990, 2000, 2010, and 2015, the LULC pattern of Rwanda in the next 30 years was simulated using an LULC transition matrix, random forest sampling, the Markov chain model, and the PLUS model."

Nsengiyumva and Valentino (2020) have used machine learning approaches to predict the susceptibility of landslides in upper Nyabarongo catchment, using various geographic features as conditioning factors, they found that land cover and use and slope angle and elevation were the top predictors of the occurrence of landslides. Furthermore, Uwayezu *et al.*, (2015) collected different spatial data on the drivers of floods in Kigali and produced a model that is able to predict the susceptibility of a given area[25]. Bizimana and Ndahigwa (2020) combine existing cadastral information and erosion modelling to monitor gullies and their effects in the Mpazi area. Sebarenzi (2022) has also demonstrated the use of geo-spatial data and techniques to improve citizen participation in case of disaster management.

6.3. International research

The impact of climate hazards and disasters on economic variables

Climate change is prominent and growing in global significance; the Intergovernmental Panel on Climate Change recently released its sixth report on impacts, adaptation and vulnerability, highlighting that the threat from climate change is worse than previously thought and provides scientific backing to the idea that climate change causes significant loss and damage to people and nature, especially in developing countries.[26] [27] Literature on the various impacts of climate change is thus vibrant and growing.[28] Dell, Jones, and Olken

[25] https://moam.info/integrated-flood-modeling-for-flood-hazard-assessment-in-kigali-city-_59f14be71723dd7842221662.html
[26] https://www.bbc.com/news/science-environment-60541816
[27] https://www.ipcc.ch/report/ar6/wg2/
[28] https://media.rff.org/documents/WP_22-1.pdf

(2014) write the following:

> *"By exploiting exogenous variation in weather outcomes over time within a given spatial area, [the] methods [employed by the new spatially disaggregated panel studies on the impact of climate change] can causatively identify effects of temperature, precipitation, and windstorm variation on numerous outcomes, including agricultural output, energy demand, labour productivity, mortality, industrial output, exports, conflict, migration, and economic growth. This literature has thus provided a host of new results about the ways in which the realisations of temperature, precipitation, storms, and other aspects of the weather affect the economy." (p741)*[29]

Some examples from the literature follow. Felbermayr et al. (2022) investigate the economic impact of weather anomalies at an unprecedented geographical resolution by bringing together data from meteorological sources on weather anomalies (including precipitation, droughts, cold spells, and storms) and night emissions in 0.5 by 0.5-degree grid cells for the entire globe from 1992 to 2013. They find that storms, heavy rainfall and cold spells reduce the growth of local economic activities, as measured by night light intensity and cause positive spillovers in neighbouring areas.

Elliott et al. (2015) showed that night light intensity data can be used to measure the relative damages of typhoons. They combine damage proxies with satellite derived night-light intensity data to estimate the impact of typhoons at a spatially highly disaggregated level (approx. 1 km). Their results reveal that a typhoon that is estimated to destroy 50% of the property reduces local economic activity by 20% for that year.

The extent of economic losses due to a natural hazard and disaster depends largely on the spatial distribution of asset values within the affected area. Wu et al. (2018) spatialize the asset value by combining three data sets, including nighttime light grid, LandScan population grid, and road density grid. Then they developed an asset value map for disaster asset management, as a way to analyse spatial characteristics of exposure and to uncover the contributions of both physical and social drivers of natural hazard and disaster across space and time.

Similarly, Liu et al. (2018) combine remote sensing data and GIS technology to extract coastal key objects and classify coastal land use for a typical coastal city in China. With proposed methods for valuing hazard and vulnerability for storm surge, they then merge remote sensing data with coastal hydrological observations to develop a storm surge risk assessment model, as a way to provide some basis reference for the city development plan and strengthen disaster prevention and mitigation.

Kocornik-Mina et al. (2020) study large urban floods using spatially detailed inundation maps and night lights data spanning the globe's cities. They found that low-elevation urban areas are flooded more frequently even though economic activities are more concentrated in

[29] https://economics.mit.edu/files/9138

them. These areas also recover as rapidly as those higher up. The authors find little permanent movement of economic activities in response to floods.

The impact of climate hazards and disasters on conflict and health

Using spatial data on weather and crops, Harari and La Farrara (2018) explore how agriculture-relevant weather shocks affected civil conflict at the subnational level in Africa between 1997 and 2011, finding that “negative shocks occurring during the growing season of local crops affect conflict incidence persistently, and local conflict spills over to neighbouring cells”.

Kudamatsu, Persson, and Stromberg (2012) combine spatially disaggregated Demographic and Health Survey data for nearly a million births in 28 African countries with ERA-40 data supplied by the European Centre for Medium-Term Weather Forecasting, to analyse how weather fluctuations have affected infant mortality in Africa over the last half century. They find that infants are more likely to die when exposed in utero to much longer malaria spells or to droughts in acid areas.

Evaluating climate change adaptation measures

As climate change and global warming have become more important and spatial data availability has been improved a lot in recent years, many studies have explored adaptation to climate change. Balboni (2019) evaluates whether large infrastructure investments should continue to favour coastal areas under the scenario that sea levels will rise in the future. She used detailed georeferenced data from Vietnam and found evidence that coastal favouritism in road investments has significant costs. Yu et al. (2017) empirically show the influence of the size and shape of green spaces on cooling cities and on climate adaptive design in subtropical areas.

Assessing climate change adaptation capacity

Using various spatial analytical tools to transform and standardise hazard, vulnerability, and exposure variables, Espada, Apan, and McDougall (2017) assess the flood risk and climate adaptation capacity of urban communities and essential infrastructures in Brisbane, Australia, as a way to help address flood risk management issues and identify climate adaptation strategies. Sirmacek (2021) proposes an AI-based framework — which extracts climate adaptation indicators from remote sensing images — to predict future states of these indicators, as a way to inform decision makers on city design.

Climate change adaptation and inequality

Kim et al. (2021) analyse spatio-temporal correlation between greenspace and climate vulnerability in the Guangdong-Hong Kong-Macau Greater Bay Area by using satellite imagery. They found that green adaptation funnels into wealthier, less vulnerable areas while bypassing more vulnerable ones, increasing their climate vulnerability and undermining the benefits of urban agglomeration, suggesting that centrally-planned climate adaptation policy must be proactively inclusive and equitable.

Analysing social media data for emergency management

Much research exists on how social media data can be used for various stages of emergency management. Thom et al., (2012) detected disasters using geo-located tweets. Social media data have been analysed using advanced deep learning techniques to estimate and geolocate disaster-induced damage and loss in order to streamline the response (Alam, Ofli, and Imran, 2020). Shan et al., (2021) have used geo-tagged social media data from the Chinese social media, Weibo, to analyse the spatiotemporal distribution of COVID-19 in Wuhan and were able to pinpoint COVID-19 spatial transmission stages and most at risk segment of the population.

At the disaster recovery stage. Eyre, De Luca and Simini, (2020) were able to estimate the recovery of small business after natural hazards events in Nepal, Puerto Rico and Mexico using the time series of social media posts and method was found to outperform traditional methods such as surveys and interviews. Geotagged tweets were also used to track population mobility in Puerto Rico after Hurricane Maria (Martín et al., 2020).

