Working paper

International Growth Centre

Climate Change Volatility and Crop Choices

Giacomo De Giorgi
Luigi Pistaferri

March 2013

When citing this paper, please use the title and the following reference number:
E-6004-NOC-1

DIRECTED BY

LSE

UNIVERSITY OF OXFORD

FUNDED BY

UKaid
from the British people

Climate Change Volatility and Crop Choices*

Giacomo De Giorgi† Luigi Pistaferri‡

First version: May 1, 2012

This version: March 6, 2013

Abstract

Climate change has generated much attention. Upward trends in average temperature are well documented facts. Relatively less studies is the impact of the increase in climate volatility, including weather extreme events, on behavior. In standard models with uncertainty or risk, precautionary behavior, and lack of formal insurance, agents self-insure by building up assets, or engaging in other type of behavior designed to reduce to impact of risk on outcomes. The goal of our project is to look at the impact of increasing climate volatility on choices made by farmers around the world, and in particular in developing countries. In this note we describe the data used and provide some descriptive evidence on rainfall and temperature volatility and on the relation between temperature volatility and crops production, cultivated land and crops diversity.

*Thanks to Michela Giorcelli and Giuseppe Maggio for research assistance. This material is based on work supported by the IGC RA grant 2011-08-004. Authors' contact information: degiorgi@stanford.edu; pista@stanford.edu.

†Stanford University.

‡Stanford University.

1 Introduction

In this note we provide a description of the data collected and organized in relation to our project on the effects of changes in climate uncertainty on the behavior of farmers/consumers around the world. Firstly, we collected data on temperatures and rainfall for the entire globe and for many years. We used both actual climatic station data as well as gridded data. We complemented these data with information on production and soil characteristics for a variety of crops. We describe an imputation method that we use to transform aggregate crop production data available at the level of individual country onto gridded data. Our data come from different international sources that are meant to be of high quality, such as the Food and Agricultural Organization of United Nations (FAO) and the National Oceanic and Atmospheric Administration (NOAA). Our final data set contains information on about 200 countries, 30,000 weather stations, and about 160 crops. We limit our descriptive analysis to the past sixty years, where we have a larger and more consistent sample to work with.

We first establish a series of facts about the time series and cross-sectional profiles of temperature and rainfall. In particular, we confirm the general increase in average temperature recorded in the past decades, as documented in Stern (2006), with however a large degree of heterogeneity across space. Second, and more importantly for our project, we establish some facts about the evolution of weather risk, expressed in terms of the volatility of the residual of temperatures and rainfall regressions.[1] In particular, we find that: (a) the (yearly) coefficient of variation of temperature is increasing over time; (b) there is a significant heterogeneity in the estimated changes in the volatility of temperatures, with some countries and locations experiencing a large increase, and others a large fall in volatility. In terms of rainfall the picture seems quite different: (a) on average the residual volatility seems to be falling over time, although (b) even in this case there is a significant amount of heterogeneity in the data when organized by country or location.

We then investigate the relation between (long-run) temperature volatility and crops yields, cultivated land and crops diversity. We find that increased temperature volatility translates into lower production of many of the studied crops, further to an expansion in cultivated land and an increase in the number of harvested crops.

2 Data

2.1 Station weather data

We analyzed weather data collected at the weather station level.[2] Data on temperatures and rainfall come from two different sources: the *FAOclim-NET* and the *National Oceanic and Atmospheric Administration*

[1] In particular, we define weather risk as the coefficient of variation, over a specified time frame, of the residual of a regression of temperature (or rainfall) on month, station, and hemisphere fixed effects.

[2] A weather station is a facility, either on land or sea, with instruments and equipment for observing atmospheric conditions to provide information for weather forecasts and to study the weather and climate. The measurements taken usually include temperature, barometric pressure, humidity and precipitation amounts.

(NOAA). The *FAOclim-NET* covers monthly data for temperatures and rainfall (measured in millimeters[2]), collected at the station level, for 28,100 stations around the world.[3] The *NOAA* has developed two different databases: the *Global Historical Climatology Network-Monthly* (GHCN-M) and the data collected by the *National Climatic Data Center* (NCDC). The *GHCN-M* has been the official land surface mean temperature data set since its release and has been widely used in several international climate assessments.[4] We used the latest version (version 3), officially released in May 2011, which collects monthly mean temperatures at the station level and improves over the previous versions with respect to both data quality and coverage. The *NCDC* collects daily climate information at station level, including temperature, barometric pressure, humidity and precipitation. [5]

Note that not all the variables are measured in the same units in these three data sets. In *FAOclim-NET* and *GHCN-M* temperatures are in Celsius, while in *NCDC* they are in Fahrenheits. We convert Fahrenheit temperatures into Celsius. Moreover, since *NCDC* data are daily, we averaged them in order to obtain monthly data. Finally, since latitude and longitude (which refer to the location of the weather station) are expressed in decimal degrees in *FAOclim-NET* and *GHCN-M* and in sexagesimal degrees in *NCDC*, we converted the sexagesimal degrees into decimal degrees. After these transformations, all the variables in the three data sets are measured in the same units and hence comparable.

2.2 Weather Gridded Data

While weather station data reports data only at the actual location of the weather station, gridded data are more comprehensive. In gridded data researchers divide the globe into cell grids defined by latitude and longitude and measure temperature (and other information) within each cell. For cell grids where weather stations are located, one uses the data points already available. For cell grids with no weather stations (say, at sea), researchers have developed sophisticated imputation/interpolation procedures. We use gridded weather data available from the *University of Delaware Terrestrial Air Temperature and Precipitation* data base (version 3.02), which contains monthly observations on precipitation and air temperature at the cell grid level spanning 1950 to 1999.[6] To produce this archive, researchers have merged the *Global Historical Climatology Network* (GHCN version 2, described above) with Legates and Willmott's (1990a, 1990b) station records of monthly and annual mean air temperature and total precipitation.

To produce values in cell grids not covered by weather stations, researchers apply an interpolation algorithm based on the spherical version of Shepard's distance-weighting method (Shepard, 1968; Willmott et al., 1985). In particular, station averages of monthly air temperature and precipitation were interpolated to a 0.5 degree by 0.5 degree of latitude/longitude grid, with grid nodes centered on 0.25 degree. Some improvements are obtained incorporating additional station information, such as altitude (see Willmott and

[3] See http://geonetwork3.fao.org/climpag/agroclimdb_en.php
[4] See ftp://ftp.ncdc.noaa.gov/pub/data/ghcn/v3/
[5] See ftp://ftp.ncdc.noaa.gov/pub/data/gsod/
[6] See http://climate.geog.udel.edu/.

Matsuura, 1995, for more details). Summary statistics for this gridded data set are reported in Table 1.

