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Evaluation of Regional Climate Models (RCMs) Using Precipitation and Temperature-Based Climatic Indices: A Case Study of Florida, USA

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Abstract: The overarching objective of this study was to evaluate the performance of nine precipitation-based and twelve temperature-based climatic indices derived from four regional climate models (CRCM5-UQUAM, CanRCM4, RCA4 and HIRHAM5) driven by three global circulation models (CanESM2, EC-EARTH and MPI-ESM-LR) and their ensemble mean for the reference period of 31 years (1975–2005). The absolute biases, pattern correlation, the reduction of variance (RV) and the Standardized Precipitation Evapotranspiration Index (SPEI at 3-, 6- and 12-month aggregate periods) techniques were used to evaluate the climate model simulations. The result, in general, shows each climate model has a skill in reproducing at least one of the climatic indices considered in this study. Based on the pattern correlation result, however, EC-EARTH.HIRHAM5 and MPI-ESM-LR.CRCM5-UQAM RCMs showed a relatively good skill in reproducing the observed climatic indices as compared to the other climate model simulations. EC-EARTH.RCA4, CanESM2.RCA4 and MPI-ESM-LR.CRCM5-UQAM RCMs showed a good skill when evaluated using the reduction of variance. The ensemble mean of the RCMs showed relatively better skill in reproducing the observed temperature-based climatic indices as compared to the precipitation-based climatic indices. There were no exceptional differences observed among the performance of the climate models compared to the SPEI, but CanESM2.CRCM5-UQAM, EC-EARTH.RCA4 and the ensemble mean of the RCMs performed relatively good in comparison to the other climate models. The good performance of some of the RCMs has good implications for their potential application for climate change impact studies and future trend analysis of extreme events. They could help in developing an early warning system to mitigate and prepare for possible future impacts of climate extremes (e.g., drought) and vulnerability to climate change across Florida.

Keywords: climate change; RCMs; climatic indices; performance evaluation

1. Introduction

Increase in the concentrations of the atmospheric greenhouse gases (i.e., carbon dioxide (CO_2), methane [CH_4], nitrous oxide [N_2O], etc.) trigger the rise in temperature that eventually changes the frequency of occurrence of extreme precipitation events (e.g., flood, drought and hurricane) in many regions across the globe [1]. Industrial growth and deforestations are among many factors that are playing a great role in raising the concentration of the atmospheric CO_2 that intensify the change in the mean climatic states [2]. As a result, the frequency of occurrence of extreme events (i.e., floods, droughts, sea level rise, etc.) has increased in recent decades and caused an impact on the socio-economic and environmental sectors at large [3–6]. The available global climate projections indicate the changes in average climate and to some extent about extreme events. The impacts of the extreme events are becoming even worse and could continue to worsen in the future unless remarkable and proper measures are taken to reduce the current greenhouse gas emissions [2,7,8]. The trends of future climate extreme events can be projected and analyzed through the use of climate projection data from the global and regional climate models [9] under different emission scenarios.

Regional climate models (RCMs) driven by the global climate models (GCMs) are increasingly used to assess potential changes in climatic states by various studies [10–14]. The North America COordinated Regional Climate Downscaling Experiment (NA-CORDEX) provides output from several RCM simulations using different boundary conditions from multiple GCMs across the majority of North America [15]. The RCM products have the potential added value of capturing detailed spatial variability, as well as non-linear effects at local and regional scales associated with their finer spatial resolutions, as compared to the GCMs [16]. However, the accuracy and performance of each RCM may vary from region to region since RCMs were derived by considering different boundary conditions (GCMs), unique physical principles and downscaling approaches [17]. Despite the increasing use of RCMs to study the impact of extreme events, considerable systematic errors and bias remain to be challenging for their efficient use and wide application [18]. Thus, several evaluation and bias correction approaches have been developed and applied in various studies to improve the accuracy and quality of the RCMs outputs [19–22].

The evaluation of the RCMs is crucial to measure their skills and accuracy in reproducing the observed data during the reference period [19]. A positive outcome of the evaluation process increases confidence in the potential applications of the RCMs for trend and other analyses of extreme events for future scenarios [9]. The evaluation process involves the computation of several climatic indices derived from the original datasets. These climatic indices, recommended by the Expert Team on Climate Change Detection and Indices (ETCCDI), mainly measure the exceedance of the fundamental characteristics (e.g., duration, intensity) of the climatic variables from certain threshold values [23,24]. In addition, to using climatic indices, the Standardized Precipitation Index (SPI) and Standardized Precipitation and Evaporation Index (SPEI) are used to evaluate the RCMs [25]. These indices are widely used to measure the deviation of a given climate event from the long-term mean value and assess the frequency of occurrence of very dry (drought) and very wet (flood) conditions.

Several studies have evaluated RCMs at continental, country and regional scales using different evaluation techniques [16,25,26]. However, more evaluation studies of the RCMs need to be conducted at smaller/local scales (e.g., watershed, basin and state level) to build confidence in the capability of RCM simulations to capture the detailed characteristics of the climatic patterns at local scales. In Florida, there are limited studies of evaluations of the climate models despite the fact that the state is vulnerable to the impacts of climate change of unprecedented magnitude [27]. Some studies follow a quantitative evaluation and bias correction approach to assess the performance of a single RCM in reproducing the variability of the observed climatic variables [28], whereas the majority of the other studies focused on the assessment of climate change impacts on agricultural productivity [29], rainfall intensity–duration–frequency (IDF) curves [30], stream flow simulation [31] and socio-economic sectors [32]. Nevertheless, several RCM evaluations studies are still limited in Florida. These evaluation studies are crucial for identifying RCMs that perform relatively better in reproducing the observed precipitation and temperature during the reference period and their potential application in the impact assessment of climate change in the future.

Thus, this study evaluates precipitation and temperature simulations from four RCMs (i.e., Canadian Regional Climate Model version 5 Université du Québec à Montréal (CRCM5-UQAM), Canadian Regional Climate Model version 4 (CanRCM4), Rossby Center Regional atmospheric model (RCA4) and HIRHAM5, a combination of High Resolution Limited Area Model (HIRLAM) and European Centre Hamburg Model (ECHAM) forced by three GCMs (i.e., Canadian Centre for Climate Modelling and Analysis (CanESM2), European community Earth-System Model (EC-EARTH) and Max Planck Institute Earth

System Mode (MPI-ESM-LR) across Florida. The ensemble mean of the four RCM simulations are also calculated and compared with each RCM in the evaluation process to identify whether any added value that is obtained could be from the combinations of the four RCMs. The evaluation is based on the climatological mean (31 years average) of the climate indices and SPEI time series data derived from the daily precipitation and temperature.

2. Materials and Methods

2.1. Study Region

The state of Florida is located in a peninsula between the Gulf of Mexico, the Atlantic Ocean and the Straits of Florida (Figure 1) at a geographic location ranging approximately between 25° N and 31° N latitude [33]. Based on measured weather data obtained from the Florida Climate Center from 1981 to 2010 (https://climatecenter.fsu.edu/products-services/data, accessed on 21 December 2019), the average annual precipitation and temperature values are ~1410 mm and ~22 °C, respectively. The state is characterized by a diverse climate suitable for growing different varieties of crops. Florida is ranked as one of the largest crop-producing states in the U.S. [29,34]. The source of the water supply for agricultural productivity is both from surface and sub-surface sources replenished from the annual precipitation. The main rainfall season is from May to October and contributes 70 percent of the annual water budget [29]. Climate change is a future challenge that threatens the availability of fresh water for crop production [35]. Some studies show that the impacts of climate change have already been observed and are affecting the agricultural sectors [29] and the availability of fresh water, prompted by saltwater intrusion due to sea level rise [36]. The sea level rise is driven mainly by melting ice sheets and thermal expansion triggered by the elevated temperature due to climate change. The occurrence of the irregular periodic variation in sea surface temperature over the Pacific Ocean caused the occurrence of El Niño Southern Oscillation (ENSO). In general, agricultural productivity is very sensitive and directly interrelated with the occurrence of ENSO [34].

Several studies have been conducted on the impact of climate change on the agricultural sector and the availability of freshwater in Florida [29,33,37]. However, specific studies are needed to evaluate the available RCMs and identify the regional climate model that could be used for the assessment and analysis of climate trend and its future impact in Florida. The climate change scenarios show an elevation in temperature and moisture-holding capacity of the air resulting in higher frequency and intensity of climate extreme events such as drought, flood, heatwave, etc. [38]. The application of more reliable RCMs is crucial for impact assessment and trend analysis of the future climatic conditions in Florida.

2.2. Data Description

2.2.1. Regional and Global Climate Models (RCMs and GCMs)

NA-CORDEX data archives covers output from various RCMs driven by different GCMs at rotated-pole grids (0.11°, 0.22° and 0.44°) and interpolated grids (0.22° and 0.44°). This study uses precipitation and temperature on the dynamically downscaled interpolated grids derived from four RCMs (CRCM5-UQUAM, CanRCM4, RCA4 and HIRHAM5) simulations archived at the NA-CORDEX data portal (https://www.earthsystemgrid.org/search/cordexsearch.html, accessed on 21 December 2019). The description and relevant characteristics of the four RCM simulations driven by three GCMs (CanESM2, EC-EARTH and MPI-ESM-LR) are provided in Table 1. In addition, the ensemble mean of the climatology of these RCMs were also considered in the evaluation process to explore any added skill of ensemble mean in reproducing the observed climatology. The selection of the RCMs is mainly based on the availability of the data for various combinations of RCM, GCM, representative concentration pathways (RCPs) and spatial resolution for the reference period (1975–2005) and future scenarios. This study only covers the evaluation of the climatic models for the reference period; however, the selection criteria accounted for the projected data of the future scenarios for their potential application in our future climate change impact assessment study. The reference period (1975–2005) represents the

30-year climatological period and the future scenarios cover the near-future (2020–2049), mid-future (2050–2079) and far-future (2080–2100) periods. The interpolated grid data at spatial resolutions of 0.44° (~50 km) and daily temporal scale were used in this study. The state (Florida) is represented by a total of 55 grid points.