6.4. Ideas for further research

Create or contribute to a digital platform to inform emergency and disaster management

Various types of geospatial data including from sensors, crowdsources and social media, could be used for all stages of disaster management. This could include disaster risk forecast and early warning, disaster response simulation and reconstruction prioritisation. Such a system was conceived through the I-REACT platform which integrates many different information sources, including satellite imagery, social media and crowdsourced data to form an integrated disaster management digital platform (Rossi et al., 2019). For Rwanda though, two caveats are in order: whilst social media data for emergency management holds huge potential, it requires high and persistent internet use; in 2019 internet penetration was 60.4% (MICT, 2019) and low in rural areas but growing rapidly. Second, the use of social media data for disaster management requires sophisticated data processing and analysis skills, as well as robust translation.

Analyse exposure to climate hazards and disasters

Property valuation has already been done for Kigali (Brimble et. al., 2020), and could be done for secondary cities and eventually for the whole country. The existing inundation modelling done by Deltares et al. (2021) could be combined with estimated property values to analyse the magnitude and spatial distribution of damage to assets that would be incurred by extreme flood events.

Track the implementation of NDC adaptation measures in rural areas

Spatial data analysis could be used to track the implementation of those NDC adaptation measures that are visible on satellite imagery. For example, an algorithm could map terracing. An index could be created to indicate the areas of the country that are most underserved by terracing and also need it the most. This would require a GIS algorithm for mapping terracing, paired with soil maps, NDVI, land use, assumptions about the value of crop per square metre, and possibly population density maps.

Analyse the inclusiveness of climate adaptation measures

It may be possible to analyse whether climate adaptation measures target all wealth levels equitably. Pairing Facebook's Relative Wealth Index – or an algorithm showing where the 'basic' vs 'villa' residential buildings are a la Bachofer et al. (2019)[30] with population density maps, flood risk maps, and maps of Nature Based Solutions (NBS) and flood defences, to see whether flood defences and NBS are being situated in areas that benefit the poor equitably with the rich, or if they are simply being built in middle class areas and are neglecting the poor.

Analyse the impact of irrigation on crop production, and explore other research possibilities relating to irrigation

Rwanda's Nationally Determined Contribution (2020) allocates 2.3 billion USD to irrigation and water management, to be sourced and spent before 2030. Spatial data on crop distribution and productivity could be combined with data on the location of irrigation and other covariates to track the impact of large-scale irrigation investments, at fine-grained spatial and temporal scales. The impact of other socioeconomic variables for which proxies exist from remote sensing data, could be estimated. Given the scale of investment in irrigation that is planned, it makes sense to make full use of the potential of spatial analysis in years to come.

Identify housing built in areas at risk of landslides

Landslides after heavy rainfall have caused many deaths in Rwanda. As noted above, Nsengiyumva and Valentino (2020) have used machine learning approaches to predict the susceptibility of landslides in upper Nyabarongo catchment. However this methodology might be extended to incorporate building footprints in Kigali and the secondary cities, and possibly to the whole country. The building footprints that have been purchased for the purpose of Rwanda's 2022 Census could, if made available, be combined with data on land cover and use, slope angle and elevation to find the location of buildings most at risk of landslides. The cells and sectors containing the highest number and proportion of buildings at risk of landslides could then be identified. When building footprints are acquired again in future, analysis of the trends from the first time period to the next time period could be used to track progress in halting building in the most risky zones or relocating existing housing outside those zones.

[30] https://www.mdpi.com/2306-5729/4/3/105

7. Urbanisation and infrastructure

7.1. Policy Relevance

Urbanisation is a pillar of Vision 2050 as a driver of economic growth, and Rwanda aims to have 70% of the population living in urban areas by 2050. The broad theme of urbanisation and infrastructure incorporates a range of sub-themes including city growth, migration & demographics; transport; housing; urban planning and land use; waste management; water and sanitation and other themes. These themes all have associated policies in Rwanda, such as the National Urbanisation Policy (2015), the National Housing Policy (2015), the forthcoming National Transport Policy, and the National Water Supply Policy (2016). The themes listed under Vision 2050 are “Universal access to quality services and amenities; universal access to affordable and decent housing; ease of mobility and efficient transport; smart and Green cities for sustainable growth; and sustainable supply and demand for energy”. Responsibility to regulate and deliver public goods and services related to these thematic areas fall under the Ministry of Infrastructure, Ministry of Local Government, City of Kigali and Districts.

Not only is urbanisation a large topic encompassing a wide range of sub-topics, it is probably the topic on which the most spatial analysis has been conducted or used thus far in Rwanda. For example, the Government of Rwanda-World Bank (2019) report “Future Drivers of Growth”, contains chapters on six major drivers of growth, of which one is urbanisation. The chapter is titled “Faster Urbanisation, Greater Agglomeration” and is the only chapter containing a significant number of maps.

7.2. Existing data and analysis in Rwanda

Table 7 shows datasets which can be used to track urbanisation and infrastructure in Rwanda spatially.

Table 7: Spatial datasets related to urbanization and infrastructure[31]

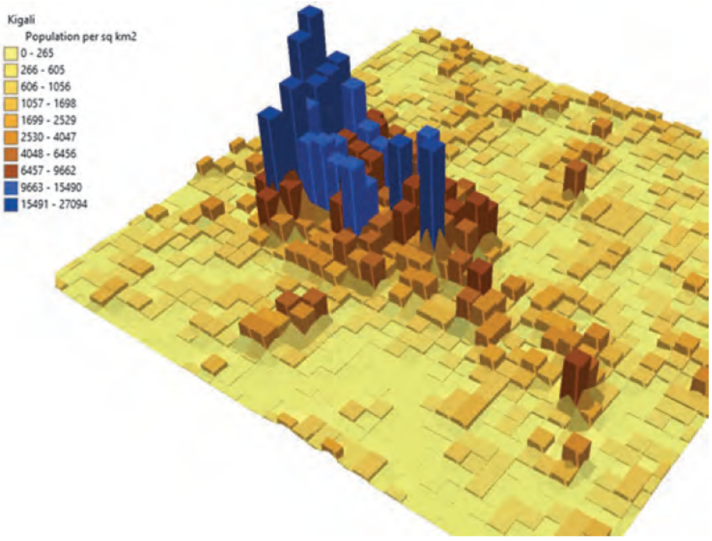
Data	Description	Source
Nightlights	Night-time lights; correlates with economic activity	NASA
Land Cover	Land use classification	ESA
Population	Population distributions	WorldPop
Social Distancing	WorldPOP-generated index on ease of social distancing	WorldPop Social Distancing Index

[31] Having access to data via an application programming interface (API) is sometimes required in order to deploy models and algorithms that are driven by these datasets

Overcrowding	The authors combined population and building footprint data to calculate measures of indoor and outdoor overcrowding for 100m squares in Kigali and secondary cities	IGC - results presented in this paper by Bower & Rajashekar
Roads	Extract road networks from Open Street Map using Osmosis	Open Street Map
Buildings	Gridded maps of building patterns	WorldPop Buildings
Building footprints	Building footprints for 2009 and 2015 in built up area of Kigali	https://www.mdpi.com/2306-5729/4/3/105
Building footprints	Detailed building footprint data procured from Ecopia for built up area of Kigali in 2019	Contact IGC; NISR have also procured building footprints also from Ecopia
Building footprints	Google building footprints - not as good as Ecopia but total national coverage	Google Open Buildings
Traffic and mobility data	Africa Urban Mobility Observatory (a consortium including GoAscendal and UN Habitat) is seeking to make traffic and mobility data for analysis	Africa Urban Mobility Observatory/ GoAscendal - pending
Cell towers	Mobile penetration	OpenCelliD
Pollution	Pollution observations	OpenWeatherMap
Pollution	NO2 pollution	European Union/ESA/Copernicus
Distances	Distances to key locations	OpenStreetMap
Land parcel data	Rwanda's land parcels have been mapped out and the dataset shows parcel boundaries, coordinates, dimensions, and unique parcel identifier numbers	Rwanda Land Management and Use Authority - with permission only
Mobile	Mobile ownership	Mobile Network Operator
Mobile calls	Mobile usage	Mobile Network Operator
Mobile transactions	Mobile payments	Mobile Network Operator