2.3 Crop data

2.4 Description of the crop data

We constructed a gridded crop data set using three data sources:

1. Aggregate national crop data from the FAO, available for the 1961-2011 period. This data set includes, for each country (c), year (t), and crop (k) the total production (in tonnes), $y^k_{c,t}$, and the total area harvested (in hectares), $a^k_{c,t}$.[7]

2. The "Global Cropland and Pasture Data from 1700-2007", a data base constructed by Ramankutty and Foley, 1999 (RF hereafter). This data set maps cropland cover at 0.5 degree resolution in latitude by longitude, on an annual basis. In particular, it reports the fraction of cell grid area that is occupied by cultivated land, $f_{j \in c,t}$.[8]

3. Monthly precipitation and average temperature data from the *University of Delaware Terrestrial Air Temperature and Precipitation* data base described above (UD hereafter).

To construct a gridded data base of crop production, we follow two methods, which we call "uniform method" and "regression-based method". The "uniform method" is based on the following steps:

1. We start by computing the total area (in hectares) in a given country that is harvested, i.e., $a_{c,t} = \sum_k a^k_{c,t}$. For example, in Albania in 1990, $a_{c,t} = 540,411$ and $a^{Maize}_{c,t} = 62,000$.

2. We next compute the fraction of harvested area in a given country that is devoted to crop k, or $\phi^k_{c,t} = a^k_{c,t}/a_{c,t}$. For Albania in 1990, $\phi^{Maize}_{c,t} = 0.11$. This means that 11% of the total harvested area in the whole of Albania harvests maize.

3. In principle, maize is not grown in the same proportion in all grid cells covering the territory of Albania, due to differences in climate, etc. However, we make a uniform distribution assumption, and compute $\phi^k_{j \in c,t} = \phi^k_{c,t} \times f_{j \in c,t}$. For example, in grid cell given by latitude 39.75 and longitude 20.25, the cultivated area is 52%. We assume that in this grid cell, the area cultivated at maize is 0.52×0.11, or 5.72%.

4. Finally, we estimate maize production in each cell grid by: $y_{j \in c,t} = y^k_{c,t} \times \frac{\phi^k_{j \in c,t}}{\sum_j \phi^k_{j \in c,t}}$. In 1990, the total maize production of Albania was 227,000 tonnes. We estimate that about 37,000 tonnes were produced in grid cell given by latitude 39.75 and longitude 20.25.

[7] Data are available for 161 crops, listed in the Appendix. See http://faostat.fao.org/default.aspx?lang=en.
[8] See http://www.geog.mcgill.ca/landuse/pub/Data/Histlanduse/.

The "regression-based method" tries to account for the fact that crops are not grown uniformly across various parts of a country. For this reason, we start by running the following regression:

$$y^k_{c,t} = X'_{c,t}\beta^k + \varepsilon_{c,t}$$

where $X_{c,t}$ captures variables that are available at the grid cell level, such as temperature, precipitations, altitude, etc (from the UD data set, averaged at the country/year level). In other words, we estimate a "pseudo-production function" for crop k using as explanatory variables only those variables that can also be measured at the grid cell level. Once we have estimates of the parameters β^k, say $\widehat{\beta}^k$, we construct

$$\widehat{y}^k_{i\in c,t} = X'_{j\in c,t}\widehat{\beta}^k$$

and then we rescale to obtain the final estimate of grids cell production:

$$\widetilde{y}^k_{i\in c,t} = \widehat{y}^k_{i\in c,t} \times \frac{y^k_{c,t}}{\sum_j \widehat{y}^k_{j\in c,t}} \tag{1}$$

which ensures that the total imputed production for country c equals total actual production as coming from the FAO data set. In what follows, we use the "uniform method" for describing the data.

Using the FAO definition, we grouped crops (described in the Appendix) into 14 different categories: Cereals, Roots and tubers, Sugar cane, Pulses, Nuts, Oil seeds, Leguminous vegetables, Vegetable fresh, Citrus fruit, Stone fruit, Berries, Fresh fruit, Spices, and Fibres. For more details, we refer the interested reader to the Appendix.

3 Descriptive Analysis

3.1 Weather data

Looking at Figure 1 we notice how the geographical coverage of our data is quite extensive. However, as one might expect, there is limited information for areas with sparsely populated or unpopulated land, e.g., the Saharan desert, the Amazon forest and the Russian tundra and taiga. What is also noticeable from Figure 2 is the large overtime variation in the number of weather stations available. These figures are based on the entire set of data we collected and organized, i.e. including all sources.

Figure 3 shows how the number of stations has changed over time in 4 countries with different level of income, (Afghanistan, Paraguay, Lybia, and the US):[9] in all of them, the number of stations increases up to 1989 and it declines after that date (a phenomenon known as "station drop out" in the climatology literature).[10]

[9] We use the current World Bank classification of 4 categories in low to high income countries.

[10] Most of the dropped out stations were located in rural areas and colder climates on average, but climate trends are hardly affected by this selectivity issue.

Figures 4 and 5 show how temperatures and precipitation have changed over time for selected countries, separately for each source. Precipitation is measured with regularity since 1950, while temperature is available since the beginning of the 20th century.

For tractability issue, we focus on the FAO data source as the most comprehensive and reliable. We provide descriptive analysis of the temperature and rainfall overtime profiles in terms of first and second moment at the **yearly** frequency. We first run the regression:

$$y_{it} = x'_{it}\gamma + f_i + u_{it}$$

where y is temperature or rainfall, i and t index the weather station (or cell grid) and the calendar month, x_{it} includes month dummies (to adjust the data for seasonal effects) and their interaction with southern vs. northern emisphere, and f_i is a station fixed effect which purges the data from time-invariant difference across locations.

Once we have computed the residual of such a regression ($\widehat{u}_{it}$), we regress $\widehat{u}_{it}$ and (a transformation of) $\widehat{u}_{it}^2$ against an appropriate time measure to verify whether the first and second moments of the weather distribution are shifting overtime and in what direction. Hence we run the regression

$$\widehat{u_{it}} = \delta t + v_{it}$$

Since preliminary analysis showed the existence of significant heterogeneity in the data, we conduct this analysis also at the country-by-country level, where we run the regression:

$$\widehat{u_{ict}} = \delta_c t + v_{ict}. \tag{2}$$

As can be seen in the summary figure 6, we confirm the well known mean temperature increase with a linear term indicating that on average temperatures have risen by 0.0003 degree Celsius per month, or equivalently, about 1/5 of a degree Celsius over the past 5 decades. This figure is in the ballpark of what found in the Stern report for example, although at the lower end of the spectrum. However, it is lower than what reported by Olken et al. (2012); and Brohan et al. (2006). In the graph we plot also the distribution of the estimated δ_c from equation (2) above.

Summary figure 7 repeats the exercise for our measure of volatility, that is (in this case) the decennial residual volatility. The world mean of the estiamated trend is positive and there is considerable heterogeneity across countries as witnessed by the wide dispersion in the estimated trend.

3.2 Crop data

In Figure 8 we plot the space/time evolution of cereal production. There are some clear trends - like the increase in output in Canada and the decline in Mongolia and the "Stans" republics of the former Soviet Unions. Data on other crop groups are available on request.

3.3 Some preliminary regression evidence

In this section we provide some preliminary evidence on the link between weather variability and crop choices.

Crop yields on temperature variances The first question we ask is: does weather volatility impact crop output? And if so, which crop is more affected?