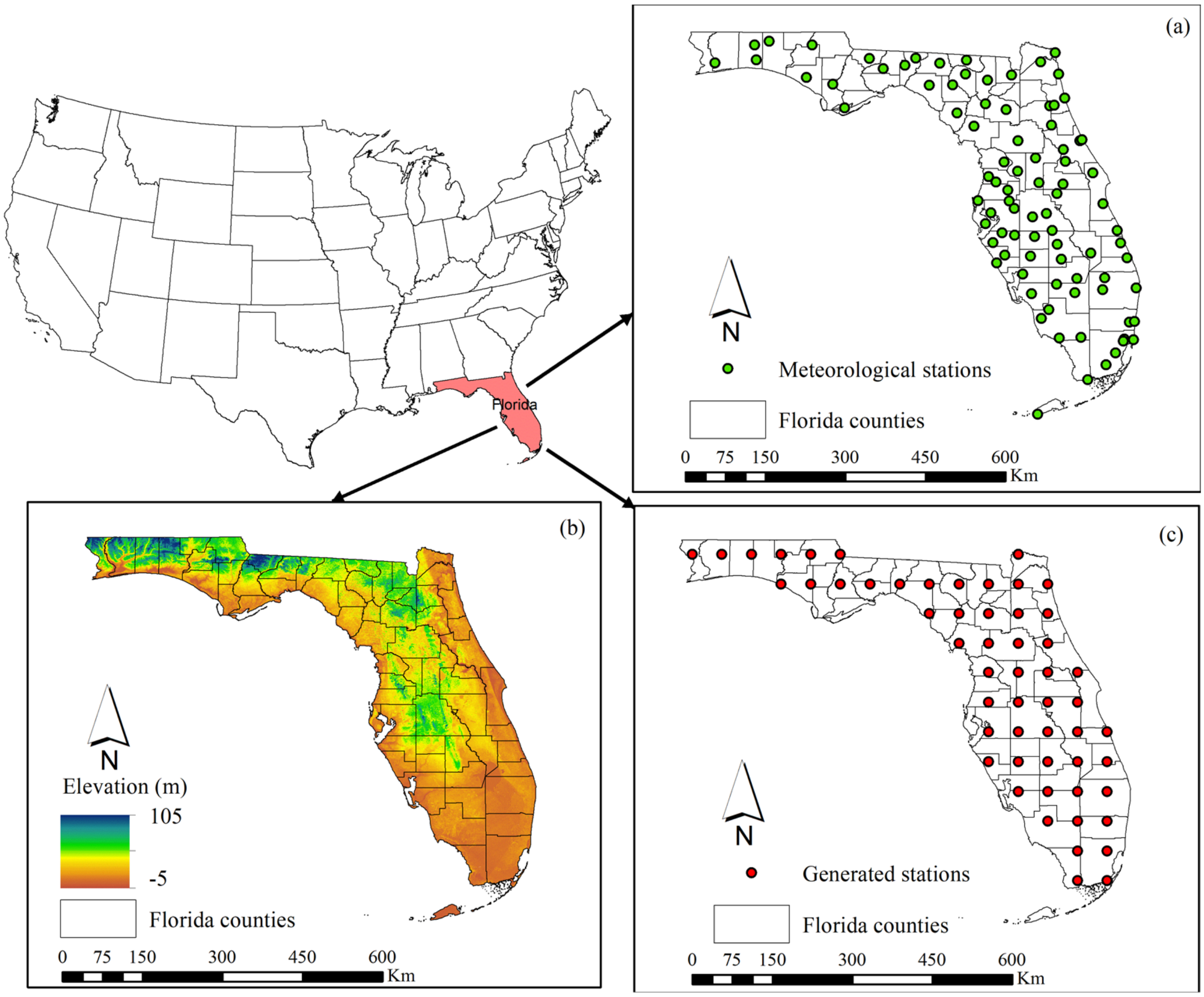

Figure 1. This figure shows the locations of the stations obtained from Florida Climate Center (**a**), the elevation distributions (**b**) and generated stations at the centroid of each grid (**c**) over Florida.

Table 1. The list, description and relevant characteristics of the RCMs and GCMs used in this study.

RCMs	GCMs (Boundary Condition)	Simulation Acronym	Description of the RCMs
CRCM5-UQAM	CanESM2 MPI-ESM-LR	CanESM2. CRCM5-UQAM MPI-ESM-LR. CRCM5-UQAM	Canadian Regional Climate Model version 5 Université du Québec à Montréal
CanRCM4	CanESM2	CanESM2. CanRCM4	Canadian Regional Climate Model version 4
RCA4	CanESM2 EC-EARTH	CanESM2. RCA4 EC-EARTH. RCA4	Rossby Center Regional Atmospheric Model
HIRHAM5	EC-EARTH	EC-EARTH. HIRHAM5	HIRHAM5, A Combination of High Resolution Limited Area Model (HIRLAM) and European Centre Hamburg Model (ECHAM)]

2.2.2. Meteorological Observations

The evaluations of the RCM based daily precipitation and temperature were carried out using station-based ground observation climate data obtained from the Florida Climate Center (https://climatecenter.fsu.edu/products-services/data, accessed on 21 December 2019). The daily gridded time series data of precipitation and maximum and minimum temperature were generated from the stations during the reference period (1975–2005) using 94 stations across Florida. Each grid value of the climatic indices derived from the climate model data represents the areal average value within each grid box and direct comparison using station (point-based) data may introduce a systematic error and misinterpretation of the result [25]. Therefore, we first generated the gridded daily time series data of the observed climatic variables (station-based) at the same spatial resolutions (~50 km) as those of the climate models. The Inverse Distance Weighted (IDW) technique is used to interpolate the station-based climatic variables. The IDW is employed because it gives a better representation and is a widely used technique in many watersheds [39–41]. The number of stations used to generate each daily gridded data varies based on the availability of the data for each day. The time series data of the observed climate variables were extracted at the center of each grid (Figure 1c) for the evaluation of the RCMs.

2.3. Climate Indices and Their Computation

The climate indices were computed as per the recommendation of the World Meteorological Organization CC1/CLIVAR Expert Team for Climate Change Detection Monitoring and Indices (ETCCDMI [23]. There are 27 core indices based on percentile and duration of an event as well as some user-defined absolute thresholds [23,24]. However, this study made use of twelve temperature and nine precipitation-based indices (Table 2) to characterize the climatic conditions in Florida. These indices were selected based on their wide application and potential uses in analyzing and assessing the changes in climate extremes [42]. The computation of the climatic indices was performed by using the RClimDex package developed under the R programing language, which is a free, powerful and robust software [24]. This computation involves checking the input data quality as a prerequisite before the computation of the climatic indices. The quality control procedure comprised the examination of the presence of outlier and unreasonable values, which include precipitation amount less than zero and maximum temperature less than the minimum temperature. The data quality assessment revealed the good quality of both precipitation and temperature data obtained from the climate models and observed data sources, except MPI-ESM-LR GCM that is forced by CRCM5-UQAM RCM. In this climate model (MPI-ESM-LR), unrealistic values (i.e., minimum temperature greater than the maximum temperature) were observed in about 14 days in each station. These erroneous values were filtered out and considered as missing values during the climate indices calculations. The observed climatic indices were derived from the gridded data generated by interpolating and resampling the meteorological stations' observed climate data to the same spatial resolutions as the RCMs. After computing each climatic indicator for each RCM, then we calculated the ensemble mean by taking simple arithmetic mean of the climatology of each individual ensemble member (RCM) instead of averaging the daily raw data and computing the ensemble climatic indices. Climate models were initialized with certain initial boundary conditions that remain for a short duration (short initial condition memory) due to uncertainties introduced owing to the erratic nature of the weather.

Table 2. List of ETCCDMI core climate indices used in this study. Further detailed explanation about these and other indices can be referred from the RClimDex user manual [24].

Indicator	Indicator Name	Definition	Units
CDD	Consecutive Dry Days	Largest Number of Consecutive Days where Precipitation <1 mm	Days
CWD	Consecutive Wet Days	Largest Number of Consecutive Days where Precipitation >1 mm	Days
RX1day	Maximum 1-Day Precipitation	Maximum 1-Day Precipitation Amount in a Given Period	mm
Rx5day	Maximum 5-Day Precipitation	Maximum Consecutive 5-Day Precipitation Amount in a Given Period	mm
R10mm	Heavy Precipitation Days	Total Number of Days when Precipitation $\geq$ 10 mm	Days
R20mm	Very Heavy Precipitation Days	Total Number of Days when Precipitation $\geq$ 20 mm	Days
R95p	Very Wet Days	Total Precipitation when Daily Rainfall >95th Percentile on Wet Days of the Reference Period from 1975 to 2005	Days
R99p	Extremely Wet Days	Total Precipitation when Daily Rainfall >99th Percentile on Wet Days of the Reference Period from 1975 to 2005	Days
SDII	Simple Daily Intensity Index	Annual Total Precipitation Divided by the Number of Wet Days (precipitation $\geq$ 1.0 mm) in the Year	mm/day
SU25	Summer Days	Number of Days where TX (Daily Maximum) >25 °C	Days
TR20	Tropical Nights	Number of Days where TN (Daily Minimum) >20 °C	Days
TXx	Max Tmax	Monthly Maximum Value of Daily Maximum Temperature	°C
TXn	Min Tmax	Monthly Minimum Value of Daily Maximum Temperature	°C
TNx	Max Tmin	Monthly Maximum Value of Daily Minimum Temperature	°C
TNn	Min Tmin	Monthly Minimum Value of Daily Minimum Temperature	°C
TN10p	Cool Nights	Percentage of Days when TN <10th Percentile	Days
TX10p	Cool Days	Percentage of Days when TX <10th Percentile	Days
TN90p	Warm Nights	Percentage of Days when TN >90th Percentile	Days
TX90p	Warm Days	Percentage of Days when TX >90th Percentile	Days
TMAXmean	Maximum Mean Temperature	Average Maximum Temperature	°C
TMINmean	Minimum Mean Temperature	Average Minimum Temperature	°C

2.4. Evaluation Metrics

Evaluating the climate models in reproducing the observed climatic variables (i.e., precipitation and temperature) for the reference period is exceptional in terms their potential application of the projected dataset for future impact studies across Florida. Several statistical approaches are commonly and widely used to evaluate the RCMs. The performances of these evaluation techniques have been explained and supported in several studies [16,43,44].

