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Assessment of uncertainty in multi-model means of downscaled south Florida precipitation for projected (2019-2099) climate

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Abstract

South Florida resource management, particularly the Everglades restoration effort, is beginning to consider projections of precipitation from multiple climate models for decision-making. Because precipitation changes can significantly affect the Everglades ecosystem, characterization of precipitation projection uncertainty is important for resource management decisions, and reduction of uncertainty is desired for better decision-making. Though uncertainty of precipitation projections has been characterized for many regions, uncertainty has not been sufficiently quantified for south Florida. This study builds upon prior results for projected Florida precipitation by considering recent climate model simulations, seasonal and spatial information, and uncertainty quantification and reduction. We identify the multi-model mean change in south Florida precipitation and characterize the uncertainty of 37 statistically downscaled Coupled Model Intercomparison Project Phase 5 models. For 2019−2045, there is a likely (over 60% of ensemble members) increase in south Florida annual mean precipitation owing to a likely to very likely (near 90% of ensemble members) increase in dry season (November, December, January) precipitation, while wet season (June, July, August) shows a more likely than not (over 50% of ensemble members) decrease in precipitation in the southern region and increase in precipitation in the northern region of south Florida. As south Florida agencies are on the verge of including precipitation projections in their upcoming planning horizon, this information will aid south Florida climate data users in decisions influenced by future rainfall.

1. Introduction

Uncertainty is inherent in all climate studies. The quantification and communication of that uncertainty represents a step forward in bridging the gap between climate scientists and the climate-data user community. As the Florida Everglades and its ecosystem can be significantly impacted by precipitation changes, resource managers desire information concerning the potential direction of projected change, associated uncertainty, and if this uncertainty can be reduced (Aumen et al., 2015; Estenoz and Bush, 2015). Here, we identify uncertainty of precipitation projections for south Florida across time and space scales. Our study area is the land-points within latitude 25.0°N to 28.8°N and longitude 277.7°E to 280.1°E, which includes the South Florida Water Management District and the greater Everglades (Fig. 1a).

Historical and projected climate are principally depicted as the multi-model mean (MMM), sometimes considered the most likely result (e.g. Tebaldi and Knutti 2007), but the MMM does not provide a quantitative measure of likelihood. Estimates of uncertainty are often desired for robust decision making; higher uncertainty reduces confidence in results (Asefa and Adams, 2013). Vavrus et al. (2015) depict a framework for describing the uncertainty of climate projections that ranges from simple to complex, depending on the needs of the user. We utilize a similar framework, including metrics such as the coefficient of variation (COV), percent of models agreeing on the sign of the projected change (a measure of robustness), and bootstrapping to estimate confidence intervals.

Uncertainty in climate models stems from three sources: model; scenario; and uncertainty surrounding the internal variability of the climate system (Hawkins and Sutton, 2009). Model uncertainty arises from incomplete representation of physical and dynamical processes and how these processes interact in climate models. For south Florida, the coarse grid-size of climate models necessitates parameterization of small-scale convective processes important for precipitation, adding to uncertainty (Obeysekera et al., 2015). Scenario uncertainty arises from uncertainties about the future of global emissions. Internal variability uncertainty results from processes that can constructively or destructively interfere, for a short period of time, with long-term trends associated with anthropogenic climate change, for example, variability associated with the El Niño Southern Oscillation (ENSO). Downscaling of climate projections (Mearns et al., 2014), sometimes necessary for projections to be relevant at local scales (Wilby and Fowler, 2010), can also add uncertainty or error (Pielke and Wilby, 2012). However, it may be possible to reduce model uncertainty by identifying a subset of models of relatively higher integrity (e.g. Brekke et al. 2008). The term “uncertainty” is loosely used in this manuscript to represent confidence of downscaled CMIP5 models in their estimation of the MMM change. Effectively, this characterization probes model uncertainty. The characterization methods used here are focused mainly on model agreement (agreement among models, not including observations), and allow for a mathematical representation of this element of uncertainty. We also qualitatively assess scenario uncertainty by comparing and contrasting the model agreement in the different CMIP5 scenarios, allowing us to identify, for example, scenarios that show relatively good model agreement. This uncertainty quantification framework does not probe the existence of uncertainty related to internal variability, or uncertainty introduced through the downscaling procedures used. Though uncertainty due to internal variability is not directly addressed in this manuscript, we note that internal climate variability is a significant contributor to the total uncertainty in climate projections, particularly in near-term projections (Fatichi et al., 2016; Peleg et al., 2019). The goal of the uncertainty quantification is to provide a clear mathematical representation of the degree of confidence the models have in their representation of the change in precipitation (given the various climate change scenarios). We foresee that climate data users can use this mathematical representation of uncertainty to better inform their decisions.