We run the following regressions:

$$y_{jt} = \alpha_j + \beta_1(mean\_temp)_{jt} + \beta_2(mean\_temp)^2_{jt} + \beta_3(var\_temp)_{jt} + \epsilon_{jt} \tag{3}$$

where y_{jt} is the crop yields for each of the 14 categories listed above in grid j in year t, α_j is a grid (node) fixed effect, $(mean\_temp)_{jt}$ is the mean temperature for the thirty years prior to year t in grid point j, and $(var\_temp)_{jt}$ is the variance of temperature of the thirty years prior to year t in grid j, and ϵ_{jt} is the error term. Hence $mean\_temp$ and var_temp are "rolling" moments that take into account potentially changing long terms as experienced in agriculture. The results of these regressions are shown in Table 3. It is clear that increased weather volatility significantly reduces output for most crops (cereals, sugar cane, legumes, fresh vegetables, citrus, stone and frresh fruits, spices, and fibres). The effects are quite heterogenous as can be noticed from Table 3, in particular for cereals the effect of one standard deviation increase in the variance of temperature translates into a small fall in terms of production of about .3 percent of a standard deviation, or 203 tonnes. The effect size for legumes is much larger, a one standard deviation increase in volatility causes an almost 1.5 percent of a standard deviation fall in production (236 tonnes or about 6 percent over the mean production). The effect is even larger for fresh vegetables, where a one standard deviation increase in the variance of temperature in the prior 30 years results in about a 10 percent fall in production.

Percentage cultivated on temperature variances The possible effects (or endogeneous response by farmers) to increased climate volatility could be a reduction in the fraction of total area devoted to agriculture, as farmers shift towards non-agricultural activities, or an expansion in the cultivated area in order to reduce the amount of risk by, for example, increasing the crop and soil diversity. To informally test this, we run the following regression:

$$farea_{jt} = \alpha_j + \beta_1(mean\_temp)_{jt} + \beta_2(mean\_temp)^2_{jt} + \beta_3(var\_temp)_{jt} + \epsilon_{jt}$$

where $farea_{jt}$ is the percentage of cultivated land in grid j in year t, and the other variables have been defined above. The results of this regression are shown in Table 4. This regression shows a significant increase in the percentage of total area devoted to farming, although small and the results are merely descriptive. It is however possible that faced with higher uncertainty in the weather patterns farmers expand the cultivated area as a risk copying strategy. As mentioned the effect is rather small as a one standard deviation increase in the variance of temperature results in a .5 percent increase in the share of cultivated land.

Number of different crops cultivated on temperature variances Another possible response to increased weather volatiliy is an increase in crop diversification. Given higher underlying risk of crop failure due to increased volatility in the fundamental weather input, farmers try to diversify their cropping pattern so to reduce the amount of risk carried in the crop portfolio. While it is possible to construct sophisticated crops indeces, here we use simply the total number of crops cultivated in each cell grid. Hence we run the following regression:

$$n\_crop_{jt} = \alpha_j + \beta_1(mean_temp)_{jt} + \beta_2(mean_temp)^2_{jt} + \beta_3(var_temp)_{jt} + \epsilon_{jt} \tag{4}$$

where n_crop_{jt} is the number of crops for which production is strictly positive in grid point j at time t. The results of this regression are shown in Table 5, and support the risk diversification hypothesis. The effects are rather small however, as a one standard deviation increase in volatility of temperatures results in .1 of an additional crop. This latter result however doesn't consider the possible change in the composition of the crops portfolio, so that even if the number of cultivated crops varies only slightly as a result of higher volatility, farmers might substantially change the composition of their crops.

4 Conclusions

This final report has discussed the climate and agricultural production data we have collected and organized, presented some descriptive statistics on such data, and reported some preliminary regression analysis. In future drafts the latter will be expanded and refined. We intend this note as a first step towards an understanding of the agricultural, and ultimately welfare, effects of changes in volatility of the weather profiles in the past decades.

Table 1: Summary statistics on Gridded Temperature Data

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**
Temperature	9.428	14.067	-33.208	36.042
Mean temperature (30 years prior)	9.243	14.068	-31.409	35.297
Mean temperature squared (30 years prior)	283.361	266.581	0	1245.855
Variance temperature (30 years prior)	0.613	0.557	0.012	26.603
N	2793699			

Table 2: Descriptive Statistics on Crops Data

Variable	**N. Obs**	**Mean**	**Stan. Dev.**	**Min**	**Max**
Fraction of Cultivable Area	2,793,699	0.1040778	0.1921323	0	0.999947
N of Cultivated Crops	2,247,539	35.13174	35.07499	0	120
Cereals Production	2,785,147	27,855.01	66325.05	0	1,929,069
Roots and Tubers Production	2,782,892	9,771.07	28774.58	0	997,014
Sugar Cane Production	2,574,887	20,988.21	74858.05	0	3,959,943
Pulses Production	2,761,251	837.7832	2376.579	0	68,047.38
Nuts Production	1,508,005	163.2909	518.0911	0	38,597.17
Oils Seeds Production	2,734,093	5,604.62	22259.33	0	1,808,186
Leguminous Vegetable Production	2,694,829	4,343.03	16689.34	0	1,316,612
Fresh Vegetable Production	2,782,993	2,610.13	10242.72	0	277,975.40
Citrus Fruit Production	2,093,339	3,044.64	11485.78	0	864,813.40
Stone Fruit Production	2,204,679	1,392.49	5055.083	0	211,097.20
Berries Production	2,000,677	86.89583	328.9854	0	15,266.24
Fresh Fruit Production	2,697,004	3,094.05	10619.9	0	708,354.30
Spices Production	2,343,918	262.1347	973.5783	0	50,735.43
Fibres Production	2,562,982	297.2316	1296.062	0	49,548.13

A Appendix

A.1 Data sources: Weather

For each of our sources, stations are identified in different ways. In the *FAOclim-NET* and the *GHCN-M* data sets, they are identified through the *WMO-code*. The *WMO-code*, often called the "index number" relies on a 5-digit numeric code to identify a land weather station. The first two digits, called "block number", refer to the geographic area (00-29 Europe, 30-59 Asia, 60-68 Africa, 69 special use, 70-79 North America, 80-89 South America, 90-99 Oceania). The last three digits are loosely referred to as the "station number" and are assigned at the country level. In the *NCDC* data set, stations are identified through the *MASLIB-code*, a six-digit code, that uses essentially the same scheme as the WMO station identifier, but adds an extra digit, allowing many more stations to be indexed. This extra digit is always 0 when referencing an actual WMO station using the 5-digit identifier, but may take values from 1 to 9 to reference other stations that exist in the vicinity. To obtain a unique data set from these different sources, at first, we averaged all the *NCDC* stations whose *MASLIB-code* has the same five first digits, then we merged the three data sets using the *WMO-code* as merging variable. However, the *WMO-code* is missing for a pretty small number of stations. To be sure not to loose these data, we merged the stations whose *WMO-code* is missing, using *latitude* and