The absolute biases between the model and the observed climatology were computed both for precipitation and temperature-based climatic indices. Negative values indicate underestimation while the positive values indicate overestimation of the climate models. The values closer to zero show minimum difference and best estimation of the climate models. The subsequent two subsections explained the absolute biases obtained for precipitation (nine climatic indices) and temperature (twelve climatic indices) based climatic indices for the selected six climate models and the ensemble mean across Florida to investigate the spatial coherence and integrity across space.

The correlation coefficient (r) and the coefficient of determination (r^2) are among many approaches commonly used in various studies [25,42]. The Pearson correlation coefficient measures the goodness of fit and linear association between two variables [25,42,45]. It measures how well the climate-model-based climate indices explain the observed climate indices. Even though the daily time series input data was used to compute the values of the climatic indices, the temporal scale of the climate indices is annual. This makes the data length relatively short for the accurate estimation of the Pearson correlation coefficient values in the reference period. Instead, the pattern correlation coefficient (occasionally referred to as map correlation) was computed between the maps using climatological mean values of the climate indices of the observed data and RCMs across Florida. The Pearson correlation coefficient (pattern correlation) is used in this study and its mathematical formulation is shown in Equation (1). Its value ranges between 1 and −1. Positive one indicates a strong positive relationship whereas negative one indicates a strong negative relationship and zero indicates weak or no relationship.

$$r = \frac{\sum_{i=1}^{n}(x_i - \overline{x})(y_i - \overline{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \overline{x})^2 \sum_{i=1}^{n}(y_i - \overline{y})^2}}, \tag{1}$$

where r is the correlation coefficient, x represents the climatological mean of the observational climatic indices, y represents the climatological mean of the RCM simulations of the climatic indices, $\overline{x}$ is the average climatological mean of the observational climatic indices, $\overline{y}$ is climatological mean of the RCM simulations of the climatic indices and n = number of data pairs.

Mean square skill score (MSSS) was used to evaluate the spatial pattern of the climatological mean of the climatic indices. The MSSS approach, in general, measures the relative accuracy of a given RCM simulation and selected reference dataset with respect to the observations [25,46,47]. There are several versions of MSSS based on the reference dataset, but the MSSS that considers the variance of the observations (known as Reduction of Variance, RV) as a reference is being applied in this study. Diaconescu et al. [48] reported the good skill of this approach in evaluating the RCM simulation-based climatic variables (i.e., precipitation and temperature) over the Canadian Arctic land areas. The mathematical formulation of this score is shown in Equation (2).

$$RV_k = 1 - \frac{\sum_{i=1}^{N}(y_{ki} - x_i)^2}{\sum_{i=1}^{N}(x_i - x')^2} \tag{2}$$

where y_{ki} represents the climatological mean of dataset k (RCM simulations of the climatic indices) at the grid point closest to station i, x_i represents the climatological mean of the observational climatic indices of station i and x' represents the spatial average of the climatological mean of the observational climatic indices across the study region (Florida). N is the number of stations. The RV, value greater than zero indicates a smaller mean squared error value of the dataset in comparison to the spatial variance in the observations.

The other evaluation criteria used in this study involves the computation of the time series of SPEI (3-, 6- and 12-month) values for each RCM and the observed datasets. The SPEI accounts for the reference evapotranspiration (ETo), in addition to precipitation, which makes it more advantageous than the SPI [49]. The computational procedure of the SPEI is similar to that of the SPI except in its consideration of the difference between precipitation and reference evapotranspiration (P–ETo) as an input variable rather than considering only precipitation, as in the case of SPI. The SPI calculation procedures can be found in Bayissa et al. [39]. The Pearson correlation coefficient values were computed using the time series of each RCM and the observed SPEI for 3-, 6- and 12-month aggregate periods and used to evaluate each RCM. In this study, SPEI at 3-, 6- and 12-month aggregate periods were used because of their suitability in characterizing the different types of drought (i.e., meteorological, agricultural and hydrological) and flood events [50].

3. Result and Discussion

3.1. Absolute Biases between Model and Observed Climatology

3.1.1. Precipitation Based Climatic Indices

Figures 2–4 show the absolute biases (model minus observation) in the climatological mean of the precipitation indices (i.e., CCD, CWD, R99p, Rx1day, R10mm, R20mm, R95p, Rx5day and SDII). Figure 2 shows the pattern of the absolute biases of some of precipitation-based climatic indices that include CDD, CWD, R99p and RX1day generated at the stations located at the center of each pixel across Florida. The observed precipitation and temperature-based climatic indices are show in Appendix A. In general, all the RCMs except EC-EARTH.HIRHAM5 overestimated the consecutive dry days (CDD; rainfall < 1 mm) since negative absolute bias values were indicated in the majority of the stations. Although the ensemble mean underestimated CDD in majority of the stations with the absolute biases of +/−5 range, it still showed good skill than some of the RCMs (e.g., CanESM2.CanRCM4, CanESM2.CRCM5-UQAM and MPI-ESM-LR.CRCM5-UQAM). Since the ensemble mean was generated using the simple arithmetic mean of the climatology of the individual ensemble member, it outperformed some of the RCMs and underperformed as compared to some of the RCMs. EC-EARTH.HIRHAM5 estimated CDD very well as compared to the other climate models with relatively minimum absolute bias of +/−5 range in 85% of the stations. EC-EARTH.RCA4 also showed good performance next to EC-EARTH.HIRHAM5 in 77% of the stations under similar CDD criteria. CDD is an effective index to indicate the dry spell or drought condition and hence there is no dry biases of the RCMs in the majority of the stations. Except EC-EARTH.HIRHAM5, most of the RCMs overestimated CWD in majority of the stations. EC-EARTH.RCA4 and CanESM2.RCA4 showed relatively better skill in explaining CWD as compared to other climate models with absolute biases ranging between −5 to 5 in 100% and 98% of the stations respectively. CanESM2.CanRCM4 overestimated CWD mainly in the southern part. Next to EC-EARTH.RCA4 and CanESM2.RCA4, MPI-ESM-LR.CRCM5-UQAM RCM and EC-EARTH.HIRHAM5 also performed very well in estimating CWD except an overestimation in 31% of the stations and underestimation in 25% of the stations, respectively. Despite some discrepancy in the skill of the EC-EARTH.HIRHAM5, EC-EARTH.RCA4 and CanESM2.RCA4 RCMs in reproducing the observed CWD in some stations, these three RCMs showed relatively better skill in explaining CDD and CWD as compared to the other RCMs. Errors in the parameterizations of the regional climate model in simulating the convective systems at the local scale often introduce systemic dry and wet biases. The wet bias (less CDD and high CWD) in most of the climate models indicates more frequent occurrence of 1 mm and above daily precipitation as compared to the observation. The climate models have been portrayed in the past by the issue of estimating more frequent precipitation events and this problem has not been significantly improved in the RCMs used in this study [51]. The ensemble mean CanESM2.RCA4 and EC-EARTH.RCA4 relatively showed a better skill as compared to the other RCMs in estimating the extreme wet days (R99p) with the absolute biases ranging between −15 to 15 in 65%, 56% and 52% of the stations, respectively. CanESM2.CanRCM4 also showed a good skill in estimating R99p in 40% of the stations, while the remaining RCMs underperformed in reproducing R99p. CanESM2.CRCM5-UQAM relatively outperformed other RCMs in estimating the maximum 1 day precipitation (Rx1day) in 67% of the stations located in different parts and followed by MPI-ESM-LR.CRCM5-UQAM (58% of the stations) compared with absolute biases +/−10 range. The ensemble mean CanESM2.RCA4 and EC-EARTH.RCA4 closely performed in estimating Rx1day in 50, 48 and 46% of the stations while the other RCMs underperformed in the majority of the stations (absolute biases ranging from −10 to 10). This result highlights relatively less performance of RCMs to fully capture the extreme precipitation events as compared to capturing less extreme events attributed to the coarser spatial resolutions of the RCMs and the high dynamics of the extreme precipitation events primarily at mesoscale, which can be difficult to fully capture using relatively coarse resolution RCMs. Diaconescu et al. [25] reported improvement in the RCMs performance in characterizing some precipitation based climatic indices during summer owing to improvement in spatial resolutions of some of the RCMs. Lower score in simulating some of the precipitation extremes (e.g., RX1day) was also reported even though finer spatial resolutions of some of the RCMs (e.g., CRCM5 and CanRCM4). The occurrence of wet and dry day events can be better reproduced through conducting a detailed analysis of the convective rainfall for some of the RCMs (e.g., CanRCM4).