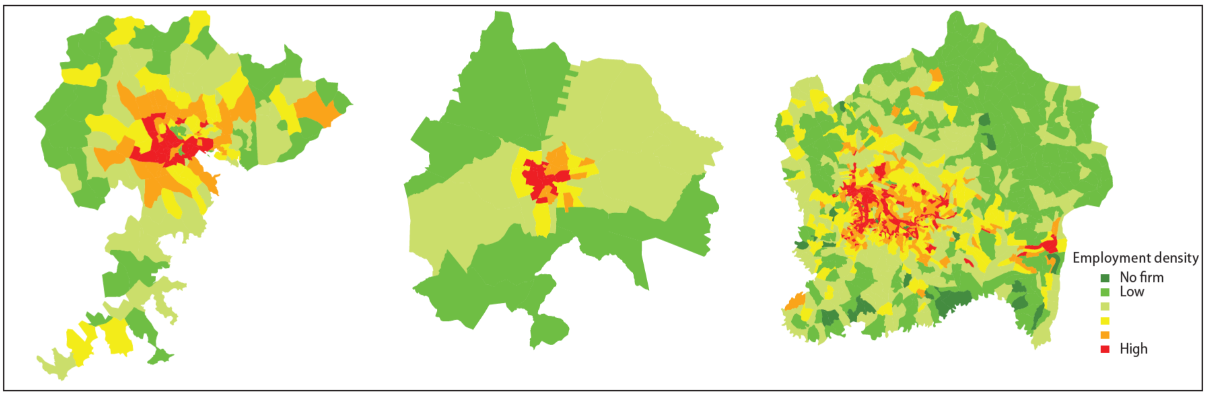
The urbanisation chapter in the joint Government of Rwanda-World Bank (2019) report "Future Drivers of Growth", examines the extent to which urbanisation is currently driving growth and examines what more could be done from a policy perspective. The chapter cites a range of spatial analysis from other sources, including Figure 8 and Figure 9, to make the point that Kigali and the secondary cities have relatively fragmented development compared to other cities and should densify. Figure 10 from the report shows the development of the footprint of the built area of three secondary cities and finds that Musanze has developed three times faster than Huye.

FIgure 8: Fragmentation of densities beyond the central business district of Kigali



Source: Henderson, Vernon, and Nigmatulina 2016,[32] cited in Future Drivers of Growth report

Figure 9: Location of formal jobs in Kampala, Uganda; Lusaka, Zambia; and Kigali, Rwanda



Sources: Jones, Bird, et al. 2016; Jones, del Frari, et al. 2016; Jones, Murray, and Ferreira 2016, cited in Future Drivers of Growth report

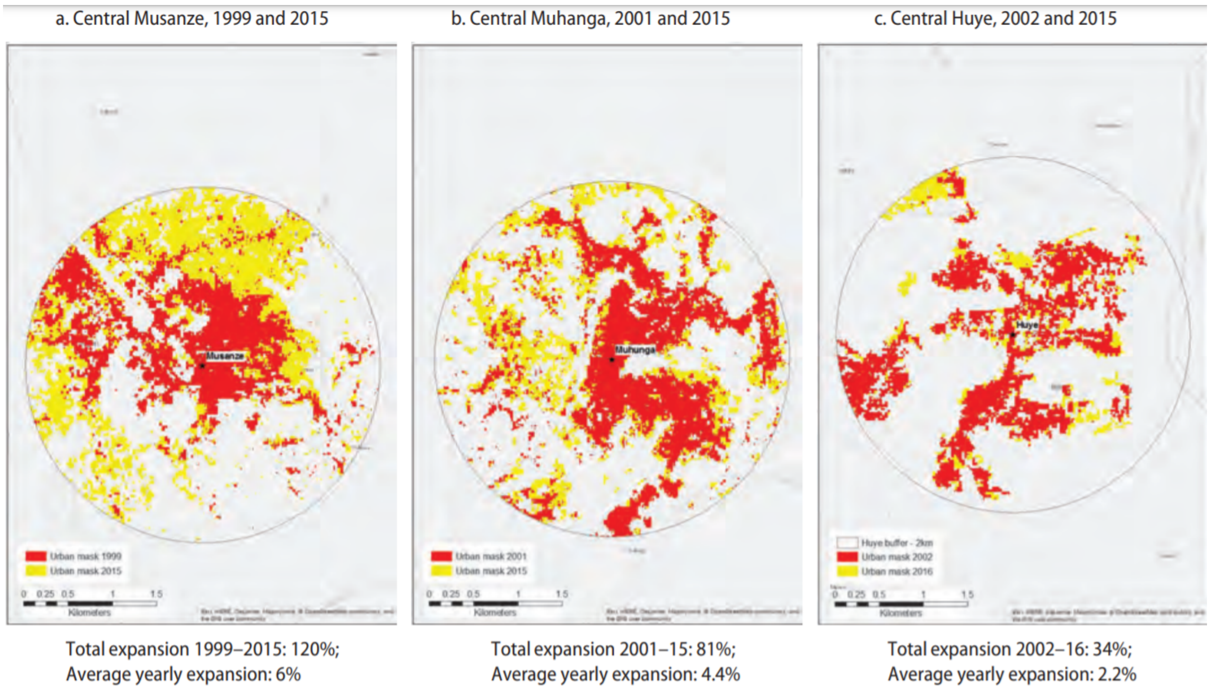
Two interesting papers by academics at University of Rwanda are of note on urban land use classification, Mugiraneza et al. (2019)[33], published in the journal "Remote Sensing", used an innovative approach to analyse a 2016 image of Kigali, classifying land in Kigali into 12

[32] Henderson, Vernon, and Dzhamilya Nigmatulina. 2016. "The Fabric of African Cities: How to Think about Density and Land Use." Draft, London School of Economics.

[33] Mugiraneza, Theodomir, Andrea Nascetti, and Yifang Ban. 2019. "WorldView-2 Data for Hierarchical Object-Based Urban Land Cover Classification in Kigali: Integrating Rule-Based Approach with Urban Density and Greenness Indices" *Remote Sensing* 11, no. 18: 2128. https://doi.org/10.3390/rs11182128

categories which included three built up area classes, high-density built-up area, low-density built-up area, and informal settlement, with an overall classification accuracy of 85%. On solid waste management, Ngwijabagabo et al. (2020) use a spatial multi-criteria evaluation approach based on seven criteria to find the most suitable sites near Musanze town in which to establish a modern landfill site.