Table 3: Weather volatility and output

VARIABLES	Cereals	Roots	Sugar	Pulses	Nuts	Oils	Legum.
$E(T)$	$3,340^{***}$	5.362	$6,463^{***}$	37.21^{***}	84.94^{***}	$1,792^{***}$	$3,611^{***}$
	(76.23)	(36.30)	(110.4)	(3.039)	(1.650)	(45.47)	(29.91)
$E(T)^2$	115.5^{***}	85.38^{***}	656.1^{***}	10.80^{***}	3.370^{***}	89.04^{***}	45.82^{***}
	(2.624)	(1.250)	(3.961)	(0.105)	(0.0586)	(1.551)	(1.038)
$Var(T)$	-362.9^{***}	266.2^{***}	-371.1^{***}	91.17^{***}	0.517	193.6^{***}	-422.2^{***}
	(72.01)	(34.29)	(105.3)	(2.871)	(1.805)	(42.52)	(28.02)
Const.	$-35,457^{***}$	$-14,598^{***}$	$-213,121^{***}$	$-2,612^{***}$	$-1,822^{***}$	$-36,573^{***}$	$-40,715^{***}$
	(839.3)	(399.4)	(1,230)	(33.36)	(18.34)	(500.7)	(328.2)
Obs.	2,785,147	2,782,892	2,574,887	2,761,251	1,508,005	2,734,093	2,694,829
R^2	0.002	0.002	0.015	0.005	0.008	0.003	0.008
Grid f.e.	58,335	58,337	54,856	58,063	44,433	57,454	57,500

VARIABLES	Fresh V.	Citrus	Stone	Berries	Fr.Fruits	Spices	Fibres
$E(T)$	$2,207^{***}$	$1,227^{***}$	820.4^{***}	54.67^{***}	$1,797^{***}$	89.19^{***}	33.05^{***}
	(19.53)	(19.08)	(8.436)	(0.512)	(15.52)	(1.489)	(1.574)
$E(T)^2$	10.44^{***}	75.35^{***}	12.50^{***}	1.753^{***}	50.33^{***}	7.282^{***}	2.676^{***}
	(0.674)	(0.603)	(0.339)	(0.0232)	(0.529)	(0.0536)	(0.0567)
$Var(T)$	-469.2^{***}	-238.0^{***}	-151.1^{***}	10.92^{***}	-373.8^{***}	-26.32^{***}	-32.68^{***}
	(18.45)	(21.11)	(7.933)	(0.479)	(14.67)	(1.438)	(1.489)
Const.	$-20,395^{***}$	$-36,800^{***}$	$-6,081^{***}$	-467.4^{***}	$-27,880^{***}$	$-2,581^{***}$	-701.2^{***}
	(215.2)	(217.6)	(82.24)	(4.700)	(171.9)	(17.19)	(17.67)
Obs.	2,782,993	2,093,339	2,204,679	2,000,677	2,697,004	2,343,918	2,562,982
R^2	0.006	0.018	0.006	0.010	0.012	0.012	0.001
Grid f.e. 58,335	47,847	48,702	45,896	57,520	53,835	54,275	

Table 4: Effects of Temperature on % of Cultivated Area

VARIABLES	farea
mean_temp	-0.000864***
	(7.09e-05)
mean_temp2	0.000331***
	(2.44e-06)
var_temp	0.000806***
	(6.70e-05)
Constant	0.0178***
	(0.000781)
Observations	2,793,699
Number of id_geo	58,514
R-squared	0.007

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5: Effects of Temperature on Number of Crops

VARIABLES	ncrops
mean_temp	4.572***
	(0.0255)
mean_temp2	0.0743***
	(0.000817)
var_temp	0.197***
	(0.0214)
Constant	-32.69***
	(0.269)
Observations	2,247,539
Number of id_geo	51,078
R-squared	0.030

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

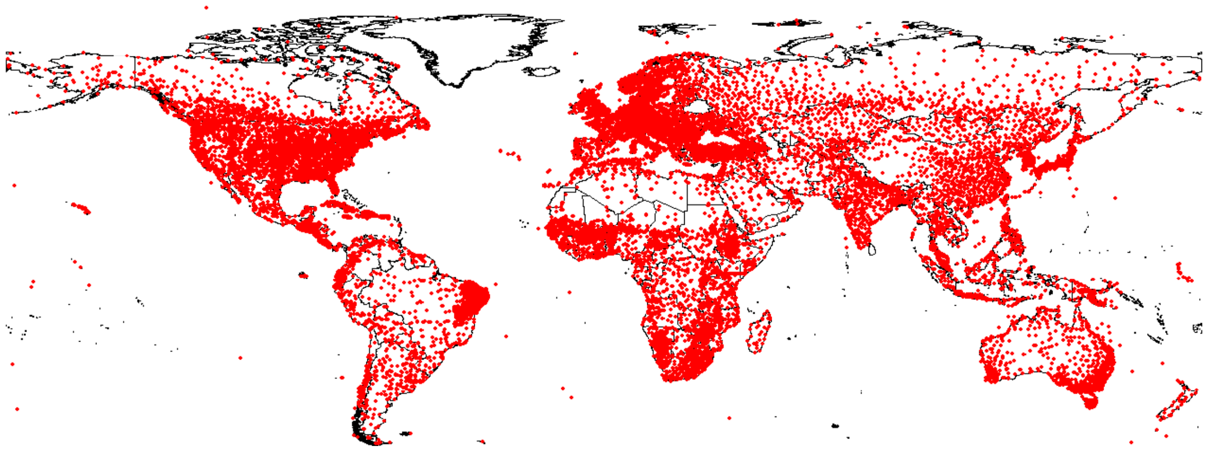

Figure 1: Weather stations around the world.

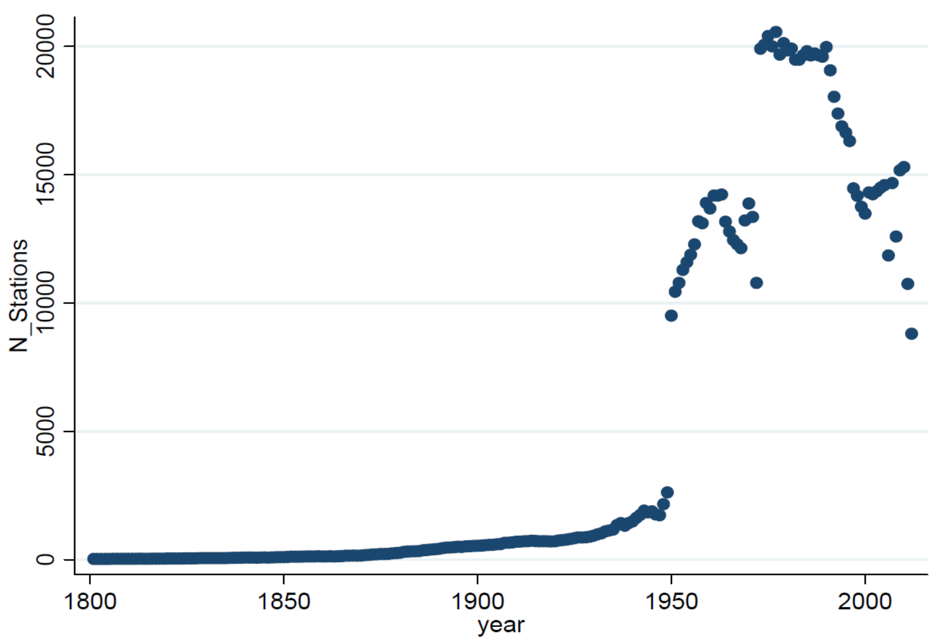

Figure 2: The number of weather stations over time.