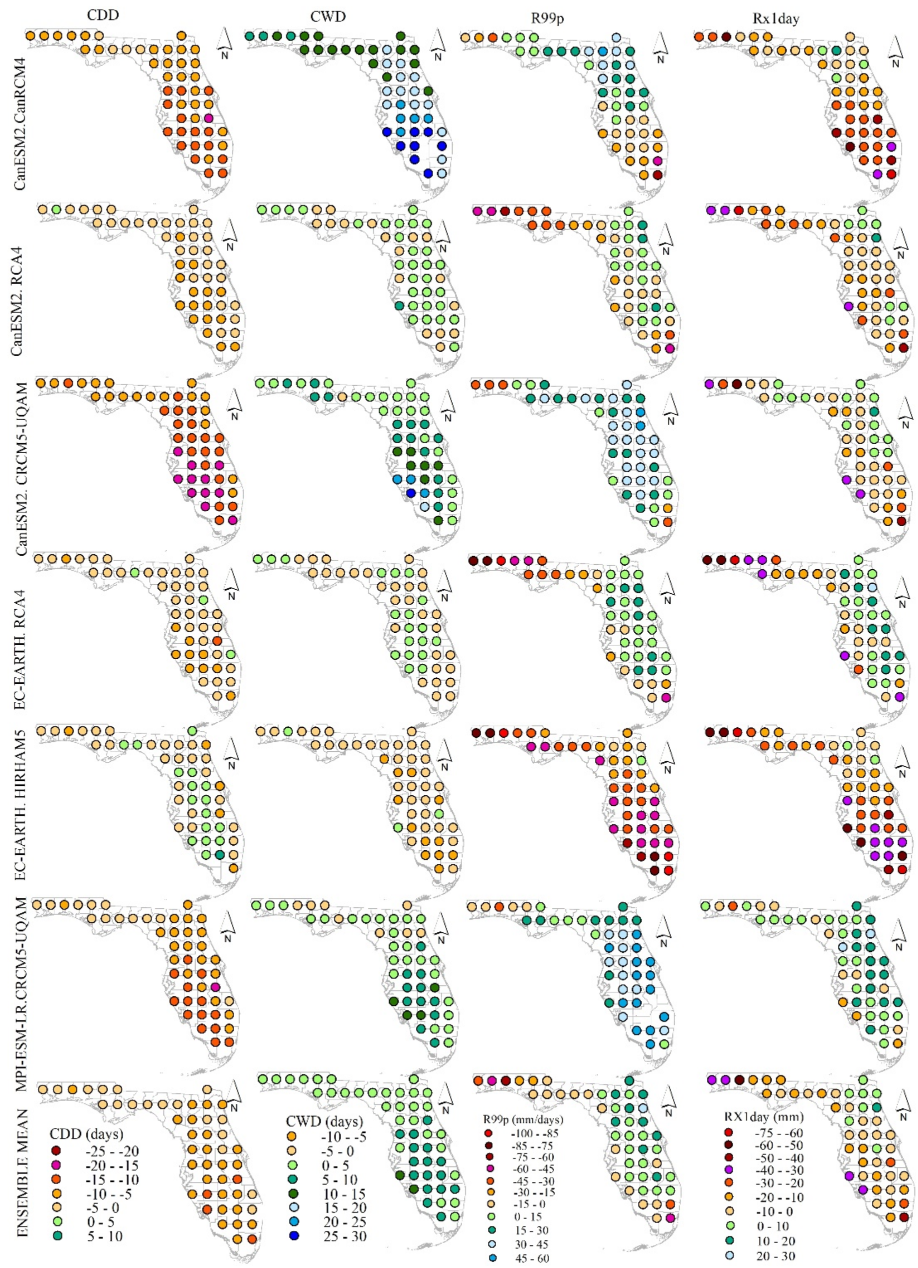

Figure 2. The absolute biases estimated using the difference between model climatology and observed climatology for CDD (first panel), CWD (second panel), R99p (third panel) and Rx1day (fourth panel) precipitation indices at the stations generated at the centroid of each grid across Florida.

Figures 3 and 4 show the absolute biases for the remaining precipitation-based climate indices (i.e., R10mm, R20mm, R95p, RX5day and SDII) for the RCMs considered in this study. Except the ensemble mean, EC-EARTH.RCA4 and MPI-ESM-LR.CRCM5-UQAM climate models, the remaining RCMs showed less performance (>90% of the stations) with reference to the observed R10mm absolute biases with +/−6 range. The ensemble mean captured the observed R10mm climatology in 65% of the stations (Figure 3) as compared to other RCMs with absolute biases with +/−6 range. Relatively, the good performance of the ensemble mean in estimating some of the climatic indices (i.e., R10mm) indicates the importance of using the average of the individual ensembles instead of using a single RCM. MPI-ESM-LR.CRCM5-UQAM explained R20mm very well in 98% of the stations (absolute biases from −6 to 6) followed by CanESM2.CRCM5-UQAM (94% of the stations) and CanESM2.RCA4 (90% of the stations) while EC-EARTH.RCM4 and the ENSEMBLE

MEAN equality performed in 79% of the stations in estimating R20mm. Similar to the other climatic indices, the skills of the climatic model in explaining the 95th percentile of precipitation, maximum 5-day precipitation (Rx5day) and Simple Daily Intensity Index (SDII) varied from one model to the other. In general, EC-EARTH.RCM4, CanESM2. RCM4, CanESM2.CRCM5-UQAM, ENSEMBLE MEAN and MPI-ESM-LR.CRCM5-UQAM have better skill in explaining these three climatic indices except relatively less performance of CanESM2.CRCM5-UQAM and MPI-ESM-LR.CRCM5-UQAM climate model in reproducing 95th percentile precipitation (R95p). The other climate models showed less performance and often overestimated in the majority of the stations. In general, the evaluation of the climate models using the precipitation based climatic indices and measured in terms of the absolute biases indicated the good performance of each model in explaining at least one climatic index better than the others except the ensemble mean. Moreover, the result further shows EC-EARTH.RCM4 climate model outperformed the other RCMs in explaining most of the climatic indices very well under the criteria considered in this section. In overall, the ensemble of the six RCMs showed the relatively good skill in reproducing some of the observation-based climatology (e.g., R10mm and R95p) than the individual ensembles. Since the ensemble mean is derived by considering the simple arithmetic mean value of the climatology of the six RCM simulations, it outperformed in some of the indices and underperformed in another climatic indices.

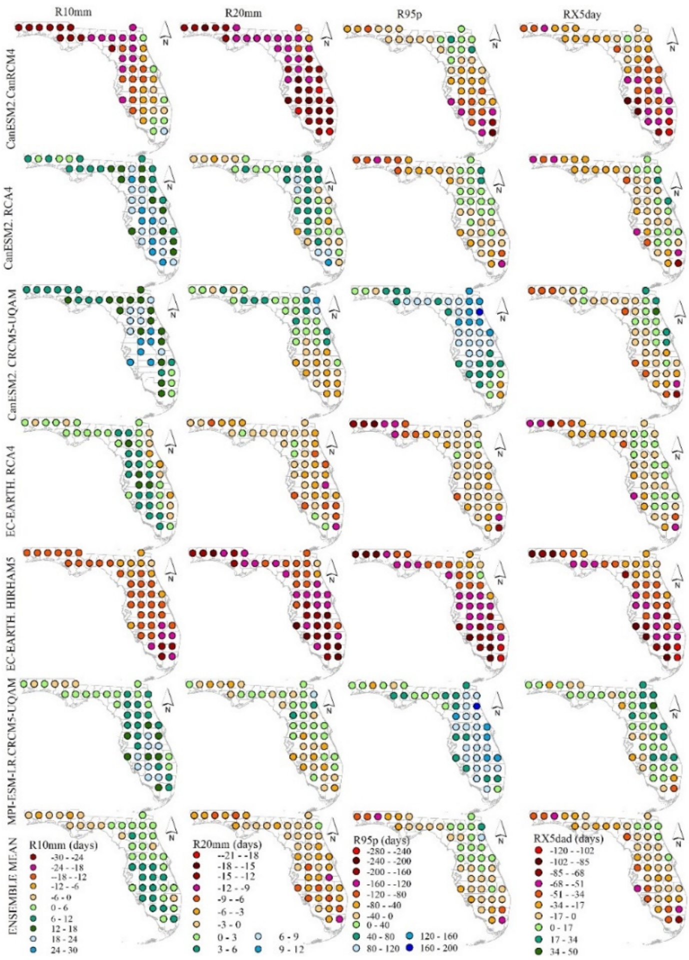

Figure 3. The absolute biases estimated using the difference between model climatology and observed climatology for R10mm (first panel), R20mm (second panel), R95p (third panel) and Rx5day (fourth panel) precipitation indices at the stations generated at the centroid of each grid across Florida.

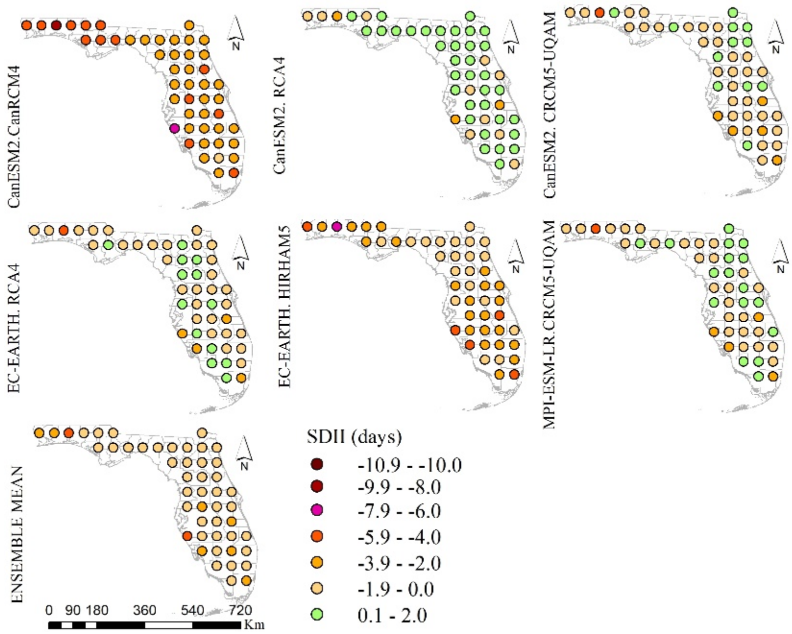

Figure 4. The absolute biases estimated using the difference between model climatology and observed climatology for SDII precipitation indices at the stations generated at the centroid of each grid across Florida.