While climate models have inherent uncertainties, there are many other sources of uncertainty in decision-making related to, for example, the quantitative uncertainties of impact models, ecological models, and biophysical responses. Moreover, there are substantial uncertainties associated with how people perceive and respond to climate models, even though related social science has been targeting this deficiency (e.g. National Research Council 1999). Finally, even given large uncertainty, climate models may still be useful to stakeholders –

provided the stakeholder needs are incorporated from the beginning (Polsky et al., 2007; Schröter et al., 2005). As uncertainty in climate projections is carried forward into these other areas, reduction of climate projection uncertainty may be desirable (Wilby and Dessai, 2010). We assert that by including additional information on model uncertainty along with discussion, this manuscript serves to better inform decision makers and climate data users who require precipitation projections.

2. Background and Motivation

A 2008 National Research Council review of Everglades restoration planning (National Research Council, 2008) noted that climate change should be factored into restoration planning, suggesting that planners pay attention to six areas that can impact Everglades restoration practices. These areas include (1) changes in the water budget and variability including the amount, temporal distribution, and seasonality/frequency of precipitation; (2) changes in return frequency and intensity of hurricanes/tropical storms; (3) temperature changes and implications to the ecosystem (4) consequences of increasing carbon dioxide on plants, carbonate sediments, and soil; (5) management practices to keep pace with sea level rise; and (6) impacts of projected sea level rise on estuaries, saltwater intrusion, and mangroves (summarized in Aumen et al., 2015). Though some work on precipitation changes has been completed (discussed below), this manuscript focuses on the first area of this review and provides information on the seasonality of precipitation changes and uncertainty.

Changing precipitation can lead to significant impacts on the Everglades ecosystem (Aumen et al., 2015). Decreasing rainfall (estimated as a 10% decrease based on data from the Coupled Model Intercomparison Project Phase 3, CMIP3, Obeysekera et al. 2015) can lead to losses in carbon- and organic-associated elements in the Everglades (Orem et al., 2015), significant decrease in Lake Okeechobee water levels (Havens and Steinman, 2015), lowered marsh water depths and shortened inundation periods (Nungesser et al., 2015), interannual water level changes that may lead to changes in vegetation types (van der Valk et al., 2015), and negative impacts on wildlife such as alligators and wading birds (Catano et al., 2015). However, in terms of the water supply, an increase in rainfall could be handled given existing features (Obeysekera et al., 2011a). The estimation of + or – 10% rainfall change was first discussed in Obeysekera et al., (2011b), and is based on a reliability ensemble average (Tebaldi et al., 2005) that combines multi-model ensembles into a single probabilistic projection for a region. This assessment showed monthly precipitation changes in Florida for CMIP3 scenarios falling roughly between -10 to 10%. These rainfall estimations were based on one single probabilistic estimation using CMIP3 and do not include information about seasonal changes, which would benefit many of these ecological and hydrological studies (Havens and Steinman 2015; Obeysekera et al. 2015).

CMIP5 is the principal climate model suite for the Intergovernmental Panel on Climate Change (IPCC) Fifth Assessment Report (Solomon et al., 2007). However, many users desire high-resolution regional climate data (Jayantha Obeysekera et al., 2011), and downscaling is often applied to achieve that goal (e.g. Giorgi et al. 2001). There have been many downscaling efforts in Florida - a recent example is the statistical Self Organizing Map (SOM) method employed by the Pennsylvania State University to downscale CMIP5 precipitation over Florida and the mid-Atlantic region (Ning et al., 2012, 2011). Here, we use statistically downscaled CMIP5 Climate and Hydrology Projections (Brekke et al. 2013).

