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Screening and Selecting Climate Change Impact Parameters as Potential Drivers of Migration

Focusing over the time period: 1975 to 2015

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Abstract

The current report is focused on a technical screening and selecting exercise of climate/weather parameters and indices to be used in a bigger JRC Project on Climate Change Induced Migration (CLICIM). The main aim of the current exercise is to select among several tenths of variables and data sets, the ones that could be potentially influence directly or indirectly drivers of migration. Besides the mainstream climate change impact parameters such as temperature, wind, humidity, clouds and precipitation, we consider an extensive set of climate/weather extreme indices that could shed light on the possible relationships between environmental degradation parameters and induced migration.

In total we examine closely ninety five parameters and indices assessing their temporal and geographical coverage and relevance on the basis of the most recent climate change and migration literature before proceeding to the final selection of thirty seven meteorological parameters and extreme climate/weather indices. The report describes the data availability for each parameter and index, limitations and capabilities in terms of coverage and spatial and temporal detail and provides references on the use of the variable mainly in the context of migration studies. Such empirical evidence has been considered as the primary criterion for selecting parameters and indices potentially influencing drivers of migration. Other criteria guiding our selection have been the technical suitability in respect of the main population and net migration data already assembled during the initial phase of the CLICIM Project.

This report will be followed by a similar screening exercise focusing on agriculture and water scarcity indices. In the final steps of CLICIM, the full set of the indices documented in these two screening reports will be put in relation with population and net migration data at high spatial resolution and utilised in statistical models exploring potential links between climate change impacts and induced migration.

1 Introduction

According to the Intergovernmental Panel on Climate Change's latest Report on Climate Change and Land (IPCC, 2019), climate change can lead to land degradation, even with the implementation of measures intended to avoid, reduce or reverse land degradation (high confidence). Such limits to adaptation are dynamic, site-specific and are determined through the interaction of biophysical changes with social and institutional conditions (very high confidence). In some situations, exceeding the limits of adaptation can trigger escalating losses or result in undesirable transformational changes (medium confidence) such as forced migration (low confidence), conflicts (low confidence) or poverty (medium confidence).

Consequently, it has been realised that the physical effects of climate change have environmental, socioeconomic, and political consequences that can augment one another. An obvious example would be the increasing frequency of heat waves combined with drought events influencing the water availability and agricultural productivity. Such "compound" events could increase the agricultural income risk affecting directly the decision of people to migrate.

Heat waves and droughts are treated as climate/weather extreme events and are considered of great importance within our study. This is due to the fact that the two main characteristics of climate events found in the centre of climate change impact models covering a wide range of sectors, are the mean (average) climate and the presence and frequency of extreme events as noted by Dosio (2016). It is also known that even a relatively small change in the frequency or intensity of extreme climate/weather events especially for those laying in the tails of the probability distribution function could have significant impacts on people's lives and environmental assets.

The current report has been the third report of the JRC's CLICIM (Climate Change Induced Migration) Project following reports on the new net migration grid (Alessandrini et al., 2020a) and on the potential relationship between population, migration and climate change in Sahel (Alessandrini et al., 2020b).

The CLICIM (Climate Change Induced Migration) Project of JRC.

The scope of CLICIM is to identify the relationship between climate change and migration in Africa, the most affected continent by environmental and demographic factors. As initial steps, the CLICIM Project has produced estimates of net migration at high resolution (Alessandrini et al., 2020a), an analysis of the potential relationship between population, migration and climate change in Sahel (Alessandrini et al., 2020b) and an extensive review of several climate/weather extreme indicators (current Report).

The knowledge stemming from the CLICIM Project will feed into the final and complex step of formulating scenarios on how many populations will be exposed and eventually move due to climate change.

This would give insights to policy debate on where the combined effects between local demographic patterns and contextual climatic factors would increase populations' vulnerability requiring the urgent definition of tailored policy intervention.

Alessandrini et al. (2020a) report provides global estimates of 8 five-year net migration (snapshots) from 1975 to 2015 at a spatial resolution of 0.25 degrees that constitutes a new high-resolution Net Migration Grid (NMG) using demographic indirect estimation techniques based on population data from the JRC's Global Human Settlement Layer (GHSL).

On the other hand, Alessandrini et al. (2020b) report provides an analysis of the potential relationship between population, migration and climate change in a selected territory within the Sahel (Western Africa) that is an already known case of climate migration.

During the next steps of the CLICIM Project, ascertain trends and correlations between potential climate drivers and the new global NMG (Net Migration Grid) are to be investigated. Accordingly all potential climatic indices and parameters should be compiled/adapted on a global gridded format as well corresponding to the full-time range of NMG snapshots covering the time interval from 1975 to 2015.

For such a task historical climate/weather raw observation sets are not the optimal choice since they do not refer to a regular global grid. Instead, global gridded fields of historical environmental parameters could be used in the form of reanalyses (historical snapshots of the earth's surface and atmospheric parameters).

Reanalyses are created via unchanging ('frozen model physics') data assimilation schemes and models that compile all available observations every 6 to 12 hours over the time reference period (days, months or years). Such dynamical consistent frameworks (reanalyses) are capable of providing estimates of the climate state at each time step (usually every 6 hours).

The main advantage of reanalysis is the fact that it provides a global data set with consistent spatial and temporal resolution sometimes longer than three (3) decades containing in most cases hundreds of variables, with some of them influencing drivers for migration as documented in Foresight (2011), Kumari et al. (2018). On the other hand, the main disadvantage of reanalysis refers to observational constrains and therefore reanalysis reliability can considerably vary depending on the location, time period, and variable considered.

The list of the main available global reanalysis sets can be found in NCAR/UCAR's site[1]. Most of reanalyses initiate from 1979, the year around that meteorological satellites started to become operational resulting in many more observations of the atmosphere and particularly the ocean to be available from the satellites than had been available before. So, starting from 1979 results in a more consistent 'climate' in a reanalyses. This is the reason why most of reanalysis data sets initiate from 1979 and they are usually considered as higher-quality analyses. The rest that could even initiate from the beginning of the 20th Century comprise relatively low-resolution data sets (of lower quality).

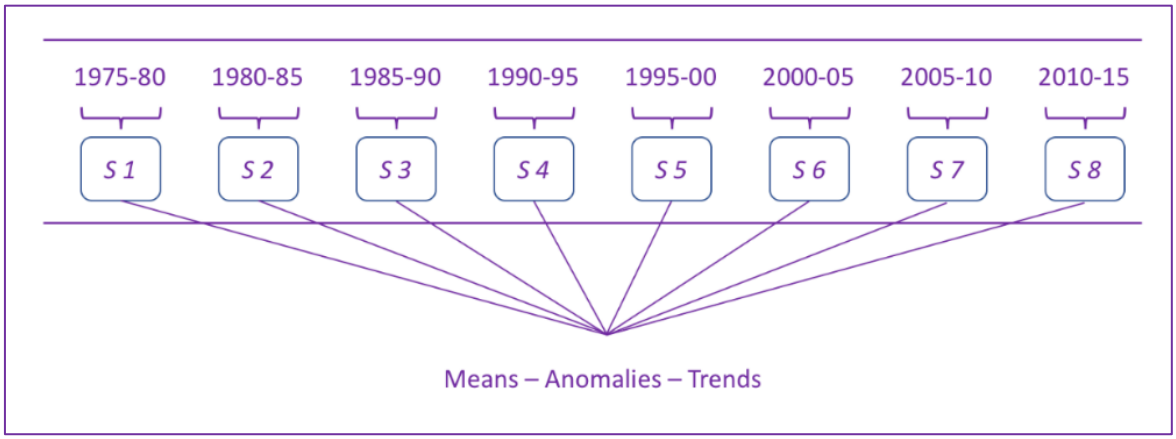
In the beginning of our investigation, emphasis had been given in Copernicus ECMWF ERA-Interim[2] and ECMWF ERA-5[3] reanalysis data although their obvious limitation of not covering the time period before 1979 resulted in the search and utilisation of another set of historical climate data as the Terrestrial Air Temperature (TAT) Gridded Monthly Time Series (Version 5.01) and the Terrestrial Precipitation (TP) Gridded Monthly Time Series (Version 5.01) of the University of Delaware covering the time interval from 1900 to 2017 (Willmott and Matsuura 2001). Consequently, the initial sets of both ERA-Interim and ERA-5 data have been frequently used for cross validation of temperature (TAT) and precipitation (TP) parameters over the common period from 1979 to 2015.

[1] https://climatedataguide.ucar.edu/climate-data/atmospheric-reanalysis-overview-comparison-tables
[2] https://www.ecmwf.int/en/forecasts/datasets/reanalysis-datasets/era-interim
[3] https://www.ecmwf.int/en/forecasts/datasets/reanalysis-datasets/era5

Referring to the selected TAT and TP data sets, these have been compiled as monthly averages of station air temperature (T) and precipitation (P) fitted in a grid of 0.5 x 0.5-degree latitude/longitude resolution with grid nodes to be cantered on the 0.25 degree. For our needs, values referring to years from 1974 to 2016 have being retrieved for compiling 5-year means, trends and anomalies covering the full set of eight (8) snapshots of NMG (global grid) from 1975 to 2015 as shown in Figure 1. The two extra years (1974 and 2016) are necessary for the estimation of trends.

Besides studying mainstream variables as temperature and precipitation in their monthly formulation, the need of better understanding and assessing the impact of extreme weather events to net migration is pointing to the actually variability of such (extreme) events as documented in Mistry (2019a). That is why, metrics like CEIs (Climate Extreme Indices) are important not only for the analysis of regional and global weather extremes but also to help modellers and policymakers in the assessment of sectoral and regional impacts. For defining such appropriate climate extreme indicators, the Expert Team[4] on Climate Change Detection and Indices (ETCCDI) of WMO took the initiative to investigate over a set of climate extreme indices (CEIs) in 1999 that could provide a comprehensive overview of temperature and precipitation statistics as noted by Donat et al. (2013a, 2013b), Sillmann et al. (2013a, 2013b).

Figure 1. Five-year time interval snapshots of NMG (New Migration Grid) over 1975 to 2015 schematic setup for estimating 5-year means, anomalies and trends of potential climate drivers.



As a result, the ETCCDI managed to compile a preliminary set of "core" climate indices comprising 27 extreme indices for moderate weather extremes (Alexander et al., 2006, Zahng et al., 2011). Due to the limitations (restricted scope/usage in assessing sectoral impacts) of this initial 27-member ETCCDI indices, additional (new) sector-relevant indices were recommended and developed by the Expert Team on Sector-specific Climate Extreme Indices. Details on the new indices can be found in the User Guide of the CLIMPACT2 R statistical package[5].

Within the CLICIM Project besides the mainstream parameters as the temperature (TAT) and precipitation (TP) we aim to examine the full extended set of available CEIs (including the original 27

[4] https://www.wcrpclimate.org/etccdi
[5] https://htmlpreview.github.io/?https://raw.githubusercontent.com/ARCCSS-extremes/climpact2/master/user_guide/ClimPACT2_user_guide.htm

ETCCDI core indices) by retrieving the relevant open-access high-resolution global gridded datasets of covering the period 1975-2015 (Mistry 2019a, 2019b).

In the current phase, 35 selected indices of CEI data have being used for compiling 5-year means, anomalies and trends in harmony with NMG snapshots being similar to TAT and TP estimates (means / anomalies / trends). The characteristics of the two mainstream parameters TAT and TP (places 01 to 02) and the selected 35 extreme indices (places 03 to 37) can be seen at Table A1.1 (Annex 1).

As already mentioned, the selected climatic variables (Table A1.1) that could be influencing potential migration drivers should be also harmonised in a global gridded format of 0.25-degree resolution covering the interval from 1975 to 2015. Mainstream parameters (TAT and TP) have been retrieved in their relatively lower (raw) resolution (0.5 x 0.5-degrees) whereas CEIs have been retrieved in their (raw) higher resolution at 0.25 x 0.25-degrees. Consequently, for both TAT and TP parameters, an appropriate conversion (adaptation) to 0.25 x 0.25-degree grid had to be applied for harmonisation to the NMG global grid. A similar adaptation for CEIs (Climate Extreme Indices) initially in netCDF format had to take place for harmonization to the exact 0.25 x 0.25-degree grid of NMG.

During the next steps of CLICIM additional mainstream parameters and the full set of extreme climate/weather indices documented so far are to be utilised for extending and complementing our study. In addition, new sector-specific parameters and indices are to be screened. The next two sectors to be investigated within the CLICIM Project are the agriculture and water sectors.

For the agricultural sector needs (i.e., historical simulations and future projections) data from both the Inter-Sectoral Impact Model Inter-comparison Project[6] (Warszawski, et al., 2013, Frieler et al., 2017) and Agricultural Model Inter-comparison and Improvement Project[7] (Rosenzweig et al., 2007, 2013, 2014, 2018, Ruane et al., 2014, 2018, McDermid et al., 2015) have been already retrieved and stored (with an estimated volume of about 10 TB) in JRC's Big Data System JEODPP[8] (JRC Earth Observation Data and Processing Platform) for further investigation and processing.

The characteristics of the mainstream TAT and TP parameters are presented in Section 2, whereas Section 3 contains the description of the main climate/weather extreme parameters. Section 4 contains the description of extreme indices for both heat and cold waves. The main characteristics of the drought and degree days extreme indices are presented in Section 5 and Section 6 respectively. Section 7 contains conclusions and a handy summary table of the selected variables to help the (time-pressed) reader to quickly grasp the contents of the Report.

[6] https://www.isimip.org/
[7] https://agmip.org/
[8] https://jeodpp.jrc.ec.europa.eu/home/

2 Mainstream climate change parameters – Temperature and precipitation

Of all of the environmental factors, temperature and precipitation appear to have the most significant effect on migration as noted in Semenza and Ebi (2019). It appears that there are multiple channels through which temperature and precipitation can influence population behaviours. As documented by Cai et al. (2016), of all underlying factors that connect migration and climate change, the most important interlinkage is the agricultural productivity (most probably in a nonlinear manner).

On a more general perspective, Bohra-Mishra et al. (2014) have demonstrated the correlation between climate change and outmigration. Although precipitation plays an important role, the increase in temperature seems to have its own distinct effect. In particular, temperature has a nonlinear effect on migration such that above 25°C, a rise in temperature is related to an increase in outmigration, potentially through its impact on economic conditions.