3.1.2. Temperature Based Climatic Indices

Figure 5 shows the absolute bias in climatology of selected temperature-based indices (i.e., cool nights-TN10p, cool days-TX10p, warm nights-TN90p and warm days-TX90p) compared to observed climatology for each model. As expected, all models captured temperature-based indices compared to precipitation-based indices with bias for the selected indices falling in +/−1 day range. Out of the four indices, relatively higher inter-model skill differences are found for TN90p while all models showing the highest agreement for TX10p. Unlike precipitation-based indices, ensemble averaging has limited effect on performance with slight improvements in terms of bias magnitudes. Although averaging resulted in a consistent underestimation compared to individual models, the spatial pattern of the bias has remained unaffected. Although bias magnitudes are very small and all models captured the indices reasonably well, models were compared based on the slight differences in skill.

In general, all the RCMs show a good performance in estimating TN10p as shown in Figure 5 in the first panel. Each RCM showed a good skill in estimating TN10p in more than 50% of the stations for the absolute bias ranging from −0.2 to 0.2. For CanESM2.RCA4, CanESM2.CRCM5-UQAM and EC-EARTH.RCA4 RCMs, 100% of stations show bias within +/−0.5 range while for the least performing RCMs MPI-ESM-LR.CRCM5-UQAM, 90% of stations show bias in this range. The other RCMs fall in between the above figures. For TN90p on the other hand, CanESM2.CanRCM4, CanESM2.RCA4 and CanESM2.CRCM5-UQAM performed relatively the least with only 90%, 83% and 70% of stations with bias in the range +/−0.5, while for remaining models, the percentage is 100%. Except CanESM2.CanRCM4 and CanESM2.RCA4, all the RCMs showed comparable performance in estimating the minimum range of TX10p in 46 to 48% of the stations. Similarly, all the RCMs showed the highest agreement in estimating TX90p in more than 44% of the stations in +/−0.2 range.

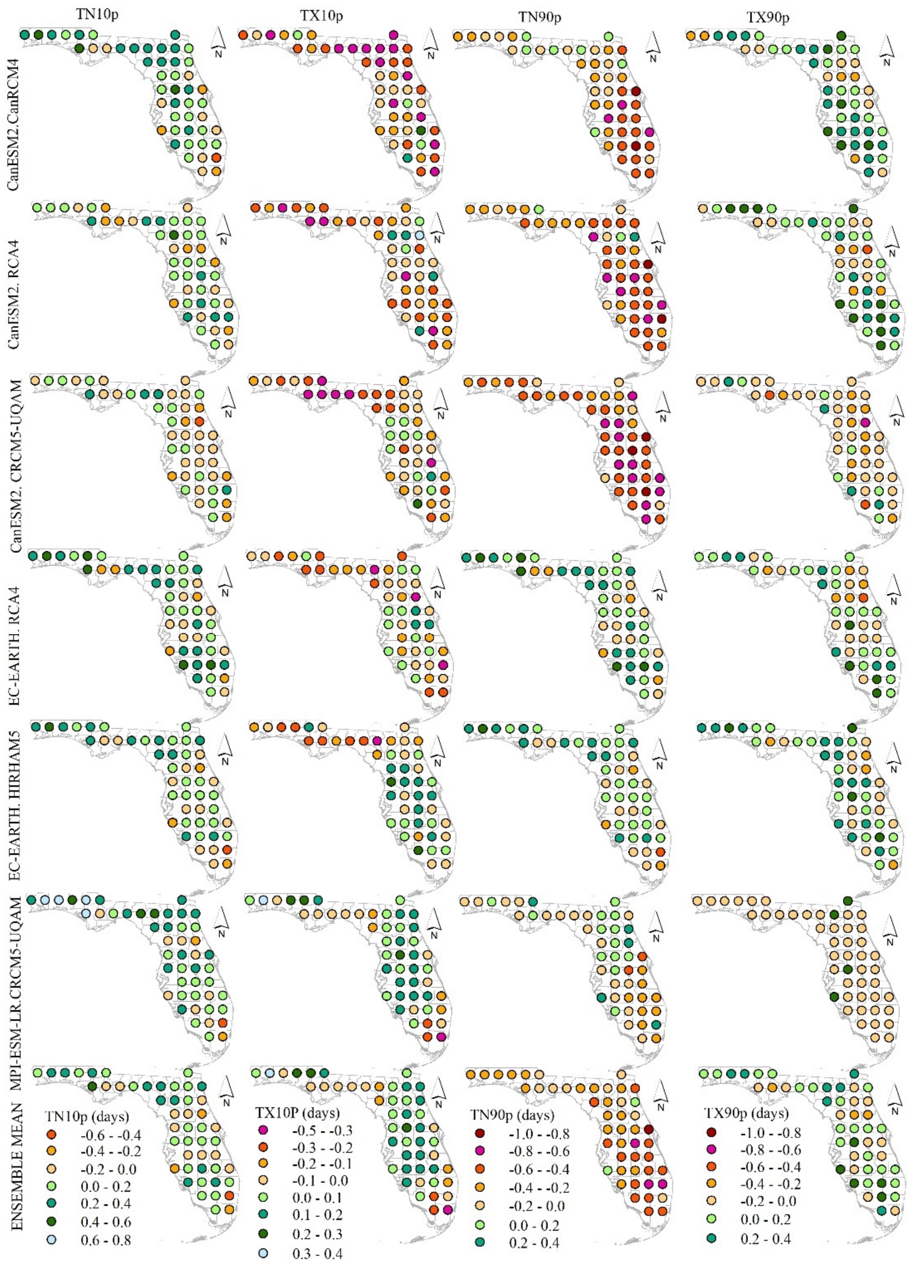

Figure 5. The absolute biases estimated using the difference between model climatology and observed climatology for TN10p (first panel), TX10p (second panel), TN90p (third panel) and TX90p (fourth panel) temperature indices at the stations generated at the centroid of each grid across Florida.

Figure 6 shows the absolute biases of TNn, TNx, TXn and TXx temperature based climatic indices. The minimum category of the absolute biases that show the closed range of the RCMs to the observed climatology is considered to compare the performance of each RCM. The result showed the best skill of EC-EARTH.RCA4 in reproducing TNx, TXn and TXx in 81, 60 and 83% of the stations as compared to the other RCMs while CanESM2.CanRCM and MPI-ESM-LR.CRCM5-UQAM outperformed in estimating TNn in 81% of the stations. There is average performance of the ENSEMBLE MEAN in estimating these four indices. In overall, most of the RCMs performed reasonably well although poor performance of some the RCMs in reproducing some of the temperature based climatic indices. The good performance of the RCMs indicates the limited influences of the boundary conditions, spectral nudging and spatiotemporal resolutions on the temperature-based indices and its less variability across space as compared to precipitation although extreme temperature is highly influenced by the physical parameterization.

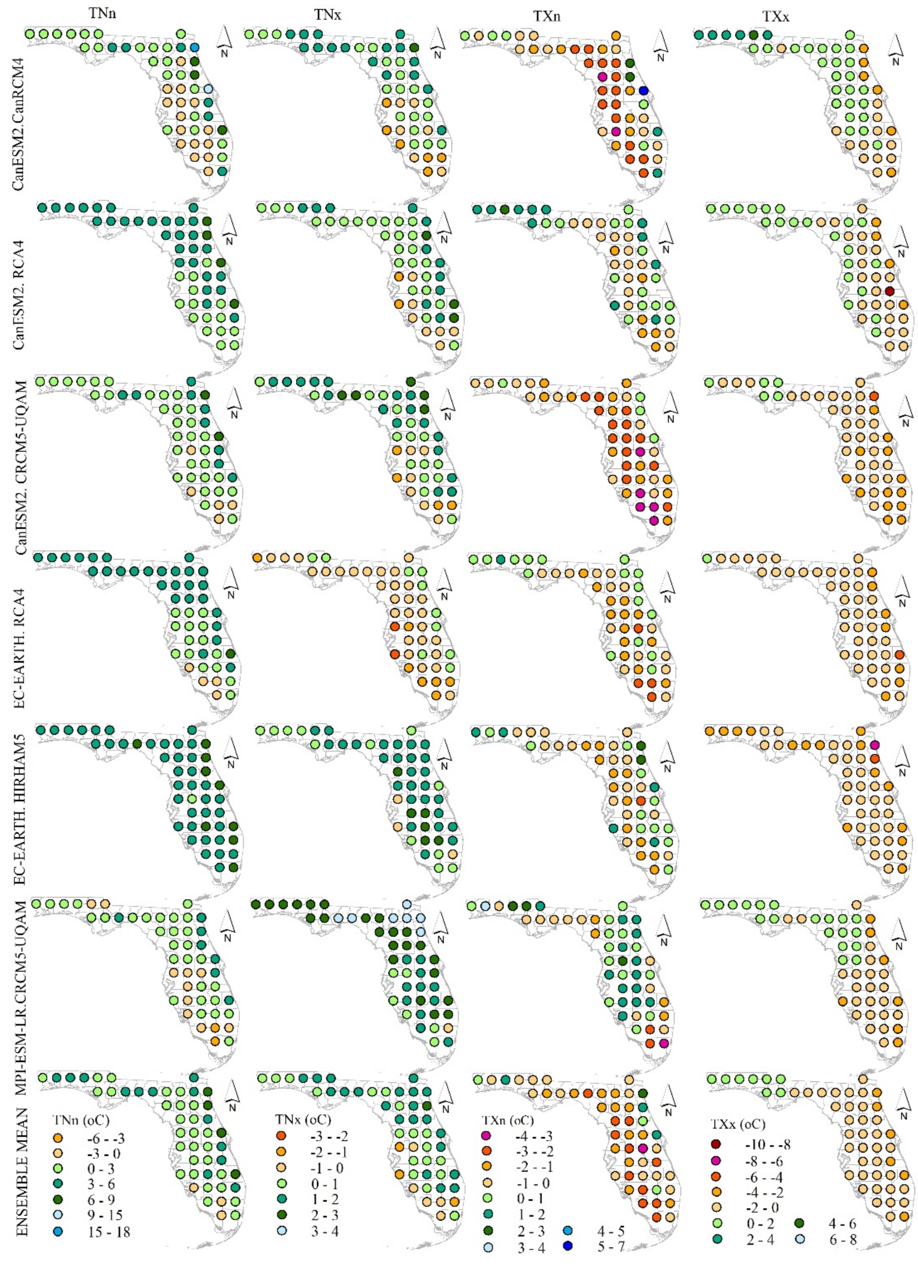

Figure 6. The absolute biases estimated using the difference between model climatology and observed climatology for TNn (first panel), TNx (second panel), TXn (third panel) and TXx (fourth panel) temperature indices at the stations generated at the centroid of each grid across Florida.