Probabilistic information on precipitation changes and trends have been studied comparatively less for CMIP5 than for CMIP3 downscaled projections in Florida. Obeysekera et al. (2015) determined that a projected change of +/- 10% in annual precipitation is a suitable estimated range for 2060 based on CMIP3. Dessalegne et al. (2016) studied Bias-Corrected Constructed Analogue (BCCA) CMIP5 statistically downscaled precipitation and air temperature projections and found that projected precipitation climatology was biased wet compared to observations by about 8% for the period 2000-2085. Here, we specifically discuss statistically downscaled CMIP5 data uncertainty characterization seasonally and spatially.

3. Data and Methods

3.1 Data

The public archive of "Downscaled CMIP3 and CMIP5 Climate and Hydrology Projections" (Brekke et al. 2013) is the source of climate data for this study, and we consider CMIP5. A CMIP5 overview can be found in Taylor et al. (2011). Data are downscaled using BCCA (daily data) and Bias-Corrected Spatial-Disaggregation (BCSD, monthly data) methodologies (Wood et al., 2004). For the United States, the downscaled grid resolution is 0.125° latitude by 0.125° longitude. Daily and monthly historical climate model output for 1950–2005 and projected for Representative Concentration Pathway 2.6 (RCP2.6), RCP4.5, RCP6.0, and RCP8.5 for 2005–2100 are included in the public archive for 37 climate models with varying ensemble members. RCPs are discussed in detail in Moss et al. (2010). We have chosen to use BCCA and BCSD data here as they both use a similar strategy for bias correction, eliminating the need for a formal comparison of downscaling methods and their biases over south Florida. An alternative downscaling methodology for daily data using localized constructed analogues (LOCA) is also available and may result in better representation of extremes than BCCA. As this manuscript mainly details the MMM change and does not specifically focus on extremes, we do not expect these biases will significantly affect the results. However, future work involving precipitation extremes may benefit from use of the LOCA dataset.

Each of the downscaled models includes a varying number of ensemble members. Model information can be found in Supplementary Material. We refer to these data collectively as realizations for brevity. Historical and RCP4.5 include 70 realizations, RCP2.6, 6.0 and 8.5 include 52, 34, and 62 realizations, respectively. Equal weight is assigned to each model and ensemble member. To date, this study incorporates the largest amount of available downscaled data compared to other studies in south Florida, allowing for a more complete representation of the uncertainty about the MMM and establishment of a complete baseline measurement. For daily assessment, we consider only RCP4.5 and 8.5 due to data size. To estimate biases in the climate model output, we use observed Climate Prediction Center Unified Gauge-Based Analysis of Daily Precipitation over the continental United States, available on a 0.25° latitude and longitude grid (Chen et al., 2008). We re-grid these data to 0.125° latitude by 0.125° longitude using bilinear interpolation.

The term “observations” describes observations of precipitation from 1974-2000; “historical” describes model runs forced by observed atmospheric composition changes reflecting anthropogenic and natural sources. “Future projections” are forced with specified concentrations corresponding to varying levels of emissions (RCPs). We define the near-, middle-, and long-term future as 2019−2045, 2046−2072, and 2073−2099, respectively.

3.2 Statistical Methods

Future precipitation changes are defined relative to historical model data from 1974−2000. The uncertainty quantification framework detailed in Vavrus et al. (2015) is used here for the region in Fig. 1a, and is intended to provide multiple measurements of uncertainty that can be used in a decision-making arena. Uncertainty is assessed using COV, model robustness, and bootstrapping estimation of confidence intervals (e.g. Vavrus et al. 2015). The COV is the inter-model standard deviation divided by the MMM change, and it measures the degree of agreement between models or realizations. This measure is subjective, lower values indicate lower uncertainty and vice versa and can be used, for example, to assess if a certain region within the domain is more or less certain than another. Robustness is calculated as the percent of realizations that agree on the sign of the change, assessed using a likelihood scale; e.g., more likely than not represents robustness as 50% to 100%, likely as 66% to 100%, and very likely as 90% to 100% (Mastrandrea et al., 2011). Robustness also measures the degree of agreement between models or realizations but is less subjective. The likelihood scale is intended to aid in comprehension of the percentages associated with robustness. Bootstrapping estimation of confidence intervals around the mean and trend (5% and 95%) is used for formal probabilistic assessment (e.g., Efron 1992). The population of projected changes or trend is randomly subsampled with replacement to generate 1000 possible realizations of the MMM. Readers who are interested in more detailed explanations of these measures are encouraged to view the above references.