Figure 10: Development of the building footprint of central areas of three secondary cities in Rwanda, 2001-2015

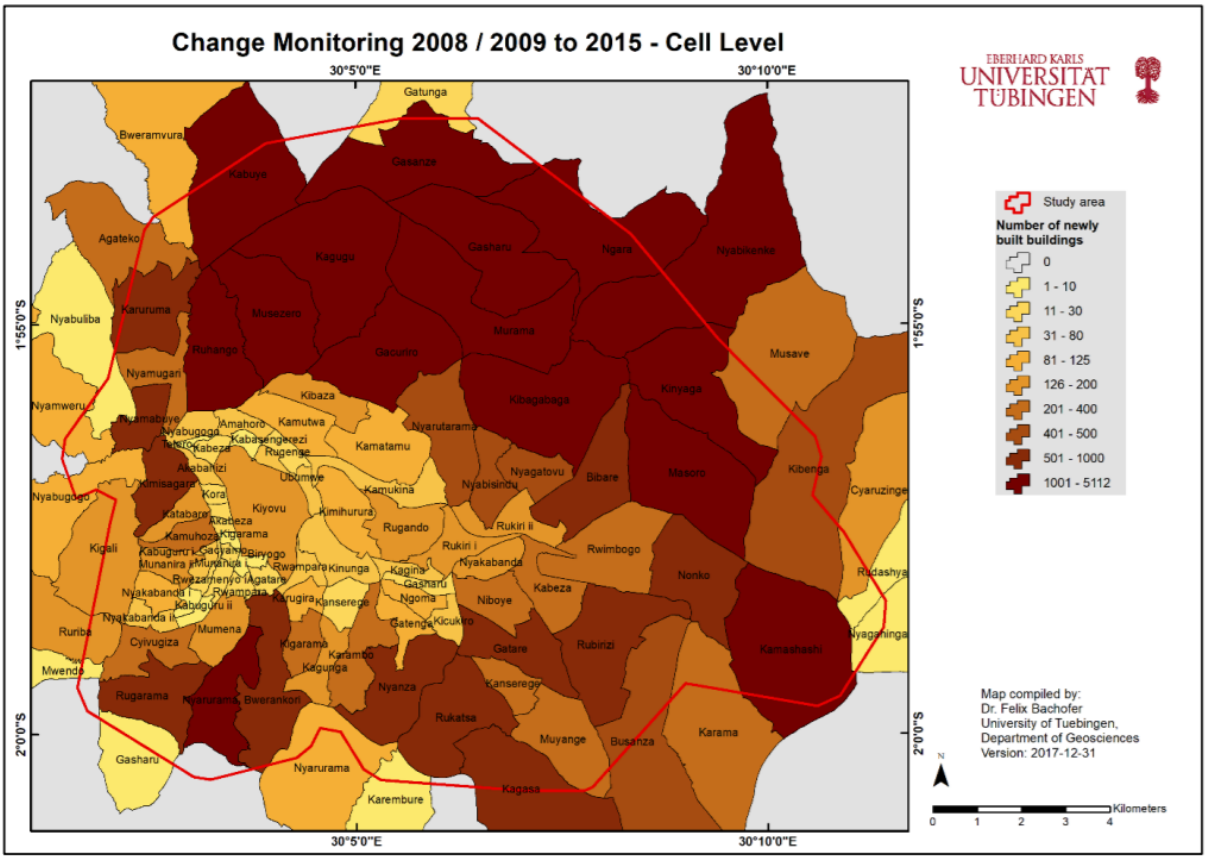


Source: World Bank (2017)

Note: the maps show the footprint of buildings for three secondary cities, in red in 1999 for Musanze, 2001 for Muhanga and 2002 for Huye, and in yellow in 2015 for Musanze and Muhanga and for 2016 in Huye.

IGC has conducted or commissioned a range of spatial analysis in relation to urbanisation and infrastructure. IGC funded building footprint data (at the individual building level, much more detailed than that used for Figure 9 above) for Kigali for 2009 and 2015, which is published in Bachofer et al. (2019), and also purchased building footprint data for 2019 for Kigali and the secondary cities. These data have enabled three pieces of analysis. First, Bachofer & Murray (2018) and Bachofer et al. (2019) use the 2009 and 2015 data to understand the numbers of additional buildings in each cell in the built up area of Kigali, showing that there has been little additional development in the Central Business District (CBD) but buildings have developed in a horseshoe around the north, east and south of the CBD, as shown in Figure 11. They also classify into nine different building types including basic informal houses, formal bungalows and villas, and commercial buildings of various types, and show how the percentage of formal buildings increased from a low base between 2009 and 2015.

Figure 11: Additional new buildings in each cell in the built up area of Kigali between 2009 and 2015

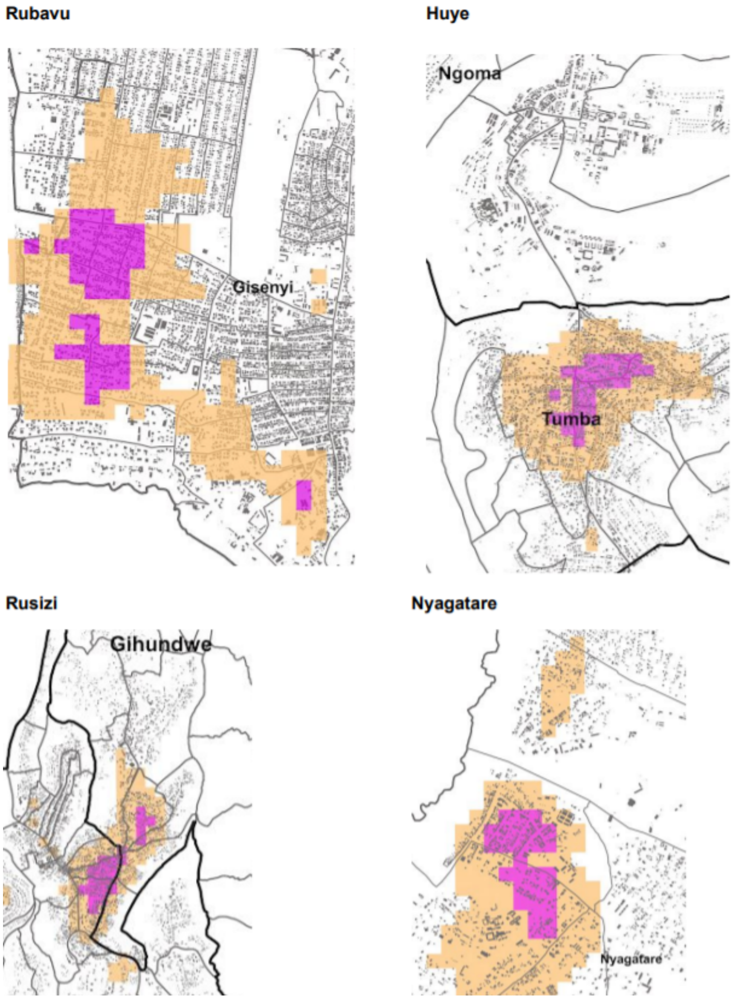


Source: Bachofer, F., and S. Murray. 2018. "Remote Sensing for Measuring Housing Supply in Kigali." Final Report, International Growth Centre, Kigali.

Using the 2015 building footprint data for Kigali, in "Using machine learning and remote sensing to value property in Rwanda", Brimble et al. (2020) overlay a range of spatial data on parcel boundary and sales data from RLMUA to estimate property values in 2015 and the authors are currently finishing an update to this analysis as of early 2022 using 2019 building footprint data that covers both Kigali and the secondary cities.