On the other hand, both the decrease (linked to drought events) or increase (linked to floods) of rainfall may enhance migration in an area of interest. Though precipitation also has a similar nonlinear effect on migration, the effect is smaller than that of temperature. It appears that sudden, serious catastrophes mainly driven by extreme precipitation events demonstrate lower permanent migration flows compared to the gradual effects of climate change mostly driven by temperature increase. Communities are uprooted due to a flood event, but they tend to return on permanent basis.

2.1 Temperature

Temperature appears to be one of most significant parameters of affecting people to migrate especially during slow-onset shocks, such as persisting extreme temperatures or droughts. In such slow-onset mode, migration can be induced, possibly by allowing households more time to gather the resources required to migrate as documented in Nawrotzki and DeWaard (2016, 2018).

Cattaneo and Peri (2015), provide a crucial insight on the effect that rising temperature have, by impoverishing rural populations and worsening their income perspectives. Long-term warming affects migration in different ways, depending on the initial income of those rural populations. It should be noted that a decline in agricultural productivity, causing a decline in rural income, seems to have a depressing effect on the possibility of emigrating in extremely poor countries. In such poor countries, where individuals usually live on subsistence income, as lower income worsens their liquidity constraint, potential migrants have a reduced ability to pay for migration costs and to afford travel and relocation costs. In this case, climate change may trap rural populations in local poverty (Peri and Sasahara, 2019).

In contrast, in countries where individuals are not extremely poor, a decline in agricultural income strengthens the incentives to migrate to cities or abroad. A possible decrease in agricultural productivity may initiate a mechanism that ultimately leads to economic success of migrants, since they could benefit their country of origin (by remittances sent home from workers residing abroad) and shifting people out of agriculture into urban environments as noted by Cai et al. (2016).

2.1.1 Datasets of temperature historical values

For reasons of including all eight (8) snapshots of net migration (NMG) in the highest possible resolution the data set of Terrestrial Air Temperature (TAT) Gridded Monthly Time Series (Version 5.01) of University of Delaware covering the time interval from 1900 to 2017 has been considered. The main characteristics of TAT are documented in Willmott and Matsuura (2001).

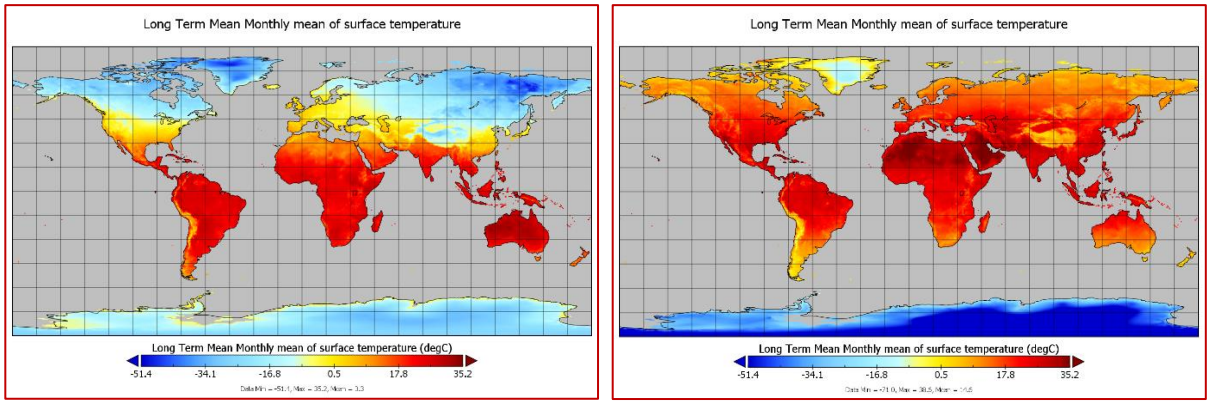
The TAT data set is somehow different from a typical set of reanalysis since it has been compiled based rather on station data, resulting in weather station-monthly-mean air temperature values from several updated sources. Sources include a recent version of the Global Historical Climatology Network Monthly (GHCNM) Version 3 (GHCN3) dataset, the Daily Global Historical Climatology Network (GHCN-Daily) archive, the Atmospheric Environment Service/Environment Canada archive, records of the State Hydrometeorological Institute, St. Petersburg, Russia, data for Greenland--taken from the GC-Net, records from the Automatic Weather Station Project (courtesy of Charles R. Stearns at the University of Wisconsin-Madison), the Global Synoptic Climatology Network archive (Dataset 9290c, courtesy of National Climatic Data Center) and observations contained within the Global Surface Summary of Day (GSOD).

2.1.2 Limitations and capabilities of Terrestrial Air Temperature Data Set

In TAT data set, monthly averages of station air temperature (T) have been interpolated to a grid of 0.5 x 0.5-degree latitude/longitude resolution with grid nodes to be cantered on the 0.25 degree. The gridded fields have been estimated from monthly station averages using a combination of spatial interpolation methods: digital-elevation-model (DEM) assisted interpolation (Willmott and Matsuura, 1995), traditional interpolation (Willmott et al., 1985) and Climatologically Aided Interpolation (CAI) as documented by Willmott and Robeson (1995).

It should be kept in mind that using a relatively high-resolution climatology also can increase the accuracy of spatially interpolated time series of monthly climate variables. Employing CAI (Climatologically Aided Interpolation), a monthly T at each time-series station has been differenced from a climatologically averaged T for that month which was available at or was interpolated to the time-series station location. Traditional interpolation then has been performed on the station differences to obtain a gridded difference field. Finally, the gridded difference field has been added to the interpolated (DEM-assisted) estimates of the climatology at the same set of grid points.

Figure 2. Long Term Monthly Mean Air Temperature for January (left) & August (right).



For our needs, values referring to years from 1974 to 2016 have being retrieved for compiling 5-year means, trends and anomalies covering the full set of eight (8) snapshots of NMG from 1975 to 2015. The two extra years (1974 and 2016) had to be included for the estimation of trends.

Anomalies have been estimated against mean (average) climate conditions over the time interval spanning from 1981 to 2010. The selection of 1981-2010 has been made since many key remotely sensed datasets begin in the 1970s and it is recommended that, where feasible, the current climatological standard normal period (1981-2010) be used for these datasets to allow comparison among different data forms on a consistent basis as defined by the WMO[9] (World Meteorological Organisation) Report on Guidelines for Climate Normals (WMO, 2017). Figure 2 contains the long term monthly air temperature mean (climate) conditions for January (left panel) and August (right panel) referring to the 1981-2010 climatology basis time period.

2.2 Precipitation

Besides mean (average) temperature and temperature variability (extremes), mean precipitation and precipitation extremes appear to be significant factors that may affect people to migrate. One of the obvious reasons could be the agricultural pathway that relates to findings that temperature and precipitation extremes above certain thresholds are even more harmful for crop yield than average changes as noted by Lobell and Field (2007), Schlenker and Roberts (2009).

From a global perspective, average precipitation seems to be restricted (bounded) by evaporation loosely connected to atmospheric moisture linked to temperature through the so-called Clausius–Clapeyron equation[10], whereas precipitation extremes are much more closely connected to the total water content of the atmosphere. In particular, convective precipitation (precipitation coming from vertical development clouds linked to showers or thunderstorms) contributes to this phenomenon as documented by Berg et al. (2013). It should be stressed that between 1980 and 2010, the number of record-breaking precipitation events per year has significantly increased on the global level as noted in Lehmann et al. (2015).

2.2.1 Datasets of precipitation historical values

As in the case of temperature, in order to include all eight (8) snapshots of net migration in the highest possible resolution the data set of Terrestrial Precipitation (TP) Gridded Monthly Time Series (Version 5.01) of University of Delaware covering the time interval from 1900 to 2017 has been considered. The main characteristics of TP are documented in Willmott and Matsuura (2001).

As in the TAT case, the TP data set is somehow different from a typical set of reanalysis since it has compiled based rather on station data, with emphasis on monthly-total rain gage-measured precipitation (P, mm) that were compiled from several updated sources including a recent version of the Global Historical Climatology Network dataset GHCN2), a version of the Daily Global Historical Climatology Network (GHCN-Daily) as documented by Menne et al. (2012), an Atmospheric

[9] https://community.wmo.int/
[10] https://www.e-education.psu.edu/meteo300/node/584

Environment Service/Environment Canada archive, data from the Hydrometeorological Institute in St. Petersburg, Russia (courtesy of Nikolay Shiklomanov), GC-Net data as documented by Steffen et al. (1996), Greenland station records from the Automatic Weather Station Project (courtesy of Charles R. Stearns at the University of Wisconsin-Madison), daily data for India from the National Center for Atmospheric Research (NCAR), Sharon Nicholsons archive of African precipitation data, South American monthly precipitation station records and daily records from the Global Surface Summary of Day (GSOD).

2.2.2 Limitations and capabilities of Terrestrial Precipitation Data Set

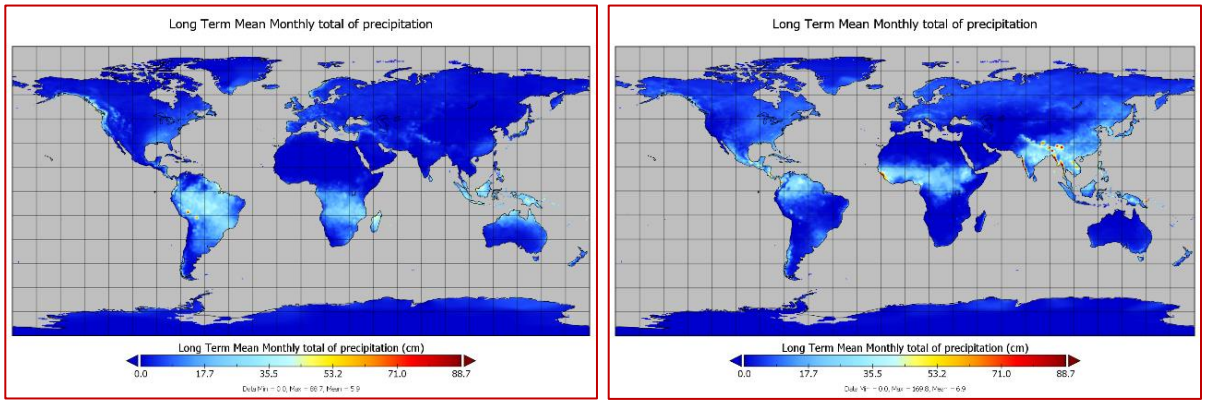
As in the case of TAT, station values of monthly total rain gage-measured precipitation (P) were interpolated to a 0.5 x 0.5-degree latitude/longitude grid, where the grid nodes are cantered on the 0.25 degree. Climatologically Aided Interpolation (CAI) – as documented in Willmott and Robeson (1995) – was used to estimate the monthly total precipitation fields. By using a background climatology based on a relatively dense network of stations, the CAI methodology can increase the accuracy of spatially interpolated time series of monthly climate variables.

For the background climatology, two station climatologies were merged. The first was calculated at those of precipitation time-series stations which had at least ten years of observations for each month. The second was the monthly station P (raw rain gage) climatology of Legates and Willmott (1990). Only those (Legates and Willmott) stations which were not collocated with the first climatology were included in the background climatology for CAI. A monthly P value at each time-series station was differenced from the first climatologically averaged P for that month, which was available at or was interpolated spatially to the time-series station location.

Initial (typical) interpolation (Willmott et al., 1985) then was performed on the monthly station differences to obtain a gridded difference field. Finally, each gridded monthly difference field was added to the gridded estimates of the month's climatology at the corresponding set of grid points.

Traditional interpolation was accomplished with the spherical version of Shepard's algorithm, which employs an enhanced distance-weighting method as noted in Shepard (1968), Willmott et al. (1985). The number of nearby stations that influenced a grid-node estimate was increased to an average of 20, from an average of 7 used in earlier applications.

Figure 3. Long Term Monthly Mean of Precipitation for January (left) & August (right).



For our needs, values referring to years from 1974 to 2016 have being retrieved for compiling 5-year means, trends and anomalies covering the full set of eight (8) snapshots of NMG from 1975 to 2015. The two extra years (1974 and 2016) had to be included for the estimation of trends.

Anomalies have been estimated against mean (average) climate conditions over the time interval spanning from 1981 to 2010 (WMO, 2017) as in the case of air temperature (Section 2.1).

Figure 3 contains the long term monthly precipitation (climate) conditions for January (left panel) and August (right panel) referring to the 1981-2010 climatology basis time period.

3 Main climate extreme indices

As already mentioned, the two main characteristics of climate events that can be found in the centre of impact models covering a wide range of sectors are the mean (average) climate and the presence and frequency of extreme events as noted by Dosio (2016).

This is the reason why besides studying mainstream (climate change) variables as temperature and precipitation in their monthly mean (average) formulation, the need of better understand extreme weather events is pointing to the actually variability of such events as documented in Mistry (2019a, 2019b). It is also known that even a relatively small change in the frequency or intensity of extreme weather events especially for those laying in the tails of the probability distribution function could have significant impacts on life and assets as analysed by Karl et al. (1999).

That is why, metrics like CEIs (Climate Extreme Indices) are important not only for the analysis of regional and global weather extremes but also to help modellers and policymakers in the assessment of sectoral and regional impacts. For defining such appropriate climate extreme indicators, the Expert Team[11] on Climate Change Detection and Indices (ETCCDI) took the initiative in 1999 to compile a set of climate extreme indices (CEIs) that provide a comprehensive overview of temperature and precipitation statistics (Donat et al., 2013a, 2013b, Sillmann et al., 2013a, 2013b).

In the initial phase, the ETCCDI has managed to compile a preliminary set of "core" climate indices comprising 27 extreme indices for moderate weather extremes (Alexander et al., 2006, Zahng et al., 2011). Due to the limitations (restricted scope/usage in assessing sectoral impacts) of this initial 27-member ETCCDI set of indices, additional sector-relevant indices were recommended and developed by the Expert Team on Sector-specific Climate Indices. Details on the new indices can be found in Alexander and Herold – Indices and R Software Package[12].