Changes in wet season statistics such as the length of the wet season (LOWS) and start and end date also are informative for many purposes (Selman et al., 2013). To calculate the LOWS and its start and end date, we follow Liebmann et al. (2007) and Misra and DiNapoli (2013). The authors define cumulative anomalous daily rainfall $A'_m(N)$ as:

$$A'_m(N) = \sum_{n=1}^{N} \left\{ R_m(n) - \bar{R}_m \right\}$$

Where $R_m(n)$ is daily rainfall on day n and m year, n is day number starting on day 1 and ending on day N (January 1st through December 31st), and $\bar{R}_m$ is annual average daily rainfall. The rainy season is the period with the largest and longest positive slope of $A'm()$. The beginning of the rainy season corresponds to the first occurrence when $A'_m(N)$ is above the annual mean, and the ending begins when anomalous accumulation is at its maximum. For further information, refer to Misra and DiNapoli (2013).

4. Results

4.1 Bias

Residual biases in model output present after the application of downscaling are classified to determine suitability of the data for this study, suggested by many studies involving climate model output (e.g., Stamm et al. 2014; Obeysekera et al. 2015). Biases over Florida in large-scale and downscaled CMIP3 model output have been extensively studied (Obeysekera et al., 2011; Obeysekera et al., 2015). Biases over Florida in CMIP5 have been studied comparatively less. Moreover, because the bias correction strategies were developed with the intent of using them across the globe, some of the issues facing south Florida precipitation, such as convective-scale processes, are not specifically corrected.

We depict seasonal climatology and the LOWS for observations, the MMM, and individual realizations in Fig. 1b,c (study area shown in Fig. 1a). Biases are very low by design due to correction through the downscaling procedure. In a first order estimation, the realizations are able to capture observed seasonal climatology and the LOWS because the observations fall within the range of realizations, though we note an overestimation of wet season precipitation in Fig. 1b. The LOWS in RCP4.5 and historical BCCA output (Fig. 1c) is longer than observed. The observed LOWS is 130 days, while the average historical BCCA LOWS is 135 days (ranging from 125 to 145 days across models). The increased LOWS may explain the BCCA wet bias reported by Dessalegne et al. (2016). Convective-scale precipitation is also misrepresented in large-scale models due to their coarse resolution (e.g. Delworth et al., 2011), adding to the biases here. We also spatially assess the climatology and variability biases over the study area, shown simply as the difference between the BCSD ensemble mean and observations (Fig. 2). Overall, climatological biases fall between -1 and 1, though the highest bias is near the transition between the urban area of Florida and the Everglades, likely due to slightly differing climatologies in these two regions, which is difficult to capture in a coarse resolution model and is not fully corrected through the downscaling procedure. Similar to the regional mean bias (Fig. 1b), winter (November-January, NDJ) biases are small (Fig. 2b) while summer (June-August, JJA) biases are larger overall (Fig. 2c), again owing to the slight bias in the length of the wet season and convective precipitation errors. We also note biases in precipitation variance in (Fig. 2d-f). The winter and summer variance biases have a similar structure to the climatological bias (Fig. 2b-c and e-f), though the annual mean is larger (Fig. 2a). We believe that these larger biases in the annual mean are due to a general overestimation of annual precipitation variability in the models, though this is not seen in the NDJ and JJA shown here, it is seen in other seasons (not shown).

Despite these slight biases, we assume that the models' ability to simulate historical climate will translate into ability to simulate projected climate (e.g. Brekke et al. 2008), and that the data are appropriate for this study. As the downscaling procedure assumes stationarity, biases in future data will be similar, though this assumption can be problematic as there could be shifts in the climatology under climate scenarios (Dixon et al., 2016). Models can also suffer from biases related to large-scale fields, ocean-model resolution, etc., and this simple metric does not encompass all impacts to precipitation (Kirtman et al., 2012).