All the climate models underestimated the number of days where the daily maximum temperature is greater than 25 °C (SU25) as shown in Figure 7 (first panel). Relatively better performance has been observed in the stations located in Northwest by the majority of the RCMs. In addition, CanESM2.CanRCM4 and EC-EARTH.HIRHAM5 relatively indicated minimum absolute biases in the southern part. The ENSEMBLE MEAN outperformed the other RCMs except CabESM2.RCA4 in reproducing the tropical nights (TR20) even though the other RCMs also showed good performance in some of the stations. Except EC-EARTH.RCA4, the rest of the RCMs overestimated the tropical nighttime temperature in majority of the stations. Except the good performance of CanESM2.CanRCM4 in few stations in northwest part, the rest of the RCMs underestimated the maximum mean temperature (TMAXmean) as shown in Figure 7 (third panel). In overall, most of the RCMs reproduced the minimum mean temperature over 21% of the stations and EC-EARTH.RCA4 performed well in 56% of the stations as compared to the other RCMs in +/−1 range. Temperature based indices that are strongly connected to the freezing and heat stress events have prominent influence on the agricultural crop production. Application of the regional climate models for agricultural management needs to apply biases correction and to quantify the uncertainty of the RCMs since crop production is very sensitive to the freezing and heat stress events in Florida.

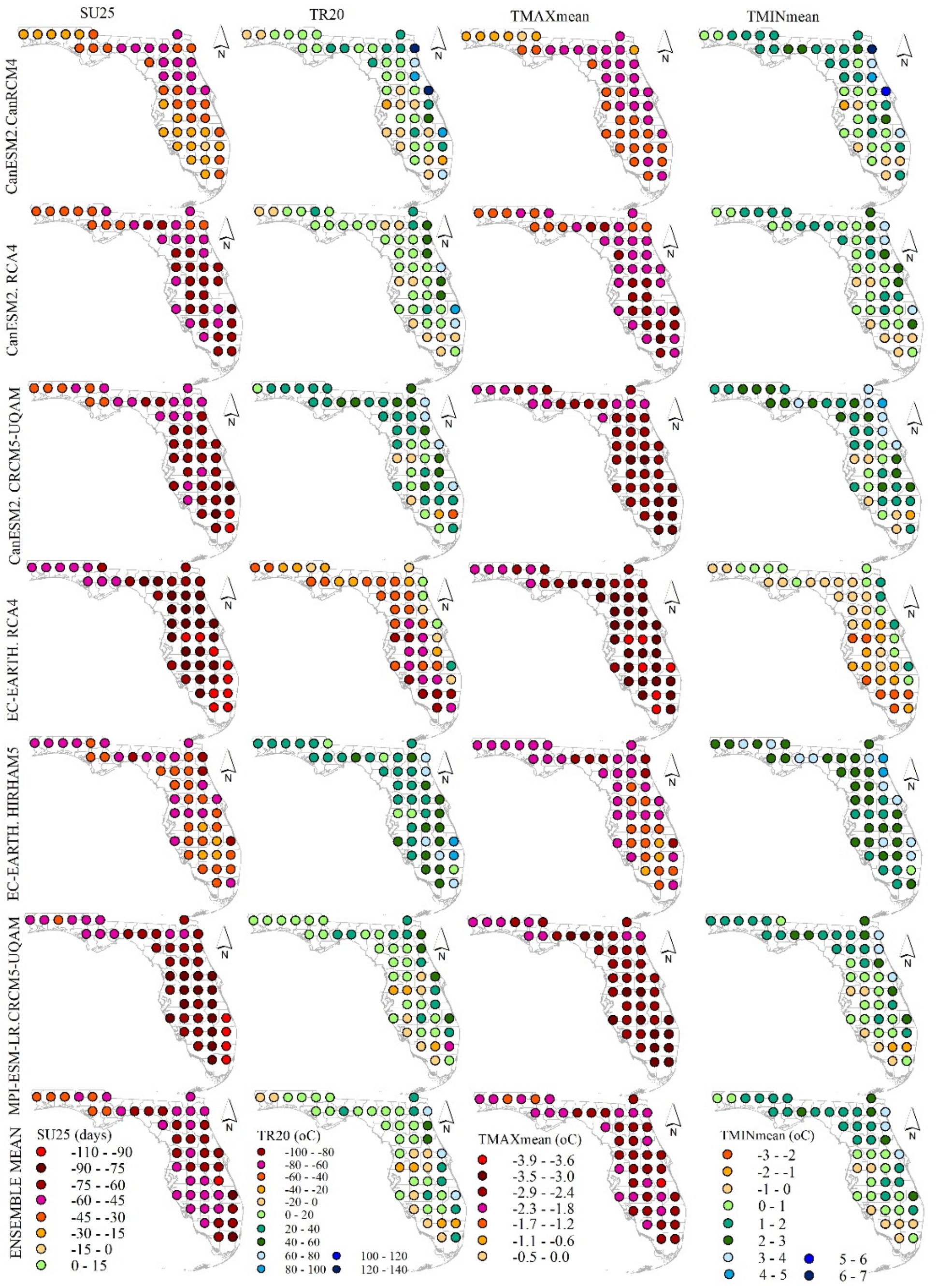

Figure 7. The absolute biases estimated using the difference between model climatology and observed climatology for SU25 (first panel), TR20 (second panel), TMAXmean (third panel) and TMINmean (fourth panel) temperature indices at the stations generated at the centroid of each grid across Florida.

3.2. Evaluation of RCMs using Pattern Correlation

Figure 8 shows the heatmap plot of the pattern correlation coefficient values derived using the climate models and the observed climatic indices of precipitation and temperature. The Pearson correlation coefficient approach was used to estimate the correlation coefficient values of the climatic indices derived from the climate models and the observed precipitation and temperature variables. The larger value of the pattern correlation coefficient of CDD was observed by EC-EARTH-HIRHAM5 (r = 0.72) and EC-EARTH.RCA4 (r = 0.62). A higher negative pattern correlation has been shown by CanESM2.CRCM5-UQAM (r = −0.6) whereas a lower value has been observed by CanESM2.CanRCM4 (r = 0.1). The climate models that showed higher skill in explaining CDD showed the lower pattern correlation in explaining CWD whereas the climate model that showed lower skill in explaining CDD showed a higher pattern correlation in explaining CWD. MPI-ESM-LR.CRCM5-UQAM showed a higher skill in explaining RX1day (r = 0.77) and RX5day (r = 0.7) than the other climate models. The ensemble mean outperformed the other climate models in explaining R10mm (r = 0.62), R20mm (r = 0.73), R95p (r = 0.7) and R99p (r = 0.62). All the climate models explained SU25, TXn, TNn, TMAXmean and TMINmean very well with a pattern correlation value greater than 0.75, except for a relatively lower value shown by CanESM2.RCA4 (SU25; r = 0.57 and TMAXmean; r = 0.59) and CanESM2.CanRCM4 (TNn, r = 0.63).

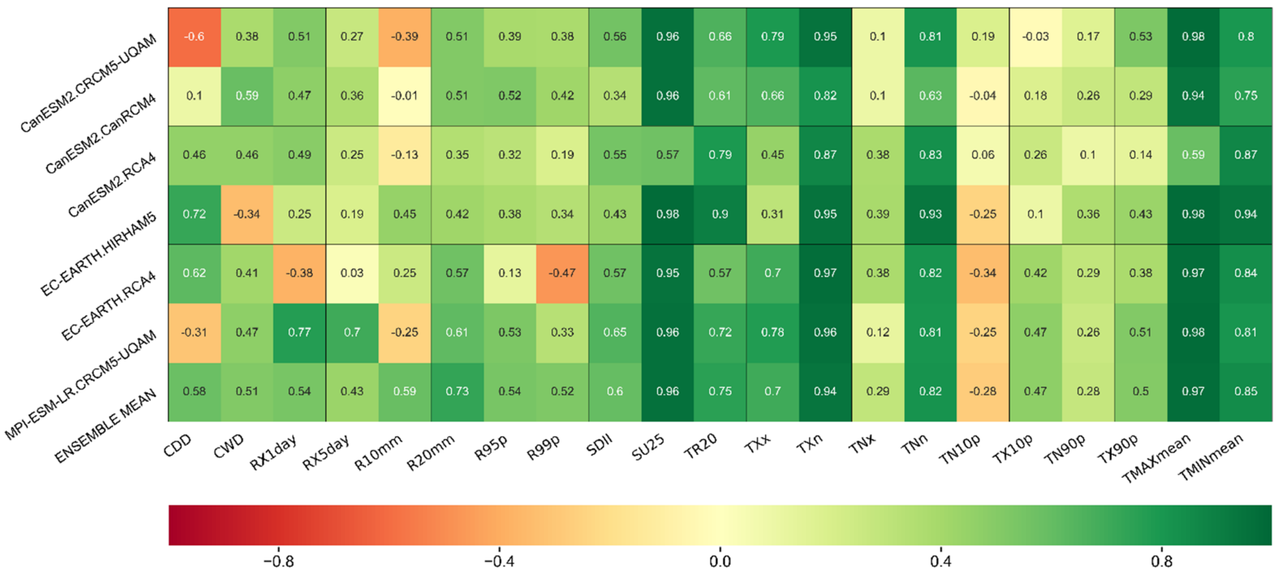

Figure 8. The heatmap plot of the pattern correlation coefficient of the climatic indices derived from the observed and climate-model-based temperature and precipitation. The number in each cell shows the numeric value of the pattern correlation coefficient.