In this study we are to examine the full set of CEIs (including the original 27 core ETCCDI indices) by retrieving the open-access high-resolution global gridded (at 0.25 × 0.25-degree resolution) datasets referring to the period 1970-2016 as documented in Mistry (2019a, 2019b). These datasets have been used for compiling 5-year mean, anomalies and trends in harmony with the new high-resolution global grid of net migration (NMG).

Based on their nature and characteristics, five (5) categories of indices have been compiled for analysis and further investigation as listed below:

- Extreme indices of temperature (XM-Temperature) in Section 3.1
- Extreme indices of precipitation (XM-Precipitation) in Section 3.2
- Extreme Indices of Heat (XM-Heat) and Cold (XM-Cold) Waves in Section 4
- Extreme indices of Drought (XM-Drought) in Section 5
- Extreme indices of Degree Days (XM-Degree Days) in Section 6

[11] https://www.wcrp-climate.org/etccdi
[12] https://htmlpreview.github.io/?https://raw.githubusercontent.com/ARCCSS-extremes/climpact2/master/user_guide/ClimPACT2_user_guide.htm

3.1 Extreme indices of temperature (XM-Temperature)

The selected indices of XM-Temperature give a comprehensive overview of the simulated changes in temperature extremes across models and historical data. While most indices are defined on an annual basis, a few are also available as monthly statistics or as continuous counts over the total data record. The selection covers both core and non-core climate extreme indices of three types as listed below:

- Absolute type in Section 3.1.1
- Threshold type in Section 3.1.2
- Duration type in Section 3.1.3

3.1.1 Absolute indices of XM-Temperature

The absolute XM-Temperature indices are compiled around the extreme temperature values defined by the minimum and maximum value on a daily basis that is also used for estimating the parameter of DTR (Daily Temperature Range). Table 1 contains the list of absolute indices of XM-Temperature. Indices labelled as "core" type are belonging into the initial 27-member ETCCDI catalogue.

Table 1. List of XM-Temperature (absolute indices).

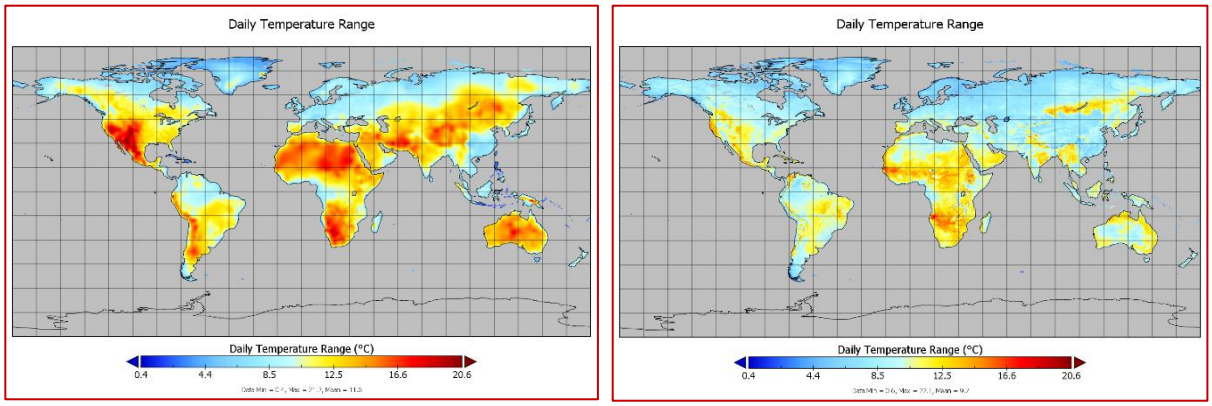
Index	Long Name	Type	Unit
DTR	Daily temperature range	Non-Core	°C
TNM	Mean minimum temperature	Non-Core	°C
TNN	Minimum minimum temperature	Core	°C
TNX	Maximum minimum temperature	Non-Core	°C
TXM	Mean maximum temperature	Non-Core	°C
TXN	Minimum maximum temperature	Non-Core	°C
TXX	Maximum maximum temperature	Core	°C

It should be stressed that all indices in Table 1 have been estimated on a daily basis (not on a monthly basis as in the case of TAT mainstream parameter presented in Section 2.1). Details, characteristics and usage of absolute indices used in this study are given below.

- DTR (Daily Temperature Range)

Changes in the mean temperature of air are considered as a useful indicator of climate change and variability, although changes in daily maximum and minimum temperatures could provide more information than the mean alone. This is because trends in mean air temperature can be due to changes in either maximum or minimum temperature, or relative changes in both (Braganza et al., 2004).

Figure 4. Annual averaged values of Daily Temperature Range (DTR) for 1975 (left) & 2015 (right).



The DTR parameter is defined as the difference between daily maximum and daily minimum of temperature of atmospheric air (measured at 2 meters above the ground). This temperature range (DTR) could be a strong risk factor in some cases even for hospital admissions due to both upper and lower respiratory infections, particularly in elderly individuals (Carreras et al., 2015).

It is noted that climate change refers to a certain and consistent change in the mean state of the climate or its variability (IPCC, 2013). In the case of DTR, a smaller/larger DTR means that people and their livelihoods are exposed to less/more variable temperatures in a 24-hour period that could influence their decision to migrate, since changes in DTR in association with higher temperatures for instance may influence negatively paddy production in tropical areas affecting production variability and people's economic stability (Shrestha et al., 2017).

Selected maps of DTR (Figure 4) for 1975 (initial year) and 2015 (last year of reference in the current report) seem to agree to relevant changes and trends over the last 50 years with DTR values to decrease over most places over the globe as documented by Easterling et al. (1997).

Further, observed air temperature warming has also been associated with relatively larger increases in daily minimum temperatures than in maximum temperatures as documented in Karl et al. (1993), New et al. (2000).

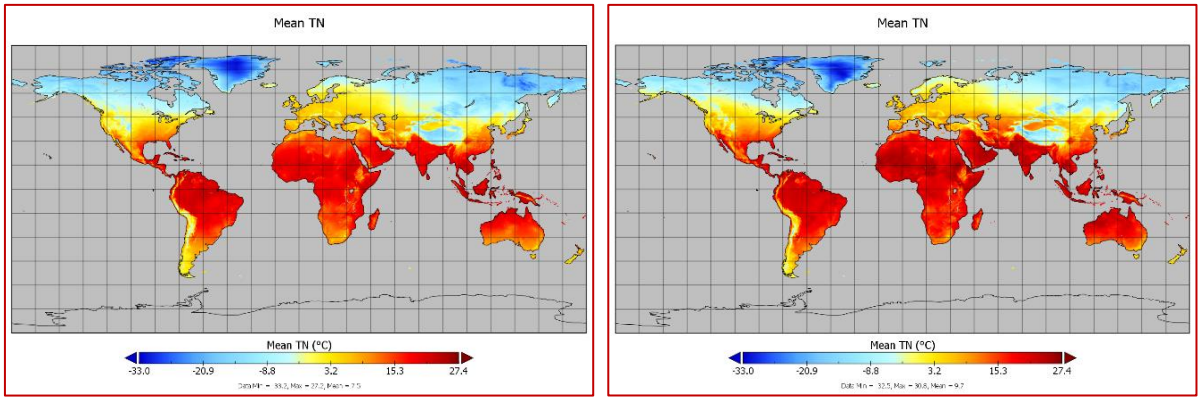
- TNM (Mean minimum temperature) – TNN (Minimum minimum temperature) – TNX (Maximum minimum temperature

Minimum temperature is defined as the lowest value of air temperature during the day usually observed half an hour after the sun rise. Averaging over a month results to the mean monthly minimum value of air temperature.

In this Report, both the annual (1-year) and 5-year mean values of minimum temperature have been estimated by averaging mean monthly values. In a similar way, anomalies and trends of maximum temperature in all available formulations (mean, minimum and maximum) are estimated on a 5-year basis.

Figure 5 contains annual averaged TNM (Mean Minimum Temperature) values for 1975 (left panel) and for 2015 (right panel).

Figure 5. Annual averaged values of daily TNM (Mean Minimum Temperature) for 1975 (left) & 2015 (right).



As mentioned in Section 2, of all environmental factors, temperature and its variability appears to have the most significant effect on migration, since there exist multiple channels through which temperature can influence migration characteristics (Bohra-Mishra et al., 2014).

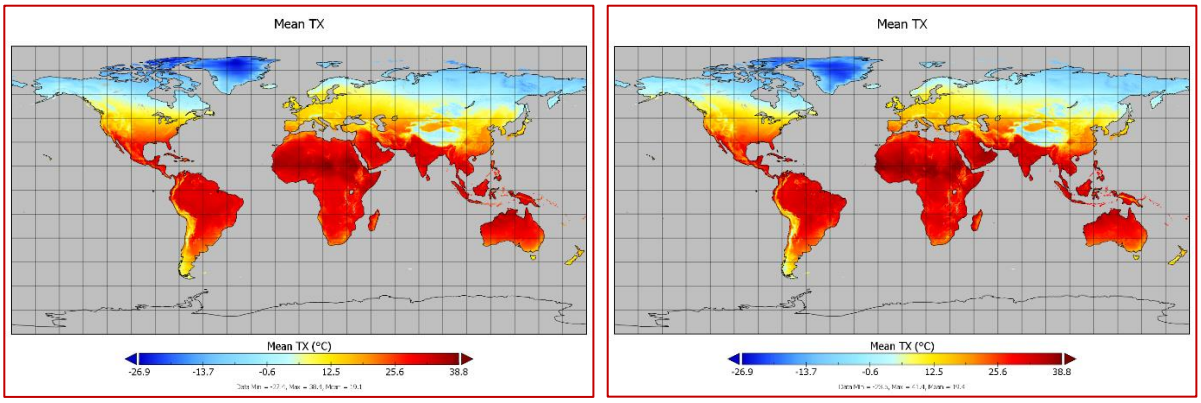
The most obvious channel is the agriculture channel (Cai et al., 2016, Nawrotzki and Bakhtsiyarava, 2016) while numerous studies exist establishing a negative effect of temperature on agriculture productivity. For instance, each 1°C increase in growing-season minimum temperature in the dry season has resulted in 10% decline in rice yield in Philippines (Peng et al., 2004).

- TXM (Mean maximum temperature) – TXN (Minimum maximum temperature) – TXX (Maximum maximum temperature

Maximum temperature is defined as the highest value of air temperature during the day usually observed at late noon hours. Averaging over a month results to the mean monthly maximum value of air temperature.

In this Report, both the annual (1-year) and 5-year mean values of maximum temperature have been estimated by averaging mean monthly values. In a similar way, anomalies and trends of maximum temperature in all available formulations (mean, minimum and maximum) are estimated on a 5-year basis. Figure 6 contains annual averaged values for TXM (Mean Maximum Temperature) for 1975 (left panel) and for 2015 (right panel).

Figure 6. Annual averaged values of daily TXM (Mean Maximum Temperature) for 1975 (left) & 2015 (right).



As in the case of minimum temperature, positive trends of temperature have the most likely negative impact on crop yields (Porter and Gawith, 1999, Ottman et al., 2012, Zhao et al., 2017). Such negative impacts on yields could be act as a push driver for outmigration (Feng et al., 2010). Further, an increase in positive temperature extremes at the origin could also act as a push effect and enhance out-migration (Mastrorillo et al., 2016).

3.1.2 Threshold indices of XM-Temperature

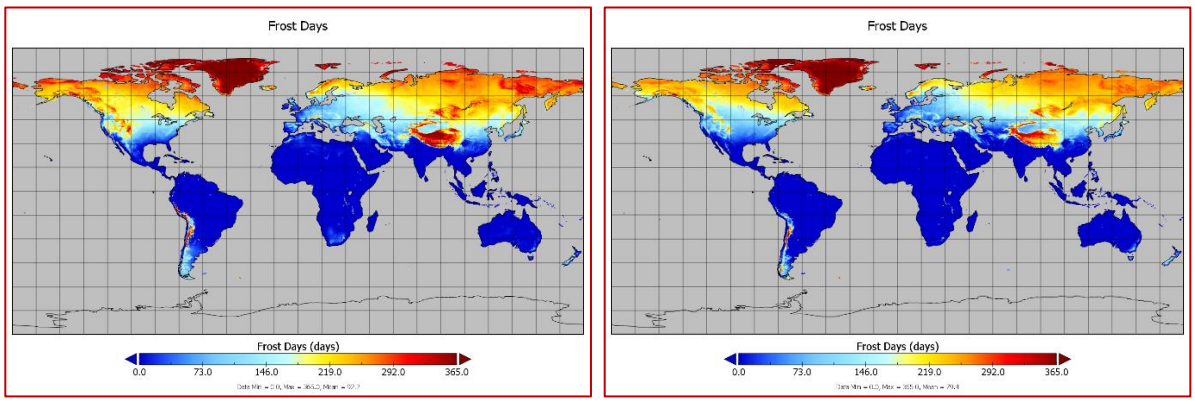
The main characteristics of threshold (XM-Temperature) parameters such as Frost Days (FD), Summer Days (SU) and Tropical Nights (TR) are shown in Table 2. Over the years, FD, SU and TR parameters have proved to be very useful for climate impact studies. Frost days (FD) parameter counts in monthly or annual basis the days with minimum temperature (TN) below 0°C. Summer days (SU) parameter counts the days with daily maximum temperature (TX) higher than 25°C. Same wise, tropical nights (TR) parameter counts the days with minimum temperature higher than 20°C.

Table 2. List of XM-Temperature (threshold indices).

Index	Long Name	Type	Unit
FD	Frost days	Core	days
SU	Summer days	Core	days
TR	Tropical nights	Core	days

Indices FD, SU and TR are all core indices and considered important since extreme climate/weather events and their variability are of particular relevance to society and ecosystems. Figure 7 contains the annually averaged values of Frost Days (FD) for 1975 (left) and 2015 (right). It should be noted that changes in FD parameter, could affect for instance agricultural practices or relevant engineering applications as documented in Terando et al. (2012).

Figure 7. Annual averaged values of Frost Days (FD) for 1975 (left) & 2015 (right).