4.2 Projected Changes and Uncertainty

We assessed the annual mean, NDJ, and JJA MMM change for 2019-2045. The remaining periods and their uncertainty, calculated by bootstrapping, are summarized in Supplementary Material Table S1. NDJ and JJA are defined as the wet and dry seasons, respectively, following Irizarry-Ortiz et al. (2013). These seasons may not be appropriate for all climate data users in south Florida but can still provide guidance. Our goal is to further refine the +/- 10% precipitation change range based on CMIP3 (Obeysekera et al. 2015).

The annual mean percent change and change in mm/day for 2019−2045 versus 1974−2000 is computed for RCPs 4.5, 8.5 (Fig. 3a,d). Precipitation is projected to increase, with smaller changes in the southern part of the domain and larger changes in the northern part, and projections significantly differ from historical precipitation (stippling, based on a t-test at the 95% confidence level, where the null hypothesis is that the 2019-2045 mean does not significantly differ from 1974-2000). The near-term percent change is projected to be roughly 2% - 5% (shading), or about 0.1 to 0.15 mm/day (contours) for both RCPs, though again we note the presence of internal variability in the near-term. The COV (Fig. 3 b,e) and robustness (Fig. 3 c,f) estimates indicate more certainty in the northern part of the domain (low COV and high robustness). Robustness is over 60% throughout the domain, i.e. characterized as “more likely than not” to “likely” to occur.

One might assume that the RCP with the strongest forcing (RCP8.5) would project the largest response, but RCP4.5 and 8.5 are roughly equal. Scenario differences are not an important contributor until later decades (Hawkins and Sutton, 2011), though RCPs incorporate differences in other trace gasses that can lead to slight differences in RCPs (Kirtman et al., 2013). A positive change in precipitation agrees dynamically with what we might expect in a warming climate, because a warmer atmosphere can hold more water. This result also agrees with the “wet get wetter” and the “dry get drier” notion of precipitation change in a warming climate (Stocker, 2014). Though the “wet get wetter” and “dry get drier” notion typically refers to extreme precipitation, it is also associated with convective rainfall (Lepore et al., 2015), which makes up a large part of south Florida rainfall variability. However, increased heating also can lead to greater evaporation, surface drying, a net soil moisture deficit and decreasing precipitation (Trenberth, 2011).

Results for NDJ indicate a positive, significant change in precipitation across the region (Fig. 4 a,d). NDJ results are similar to, though larger than, the annual mean, and are similarly robust, classified as "more likely than not" to "likely" (Fig. 4 c,f). However, the largest and most certain changes are seen in the southern part of the domain (Fig. 4 b,e). As shown in Table S2, RCP6.0 shows a smaller percent change in the near-term and is not significant with a much larger range (change of about 5% compared to about 12% for the other RCPs, with a range spanning zero in the confidence interval). We are more confident in the results from RCP4.5, 8.5 due to relatively smaller uncertainty and higher robustness. Though RCP differences are not seen in the near-term, RCP6.0 includes a smaller amount of realizations that have a wider range than the remaining RCPs, causing the differences here.

JJA differs from the annual mean and NDJ in that it shows a smaller percent change of approximately +/- 3%, equating to about +/- 0.2 mm/day, and a negative-to-positive gradient (Fig. 5a,d). Because projected change is negative in the southern part of the domain, this seasonality is likely affecting the near-term annual mean and causing the southern decreased, but still positive, precipitation (Fig. 3a,d). Held and Soden (2006) note that the global change pattern includes migration of storm tracks towards the poles, producing more rain at higher latitudes and reducing frontal passages over Florida, leading to less rainfall. Lee et al. (2010) and Rauscher et al. (2010) presume that Caribbean summer drying (including south Florida) is related to differential ocean-warming in the tropical Indo-Pacific and increased static stability along with decreased convection over the tropical North Atlantic. While the negative (positive) changes in the southern (northern) part of the domain show some robustness in the "more likely than not" category (Fig. 5 c,f), the transition line is respectively more uncertain based on the COV (Fig. 5 b,e). Noticeably in the COV is a band of high uncertainty roughly across the center of the domain. This is due to the nature of the calculation of the COV, which is based on the inter-model standard deviation divided by the MMM change. The division by the MMM change causes the measurement to “blow up” for MMM changes nearing zero, and weaker changes are typically more uncertain than stronger changes. However, we note that the location of this zero-line is highly uncertain given results from individual realizations (not shown).