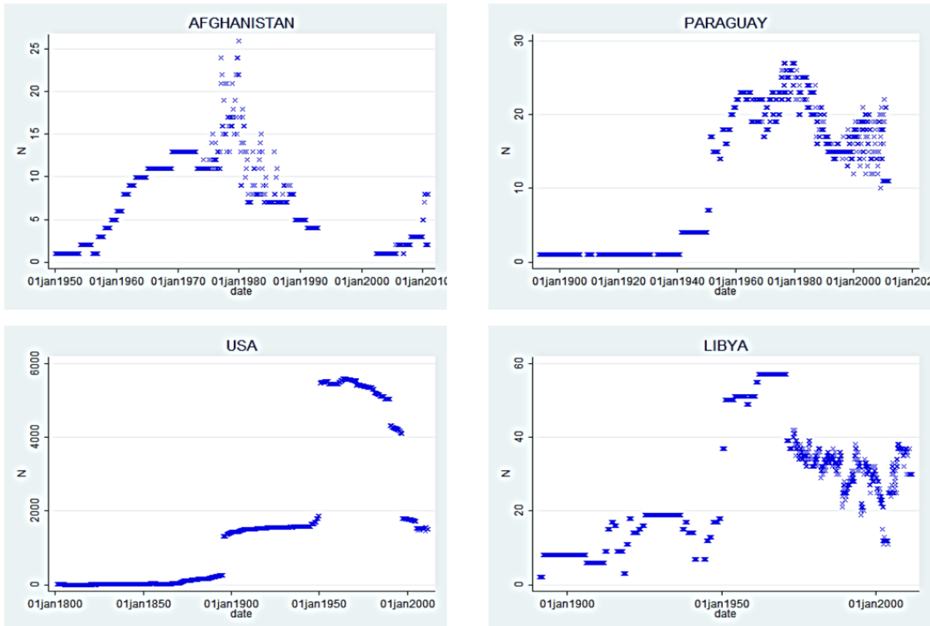

Figure 3: The number of weather stations for four selected countries.

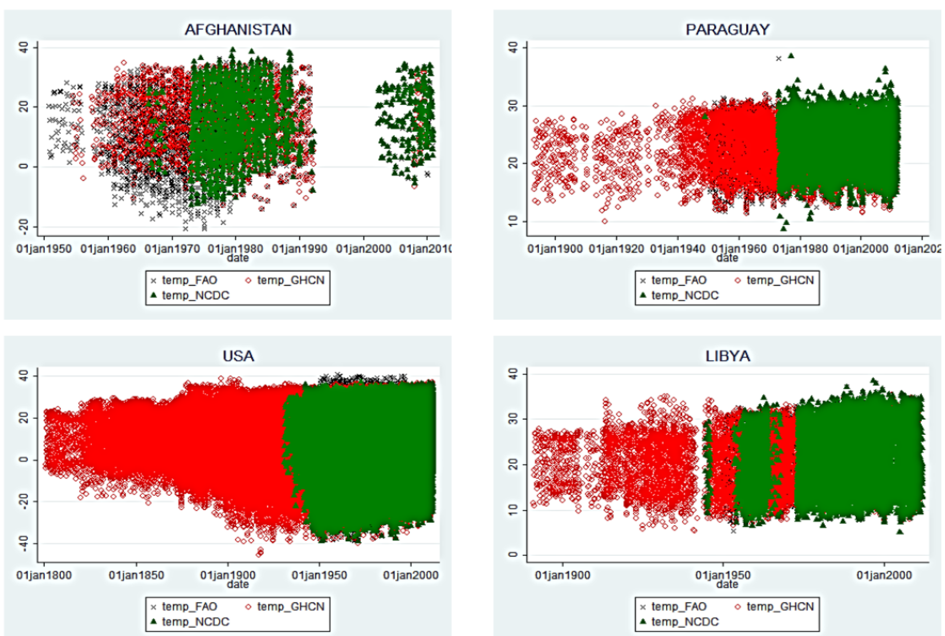

Figure 4: The evolution of average temperature for four selected countries.

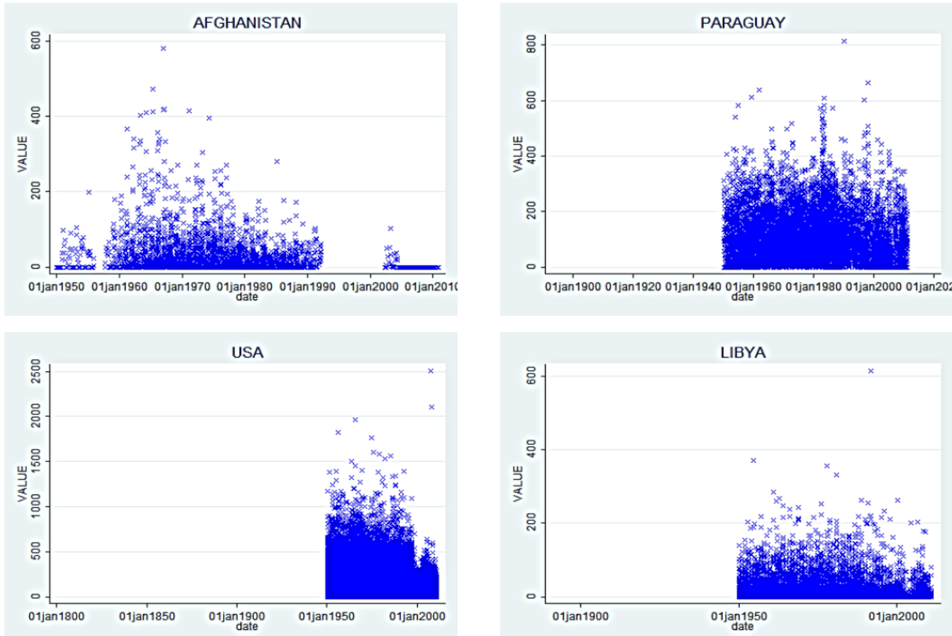

Figure 5: The evolution of average precipitation levels for four selected countries.

longitude as merging variables. Due to some approximation errors, sometimes, *latitude* and *longitude* for the same station differ by hundredth of degree. So, we approximated *latitude* and *longitude* at first decimal digit and merged the stations not merged in the first two steps, using *latitude* and *longitude*, approximated at first decimal digit, as merging variables. At this point, we have a data set with variables described in Table1.