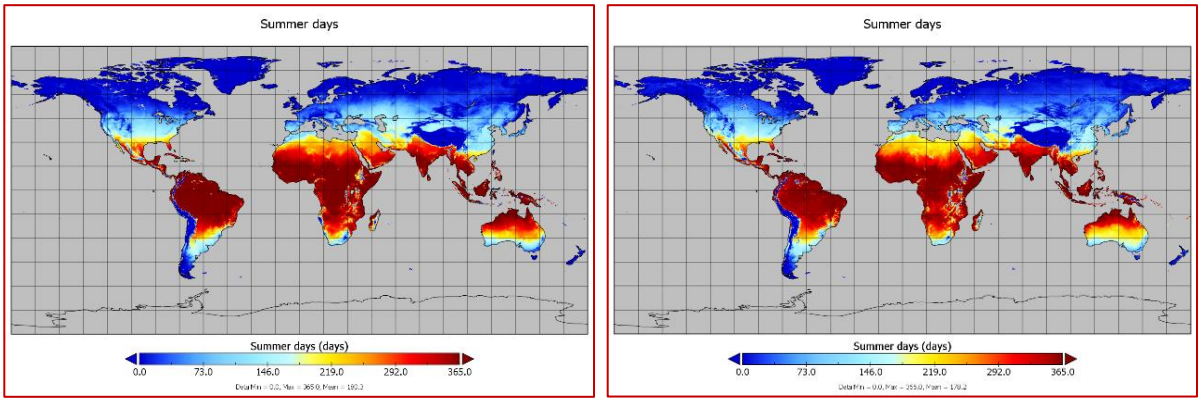
From a global perspective, it has become evident that fewer frost days were recorded in much of the middle and high latitudes in the Northern Hemisphere during the second half of the 20th century as noted by Frich et al. (2002).

Significant decreases in the annual number of frost days were also documented by Alexander et al. (2006) over Western Europe and large parts of Russia for the period from 1951 to 2003.

Further, changes in summer days (SU) appears to be linked to heat extremes that keep intensifying over the past few decades and this trend is expected to continue (projected) with future global warming.

A long persistence of extremes often leads to societal impacts with warm-and-dry conditions severely affecting agriculture (Pfleiderer et al., 2019). Figure 8 contains the annually averaged values of Summer Days (SU) for 1975 (left) and 2015 (right).

Figure 8. Annual averaged values of Summer Days (SU) for 1975 (left) & 2015 (right).



For Tropical Nights (TR) that usually occur in combination with extended periods of heat there has been evidence to be problematic for human health as documented in Weisskopf et al. (2002), Patz et al. (2005).

Figure 9. Annual averaged values of Tropical Nights (TR) for 1975 (left) & 2015 (right).

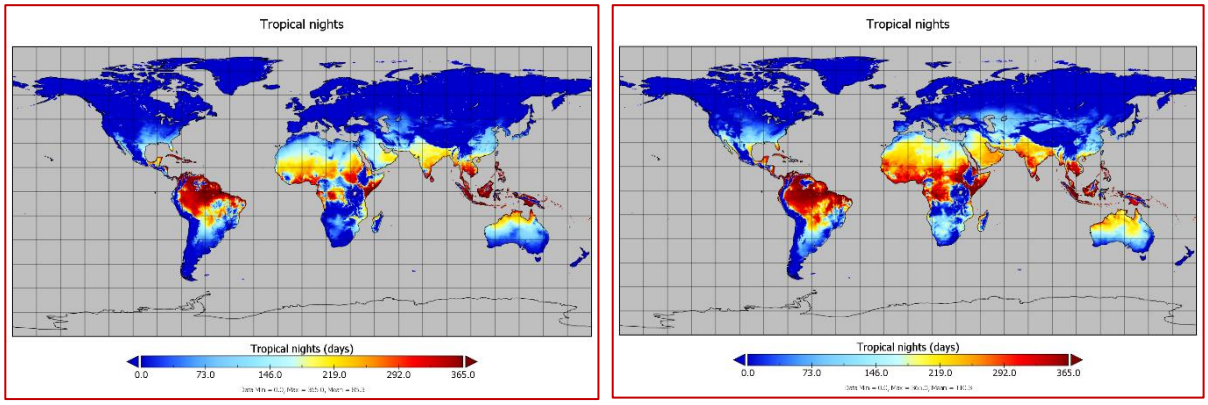


Figure 9 contains the annually averaged values of Tropical Nights (TR) for 1975 (left) and 2015 (right). It should be noted that the frequency of tropical nights has also increased during the last 50 years in the most parts of the world, despite a decreasing trend that could be seen in a small part of the central United States as noted by Zhang et al. (2011).

3.1.3 Duration indices of XM-Temperature

Climate indicators of variability and extremes are used to assess the number of days with temperature or precipitation observations above or below selected physically based thresholds.

The characteristics of the two selected parameters in this XM-Temperature category, the Growing Season Length (GSL) and Warm Spell Duration Indicator (WSDI) are contained in Table 3. Both the GSL and WSDI parameters belong to the core category of climate extreme indices (CEIs).

Table 3. List of XM-Temperature (duration indices).

Index	Long Name	Type	Unit
GSL	Growing Season Length	Core	days
WSDI	Warm Spell Duration Indicator	Core	days

Following Zhang et al. (2011), the GSL parameter in annual mode is estimated as the growing season length from 1 January to 31 December in Northern Hemisphere (NH), whereas from 1 July to 30 June in Southern Hemisphere (SH) counting between the first span of at least 6 days with daily mean temperature (TM) > 5°C and the first span after July 1st (January 1st in SH) of 6 days with TM < 5°C.

Figure 10. Annual averaged values of Growing Season Length (GSL) for 1975 (left) & 2015 (right).

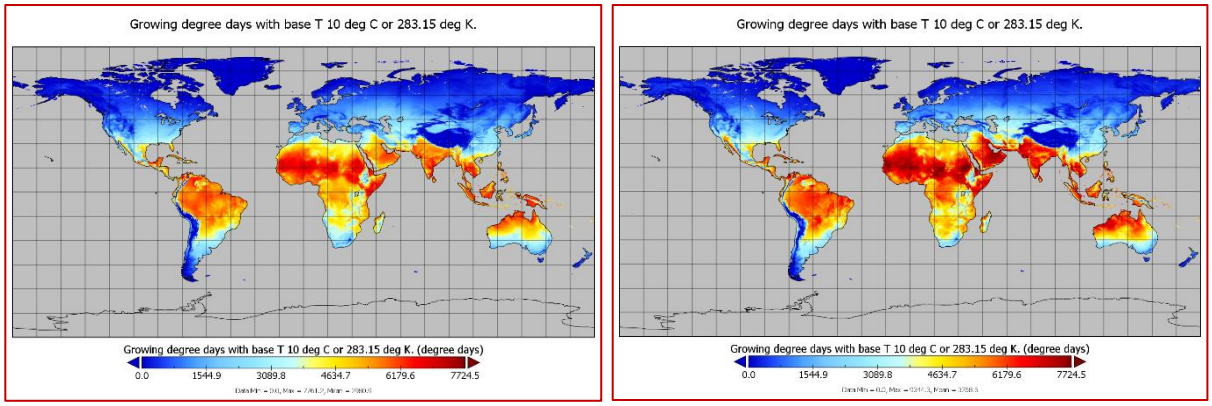


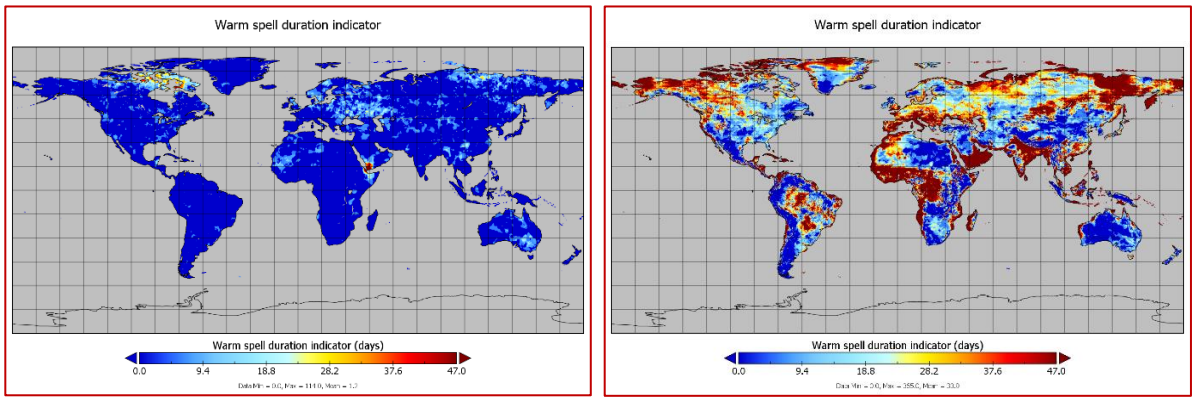
Figure 10 contains the annually averaged values of Growing Season Length (GSL) for 1975 (left) and 2015 (right). For areas with a distinct increase in the length of the growing season accompanied by a warmer climate during the growing season, this may result in increasing the potential for growing thermophilic vegetables in open fields in lowland areas in Central Europe and also increasing the potential number of harvests. For spring crops, future climate warming may allow earlier planting or sowing than at present (Potopova et al., 2015).

For the WSDI parameter, following Sillmann et al. (2013a), if TX_{ij} be the daily maximum temperature on day i in period j and TXp90 be the calendar day of 90th percentile cantered on a 5 day window for the base period 1961–1990, then the number of days per period can be summed (as WSDI parameter) as intervals of at least 6 consecutive days with TX_{ij} values are exceeding TXp90 values.

Figure 11 contains the annually averaged values of Warm Spell Duration Indicator (WSDI) for 1975 (left) and 2015 (right). Globally averaged, WSDI has increased by approximately 8 days (in global average) since the middle of the twentieth century, however, with most of this increase having

occurred since 1980. Conversely, the duration of cold spells has significantly decreased over large areas, by about 4 days since 1950 when considering the global average (Donat et al., 2013b).

Figure 11. Annual averaged values of Warm Spell Duration Indicator (WSDI) for 1975 (left) & 2015 (right).



Understanding the effects of climate change on the vegetative growing season is key to quantifying future hydrologic water budget conditions (Christiansen et al., 2011). It should be noted that the impact of climate variability on agricultural production is strongest during the crop-specific growing season (Lobell and Field, 2007). With the existence of an agricultural pathway, we would therefore expect to observe the strongest association between climate variability and migration during the growing season months as noted by Nawrotzki et al. (2013), Nawrotzki and Bakhtsiyarava (2016).

3.2 Extreme indices of precipitation (XM-Precipitation)

The selected indices of XM-Precipitation give a comprehensive overview of the simulated changes in precipitation extremes across models and historical data. While most indices are defined on an annual basis, a few of the indices are also available as monthly statistics or as continuous counts over the total data record. The selection covers both core and non-core climate extreme indices of three types (with no absolute type indices in this case) as listed below:

- Threshold type in Section 3.2.1
- Duration type in Section 3.2.2
- Special extreme (precipitation) indices in Section 3.2.3

3.2.1 Threshold indices of XM-Precipitation

Heavy or very heavy precipitation and inundation events affect agricultural systems since they can delay planting or causing crop losses through anoxia and root diseases (Posthumus et al., 2009). Flooding events associated with tropical cyclones can also lead to crop failure due to rainfall and/or storm surge.

It should be noted that flooding can affect yield more than drought, not only in tropical regions but also in some mid/high latitude countries such as China and central and northern Europe (Zampieri et al., 2017).

Table 4. List of XM-Precipitation (threshold indices).

Index	Long Name	Type	Unit
R10mm	Heavy precipitation days	Non-Core	days
R20mm	Very heavy precipitation days	Core	days

According to the Intergovernmental Panel on Climate Change (IPCC, 2007a, 2007b) one of the most threatening potential causes of migrations is the increase in the strength of tropical hurricanes and the frequency of heavy rains and flooding, due to the rise in evaporation with increased temperatures.

In a similar mode, the later IPCC Reports (2013, 2019), provided evidence that future (projected) rainfall is to be concentrated into more intense events, with longer periods of little rains in between, which will have negative consequences for rainfall dependent economies.

Further, based on a global assessment of extreme daily precipitation spanning from local to global scales for the period spanning from 1964 to 2013 (during which global warming has been particularly marked), distinct frequency changes reveal a coherent spatial pattern with increasing trends being detected in large parts of Eurasia, North Australia, and the Midwestern United States.

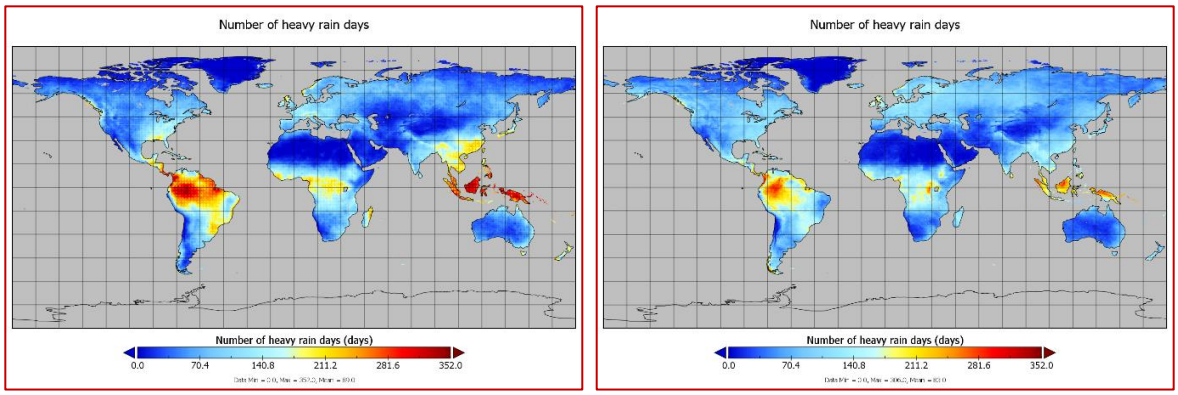
Globally, over the last decade, an increase of 7% of the number of extreme events has been documented by Papalexiou and Montanari (2019).

The main indices in this category, the non-core R10mm (heavy precipitation) parameter and R20mm (very heavy precipitation) that is a core index and their units are shown in Table 4.