Temporal projected changes in precipitation are evaluated by computing the MMM percent change relative to 1974-2000 and trend for 2019-2099 with confidence around the MMM trend estimated by bootstrapping for the domain indicated in Fig. 1a (Fig. 6). Significance of the trend is estimated using a Mann-Kendall test, and p-values are noted on Fig. 6 (over 0.95 indicates significance). Results are as expected for the annual mean, NDJ, and JJA given the above discussion, and all trends are significant (Fig. 6 a-f). A negative trend is found in annual mean RCP8.5 (Fig. 6 b) related to decreasing precipitation at the end of the time period. However, the percent change from 2019 – 2099 is typically above zero. Scenario differences are a key player in this downward trend, as this roughly corresponds to when scenario uncertainty dominates (Hawkins and Sutton, 2011), and the annual mean may also reflect the large negative change in JJA 2073 - 2099 in RCP8.5 (Table S1).

Changes in the near-term wet season characteristics are assessed and agree conceptually with the above (Fig. 7). RCP4.5, 8.5 show a robust decrease in the LOWS over most of the domain (Fig. 6a,b,c,d). The wet season is projected to be drier, whereas the beginning of the dry season is projected to be wetter (Fig. 7e). More than 60% of realizations show decreasing wet season precipitation and increasing precipitation in the beginning of the dry season (changes are “likely”, Fig. 7f). The wet season is projected to start later but end at about the same time. The average wet season start dates in historical, RCP4.5, and 8.5 are June 3, June 7, and June 10, respectively. The end dates are October 17, October 17, and October 19, respectively. These results agree with observations; the observed wet season has experienced later start dates, leading to a general decrease (increase) in wet (dry) season precipitation (Irizarry-Ortiz et al., 2013). We do not expect that this shift in the start of the wet season is enough to alter the timing of wet and dry seasons significantly for the near-term.

We assert that from a user standpoint, this additional information and quantification of model uncertainty will increase confidence in the results. However, here we have included all possible models/realizations without attempt to determine model weights, best model combinations, or model credibility. It is an open research question on how best to combine and/or cull the models. Brekke et al. (2008) forms a credible set of models based on regionally relevant climate variables such as the mean, variance, and correlation with NINO indices, etc. Model weighting, i.e. weighting models in which we have higher confidence than others based on statistical assessment, is another method that may have merit (Sanderson et al., 2017). The 'Emergent Constraint' on the Equilibrium Climate Sensitivity (ECS) technique from Cox et al. (2018) focuses on the variability of temperature about the long-term warming in a scenario that assumes the atmospheric carbon dioxide (CO2) concentration is instantly doubled, which reduced uncertainty compared to the IPCC likely ranges. Decadal predictions may also hold some ability in better quantifying the near-term uncertainty range (Meehl et al., 2009). Finally, high-resolution global models may better represent physical processes leading to regional rainfall, reducing added uncertainties due to downscaling (Siqueira and Kirtman, 2016).

5. Concluding Remarks

In this manuscript, we build upon results from Obeysekera et al. (2011a) and Dessalegne et al. (2016) by adding uncertainty characterization spatially, temporally, and across RCPs in statistically downscaled CMIP5 precipitation data over south Florida. While climate projections have many sources of uncertainty related to scenario, model, and internal variability, the results presented here characterize the uncertainty surrounding the MMM change, or model uncertainty. In addition, we use these uncertainty calculations to dismiss one of the scenarios due to higher uncertainty, thus qualitatively decreasing the uncertainty surrounding scenarios. Internal variability uncertainty and uncertainty added during the downscaling process are not sampled here. We find four conclusions associated with the emphasis on model uncertainty in downscaled projections of Florida precipitation:

1. 2019-2045 annual mean precipitation is projected to increase (likely), with more uncertainty in the southern part of the domain. 2019-2099 spatial MMM changes range from 1.5% to 6.3% (0.05mm/day to 0.23mm/day) (Table S2). RCP4.5 has an increasing trend, and RCP8.5 has a decreasing trend owing to 2080-2099.
2. 2019-2045 NDJ precipitation is projected to increase (likely to very likely), with results from RCP6.0 showing greater uncertainty. 2019-2099 domain-average MMM change ranges from 11.7% to 21.5% (0.2mm/day to 0.37mm/day) (Table S2), with a positive trend in RCP4.5 and 8.5.
3. 2019-2045 JJA precipitation is projected to decrease in the southern part of the domain and increase in the northern part (more likely than not to likely). The location of the transition from dry to wet is highly uncertain. 2019-2099 domain-average MMM change ranges from -9.1% to 2.0% (-0.55mm/day to 0.12mm/day) (Table S2) with a negative trend.
4. The LOWS is projected to decrease in RCP4.5 (more likely than not) and RCP8.5 (likely), due to a later start. The wet season is projected to get drier (likely) and dry season wetter (likely).

Climate models do not represent the full spectrum of uncertainty because they are not exhaustive of all factors impacting future emissions and may be missing sources of uncertainty such as Gulf Stream variability, which acts on spatial scales finer than many global climate models currently resolve (i.e. Siqueira and Kirtman 2016). Internal variability in the near-term can also impact these changes (Fatichi et al., 2016). Changes to large-scale modes of variability such as ENSO, the Pacific Decadal Oscillation (PDO), and the Atlantic Multi-Decadal Oscillation (AMO) under climate change scenarios may impact Florida teleconnections (Oh et al., 2014); and while ENSO is fairly well simulated in climate models, the PDO and AMO may represent another source of bias or uncertainty (Fuentes-Franco et al., 2016; Ruiz-Barradas et al., 2013). In addition, statistical downscaling methods and the bias identification utilized in this manuscript have the inherent assumption of stationarity, i.e. that the future biases will be the same as past biases. While this is a common assumption in climate projection studies, it is problematic because future climate is then viewed as anomalous about the current climate, and the current climate may shift in a changing climate. This uncertainty is not addressed in this manuscript. However, we assert that we have included a sufficient number of models to sample the diversity within the given RCP and provide a baseline assessment of uncertainty. Our future goal is to formulate a more credible set of models for projections of Florida precipitation, rather than including all possible models and realizations in the assessment.

As noted in the section on Motivation and Background, a National Resource Council study recommended Everglades resource planners factor in climate change, including the amount of precipitation and temporal distribution such as seasonality and frequency (Aumen et al., 2015). Precipitation changes can impact the Everglades ecosystem (Aumen et al., 2015; Obeysekera et al., 2015). Havens and Steinman (2015) note that information on potential spatial and seasonal distribution of rainfall changes and associated uncertainties would be of considerable benefit for climate data users. For example, substantially increased wet season precipitation could overwhelm flood capabilities of Lake Okeechobee, while decreased dry season precipitation could impact downstream water supplies. As the Everglades ecosystem may react differently given seasonal and spatial changes, we emphasize that these results will act to increase credibility in the direction of projected change across space and time for climate data users working in south Florida and Everglades restoration. This manuscript is intended to provide scientific background pertaining to future precipitation changes and uncertainty; we do not provide specific management recommendations. We envision these results can be used by planners to more adequately determine seasonality of precipitation changes and their uncertainty, leading to more informed decisions about infrastructure to capture, store, clean, and deliver water at the right times and right places (Estenoz and Bush, 2015). The uncertainty and seasonality information about potential precipitation changes is highly sought after by Everglades scientists and managers, and high levels of scientific uncertainty do not lead to a lack of management decisions. More information, however, can lead to better informed decisions. While we do not recommend any particular RCP over another for impact assessment at this time, a potential direction for future study is considering which scenarios produce significant end-member changes in the Everglades ecosystem.