Also using building footprint data as an input, Rajashekar & Bower (2020) estimate the location of overcrowding hotspots in Kigali and five secondary cities in Rwanda; they define indoor and outdoor overcrowding and a composite measure of overcrowding containing both, using WorldPOP and building footprints to generate measures for each square of a 100m x 100m grid. Figure 12 shows the most overcrowded locations according to the composite measure for four secondary cities; the paper calculates these for Kigali and five secondary cities (except Musanze due to missing building footprint data). The policy relevance of this analysis is: i) to show where in Rwanda social distancing may be most difficult during the COVID-19 pandemic, increasing the risk of contagion; ii) from a housing policy perspective, to understand the pattern of overcrowding within cities; and iii) to address the question of whether the densification pillar of Rwanda's National Urbanisation Policy should still be pursued (they argue in favour).

Figure 12: Composite (indoor plus outdoor) measure of top 1% (purple) and 5% (peach/orange) overcrowding hotspots in 4 secondary cities

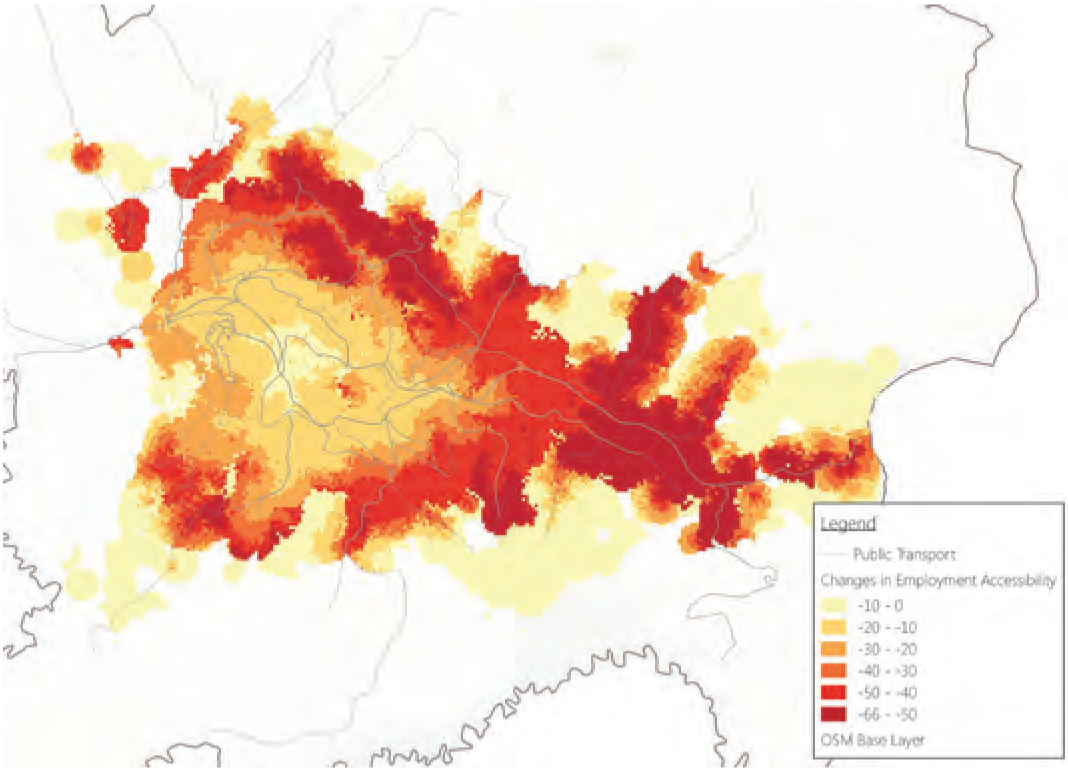


Source: Rajashekar & Bower (2020) "Densification without contagion: overcrowding and pandemic risk hotspots in Rwanda". Final report. International Growth Centre. p19

On roof materials for buildings in Kigali, Braun et al. (2019) and Matabishi et al. (2022) published journal articles on methodologies for detecting roof materials of buildings in Kigali, indicating that analysis of roof materials may be used as an input for planning decisions and monitoring of urban expansion.

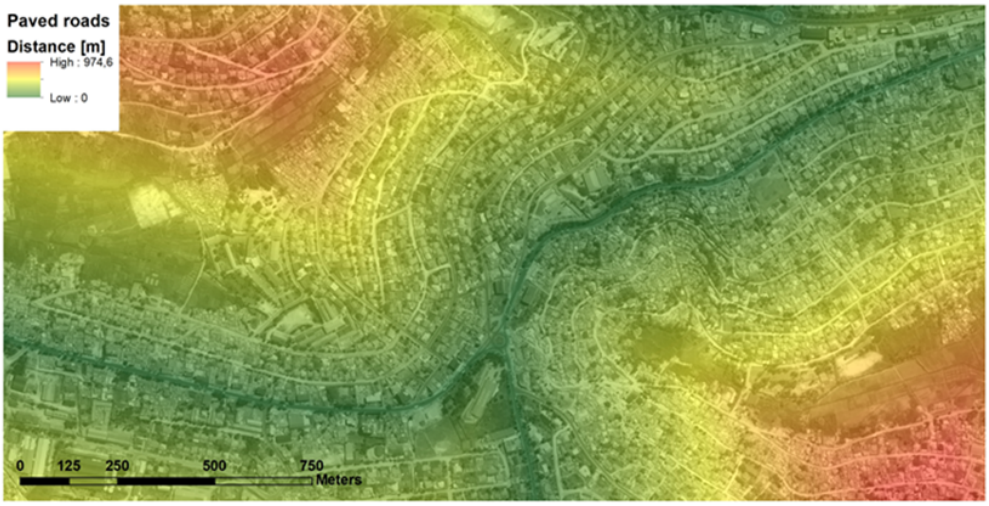
On transport, in "Managing Accessibility for Sustainable Development of Kigali", Bajpai et al (2016) do accessibility analysis in Kigali, assessing the impacts of potential policies to increase accessibility on transit times and on activity location decisions. A simulated change in access to employment from a 50% drop in bus speed is shown in Figure 13. Below it, Figure 14 shows a graphic of the distance to paved roads.

Figure 13: Simulated change in access to employment in Kigali with a 50 percent drop in bus journey speed



Source: Quiros, Murray, and Bajpai 2016[34]

Figure 14: Average distance to paved roads



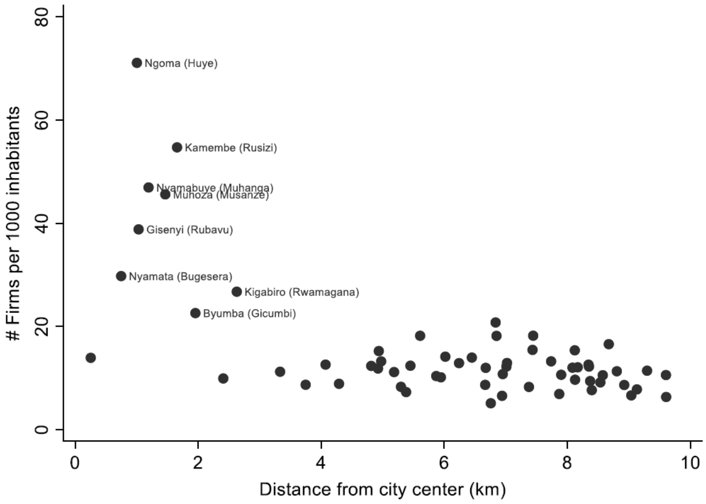
Source: unpublished IGC presentation on property valuation

The Rajashekar et al. (2018) study “Economic geography of Rwanda”, contains a rich array of spatial analysis about economic activity and firms and rewards a close read. To cite just two examples, Figure 15, which includes secondary and emerging towns but excludes Kigali, shows a strong relationship between the distance to city or town centre and the number of firms per 1000 people - not simply the number of firms - showing that proximity to the city or town centre is important both for productivity and for job seekers. Figure 16 shows that Kigali is at the very centre of Rwanda’s

[34] Quiros, T., S. Murray, and J. Bajpai. 2016. Managing Accessibility for Sustainable Development of Kigali. Final report, International Growth Centre, London.