- Heavy precipitation days (R10mm)

The heavy precipitation days index (R10mm) counts the number of days with more than 10 mm of (daily) precipitation. This index is associated with the wet part of the precipitation distribution but does not necessarily describe extreme precipitation.

Figure 12. Annual averaged values of Heavy Precipitation Days (R10mm) for 1975 (left) & 2015 (right).



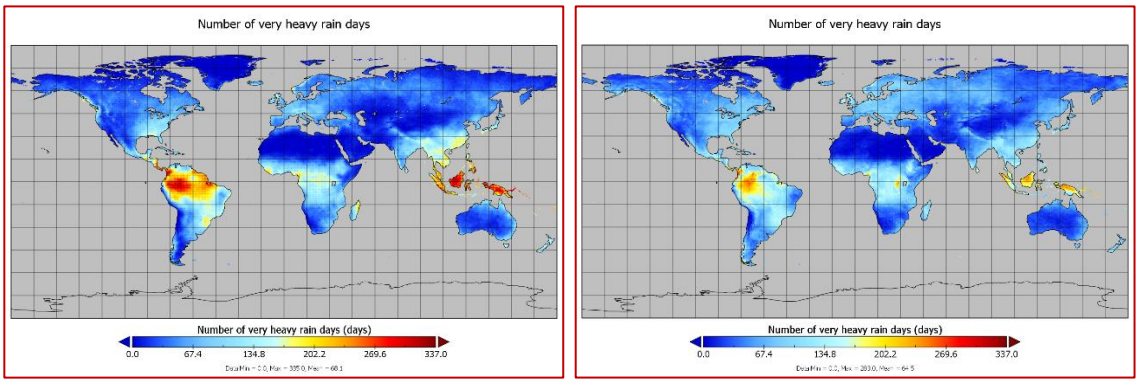
For the estimation of R10mm we consider PR_{ij} to be the daily precipitation amount on day i in period j. Then by counting the number of days with values of PR higher than 10 mm the R10mm parameter is compiled. Figure 12 contains the annually averaged values of Heavy Precipitation Days (R10mm) for 1975 (left) and 2015 (right).

- Very heavy precipitation days (R20mm)

The very heavy precipitation days index (R20mm) counts the number of days with more than 20 mm of (daily) precipitation. Figure 13 contains the annually averaged values of Very Heavy Precipitation Days (R20mm) for 1975 (left) and 2015 (right).

In a similar way (as in the R10mm case) for the estimation of R20mm we consider PR_{ij} to be the daily precipitation amount on day i in period j. Then by counting the number of days with values of PR higher than 20 mm the R20mm parameter is compiled.

Figure 13. Annual averaged values of Very Heavy Precipitation Days (R20mm) for 1975 (left) & 2015 (right).



It should be stressed that although no reliable global estimates of past and current migration flows in response to extensive risks seems to exist (Gemenne, 2011), many cases of induced migration due to rainfall variability have been documented. For instance in Bangladesh, Ghana, Guatemala, India, Peru, Tanzania, Thailand and Viet Nam people have migrated to manage risks related to rainfall variability and livelihood insecurity as documented by Warner and Afifi (2014).

3.2.2 Duration indices of XM-Precipitation

Although there exists evidence of clear association between locally prevailing weather conditions and migration, the exact mechanisms are not known so far. Prior work has suggested that disruptions to agricultural livelihoods most probably is the primary pathway as documented by Feng et al. (2012), Feng and Oppenheimer (2012), Cai et al. (2016), Nawrotzki and Bakhtsiyarava (2016).

In accordance with such a potential agricultural pathway, findings so far point to the direction that climate shocks are expected to have stronger migration effect in areas that are more dependent on agriculture (Nawrotzki et al., 2015) or when such a shock is experienced during crop's growing season as noted in Nawrotzki and Bakhtsiyarava (2016).

The knowledge about the spells of dry days or the prevailing of rain in consecutive days is an important factor for both agricultural planning and management. The spells of dry days captured by the CDD (Consecutive Dry Days) parameter or rain in consecutive days captured by the CWD (Consecutive Wet Days) are affected by climate/weather factors, such as the maximum temperature, minimum temperature, relative humidity, sea level pressure, cloud cover, and duration of sunshine (Mahmud et al., 2020).

The consecutive dry-day index (CDD) represents the length of the longest period of consecutive dry days (i.e., days with precipitation PR < 1 mm). In the case that a dry spell does not end in a particular year and spans a period longer than 1 year (as it might be the case in very dry regions), then CDD is not reported for that year and the accumulated dry days are carried forward to the year when the spell ends (Tebaldi et al., 2006). However, this definition could unavoidably lead to problems in regions with very long dry spells, resulting in very large values at some grid points as noted in Sillmann et al. (2013b) and that is why a cut-off to CDD values is applied bounding them (to be valid) in each one year.

The main (core and non-core) indices in this category, CDD (Consecutive Dry Days) and CWD (Consecutive Wet Days) and their units are contained in Table 5.

Table 5. List of XM-Precipitation (duration indices).

Index	Long Name	Type	Unit
CDD	Consecutive Dry Days	Core	days
CWD	Consecutive Wet Days	Non-Core	days

It should be noted that the CDD index is the only ETCCDI index that describes the lower tail of the precipitation distribution and is often considered as a drought indicator.

Since drought is a complex phenomenon depending on various other factors besides lack of precipitation, the CDD index can only provide an indication for meteorological drought and should be interpreted in combination with other precipitation indices as noted by Tebaldi et al. (2006), Orlowsky and Seneviratne (2012) or with other drought indices as documented by Cardona et al. (2012).

- Consecutive Dry Days (CDD)

The CDD parameter represents the maximum consecutive number of dry days with less than 1 mm of daily precipitation. For the estimation of CDD we consider PR_{ij} to be the daily precipitation amount on day i in period j. Then by calculating the highest number of consecutive days with precipitation PR_{ij} values less than 1 mm the CDD parameter is compiled.

Figure 14. Annual averaged values of Consecutive Dry Days (CDD) for 1975 (left) & 2015 (right).

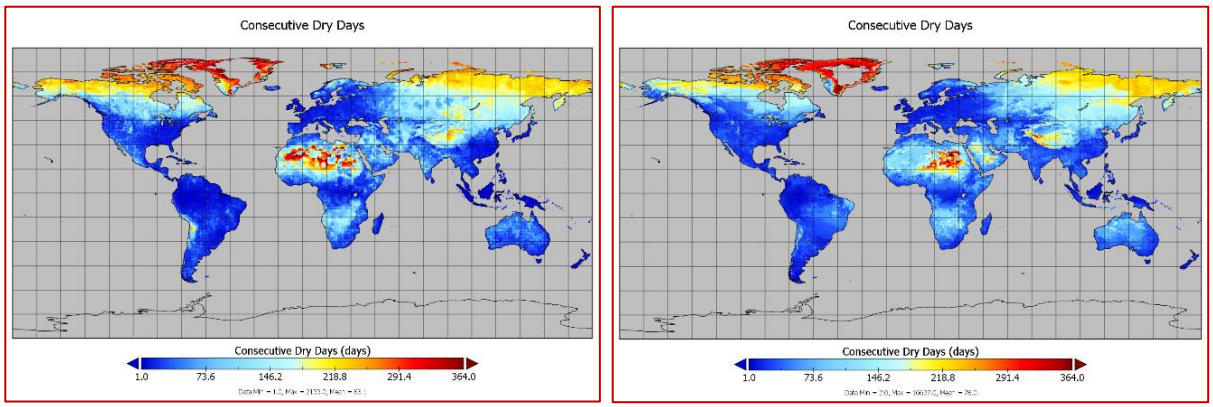


Figure 14 contains the annually averaged values of Consecutive Dry Days (CDD) for 1975 (left) and 2015 (right) and it seems to be in agreement with results by Alexander et al. (2006) that have documented a trend toward more humid conditions and significant warming in North America, Eurasia and parts of Australia over the twentieth century.

- Consecutive Wet Days (CWD)

The CWD parameter represents the maximum consecutive number of wet days with more than 1 mm of daily precipitation. For the estimation of CWD we consider PR_{ij} to be the daily precipitation amount on day i in period j. Then by calculating the highest number of consecutive days with precipitation PR_{ij} values more than 1 mm the CWD parameter is compiled.

Figure 15. Annual averaged values of Consecutive Wet Days (CWD) for 1975 (left) & 2015 (right).

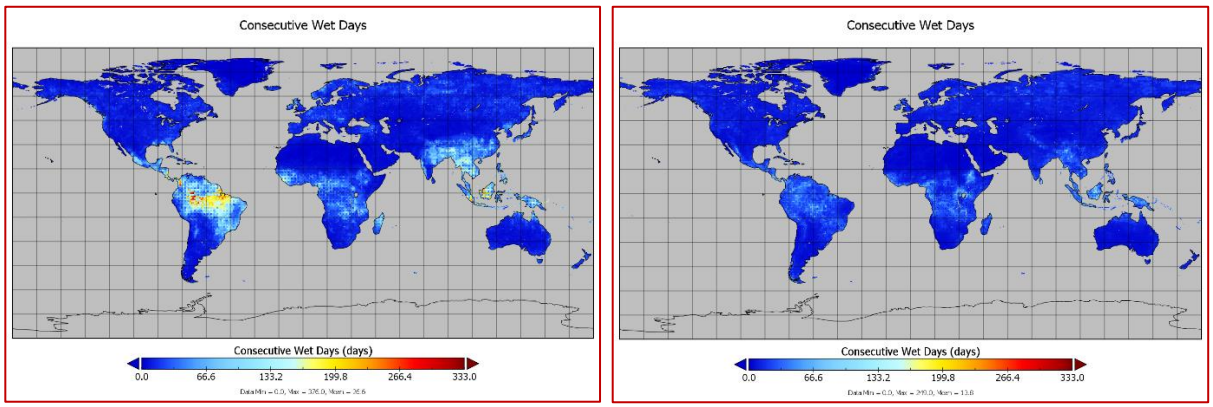


Figure 15 contains the annually averaged values of Consecutive Wet Days (CWD) for 1975 (left) and 2015 (right). It should be noted that the trend precipitation extremes is considered more significant than the trend of the mean precipitation, especially for higher percentiles, in agreement with the Clausius–Clapeyron relation[13] that describes how a warmer atmosphere can hold more water vapour, which produces in turn more intense precipitation and this can be of high importance especially over areas where CWD values have the tendency to become shorter.

3.2.3 Special extreme indices of XM-Precipitation

Besides the threshold- and duration- type of indices defined by the ETCCDI (Expert Team on Climate Change Detection and Indices) there are two more indices that seem to be of great importance for studying precipitation trends, namely the PRCPTOT and SDII indices.

The PRCPTOT index stands for the total wet-day precipitation describing the total annual amount of precipitation on wet days defined as days with more than 1 mm of precipitation.

[13] https://www.e-education.psu.edu/meteo300/node/584

The SDII index on the other hand describes the daily precipitation amount averaged over all wet days in a year. Details can be found in Karl et al. (1999) and Peterson et al. (2001).

Table 6. List of special extreme precipitation indices of XM-Precipitation.

Index	Long Name	Type	Unit
PRCPTOT	Annual Total Wet-Day Precipitation Index	Core	mm (rain)
SDII	Simple Precipitation Intensity Index	Non-Core	mm (rain)

The main characteristics of the PRCTOT and SDII indices are shown in Table 6. Typical annual average values of PRCTOT for 1975 (left) and 2015 (right) are shown in Figure 16. For SDII, typical annual average values for 1975 (left) and 2015 (right) are shown in Figure 17.

Figure 16. Annual averaged values of PRCPTOT for 1975 (left) & 2015 (right).

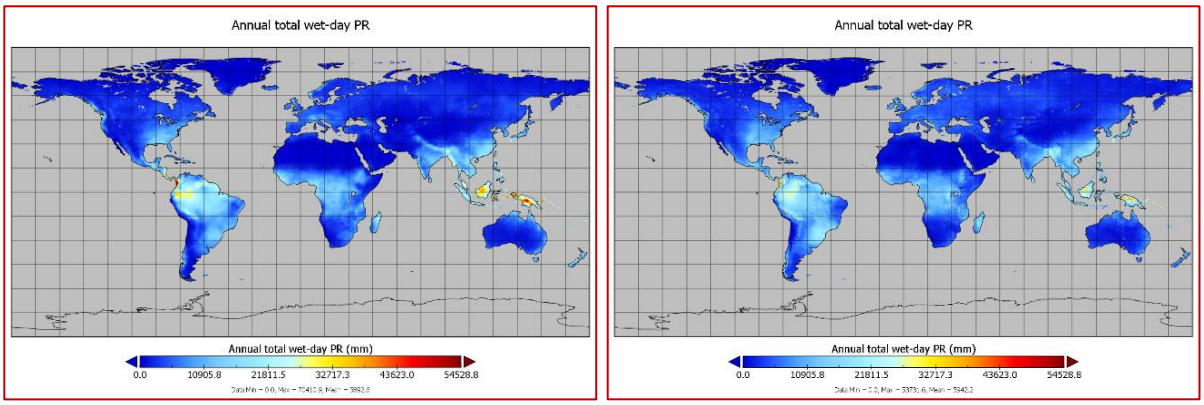
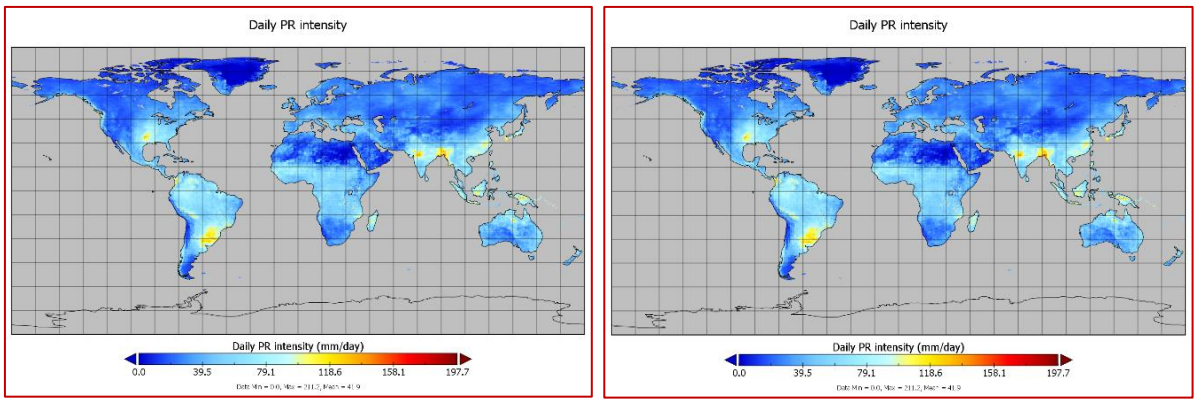


Figure 17. Annual averaged values of SDII for 1975 (left) & 2015 (right).