We obtained observations for 229 countries: Afghanistan, Albania, Algeria, Amsterdam Island (Fr), Angola, Anguilla (Uk), Antarctica, Antigua and Barbuda, Argentina, Argentine(Antarctica), Armenia, Aruba, Australia, Austria, Azerbaijan, Bahamas, Bahrain, Bangladesh, Barbados, Belarus, Belau, Belgium, Belize, Benin, Bermuda, Bolivia, Bosnia and Herzegovina, Botswana, Bouvet Island (Norway), Brazil, British Overseas Territories (Uk), Brunei Darussalam, Bulgaria, Burkina Faso, Burundi, Cambodia, Cameroon, Canada, Canary Islands (Sp), Cape Verde, Cayman Islands, Central African Republic, Ceuta (Sp), Chad, Chile, China, Christmas Island (Australia), Cocos Islands (Australia), Colombia, Comoros, Congo, Cook Islands, Coral Sea Islands (Australia), Costa Rica, Cote d'Ivoire, Croatia, Cuba, Cyprus, Czech Republic, Denmark, Detached Islands, Djibouti, Dominican Republic, Ecuador, Egypt, El Salvador, Equatorial Guinea, Eritrea, Estonia, Ethiopia, Falkland Islands Malvinas (Uk), Faroe Islands (Denmark), Federated States of Micronesia, Fiji, Finland, France, French Guiana (Fr), French Polynesia (Fr), Gabon, Gambia, Georgia, Germany, Ghana, Gibraltar, Greece, Greenland (Denmark), Grenada, Guadeloupe (Fr), Guatemala, Guinea Bissau, Guyana, Haiti, Honduras, Hungary, Iceland, India, Indonesia, Iran, Iraq, Ireland, Israel, Italy, Jamaica, Japan, Jordan, Kazakhstan, Kenya, Kiribati, Kuwait, Kyrgyzstan, Laos, Latvia, Lebanon, Lesotho,

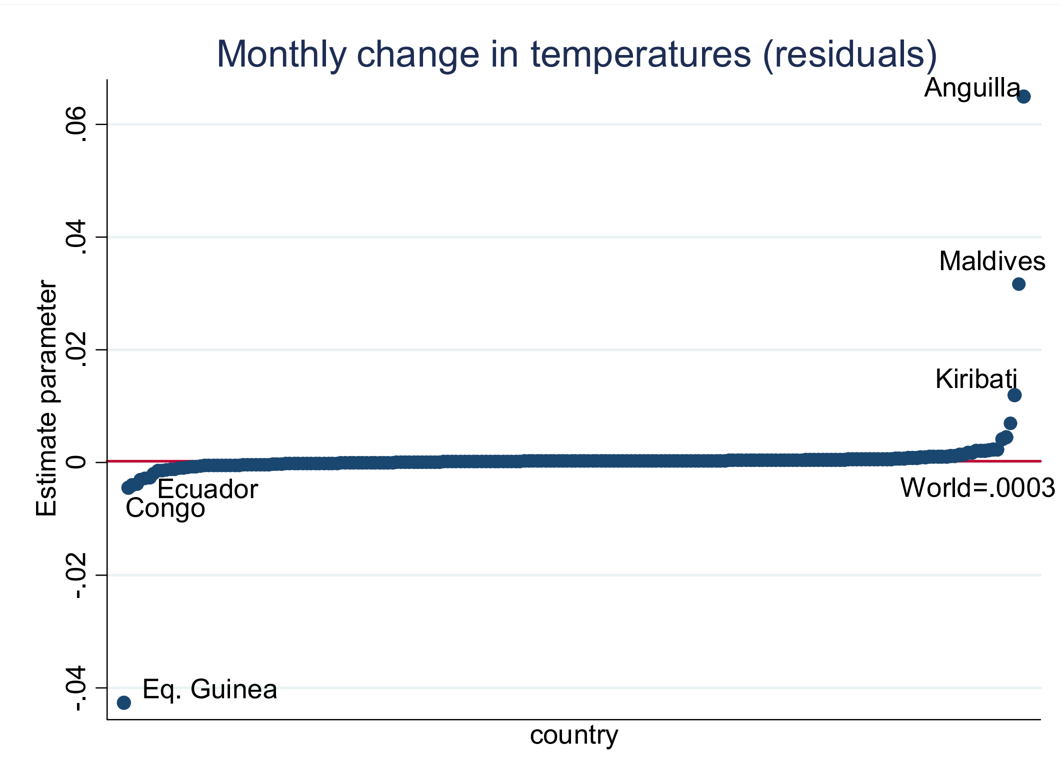

Figure 6: The time trend in residual temperature.

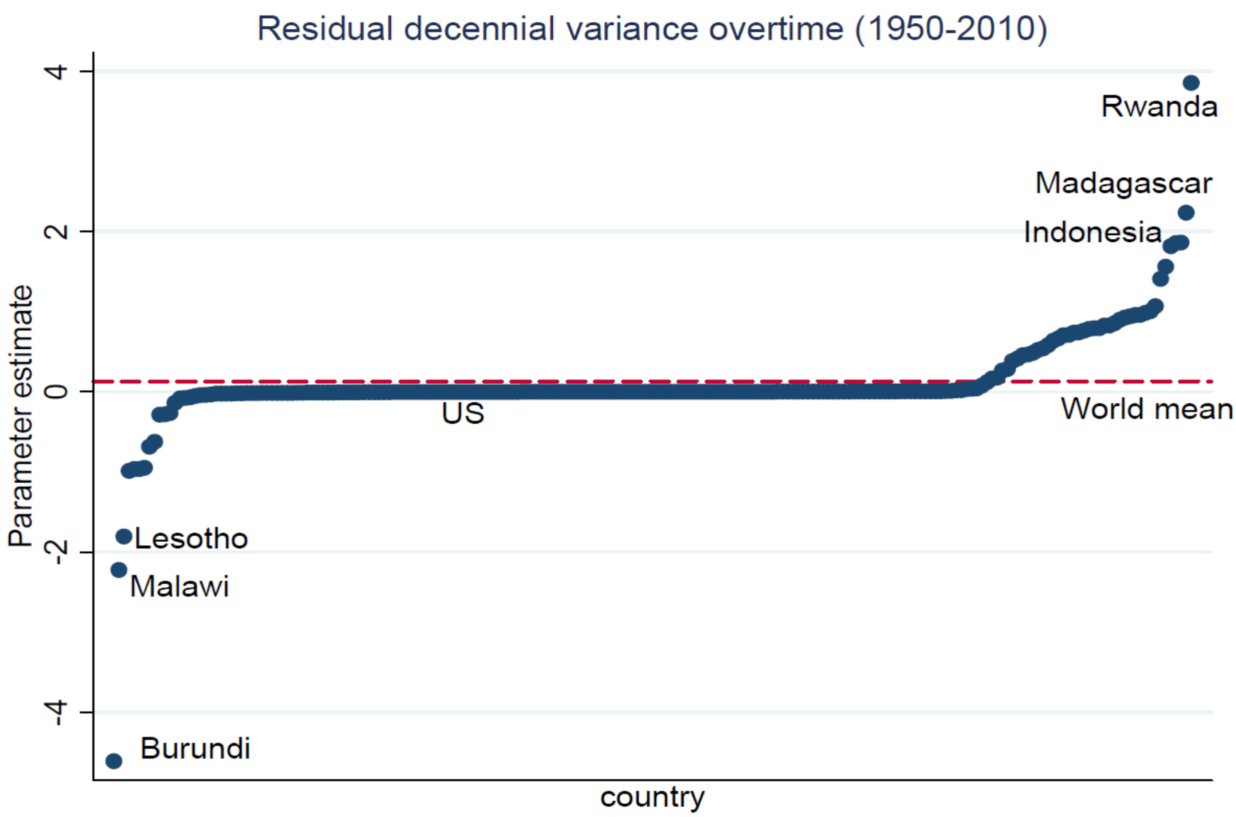

Figure 7: The time trend in residual temperature volatility.