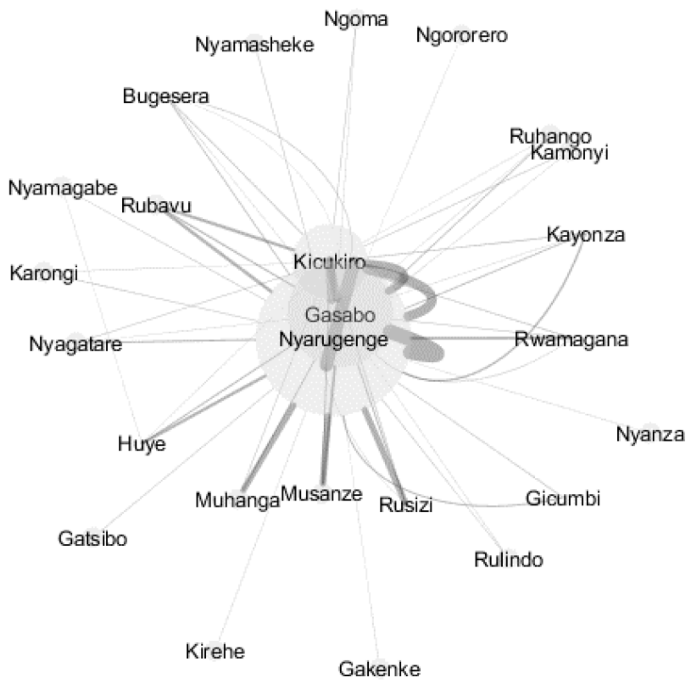
internal trade system and that there are few connections linking other parts of the country together directly.

Figure 15: Firms per 1000 inhabitants per Sector, by distance to city centre (Kigali excluded)



Source: Rajashekar et al. (2018). Economic geography of Rwanda. Final report, Laterite and International Growth Centre.
Note: Excluded Sectors are those in Kigali and those that are further than 10 km of secondary city centres

Figure 16: District-to-district trade in Rwanda



Source: Rajashekar et al. (2018). Economic geography of Rwanda. Final report, Laterite and International Growth Centre.
Note: Only links above 5 billion RWF represented – size of line is proportional to trade between two Districts; size of node proportional to total trade by District

7.3. International research

The field of urban and regional economics - and thus its usefulness for policymakers - has advanced greatly in recent decades, and has been accelerated by the increased availability of spatial data over time. Urban economics contains many sub-fields including the nature and drivers of agglomeration economies (in which proximity increases productivity), urban built form, land use, municipal finance, housing, transport and commuting, infrastructure, waste, crime, health and other fields, many of which have spatial dimensions. Our review cannot thus be exhaustive; our goal is to stimulate thinking through interesting examples.

Urban form

Professor Solly Angel has made a seminal contribution on how the footprint of cities grows as population grows, and in "The dynamics of global urban expansion" (with Sheppard & Civco, 2005)[35] analyses classifications of land use based on Landsat satellite data to find a robust pattern that if a city's population is doubled, the city's land area increases by more than double and that densities in cities systematically decline over time. Densities in developing-country cities were found to be three times higher than densities in cities in high income countries; moreover, densities in all regions were found to be decreasing over time. They state that this implies that whilst *"it is quite common to hear of urban planners and decision makers speaking of their cities as exceptions to the rule, asserting that other cities will grow and expand and their city will not, simply because it is already bursting at the seams"*, urban expansion is inevitable, and that policymakers in developing country cities should usually place more focus on what should be done to accommodate city growth rather than resist it. This logic certainly applies to Kigali, which is set to expand to 3.8 million people (Kigali Master Plan, 2020) or 4 million people (Bower & Murray, 2019), yet policymakers in Rwanda focus on preventing sprawl, upgrading existing unplanned settlements and expanding the secondary cities rather than accommodating the inevitable growth of the capital city through grids.

Harari (2020) uses historical maps and satellite-derived dataset of nighttime lights to derive the shape of cities in India over time. She then finds that cities with more compact shapes - that is to say, rounder shapes in which each location is as close to each other location as geometrically possible - are characterised by larger population, lower wages, and higher housing rents, consistent with compact shape being a consumption amenity. She estimates that the welfare cost of deteriorating city shape is sizable. She finds that unfavourable topography that makes cities less compact, is exacerbated by restrictive housing policy, but that the costs of these factors are mitigated by good road infrastructure.[36]

To assess the impact of urban renewals and demolitions at a more local level, Getcher and Tsivanidis (2018) applied a machine learning technique called "deep convolutional neural network" to measure changing slum cover from daytime satellite imagery. They found that redevelopment of the 15% of central city land in Mumbai occupied by the city's defunct textile mills into high-rises during the 2000s had strong spatial spillovers on surrounding locations in terms of gentrification in the form of higher formal sector house prices and lower slum cover.

[35] Angel, S, Sheppard, S. C., Civco, D. L., Buckley, R., Chabaeva, A., Gitlin, L. , Kraley, A. , Parent, J. , Perlin, M. (2005). The dynamics of global urban expansion (p. 205). Washington, DC: World Bank, Transport and Urban Development Department.
[36] Harari, M. (2020). Cities in bad shape: Urban geometry in India. *American Economic Review*, *110*(8), 2377-2421.

Housing
Hsieh and Moretti (2019) find that housing restrictions in high-productivity US cities lead to misallocation of labour, by artificially restricting the growth (and thus labour demand) of these cities. They use a spatial equilibrium model and data from 220 metropolitan areas to find that these constraints lowered aggregate US growth by 36 percent from 1964 to 2009.

Marx, Stoker, and Suri (2019) used the luminosity reflected by metal roofs in high-resolution daytime satellite pictures to investigate slum structures in Nairobi, Kenya. Their idea is based on the fact that 96 percent of slum residents have corrugated iron roofs and that metal roofs are shiny when new or recently renovated. Using the classification of slums, they provide evidence of ethnic patronage in the determination of rental prices and investments.

Chyn (2018) found that urban housing demolitions in Chicago — which forced low-income households to relocate to less disadvantaged neighbourhoods using housing vouchers — led to more violent crime arrests and earlier employment among displaced children. They rely on detailed data on building height to define demolition status of buildings.

Firms and economic activity
Dong, Ratti, and Zheng (2019) show that an easily accessible and fairly regularly updated neighbourhood attribute, the restaurant, when combined with machine-learning models, can be used to effectively predict a range of socioeconomic attributes, which has not been well-documented for many developing cities and countries. They merge restaurant data from an online platform with 3 micro-datasets for 9 Chinese cities. Using features extracted from restaurants, they train machine-learning models to estimate daytime and nighttime population, number of firms, and consumption level at various spatial resolutions.

Transport
Many studies have studied the welfare impact of both inter-city transportation infrastructure such as highways and railways, and intra-city transportation infrastructures such as Bus Rapid Transit (BRT) systems.