It should be noted that PRCPTOT and SDII indices are not necessarily solely associated with climate extremes but provide useful information about the relationship between changes in extreme conditions as for instance for Rx5day (monthly maximum consecutive 5-day precipitation) or for R95pTOT (annual total precipitation for days with precipitation over the 95th percentile) and other aspects of the distribution of daily precipitation as noted in Sillmann et al. (2013b).

4 Extreme Indices of Heat (XM-Heat) and Cold (XM-Cold) Waves

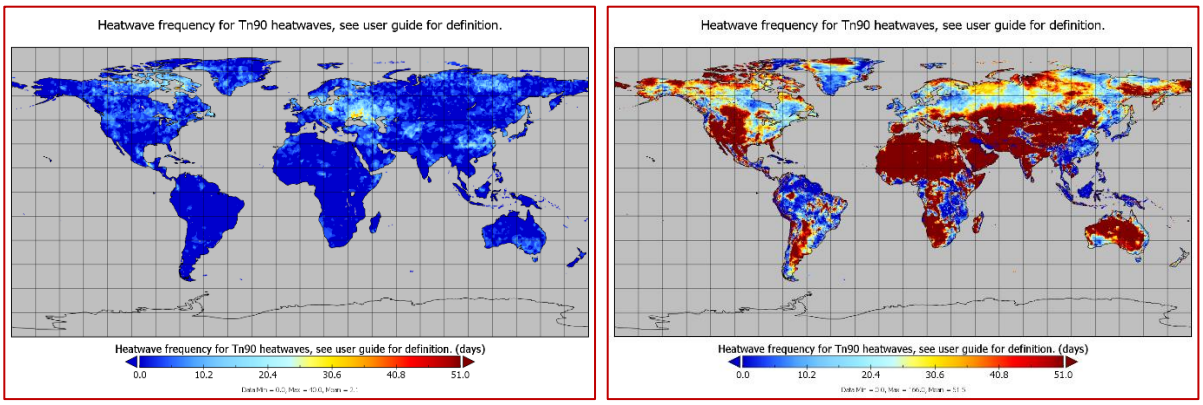
The increasing amount of heat due to climate change can negatively have impact to communities in many different ways. Due to excessive temperatures, daily life could be inhibited through the loss of capacity to carry out physical activities and labour productivity (Climate Vulnerable Forum, 2016).

Increasing heat due to climate change is more likely to result in more extreme natural events as more frequent droughts, wildfires, episodes of very hot temperatures and related heat waves, affecting rural and urban communities as documented by Ionesco et al. (2016).

In the case of heat waves, the overall definition remains very broad in describing a period of consecutive days where conditions are excessively hotter than normal (Perkins and Alexander, 2013).

Based on this definition, heat waves can be both summertime and annual events. This can include minimum temperature (TN) as well as maximum temperature (TX) since high night time temperatures can further exacerbate heat wave conditions as noted in Pattenden et al. (2003), Trigo et al. (2005), Nicholls et al. (2008), Nairn et al. (2009).

Figure 18. Annual averaged values of Heat Wane Frequency for 1975 (left) & 2015 (right).



XM-Heat and XM-Cold Wave Indices have been put as separate category since there are many different definitions for such events. The full range of the heat and cold wave extreme listed in Table S2 contained in the Supplementary Package of Mistry (2019a) can be found within rows 22 to 41 of Table A2.1 (Annex 2).

The limited set of heat wave parameters (namely HWN_Tn90, HWF_Tn90, HWD_Tn90, HWM_Tn90, HWA_Tn90) that has been strategically selected in the current phase to be tested as potential drivers is contained in Table 7.

Typical annual average values of Heat Wave Frequency (HWF_Tn90) for 1975 (left) and 2015 (right) are shown in Figure 18.

Climate Extreme Indices (CEIs) as the XM-Heat and XM-Cold Indices provide the modelling community with a detailed set of indicators enabling the comparison of different input data sources in the effort to model extremes as noted in Sillmann et al. (2013a, 2013b) and Alexander et al. (2006).

It should be also stressed that the usage of such extreme indices seems to be necessary if someone is after extremes. While the mean climatology of a location is invariably well-captured by the state-of-the-art reanalysis data products and Earth System Models (ESMs), extremes (particularly in

precipitation) at fine spatial scales have been difficult to replicate as documented in Sillmann et al. (2017).

Table 7. XM-Heat and XM-Cold Wave Extreme Indices.

Index	Long Name	Type	Unit
HWN_Tn90	Heat wave number (HWN) as defined by the 90th percentile of Tn (Minimum Temperature)	Non-Core	events
HWF_Tn90	Heatwave frequency (HWF) as defined by the 90th percentile of Tn (Minimum Temperature)	Non-Core	days
HWD_Tn90	Heatwave duration (HWD) as defined by the 90th percentile of Tn (Minimum Temperature)	Non-Core	days
HWM_Tn90	Heatwave magnitude (HWM) as defined by the 90th percentile of Tn (Minimum Temperature)	Non-Core	°C
HWA_Tn90	Heatwave amplitude (HWA) as defined by the 90th percentile of Tn (Minimum Temperature)	Non-Core	°C

Nonetheless, according to Migali et al. (2018) findings, the regions in which the combination of population and extreme events is expected to substantially increase in the coming decades are: Northern, Eastern, and Western Africa, while Central Africa is expected to be more subject to heatwaves than droughts; Southern and Eastern Asia are expected to be particularly affected by drought events, while the South-Eastern and Western Asian regions are more exposed to heatwaves; Central and South America and Southern Europe are also projected to experience an increasing exposure of population to climate extremes.

5 Extreme Indices of Drought (XM-Drought)

As denoted in IPCC (2019), global warming has resulted in an increased frequency, intensity and duration of heat-related events, including heatwaves in most land regions (high confidence) while the frequency and intensity of droughts have increased in some regions including the Mediterranean, West Asia, many parts of South America, much of Africa, and north-eastern Asia (medium confidence).

It is also worth noted that even among drought experts, a single definition of drought is hard to agree on. Droughts usually become evident after long periods without precipitation although it is difficult to establish their onset, extent, and end. Drought indices used in the current approach are expressed by both the SPI (Standardised Precipitation Index) and SPEI (Standardised Precipitation Evapotranspiration Index) on time scales of 3, 6, 12, 24, 36 and 48 months.

The SPI index is specified as a deficit of total precipitation whereas the SPEI index is based on precipitation and temperature data, and it has the advantage of combining multi-scalar character with the capacity to include the effects of temperature variability on drought assessment (Vicente-Serrano et al., 2010). In mathematical terms, the estimation of SPEI is similar to the estimation of the standardized precipitation index (SPI), but it includes the role of temperature.

Typical values of monthly averaged values of SPI index for August 1975 (left) and August 2015 (right) are shown in Figure 19, whereas typical values of monthly averaged values of ESPI index for August 1975 (left) and August 2015 (right) are shown in Figure 20.

Figure 19. Monthly averaged values of SPI for August 1975 (left) & August 2015 (right).

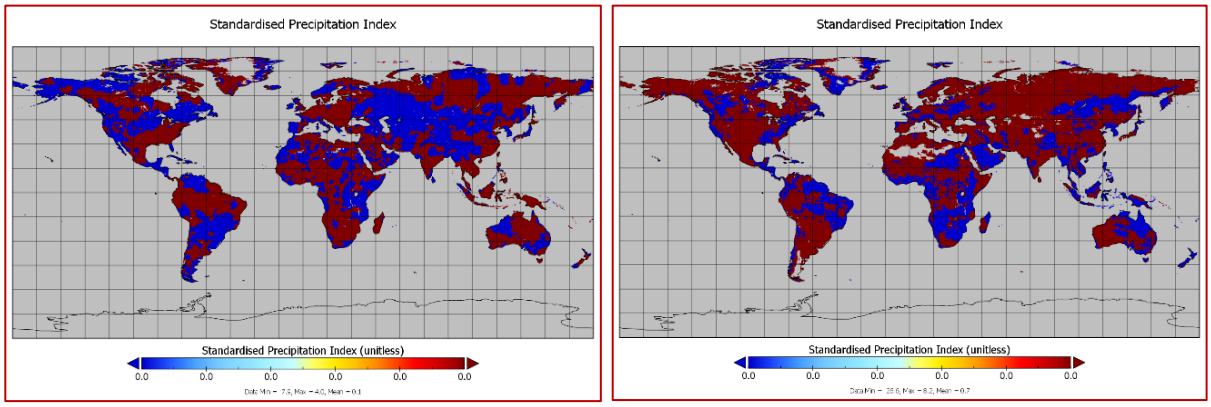
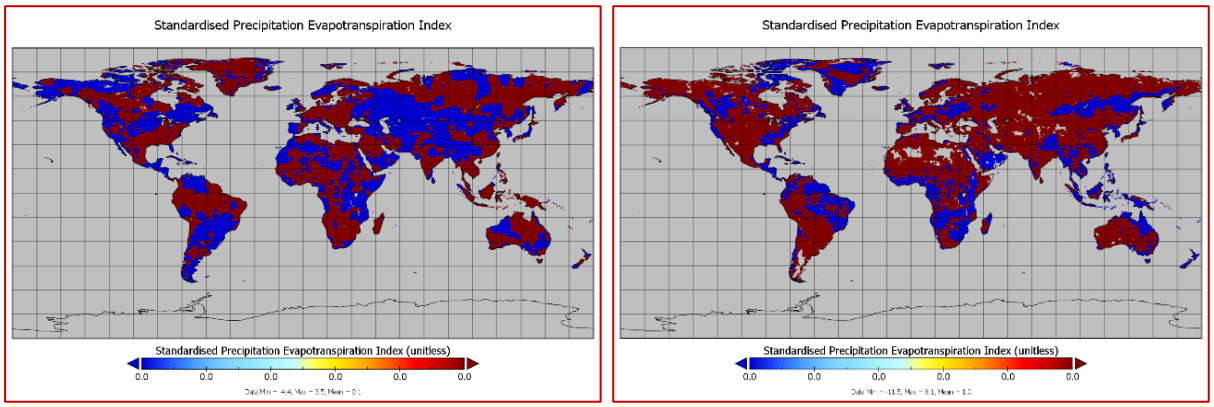


Figure 20. Monthly averaged values of SPEI for August 1975 (left) & August 2015 (right).



The full range of the SPI and SPEI extreme indices listed in Table S2 contained in the Supplementary Package of Mistry (2019a) can be found within rows 42 to 53 of Table A2.1 (Annex 2).

The limited set of SPI and SPEI XM-Drought indices (namely SPI_TS6M, SPI_TS12M, SPI_TS24M, SPEI_TS6M, SPEI_TS12M, SPEI_TS24M) that has been strategically selected in this first phase to be tested as potential drivers is contained in Table 8.

Table 8. SPI and SPEI XM-Drought Extreme Indices.

Index	Long Name	Type	Unit
SPI_TS6M	Standardised Precipitation Index on time scale of 6 months	Non-Core	Unitless
SPI_TS12M	Standardised Precipitation Index on time scale of 12 months	Non-Core	Unitless
SPI_TS24M	Standardised Precipitation Index on time scale of 24 months	Non-Core	Unitless
SPEI_TS6M	Standardised Precipitation Evapotranspiration Index on time scale of 6 months	Non-Core	Unitless
SPEI_TS12M	Standardised Precipitation Evapotranspiration Index on time scale of 12 months	Non-Core	Unitless
SPEI_TS24M	Standardised Precipitation Evapotranspiration Index on time scale of 24 months	Non-Core	Unitless

It should bear in mind that XM-Drought indices are related to the consecutive dry-day index (CDD) which represents the length of the longest period of consecutive dry days (i.e., days with PR < 1 mm) in a year ending in that year (for details see Section 3.2.2).

As drought is a complex phenomenon depending on various other factors besides lack of precipitation, the CDD parameter can only provide an indication for meteorological drought and should be interpreted in combination with other precipitation indices. Nonetheless, drought affects natural environments and socioeconomic systems in global scale as noted by Van Loon (2015), Vicente-Serrano (2007).

A wide range of impacts due to drought may include crop failure, food shortage, famine, epidemics and even mass migration as documented by Wilhite et al. (2007), Ding et al. (2011), Zhou et al. (2018).

6 Extreme Indices of Degree Days (XM-Degree Days)

Degree-days are important climatic indicators, commonly used to estimate the climate-dependent cooling and heating demands primarily in buildings (Cibse, 2006). Degree-days can be defined as monthly or annual sum of the difference between a base temperature (T_{base}) and daily mean outdoor air temperature (T_{mean}), whenever the T_{mean} is greater or lower than T_{base} as defined in ASHRAE (2009). In the first case ($T_{mean} > T_{base}$) the values of HDD (Hot Degree-Days) are estimated whereas in the second ($T_{mean} < T_{base}$) the values of CDD (Cold Degree-Days) are calculated. The T_{base} is also considered as 'threshold' temperature or 'set-point' temperature, and it denotes the T_{mean} at which the indoor cooling or heating systems do not need to run in order to maintain human comfort levels as explained in detail in Cibse (2006) and ASHRAE (2009).

Global gridded values of degree-days used in our net migration studies have been based on a unique high-spatial resolution, global gridded database of two types of degree-days, namely CDD (Cold Degree-Days), HDD (Hot Degree-Days) as compiled by Mistry (2019b) and it can be retrieved and processed from PANGAEA[14] (Data Publisher for Earth & Environmental Science).

Figure 21. Annual averaged values of CDD with base 18°C for 1975 (left) & 2015 (right).