The percentage of the pattern correlation coefficient of each climate model was calculated by taking the ratio of the number of higher values (pattern correlation value >0.7) to the total number of climatic indices (21 indices). This helps to compare the skill of each climate model in explaining the climatic indices derived from the observed climatic variables. The result shows that EC-EARTH.HIRHAM5 and MPI-ESM-LR.CRCM5-UQAM were able to score relatively the maximum percentage (33 and 38 percent), which indicates the good skill of these two climate models in comparison to the other models. In other words, these two climate models scored pattern correlation coefficient values greater than 0.7 in 33 to 38 percent of the climatic indices. The ensemble mean is also showed equivalent skill as that of EC-EARTH.HIRHAM5 in capturing the pattern of most of the climatic indices. CanESM2.CanRCM4 and CanESM2.RCA4 climate models show the minimum percentage (5 percent), which shows a weak performance in capturing the pattern of the climatic indices. Despite the weak skill of the ensemble mean in estimating the values of the climate indices, its performance in capturing the pattern of the climatic indices was substantial (29 percent) compared to the other climate models. Although all the climate models showed reasonable skill in capturing the pattern of at least some of the climatic indices, the skill of MPI-ESM-LR.CRCM5-UQAM in capturing the pattern and the values makes it one of the preferred climate models for future impact assessment study in Florida.

3.3. Evaluation of RCMs using Reduction of Variance (RV)

The heatmap (Figure 9) shows the values of the reduction of variance (RV) that were calculated among the climate models and the observed precipitation- and temperature-based climatic indices. The numeric values of RV were labeled in each cell, except for a few cells highlighted with a white color. These cells have much lower RV values (-1.39 to -46) that represent poor performance of some of the climate models in reproducing some of the climatic indices. In general, RV values greater than zero indicate the best performance whereas the negative values indicate poor performance of the climate models. All the climate models showed low skill in reproducing CDD (column 1) and TNx (column 14) climate indices, except for EC-EARTH.RCA4 with an exceptional value greater than zero (0.12) in reproducing the TNx index. The RV result also showed that the ensemble mean performed better in reproducing the temperature-based indices (row 7) than in reproducing the precipitation-based climatic indices. This might be associated with the high spatial and temporal variability of precipitation as compared to temperature. Moreover, the extreme values might be attenuated in the process of averaging several climate models together. EC-EARTH.RCA4 reproduced all the climatic indices (except CDD) relatively better than the other climate models. The ensemble mean, MPI-ESM-LR.CRCM5-UQAM, CanESM2.RCA4 and CanESM2.CRCM5-UQAM were also shown to be capable of reproducing all the climatic indices except CDD and TNx. All the climate models have shown good performance with the same RV values (RV = 1) in simulating some of the temperature-based climatic indices (TN10p, TX10p, TN90p and TX90p).

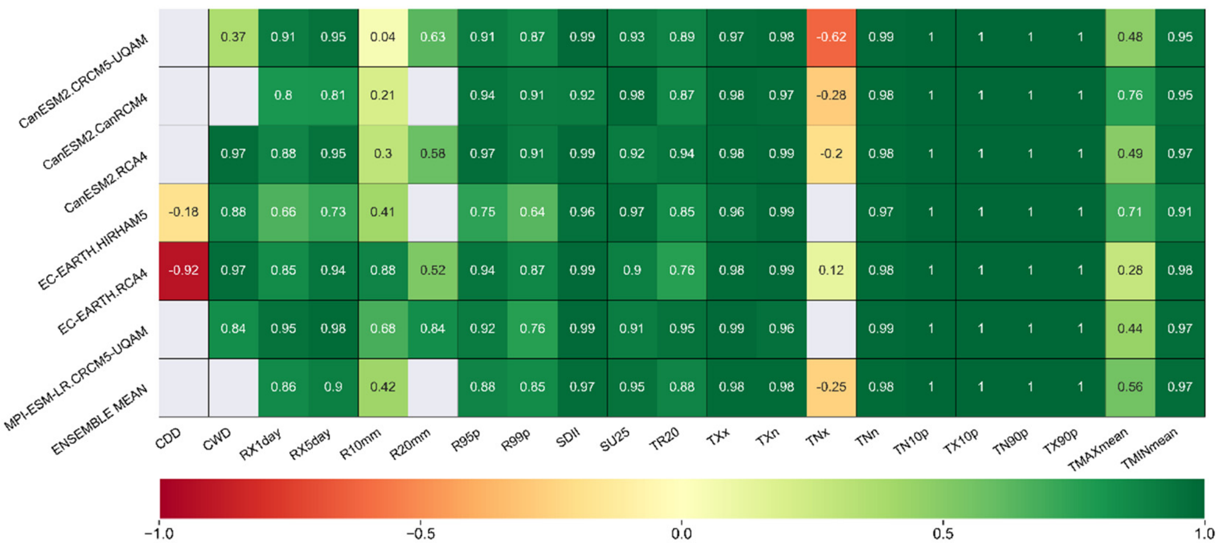

Figure 9. The heatmap plot of the reduction of variance (RV) of the climatic indices derived from the observed and climate-model-based temperature and precipitation variables. The number in each cell shows the numeric value of the Reduction of Variance and the empty grey cells show values less than -1 (-1.39–46).

3.4. Evaluation of the Climate Model Based on SPEI

The SPEI was computed at 3-, 6- and 12-month aggregate periods for each climate model and the observed dataset for all the stations (Figure 1). Figure 10 shows the box-and-whisker plots of SPEI for each aggregate period and each box was generated using the correlation coefficient result obtained for all 55 stations. The evaluation of the climate models using the SPEI drought index is crucial to identify the climate model that can be used to assess future drought conditions across Florida. In general, the result shows similar performance of each climate model (except for the relatively lower performance of EC-EARTH-HIRHAM5) as the aggregate period increases. The evaluation of each climate model based on SPEI-3 shows minimum difference of the correlation coefficient values among the climate models as compared to the other aggregate periods. CanESM2.CRCM5-UQAM showed relatively better performance than the other models with a maximum correlation coefficient of 0.6 (SPEI-3), 0.67 (SPEI-6) and 0.76 (SPEI-12). The performances of EC-EARTH.RCA4 and the ensemble mean were also remarkable and comparable to CanESM2.CRCM5-UQAM, except for underestimating the minimum values in the case of SPEI-12. The result further indicates the potential application of the RCMs in developing a drought monitoring and early warning system and future trends to mitigate its impacts.

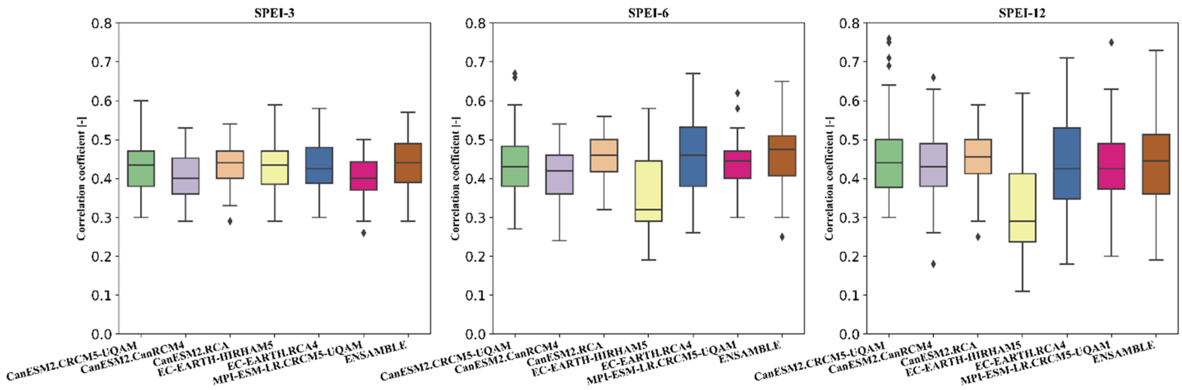

Figure 10. The correlation coefficient values of the climate-model-based SPEI and the observed SPEI for 3- (**left**), 6- (**middle**) and 12-month aggregates (**right**).

4. Conclusions

This study evaluates four RCM models (CRCM5-UQUAM, CanRCM4, RCA4 and HIRHAM5) driven by three GCMs (EC-EARTH, CanESM2 and MPI-ESM-LR) and the ensemble mean (averaging values of the climate models climatology) by considering four evaluation techniques (absolute bias, pattern correlation, reduction of variance and SPEI) for Florida. Several climatic indices suggested by the international Joint CCl/CLIVAR/JCOMM Expert Team on Climate Change Detection and Indices (ETCCDI) were derived from the daily time series of each climate model and used in the evaluation process. The main objective of this evaluation is to identify the climate model with the best skill in reproducing the climatic variables during the reference period of 31 years (1975–2005) and to use the future projection data for our imminent impact study and trend analysis of extreme events.