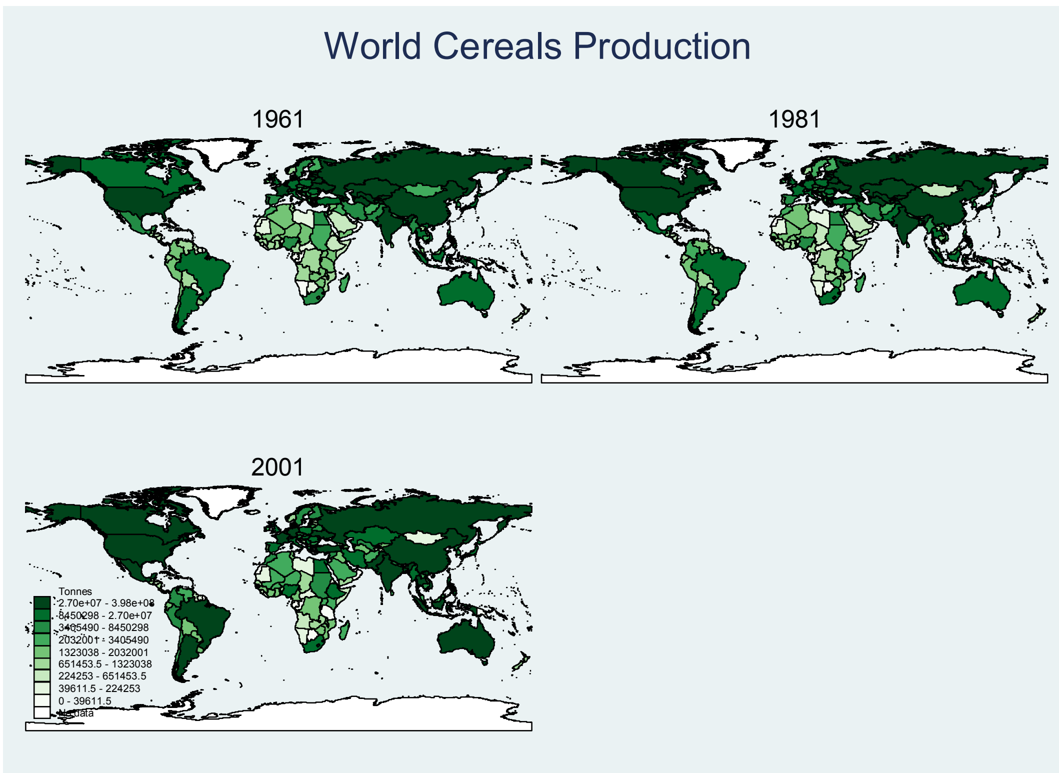

Figure 8: Cereals production over time and space.

Liberia, Libya, Liechtenstein, Lithuania, Luxembourg, Macau (Portugal), Macedonia, Madagascar, Madeira Islands (Portugal), Malawi, Malaysia, Maldives, Mali, Malta, Marshall Islands, Martinique (Fr), Mauritania, Mauritius, Mayotte (Fr), Mexico, Moldova, Mongolia, Montenegro, Morocco, Mozambique, Myanmar, Namibia, Nauru, Nepal, Netherlands, Antilles(Netherlands), New Caledonia (Fr), New Zealand, Nicaragua, Niger, Nigeria, Niue (New Zealand), Norfolk Island (Australia), North Korea, Norway, Oman, Pacific Islands, Pakistan, Panama, Papua New Guinea, Paraguay, Peru, Philippines, Poland, Portugal, Puerto Rico, Qatar, Reunion Island (Fr), Romania, Russian Federation, Rwanda, Saint Kitts and Nevis, Saint Pierre and Miquelon Island (Fr), Samoa, Sao Tome and Principe, Saudi Arabia, Senegal, Serbia and Montenegro, Seychelles, Ship Stations, Sierra Leone, Singapore, Slovakia, Slovenia, Solomon Islands, Somalia, South Africa, South Korea, Spain, Sri Lanka, Saint Lucia, Saint Vincent and Grenadines, Sudan, Suriname, Swaziland, Sweden, Switzerland, Syria, Taiwan, Tajikistan, Tanzania, French Territories d'Outremar, Thailand, Timor Leste, Togo, Tokelau, Tonga, Trinidad and Tobago, Tromelin Island (Fr), Tunisia, Turkey, Turkmenistan, Tuvalu, Uganda, Ukraine, United Arab Emirates, United Kingdom, United States of America, Uruguay, Uzbekistan, Vanuatu, Venezuela, Vietnam, Virgin Islands (Uk), Wallis and Futuna (Fr), Western Sahara (Morocco), Yemen, Zaire, Zambia and Zimbabwe. However, for some of these countries, due to their small dimensions, no or very few observations were available, so we decided to drop them. The final sample is made of 157 countries: Afghanistan, Albania, Algeria, Angola, Argentina, Armenia, Australia, Austria, Azerbaijan, Bahrain, Bangladesh, Belgium, Belize, Benin, Bolivia, Bosnia and Herzegovina, Botswana, Brazil, Brunei Darussalam, Bulgaria, Burkina Faso, Burundi, Cambodia, Cameroon, Canada, Central African Republic, Chad, Chile, China, Colombia, Congo, Costa Rica, Cote d'Ivoire, Croatia, Cuba, Czech Republic, Denmark, Djibouti, Dominican Republic, Ecuador, Egypt, El Salvador, Equatorial Guinea, Eritrea, Estonia, Ethiopia, Finland, France, Gabon, Gambia, Georgia, Germany, Ghana, Greece, Guatemala, Guinea Bissau, Guyana, Haiti, Honduras, Hungary, Iceland, India, Indonesia, Iran, Iraq, Ireland, Israel, Italy, Jamaica, Japan, Jordan, Kazakhstan, Kenya, Kiribati, Kuwait, Kyrgyzstan, Laos, Latvia, Lebanon, Lesotho, Liberia, Libya, Liechtenstein, Lithuania, Luxembourg, Macedonia, Madagascar, Malawi, Malaysia, Mali, Mauritania, Mexico, Moldova, Mongolia, Montenegro, Morocco, Mozambique, Myanmar, Namibia, Nepal, Netherlands, New Zealand, Nicaragua, Niger, Nigeria, North Korea, Norway, Oman, Pacific Islands, Pakistan, Panama, Papua New Guinea, Paraguay, Peru, Philippines, Poland, Portugal, Puerto Rico, Qatar, Romania, Russian Federation, Rwanda, Saudi Arabia, Senegal, Serbia and Montenegro, Sierra Leone, Singapore, Slovakia, Slovenia, Somalia, South Africa, South Korea, Spain, Sudan, Suriname, Swaziland, Sweden, Switzerland, Syria, Taiwan, Tajikistan, Tanzania, Thailand, Togo, Tunisia, Turkey, Turkmenistan, Uganda, Ukraine, United Arab Emirates, United Kingdom, United States of America, Uruguay, Uzbekistan, Venezuela, Vietnam, Western Sahara (Morocco), Yemen, Zaire, Zambia and Zimbabwe.