On inter-city transportation, Baum-Snow et al. (2017) found that in China each radial highway displaces 4% of central city population to surrounding regions, and ring roads displace about an additional 20%. They also provide evidence that radial highways decentralised service sector activity, radial railroads decentralised industrial activity, and ring roads decentralised both.

Baum-Snow et al. (2020) investigated how the construction of China's national highway system affects local economic outcomes. The results indicate that highways also affect patterns of specialisation. With better regional highways, regional primate cities specialise more in manufacturing and services, while peripheral areas lose manufacturing but gain in agriculture.

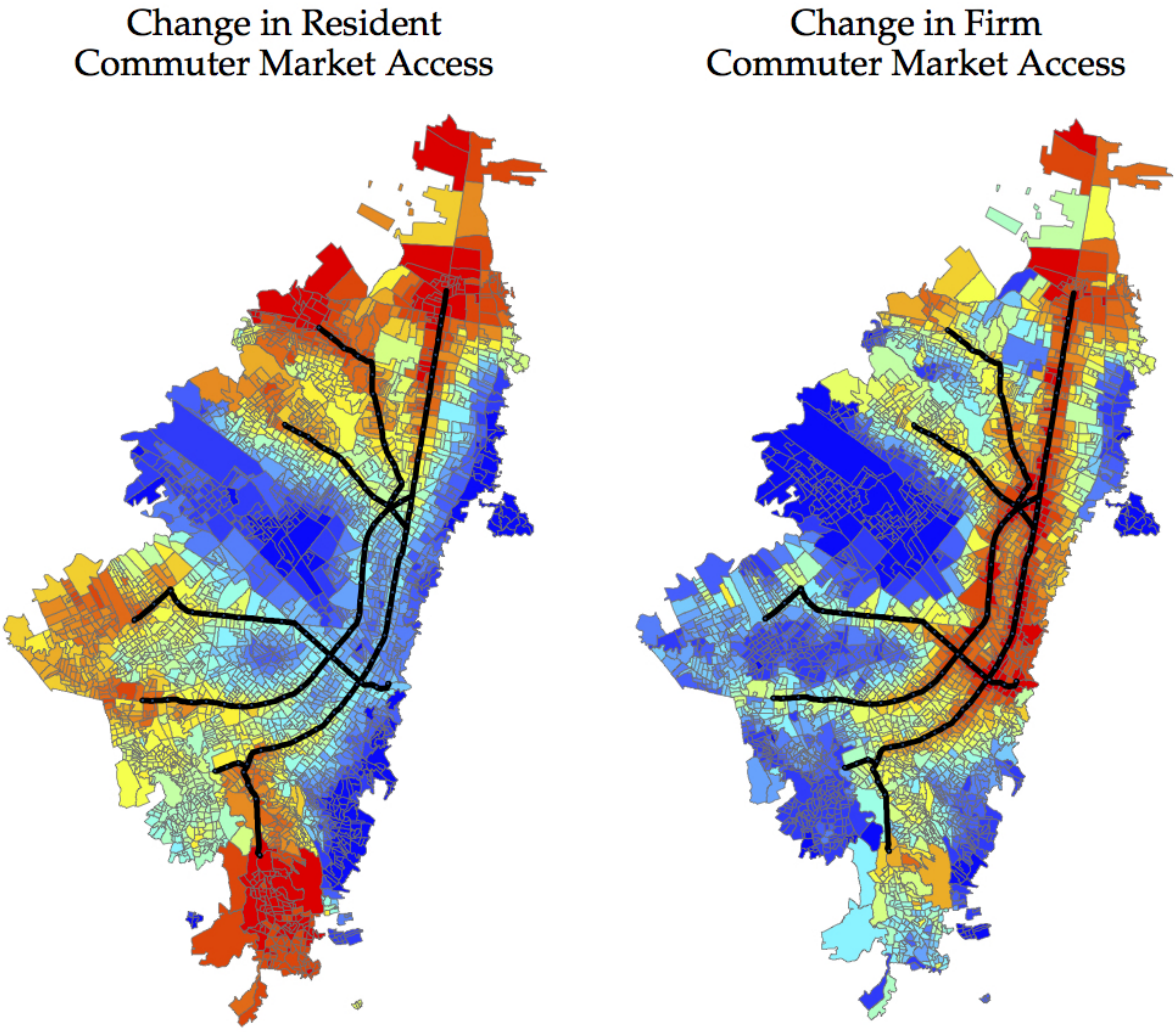
Asher and Novosad (2020) found that India's national rural road construction program facilitates the movement of workers out of agriculture in the rural areas, but the impacts on people's income and firms' size are modest, indicating that remote areas may still lack economic opportunities even with better market connection.

On Bus Rapid Transit, Balboni, Bryan, and Morten (2020) explored the distributional effects of urban infrastructure improvement by studying the BRT system in Dar es Salaam, Tanzania. They used original panel data tracked on two dimensions (following households if they move and surveying all new residents of buildings) and found that the BRT was a pro-poor investment.

Tsivanidis (2021) estimated the effects of improving transit infrastructure on city structure and welfare by studying the construction of the world's largest BRT system – TransMilenio – in Bogotá, Colombia. His most conservative estimates found that the BRT system increased aggregate welfare in the city by 1.5% and output by 1%. He estimated a "commuter market access" (CMA) index that summarises the impact of the entire transit network on equilibrium outcomes in any location. The CMA for residents represents access to jobs and the CMA for workers represents access to workers. Figure 17 shows how the CMA is affected for residents and for firms; warmer colours (red) represent an increase in the CMA. The policy implications of this research included the following: i) there are high returns to cheap, complementary bus services or last-mile connections; ii) "lines that connect poor neighbourhoods with jobs in low-skill intensive industries benefit unskilled workers the most"; and iii) there is a need for integrated transit and housing policy in which housing policy does not restrict housing supply from responding to the new presence of a BRT line.[37]

[37] https://blogs.worldbank.org/impactevaluations/ticket-ride-building-efficient-and-equitable-cities-bus-rapid-transit-guest-post-nick-tsivanidis

Figure 17: Change in Commuter Market Access from TransMilenio



Note: Figures show deciles of change in CMA, with warmer colors representing larger increases

Source: Tsivanidis, Nick (2019). "The aggregate and distributional effects of urban transit infrastructure: Evidence from Bogotá's TransMilenio," Technical Report, University of Chicago Booth School of Business 2019.

Gaduh, Gračner, and Rothenberg (2021) studied the effects of cheaper BRT systems with lower-quality implementation on city congestion and people's welfare by looking at TransJakarta, a large BRT system. Their model and counterfactual find that increasing the quality of expansion corridors would significantly improve welfare with only modest costs.

Urban land use

In the study of economic geography, it is important to understand why cities exist, how they are shaped, and spatial distributions of economic activities within them. The availability of satellite imagery and machine-learning techniques for image classification have led to rapid advances in detecting land use in the remote sensing literature. Several studies managed to construct urban layers for the world as a whole based on different data sources, Pesaresi et al. (2015) use Landsat imagery to detect urban land for grid cells at a 38m resolution, Channan et al. (2014) use MODIS imagery to detect multiple types of land use for grid cells at a 500m resolution, and Zhou et al. (2014, 2015) use night light intensity to detect urban land at a 1 km resolution.