Each climate model has shown a unique skill in reproducing some of the climatic indices considered in this study and their skill, however, varies from one evaluation technique to the other. EC-EARTH.RCA4 relatively reproduced precipitation based climatic indices with minimum absolute biases as compared to other RCMs. Majority of the RCMs including the ensemble mean showed comparable performance in reproducing temperature based climatic indices under the same evaluation criteria. Based on the pattern correlation criteria, the ensemble mean, EC-EARTH.HIRHAM5 RCM and MPI-ESM-LR.CRCM5-UQAM RCMs showed relatively better skill in reproducing most of the climatic indices as compared to the other climate models. The ensemble mean, EC-EARTH.RCA4, CanESM2.RCA4 and MPI-ESM-LR.CRCM5-UQAM RCMs showed good skill when evaluated using the reduction of variance and absolute biases. The ensemble mean showed relatively better skill in reproducing the temperature-based climatic indices compared to its skill in reproducing the precipitation-based climatic indices. There were no remarkable differences among the performances of the climate models compared to the SPEI. However, CanESM2.CRCM5-UQAM, EC-EARTH.RCA4 and the ensemble mean performed relatively better than the other model simulations. The better performances of these RCMs under different criteria have a positive implication for their potential use/application in climate change impact studies and future trend analysis of extreme events. This result could help in identifying better information to understand, analyze and mitigate possible future impacts of climate change across Florida.

Even though the climate models have shown reasonable skill in reproducing the observed climate variable, their performance may further improve through applying a bias correction approach (in addition to the evaluation efforts) that is planned for our future studies. Moreover, the coarser spatial resolution of the climate models might contribute to the lesser accuracy of the skills of each climate model, particularly when they are evaluated relatively in a smaller study region. Hence, downscaling the climate models to a finer spatial resolution using robust dynamical or statistical downscaling approaches may improve the accuracy of each RCM and this is recommended for future studies. The evaluation of the RCMs was carried out in this study using the data for the reference period 1975–2005. The performance of the RCMs may be altered when using different reference periods.

Author Contributions: Y.B., A.M. and M.B. framed the research, analyzed the results and contributed to the preparation of the draft version of the manuscript. T.T. and A.S. were involved in data collection and pre-processing. All the authors contributed to reviewing and commenting on the result and conclusion sections of the manuscript. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest: The authors declare there is no conflict of interest.

Appendix A

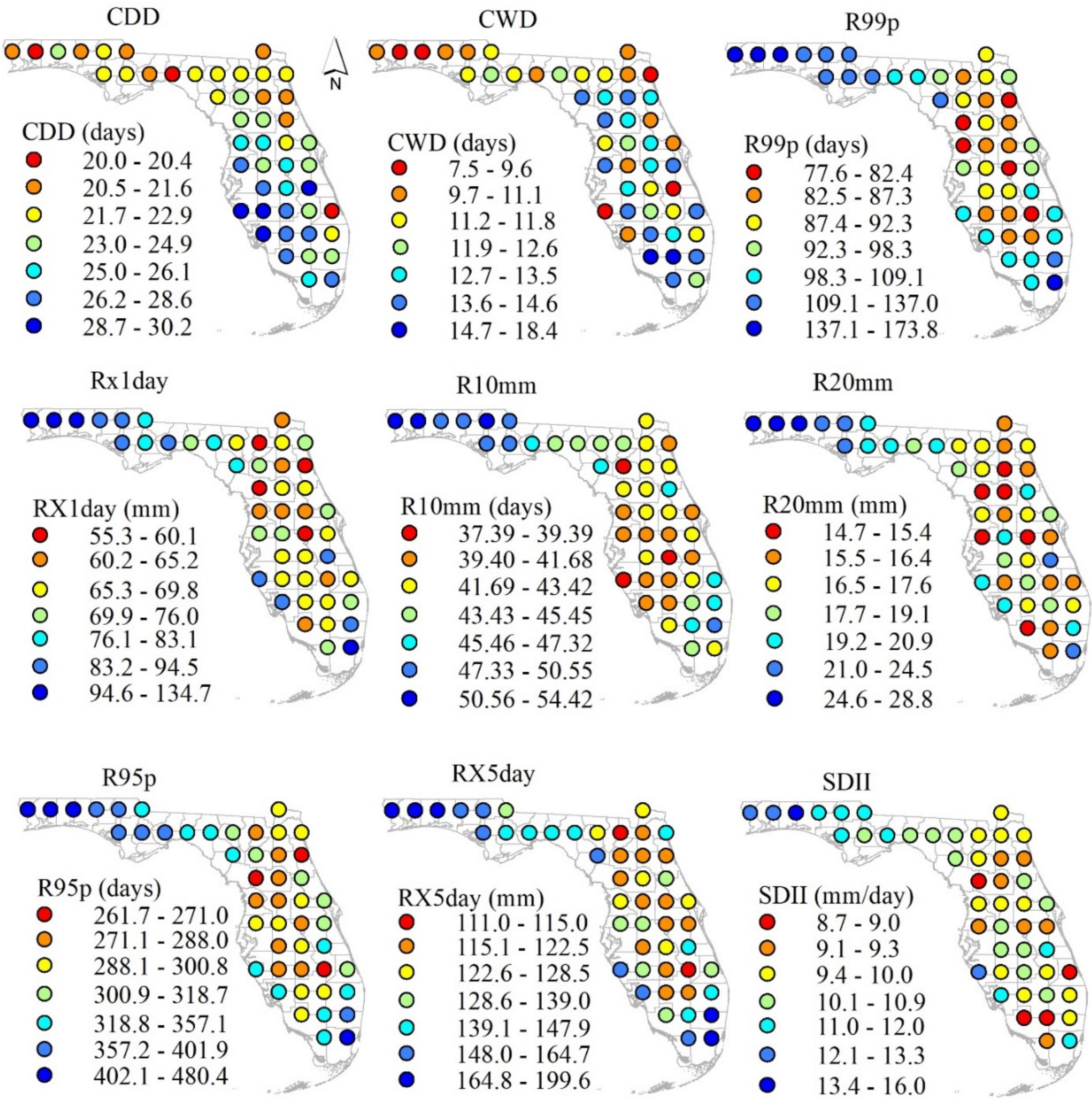

Figure A1. Precipitation-based selected climatic indices for stations located at the centroid of each grid across Florida.

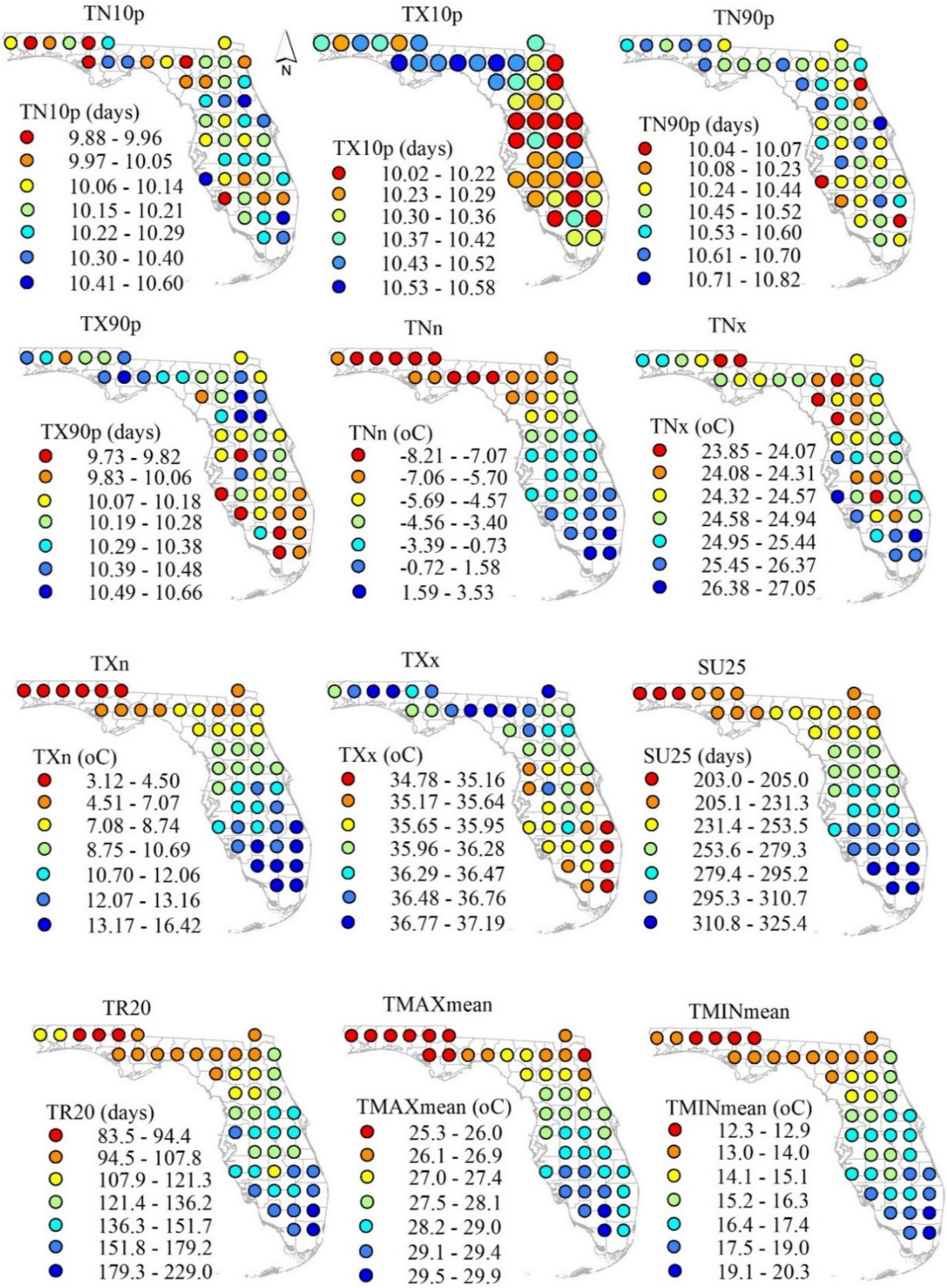

Figure A2. Temperature-based selected climatic indices for stations located at the centroid of each grid across Florida.

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