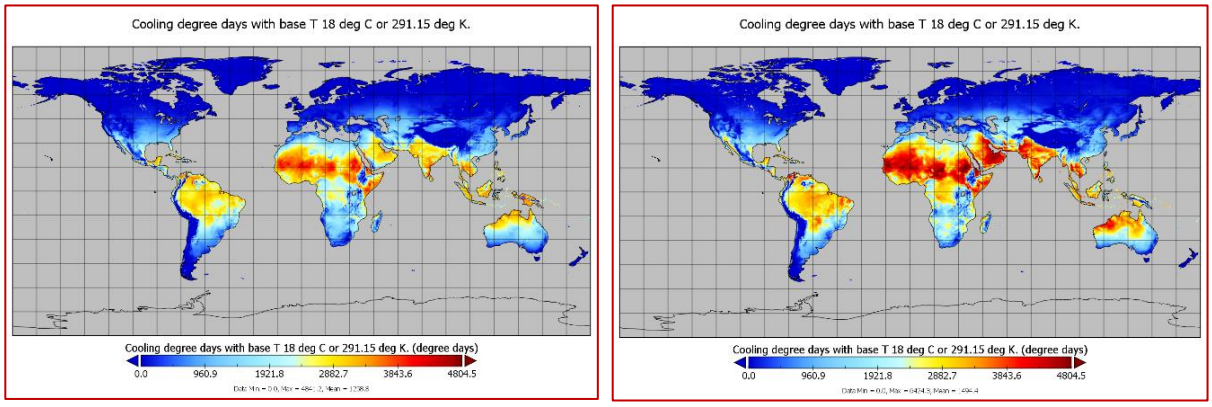
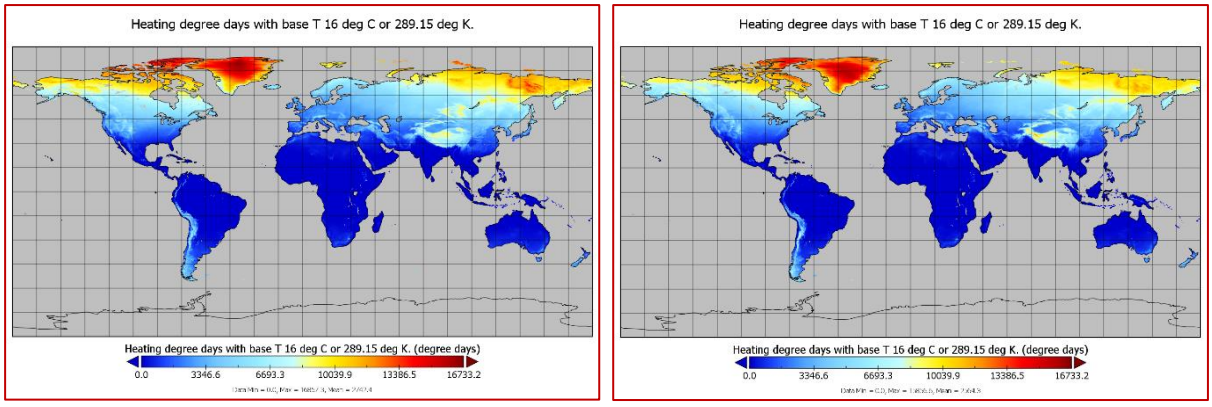


Figure 22. Annual averaged values of HDD with base 16°C for 1975 (left) & 2015 (right).



[14] https://doi.pangaea.de/10.1594/PANGAEA.903123

Typical values of annual averaged values of CDD with base 18°C for 1975 (left) and 2015 (right) are shown in Figure 21, whereas typical values of annual averaged values of HDD with base 16°C for 1975 (left) and 2015 (right) are contained in Figure 22.

The full range of the CDD and HDD extreme parameters listed in Table S2 contained in the Supplementary Package of Mistry (2019a) can be found within rows 54 to 65 of Table A2.1 (Annex 2). The limited set of CDD and HDD parameters (namely CDD_T18, CDD_T22, CDD_T24, HDD_T10, HDD_T16, HDD_T18) that has been strategically selected in the current phase to be tested as potential drivers is contained in Table 9.

Table 9. CDD and HDD XM-Degree Days Indices.

Index	Long Name	Type	Unit
CDD_T18	Cooling Degree-Days (CDD) utilising the threshold of 18°C	Non-Core	days
CDD_T22	Cooling Degree-Days (CDD) utilising the threshold of 22°C	Non-Core	days
CDD_T24	Cooling Degree-Days (CDD) utilising the threshold of 23°C	Non-Core	days
HDD_T10	Heating Degree-Days (HDD) utilising the threshold of 10°C	Non-Core	days
HDD_T16	Heating Degree-Days (HDD) utilising the threshold of 16°C	Non-Core	days
HDD_T18	Heating Degree-Days (HDD) utilising the threshold of 18°C	Non-Core	days

From Table 9 it is obvious that both CDD and HDD parameters have been computed using multiple wide-ranging T_{base} (threshold / set-point) and meteorological variables from a quality-controlled reanalysis data product, the so-called GLDAS (Rodell et al., 2004) ver. 2 at 0.25 degree global gridded resolution.

Based on the GLDAS (Global Land Data Assimilation System) reanalysis sub-daily temperature the degree-days dataset includes monthly and annual degree-days, spanning the most recent 49 years (1970–2018) in the commonly used scientific Network Common Data Form 4 (NetCDF4) and Georeferenced Tagged Image File (GeoTIFF) formats.

Degree days (parameters) are considered important since they have been used in a series of statistical studies linking agricultural yields to weather fluctuations that inevitably may influence decisions to migrate. Documented by D'Agostino A.L and W. Schlenker (2016), prognoses from statistical models using historic data from 1950 to 2011 have been very capable of predicting US aggregate yields out-of-sample for the years 2012–2015. The single best predictor has been a measure of hot degree days that only counts for how long and by how much temperatures exceed 29°C (acting here as a base temperature). Going a step forward, aggregate production forecasts are the key variable needed to predict changes in prices.

7 Conclusions and summary table

In the current phase of the CLICIM Project, ascertain trends and correlations between potential climate drivers and the new Net Migration Grid (NMG) are being investigated. The NMG comprises a set of eight (8) global gridded 5-year snapshots of net migration values from 1975 to 2015.

In the beginning of our investigation, emphasis had been given in Copernicus ECMWF ERA-Interim and ECMWF ERA-5 reanalysis data although their obvious limitation of not covering the time period before 1979 resulted in the search and utilisation of another set of historical climate data as the Terrestrial Air Temperature (TAT) Gridded Monthly Time Series (Version 5.01) and the Terrestrial Precipitation (TP) Gridded Monthly Time Series (Version 5.01) of the University of Delaware covering the time interval from 1900 to 2017 (Willmott and Matsuura 2001).

Besides studying mainstream variables as temperature and precipitation, the need of better understanding and assessing the impact of extreme weather events to net migration has pointed to the actually variability of such (extreme) events as documented in Mistry (2019a). That is why, metrics like CEIs (Climate Extreme Indices) are considered important not only for the analysis of regional and global weather extremes but also to help modellers and policymakers in the assessment of sectoral and regional impacts.

During CLICIM Project we are to examine the full set of the extended set of 93 CEIs (including the original 27 ETCCDI indices) by retrieving a relevant open-access high-resolution global gridded (at 0.25 × 0.25 degree resolution) dataset of covering the period 1970-2016. For the current phase besides the 2 mainstream variables (TAT and TP), additional 35 CEIs have been selected (all listed in Table 10) for compiling 5-year mean, anomalies and trends in harmony with the new high-resolution global grid of net migration (NMG).

Table 10. Summary of 37 selected variables during the current phase of CLICIM as potential migration drivers.

	Variable	Long Name	Type	Page
01	TAT	Terrestrial Air Temperature	Mainstream Variable	09
02	TP	Terrestrial Precipitation	Mainstream Variable	10
03	DTR	Daily temperature range	Absolute Index	14
04	TNM	Mean minimum temperature	Absolute Index	14
05	TNN	Minimum minimum temperature	Absolute Index	14
06	TNX	Maximum minimum temperature	Absolute Index	14
07	TXM	Mean maximum temperature	Absolute Index	14
08	TXN	Minimum maximum temperature	Absolute Index	14
09	TXX	Maximum maximum temperature	Absolute Index	14
10	FD	Frost days	Threshold Index	17
11	SU	Summer days	Threshold Index	17
12	TR	Tropical nights	Threshold Index	17

13	GSL	Growing season length	Duration Index	19
14	WSDI	Warm spell duration indicator	Duration Index	19
15	R10mm	Heavy precipitation days	Threshold Index	21
16	R20mm	Very heavy precipitation days	Threshold Index	21
17	CDD	Consecutive Dry Days	Duration Index	23
18	CWD	Consecutive Wet Days	Duration Index	23
19	PRCPTOT	Annual Total Wet-Day Precipitation	Special Index	25
20	SDII	Simple Precipitation Intensity Index	Special Index	25
21	HWN_Tn90	Heatwave number (90th percentile of TN)	Extreme Index	27
22	HWF_Tn90	Heatwave frequency (90th percentile of TN)	Extreme Index	27
23	HWD_Tn90	Heatwave duration (90th percentile of TN)	Extreme Index	27
24	HWM_Tn90	Heatwave magnitude (90th percentile of TN)	Extreme Index	27
25	HWA_Tn90	Heatwave amplitude (90th percentile of TN)	Extreme Index	27
26	SPI_TS6M	Standardised Precipitation (6 months)	Extreme Index	29
27	SPI_TS12M	Standardised Precipitation (12 months)	Extreme Index	29
28	SPI_TS24M	Standardised Precipitation (24 months)	Extreme Index	29
29	SPEI_TS6M	Precipitation Evapotranspiration (6 months)	Extreme Index	29
30	SPEI_TS12M	Precipitation Evapotranspiration (12 months)	Extreme Index	29
31	SPEI_TS24M	Precipitation Evapotranspiration (24 months)	Extreme Index	29
32	CDD_T18	Cooling Degree-Days of threshold 18°C	Extreme Index	31
33	CDD_T22	Cooling Degree-Days of threshold 22°C	Extreme Index	31
34	CDD_T24	Cooling Degree-Days of threshold 24°C	Extreme Index	31
35	HDD_T10	Heating Degree-Days of threshold 10°C	Extreme Index	31
36	HDD_T16	Heating Degree-Days of threshold 16°C	Extreme Index	31
37	HDD_T18	Heating Degree-Days of threshold 18°C	Extreme Index	31

Closing, the current report will be followed by a similar screening exercise focusing on agriculture and water scarcity indices. Eventually, during the final steps of CLICIM, the full set of the indices documented in these two screening reports will be put in relation with population and net migration data at high spatial resolution and utilised in statistical models exploring potential links between climate change impacts and induced migration.

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List of abbreviations and definitions

AgMIP	Agricultural Model Inter-comparison and Improvement Project
ASCII	American Standard Code for Information Interchange
CAI	Climatologically Aided Interpolation
CEI	Climate Extreme Indices
Copernicus	European Union's Earth observation programme
CLICIM	Climate Change Induced Migration
DEM	Digital Elevation Model
ECMWF	European Centre for Medium-Range Weather Forecasts
ETCCDI	Expert Team on Climate Change Detection and Indices (WMO)
ERA-5	Global high-resolution atmospheric reanalysis from 1 January 1979 onward
ERA-Interim	Global atmospheric reanalysis from 1 January 1979 to 31 August 2019
GHSL	Global Human Settlement Layer
JEODPP	Joint Observation Data and Processing Platform
IPCC	Intergovernmental panel of Climate Change
ISIMIP	Inter-Sectoral Impact Model Inter-comparison Project
NCAR	National Center for Atmospheric Research
NETCDF	Network Common Data Form
NMG	Net Migration Grid
RCPs	Representative Concentration Pathways
SSPs	Shared Socioeconomic Pathways
TAT	Terrestrial Air Temperature
TP	Terrestrial Precipitation
UCAR	University Corporation for Atmospheric Research
WMO	World Meteorological Organisation

Annexes

Annex 1. Selected Parameters and Extreme Indices

In the current study we have closely examined ninety five parameters and indices assessing their temporal and geographical coverage and relevance on the basis of the most recent climate change and migration literature before proceeding to the final selection of thirty seven meteorological parameters and extreme climate/weather indices. The selected parameters and indices are shown in Table A1.1.

Table A1.1. List of 37 selected variables during the current phase of CLICIM as potential migration drivers.