Remote sensing data could delineate urban areas but not restricted to administrative boundaries. For example, Burchfield et al. (2006) use contiguous pixels to measure sprawl in the U.S. based on Landsat satellite imagery from 1976-1992. Harari (2020) uses nightlights to track urban sprawl in large Indian metropolitan areas. Dingel et al. (2021) utilises clusters of pixels above nightlight thresholds to construct metro areas in Brazil, China, and India. Recent work by Duranton (2015) proposes an alternative algorithm to construct markets based on commuting patterns for Colombia. De Bellefon et al. (2019) develop a statistical approach to detect urban areas using precise locational data covering 34 million buildings in France. Baragwanath et al. (2021) proposed a new approach to define urban markets based on built-up land-cover classified from daytime satellite imagery in India. They find that, compared to nighttime light intensity, daytime imageries can identify more markets, capture more of India's urban population, are more realistic in shape, and reveal more variation in the spatial distribution of economic activity.

7.4. Ideas for further research

Create a housing suitability index and other urban applications using the Suitability tool, to inform urban planning and the placement of social housing

Rwanda's city master plans contain zoning for residential housing, and Rwanda Housing Authority selects sites on which to build social housing. Spatial analysis could be used to inform the suitability of zoning and sites selected for social housing. A housing suitability index could be developed based on data layers for environmental suitability, jobs, transport facilities and a range of urban amenities including schools, public spaces, hospitals. Such an index was developed by the World Bank-funded initiative City Planning Labs[38] using the tool "Suitability", which is described as "an urban planning tool that identifies optimal location for a specific activity within a city".[39] The tool can be used to support national urban planning agencies and city governments to perform land suitability assessment to plan for infrastructure deficits at the city and local levels, enabling inter-departmental coordination and a strategic planning approach."

Track urban spatial growth, compactness and relative growth of formal housing

The building footprint data purchased for the 2022 Census could be combined with building footprint data from 2015 and 2009 to show by how much, and in which locations, the spatial footprint of Kigali has grown. Analysis could also be conducted to understand whether housing develops contiguously or if there is scope for infill development. Research could also investigate housing density trends, or to understand whether - subject to topography constraints - Rwanda's cities are as compact as they could be. Moreover, a similar algorithm to that used in Bachofer & Murray (2019), could be used to detect building types including

[38] https://pubdocs.worldbank.org/en/895401614014851662/WB-Indonesia-urban-planning-final-report-v3.pdf
[39] https://www.suitability.in/

basic informal housing, bungalows, villas and various types of commercial buildings, to show whether new formal housing is keeping pace with, lagging behind, or overtaking informal housing, and in which locations.

Conduct a nationwide property valuation

As noted above, Brimble et al. (2020) conducted a property valuation exercise for Kigali using building footprints from 2015, and recently completed an unpublished model update using building footprints from 2019, funded by GIZ and IGC. The building footprint data purchased by the Government of Rwanda for use in the 2022 Census could be readily paired with other data sources on roads, vegetation, parcel data from the Rwanda Land Management and Use Authority, and other layers, to conduct a property valuation exercise for the entire country. Such an exercise would provide an excellent foundation for the development of a country-wide property price index.

This would be useful for property tax implementation enforcement as the building footprints would enable RRA to identify which property owners who own buildings have not declared them, and how much property tax is thus foregone nationally by failure to declare buildings. The national property valuation exercise would also enable an evaluation of the fairness and consistency of the land tax rates set in the Ministerial order in relation to land values as well as whether some districts result in being ‘overtaxed’ and others ‘undertaxed’ as an accidental side-effect of the current rates. The (unpublished) national land valuation exercise conducted by Sebarenzi et al. in 2021 for the Ministry of Environment for the purpose of compensation in cases of expropriation, could also be used for this purpose.

Assess the impact of roads on economic activity and assets

It is possible to track the construction of roads/highways through satellite images, and see how the improvement of infrastructures affects local economic and environmental outcomes (Hsiao, 2021). All of these could provide insights for urban development master plans in Rwanda. Bernard et al. (2016) conduct a computable general equilibrium model to estimate the impact of Kampala’s new ring road[40]; as Kigali is planning both a BRT and a ring road in the coming decade, spatial analysis could be conducted to estimate its impact. The World Bank also conducted research on the impact of agricultural feeder roads in Rwanda; this research could be extended over more districts as more feeder roads are built. Ministry of Infrastructure plans to invest in roads in secondary cities, in partnership with a range of development partners including the World Bank, European Union, Enabel and others[41]; an evaluation of the impact of those roads on house-building and economic activity could be conducted if there is a way to randomise their construction ex-ante, or a way to identify an exogenous source of randomness.

[40] Bernard, L., Bird, J., & Venables, A.J. (2016). Transport in a congested city: A computable equilibrium model applied to Kampala City. First draft, available at https://www.slurc.org/uploads/1/0/9/7/109761391/transport_in_a_congested_city-_a_computable_equilibrium_model_applied_to_kampala_city.pdf

[41] Learned by Jonathan Bower, Country Economist, IGC when attending Urbanization, Human Settlements and Housing Sector Working Group meetings hosted by Ministry of Infrastructure

Conduct transport analysis and updated accessibility analysis for Rwanda's cities
Mobile phone data is hard to access in Rwanda but if made available, could be used to understand traffic and commuting patterns. This can inform the design and upgrading of transportation infrastructures and the allocation of resources to these upgrades. The African Urban Mobility Observatory aims to "promote inclusive, low-carbon mobility in African LIC cities, by piloting Big Data applications to generate data, benchmark performance", and intends to use a mix of "a mix of User Movement Analytics integrated mobile apps, USSD/WhatsApp/Web based surveys, and limited field surveys".[42] Rwanda is one of their target countries, but any analysis they do may just be the starting point and open the way to further analysis.

Use restaurants, roofs or other unconventional data sources to estimate economic activity or assets in Rwanda's cities at detailed spatial scale
Finely granular and regularly updated urban socioeconomic data are not available in Rwanda as in most countries. However the restaurant industry puts data online to attract customers, and is also correlated with socioeconomic indicators. An attempt might be made to follow Dong et al. (2019) who train an algorithm to predict a range of socioeconomic attributes using restaurant attributes including the location, average price of a meal, cuisine category, and number of reviews in combination with datasets on population, firms and consumption. Other unconventional data sources could also be tested as predictors of socioeconomic attributes or assets - whilst Marx, Stoker, and Suri (2019) used the luminosity reflected by metal roofs to investigate investment in assets (a shinier roof is newer) in Kibera slum, Nairobi, a similarly innovative proxy for assets that is visible in satellite imagery, might be found for Rwanda.

Conclusion

In Vision 2050, Rwanda aspires to be a knowledge-intensive economy that is data-driven and fosters excellence in research & development. Spatial data analysis can play an important role in this picture and can take advantage of the increasing range of spatial data available to yield new insights for the Government and the private sector. The Government has signalled its seriousness about its aspirations to use spatial data, with the formation of the geoportal and National Spatial Data Infrastructure at Rwanda Land Management and Use Authority, Smart City Master Plan and with the creation of the Rwanda Space Agency. Researchers at the Centre for GIS at University of Rwanda, as well as a few international researchers, have made a promising start. However, spatial analysis is a nascent and under-utilised lens and there is a need for creative thinking about how to deploy it, as well as a need to open up valuable existing data sources to researchers. This paper represents our attempt to think about how the promising potential of spatial economic analysis can be met for six policy areas, and it is our hope that the ideas in it will inspire further research.

[42] https://transport-links.com/research-project/africa-urban-mobility-observatory-goascendal/

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