We assigned a country identifier, called *id_ country*, in alphabetical order, within the same country, we assigned a station identifier, called *id_ lat_ lon*, using latitude and longitude.

A.2 Data sources: Crop data

Table 6: Alphabetic List of FAO Crops with Classification (NES: not elsewhere specified)

Item Name	Classification	Item Name	Classification	Item Name	Classification
Agave Fibres (NES)	Fibres	Fruit tropical fresh (NES)	Fresh Fruit	Pepper (Piper spp.)	Spices
Almonds, with shell	Nuts	Garlic	Legumes	Peppermint	Fibres
Anise etc	Spices	Ginger	Spices	Persimmons	Fresh Fruit
Apples	Stone fruit	Gooseberries	Berries	Pigeon peas	Pulses
Apricots	Stone fruit	Grapefruit (inc. pomelos)	Citrus fruit	Pineapples	Fresh Fruit
Arecanuts	Nuts	Grapes	Fresh Fruit	Pistachios	Nuts
Artichokes	Legumes	Groundnuts, with shell	Oil Seeds	Plantains	Citrus fruit
Asparagus	Legumes	Gums Natural	Fibres	Plums and sloes	Stone fruit
Avocados	Fresh Fruit	Hazelnuts, with shell	Nuts	Pome fruit (NES)	Stone fruit
Bambara beans	Pulses	Hemp Tow Waste	Fibres	Popcorn	Cereals
Bananas	Citrus fruit	Hempseed	Oil Seeds	Poppy seed	Oil Seeds
Barley	Cereals	Hops	Spices	Potatoes	Roots and Tubers
Beans, dry	Pulses	Jojoba Seeds	Oil Seeds	Pulses (NES)	Pulses
Beans, green	Legumes	Jute	Fibres	Pumpkins, squash	Legumes
Berries (NES)	Berries	Kapok Fibre	Fibres	Pyrethrum, Dried	Fibres
Blueberries	Berries	Kapok Fruit	Oil Seeds	Quinces	Stone fruit
Brazil nuts, with shell	Nuts	Kapokseed in Shell	Oil Seeds	Quinoa	Cereals
Beans	Pulses	Karite Nuts (Sheanuts)	Oil Seeds	Ramie	Fibres
Buckwheat	Cereals	Kiwi fruit	Fresh Fruit	Rapeseed	Oil Seeds
Cabbages	Legumes	Kolanuts	Nuts	Raspberries	Berries
Canary seed	Cereals	Leeks	Legumes	Rice, paddy	Cereals
Carobs	Vegs fresh	Legumes (NES)	Legumes	Roots/Tubers (NES)	Roots and Tubers
Carrots and turnips	Vegs fresh	Lemons and limes	Citrus fruit	Rye	Cereals
Cashew nuts	Nuts	Lentils	Pulses	Saffl ower seed	Oil Seeds
Cashewapple	Fresh Fruit	Lettuce and chicory	Legumes	Seed cotton	Oil Seeds
Cassava	Roots and Tubers	Linseed	Oil Seeds	Sesame seed	Oil Seeds
Cassava leaves	Legumes	Lupins	Pulses	Sisal	Fibres
Castor oil seed	Oil Seeds	Maize	Cereals	Sorghum	Cereals
Cauliflowers and broccoli	Legumes	Maize, green	Vegs fresh	Sour cherries	Stone fruit
Cereals (NES)	Cereals	Mangoes, guavas	Fresh Fruit	Soybeans	Oil Seeds
Cherries	Stone fruit	Manila Fibre (Abaca)	Fibres	Spices (NES)	Spices
Chestnuts	Nuts	Mate	Spices	Spinach	Legumes
Chick peas	Pulses	Melonseed	Oil Seeds	Stone fruit (NES)	Stone fruit
Chicory roots	Vegs fresh	Millet	Cereals	Strawberries	Berries
Chillies/peppers, dry	Spices	Mixed grain	Cereals	String beans	Vegs fresh
Chillies/peppers, green	Legumes	Mushrooms and truffl es	Vegs fresh	Sugar beet	Sugar cane
Cinnamon	Spices	Mustard seed	Oil Seeds	Sugar cane	Sugar cane
Citrus fruit (NES)	Citrus fruit	Natural rubber	Fibres	Sugar crops (NES)	Sugar cane
Cloves	Spices	Nutmeg, mace, cardamoms	Spices	Sunflower seed	Oil Seeds
Cocoa beans	Spices	Nuts (NES)	Nuts	Sweet potatoes	Roots and Tubers
Coconuts	Oil Seeds	Oil palm fruit	Oil Seeds	Tallowtree Seeds	Oil Seeds
Coffee, green	Spices	Oilseeds (NES)	Oil Seeds	Tangerines, mandarins	Citrus fruit
Coir	Fibres	Okra	Vegs fresh	Taro (cocoyam)	Roots and Tubers
Cotton lint	Fibres	Olives	Oil Seeds	Tea	Spices
Cottonseed	Oil Seeds	Onions	Legumes	Tobacco	Fibres
Cow peas, dry	Pulses	Onions, dry	Legumes	Tomatoes	Legumes
Cranberries	Berries	Oranges	Citrus fruit	Triticale	Cereals
Cucumbers	Legumes	Other Bastfibres	Fibres	Tung Nuts	Oil Seeds
Currants	Berries	Other melons	Fresh Fruit	Vanilla	Spices
Dates	Fresh Fruit	Palm kernels	Oil Seeds	Vegs fresh (NES)	Vegs fresh
Eggplants	Legumes	Palm oil	Oil Seeds	Vetches	Pulses
Fibre Crops (NES)	Fibres	Papayas	Fresh Fruit	Walnuts	Nuts
Figs	Fresh Fruit	Peaches/nectarines	Stone fruit	Watermelons	Fresh Fruit
Flax fibre	Fibres	Pears	Stone fruit	Wheat	Cereals
Fonio	Cereals	Peas, dry	Pulses	Yams	Roots and Tubers
Fruit Fresh (NES)	Fresh Fruit	Peas, green	Legumes	Yautia (cocoyam)	Roots and Tubers

The International Growth Centre (IGC) aims to promote sustainable growth in developing countries by providing demand-led policy advice based on frontier research.

Find out more about
our work on our website
www.theigc.org

For media or communications
enquiries, please contact
mail@theigc.org

Subscribe to our newsletter
and topic updates
www.theigc.org/newsletter

Follow us on Twitter
@the_igc

Contact us
International Growth Centre,
London School of Economic
and Political Science,
Houghton Street,
London WC2A 2AE

International Growth Centre

DIRECTED BY

FUNDED BY

Designed by soapbox.co.uk