	Variable	Long Name	Resolution	Page
01	TAT	Terrestrial Air Temperature	0.5 x 0.5-deg	ascii
02	TP	Terrestrial Precipitation	0.5 x 0.5-deg	ascii
03	DTR	Daily temperature range	0.25 x 0.25-deg	netCDF
04	TNM	Mean minimum temperature	0.25 x 0.25-deg	netCDF
05	TNN	Minimum minimum temperature	0.25 x 0.25-deg	netCDF
06	TNX	Maximum minimum temperature	0.25 x 0.25-deg	netCDF
07	TXM	Mean maximum temperature	0.25 x 0.25-deg	netCDF
08	TXN	Minimum maximum temperature	0.25 x 0.25-deg	netCDF
09	TXX	Maximum maximum temperature	0.25 x 0.25-deg	netCDF
10	FD	Frost days	0.25 x 0.25-deg	netCDF
11	SU	Summer days	0.25 x 0.25-deg	netCDF
12	TR	Tropical nights	0.25 x 0.25-deg	netCDF
13	GSL	Growing season length	0.25 x 0.25-deg	netCDF
14	WSDI	Warm spell duration indicator	0.25 x 0.25-deg	netCDF
15	R10mm	Heavy precipitation days	0.25 x 0.25-deg	netCDF
16	R20mm	Very heavy precipitation days	0.25 x 0.25-deg	netCDF
17	CDD	Consecutive Dry Days	0.25 x 0.25-deg	netCDF
18	CWD	Consecutive Wet Days	0.25 x 0.25-deg	netCDF
19	PRCPTOT	Annual Total Wet-Day Precipitation Index	0.25 x 0.25-deg	netCDF
20	SDII	Simple Precipitation Intensity Index	0.25 x 0.25-deg	netCDF
21	HWN_Tn90	Heat wave number (HWN) as defined by the 90th percentile of Tn (Minimum Temperature)	0.25 x 0.25-deg	netCDF
22	HWF_Tn90	Heatwave frequency (HWF) as defined by the 90th percentile of Tn (Minimum Temperature)	0.25 x 0.25-deg	netCDF

23	HWD_Tn90	Heatwave duration (HWD) as defined by the 90th percentile of Tn (Minimum Temperature)	0.25 x 0.25-deg	netCDF
24	HWM_Tn90	Heatwave magnitude (HWM) as defined by the 90th percentile of Tn (Minimum Temperature)	0.25 x 0.25-deg	netCDF
25	HWA_Tn90	Heatwave amplitude (HWA) as defined by the 90th percentile of Tn (Minimum Temperature)	0.25 x 0.25-deg	netCDF
26	SPI_TS6M	Standardised Precipitation Index on time scale of 6 months	0.25 x 0.25-deg	netCDF
27	SPI_TS12M	Standardised Precipitation Index on time scale of 12 months	0.25 x 0.25-deg	netCDF
28	SPI_TS24M	Standardised Precipitation Index on time scale of 24 months	0.25 x 0.25-deg	netCDF
29	SPEI_TS6M	Standardised Precipitation Evapotranspiration Index on time scale of 6 months	0.25 x 0.25-deg	netCDF
30	SPEI_TS12M	Standardised Precipitation Evapotranspiration Index on time scale of 12 months	0.25 x 0.25-deg	netCDF
31	SPEI_TS24M	Standardised Precipitation Evapotranspiration Index on time scale of 24 months	0.25 x 0.25-deg	netCDF
32	CDD_T18	Cooling Degree-Days (CDD) utilising the threshold of 18°C	0.25 x 0.25-deg	netCDF
33	CDD_T22	Cooling Degree-Days (CDD) utilising the threshold of 22°C	0.25 x 0.25-deg	netCDF
34	CDD_T24	Cooling Degree-Days (CDD) utilising the threshold of 24°C	0.25 x 0.25-deg	netCDF
35	HDD_T10	Heating Degree-Days (HDD) utilising the threshold of 10°C	0.25 x 0.25-deg	netCDF
36	HDD_T16	Heating Degree-Days (HDD) utilising the threshold of 16°C	0.25 x 0.25-deg	netCDF
37	HDD_T18	Heating Degree-Days (HDD) utilising the threshold of 18°C	0.25 x 0.25-deg	netCDF

Annex 2. Inventory of Parameters and Extreme Indices

The inventory of the full set of the ninety five parameters and climate/weather extreme indices examined so far are listed in Table A2.1.

Table A2.1. List of 95 parameters and climate/weather indices examined during the current phase of CLICIM.

	Variable	Long Name	Resolution	Format
01	TAT	Terrestrial Air Temperature	0.5 x 0.5-deg	ascii
02	TP	Terrestrial Precipitation	0.5 x 0.5-deg	ascii
03	DTR	Daily temperature range	0.25 x 0.25-deg	netCDF
04	TNM	Mean minimum temperature	0.25 x 0.25-deg	netCDF
05	TMM	Mean daily mean temperature	0.25 x 0.25-deg	netCDF
06	TNN	Minimum minimum temperature	0.25 x 0.25-deg	netCDF
07	TNX	Maximum minimum temperature	0.25 x 0.25-deg	netCDF
08	TXM	Mean maximum temperature	0.25 x 0.25-deg	netCDF
09	TXN	Minimum maximum temperature	0.25 x 0.25-deg	netCDF
10	TXX	Maximum maximum temperature	0.25 x 0.25-deg	netCDF
11	FD	Frost days	0.25 x 0.25-deg	netCDF
12	SU	Summer days	0.25 x 0.25-deg	netCDF
13	TR	Tropical nights	0.25 x 0.25-deg	netCDF
14	GSL	Growing season length	0.25 x 0.25-deg	netCDF
15	WSDI	Warm spell duration indicator	0.25 x 0.25-deg	netCDF
16	R10mm	Heavy precipitation days	0.25 x 0.25-deg	netCDF
17	R20mm	Very heavy precipitation days	0.25 x 0.25-deg	netCDF
18	CDD	Consecutive Dry Days	0.25 x 0.25-deg	netCDF
19	CWD	Consecutive Wet Days	0.25 x 0.25-deg	netCDF
20	PRCPTOT	Annual Total Wet-Day Precipitation Index	0.25 x 0.25-deg	netCDF
21	SDII	Simple Precipitation Intensity Index	0.25 x 0.25-deg	netCDF
22	CWN_ECF	Cold wave number (CWN) as defined by the Excess Cold Factor (ECF)	0.25 x 0.25-deg	netCDF
23	CWF_ECF	Cold wave frequency (CWF) as defined by the Excess Cold Factor (ECF)	0.25 x 0.25-deg	netCDF
24	CWD_ECF	Cold wave duration (CWD) as defined by the Excess Cold Factor (ECF)	0.25 x 0.25-deg	netCDF

25	CWM_ECF	Cold wave magnitude (CWM) as defined by the Excess Cold Factor (ECF)	0.25 x 0.25-deg	netCDF
26	CWA_ECF	Cold wave amplitude (CWA) as defined by the Excess Cold Factor (ECF)	0.25 x 0.25-deg	netCDF
27	HWN_ECF	Heat wave number (HWN) as defined by the Excess Heat Factor (ECF)	0.25 x 0.25-deg	netCDF
28	HWN_Tn90	Heat wave number (HWN) as defined by the 90th percentile of Tn (Minimum Temperature)	0.25 x 0.25-deg	netCDF
29	HWN_Tx90	Heat wave number (HWN) as defined by the 90th percentile of Tx (Maximum Temperature)	0.25 x 0.25-deg	netCDF
30	HWF_ECF	Heat wave frequency (HWF) as defined by the Excess Heat Factor (ECF)	0.25 x 0.25-deg	netCDF
31	HWF_Tn90	Heatwave frequency (HWF) as defined by the 90th percentile of Tn (Minimum Temperature)	0.25 x 0.25-deg	netCDF
32	HWF_Tx90	Heatwave frequency (HWF) as defined by the 90th percentile of Tx (Maximum Temperature)	0.25 x 0.25-deg	netCDF
33	HWD_ECF	Heatwave duration (HWD) as defined by the Excess Heat Factor (ECF)	0.25 x 0.25-deg	netCDF
34	HWD_Tn90	Heatwave duration (HWD) as defined by the 90th percentile of Tn (Minimum Temperature)	0.25 x 0.25-deg	netCDF
35	HWD_Tx90	Heatwave duration (HWD) as defined by the 90th percentile of Tx (Maximum Temperature)	0.25 x 0.25-deg	netCDF
36	HWM_ECF	Heatwave magnitude (HWM) as defined by the Excess Heat Factor (ECF)	0.25 x 0.25-deg	netCDF
37	HWM_Tn90	Heatwave magnitude (HWM) as defined by the 90th percentile of Tn (Minimum Temperature)	0.25 x 0.25-deg	netCDF
38	HWM_Tx90	Heatwave magnitude (HWM) as defined by the 90th percentile of Tx (Maximum Temperature)	0.25 x 0.25-deg	netCDF
39	HWA_ECF	Heatwave amplitude (HWA) as defined by the Excess Heat Factor (ECF)	0.25 x 0.25-deg	netCDF
40	HWA_Tn90	Heatwave amplitude (HWA) as defined by the 90th percentile of Tn (Minimum Temperature)	0.25 x 0.25-deg	netCDF
41	HWA_Tx90	Heatwave amplitude (HWA) as defined by the 90th percentile of Tx (Maximum Temperature)	0.25 x 0.25-deg	netCDF
42	SPI_TS3M	Standardised Precipitation Index on time scale of 3 months	0.25 x 0.25-deg	netCDF
43	SPI_TS6M	Standardised Precipitation Index on time scale of 6 months	0.25 x 0.25-deg	netCDF

44	SPI_TS12M	Standardised Precipitation Index on time scale of 12 months	0.25 x 0.25-deg	netCDF
45	SPI_TS24M	Standardised Precipitation Index on time scale of 24 months	0.25 x 0.25-deg	netCDF
46	SPI_TS36M	Standardised Precipitation Index on time scale of 36 months	0.25 x 0.25-deg	netCDF
47	SPI_TS48M	Standardised Precipitation Index on time scale of 48 months	0.25 x 0.25-deg	netCDF
48	SPEI_TS3M	Standardised Precipitation Evapotranspiration Index on time scale of 3 months	0.25 x 0.25-deg	netCDF
49	SPEI_TS6M	Standardised Precipitation Evapotranspiration Index on time scale of 6 months	0.25 x 0.25-deg	netCDF
50	SPEI_TS12M	Standardised Precipitation Evapotranspiration Index on time scale of 12 months	0.25 x 0.25-deg	netCDF
51	SPEI_TS24M	Standardised Precipitation Evapotranspiration Index on time scale of 24 months	0.25 x 0.25-deg	netCDF
52	SPEI_TS36M	Standardised Precipitation Evapotranspiration Index on time scale of 36 months	0.25 x 0.25-deg	netCDF
53	SPEI_TS48M	Standardised Precipitation Evapotranspiration Index on time scale of 48 months	0.25 x 0.25-deg	netCDF
54	CDD_T18	Cooling Degree-Days (CDD) utilising the threshold of 18°C	0.25 x 0.25-deg	netCDF
55	CDD_T18.3	Cooling Degree-Days (CDD) utilising the threshold of 18.3°C	0.25 x 0.25-deg	netCDF
56	CDD_T22	Cooling Degree-Days (CDD) utilising the threshold of 22°C	0.25 x 0.25-deg	netCDF
57	CDD_T23	Cooling Degree-Days (CDD) utilising the threshold of 23°C	0.25 x 0.25-deg	netCDF
58	CDD_T24	Cooling Degree-Days (CDD) utilising the threshold of 23°C	0.25 x 0.25-deg	netCDF
59	CDD_T25	Cooling Degree-Days (CDD) utilising the threshold of 23°C	0.25 x 0.25-deg	netCDF
60	HDD_T10	Heating Degree-Days (HDD) utilising the threshold of 10°C	0.25 x 0.25-deg	netCDF
61	HDD_T15	Heating Degree-Days (HDD) utilising the threshold of 15°C	0.25 x 0.25-deg	netCDF
62	HDD_T15.5	Heating Degree-Days (HDD) utilising the threshold of 15.5°C	0.25 x 0.25-deg	netCDF

63	HDD_T16	Heating Degree-Days (HDD) utilising the threshold of 16°C	0.25 x 0.25-deg	netCDF
64	HDD_T17	Heating Degree-Days (HDD) utilising the threshold of 17°C	0.25 x 0.25-deg	netCDF
65	HDD_T18	Heating Degree-Days (HDD) utilising the threshold of 18°C	0.25 x 0.25-deg	netCDF
66	ID	Ice Days – Number of days with maximum temperature lower than 0°C	0.25 x 0.25-deg	netCDF
67	TNlt2	Number of days with minimum temperature below 2°C	0.25 x 0.25-deg	netCDF
68	TNltm2	Number of days with minimum temperature below minus 2°C	0.25 x 0.25-deg	netCDF
69	TNltm20	Number of days with minimum temperature below minus 20°C	0.25 x 0.25-deg	netCDF
70	WSDId	User-defined of annual number of days with maximum temperature higher than 90th percentile	0.25 x 0.25-deg	netCDF
71	CSDI	Cold Spell Duration Indicator	0.25 x 0.25-deg	netCDF
72	CSDId	User-defined of annual number of days with minimum temperature lower than 10th percentile	0.25 x 0.25-deg	netCDF
73	TXgt50p	Percentage of days with maximum temperature higher than 50th percentile	0.25 x 0.25-deg	netCDF
74	TX95t	Value of 95th percentile of maximum temperature	0.25 x 0.25-deg	netCDF
75	TMge5	Number of days with average (mean) temperature higher or equal to 5°C	0.25 x 0.25-deg	netCDF
76	TMlt5	Number of days with average (mean) temperature lower than 5°C	0.25 x 0.25-deg	netCDF
77	TMge10	Number of days with average (mean) temperature higher or equal to 10°C	0.25 x 0.25-deg	netCDF
78	TMlt10	Number of days with average (mean) temperature lower than 10°C	0.25 x 0.25-deg	netCDF
79	TXge30	Number of days with maximum temperature higher or equal to 30°C	0.25 x 0.25-deg	netCDF
80	TXge35	Number of days with maximum temperature higher or equal to 35°C	0.25 x 0.25-deg	netCDF

81	TXdTNd	User-defined number of consecutive hot days and nights	0.25 x 0.25-deg	netCDF
82	GDDgrown	Growing Degree Days – A measure of heat accumulation to predict plant and animal developmental rates	0.25 x 0.25-deg	netCDF
83	R95pTOT	Fraction of total wet-day rainfall that comes from very wet days	0.25 x 0.25-deg	netCDF
84	R99pTOT	Fraction of total wet-day rainfall that comes from extremely wet days	0.25 x 0.25-deg	netCDF
85	RXdday	User-defined consecutive days of PR (precipitation) amount	0.25 x 0.25-deg	netCDF
86	TXbdTNbd	User-defined consecutive number of cold days and nights	0.25 x 0.25-deg	netCDF
87	TX10p	Fraction of days with cool day time temperatures	0.25 x 0.25-deg	netCDF
88	TX90p	Fraction of days with hot day time temperatures	0.25 x 0.25-deg	netCDF
89	TN10p	Fraction of days with cold night time temperatures	0.25 x 0.25-deg	netCDF
90	TN90p	Fraction of days with warm night time temperatures	0.25 x 0.25-deg	netCDF
91	Rnnmm	Number of days with precipitation of at least 10mm	0.25 x 0.25-deg	netCDF
92	R95p	Total annual precipitation (PR) from heavy rain days	0.25 x 0.25-deg	netCDF
93	R99p	Total annual precipitation (PR) from very heavy rain days	0.25 x 0.25-deg	netCDF
94	Rx1day	Maximum amount of precipitation falling in one day	0.25 x 0.25-deg	netCDF
95	Rx5day	Maximum amount of precipitation falling in five consecutive days	0.25 x 0.25-deg	netCDF

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