We note that climate projections are based on conditional assumptions about changes in external forcing. RCPs are created with assumptions about the future state of economics and society, and are they intended for use as plausible trajectories of different aspects of the future (van Vuuren et al., 2011). For example, RCP8.5 assumes a future with increasing emissions (similar to a "Business as Usual" scenario), whereas RCP4.5 assumes a future with still increasing emissions, but an overall decrease compared to a business as usual approach. Scenarios are not meant to be a prediction of the future but intend to aid in better understanding of uncertainties and alternative futures (Moss et al., 2010). This research represents a step forward in characterization of the structural uncertainty associated with precipitation projections over south Florida, leading to development of new ways of reducing uncertainty. Ultimately, we hope that this research will be useful for resource managers in the area of Everglades restoration and other resource management activities in south Florida.

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Figure Captions

Fig. 1 Comparison of downscaled bias-corrected spatial dissagreggated (BCSD) and bias-corrected constructed analogue (BCCA) data with observations. All values in mm/day. (a) Study Area, represented by small box on the left hand side, showing south Florida. The larger region is provided for context and ease of understanding. (b) Seasonal mean climatology. (c) Length of the wet season (LOWS). RCP=Representative Concentration Pathway.

Fig. 2 Comparison of downscaled bias-corrected spatial dissagreggated (BCSD) data with observations.(a) – (c) BCSD annual mean, November – January (NDJ) mean, and June – August (JJA) ensemble and temporal mean minus corresponding temporal mean observations. Values in mm/day. (d) – (f) as in (a) – (c) but for BCSD variance minus corresponding observed variance. Unitless.

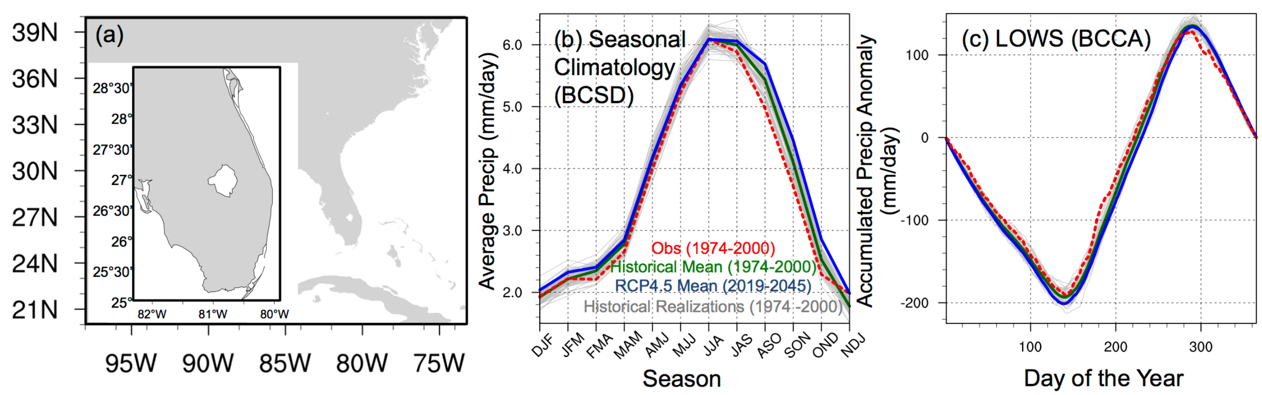
Fig. 3 Near-term projected change in annual-mean precipitation and associated uncertainty for 2019-2045 compared to 1974-2000. (a) Multi-Model Mean (MMM) percent change (shading), MMM change in mm/day (contours), significance of difference based on a t-test at 95% confidence level (stippling) for RCP4.5. (b) RCP4.5 coefficient of variation (COV, unitless). (c) Robustness (%). (d)-(f) as in (a)-(c) but for RCP8.5. RCP=Representative Concentration Pathway.

Fig. 4 As in Fig. 2, but for November–January (NDJ). MMM=Multi-Model Mean, COV=Coefficient of Variation, RCP=Representative Concentration Pathway; NT=Near Term.

Fig. 5 As in Fig. 2, but for June-August (JJA). MMM=Multi-Model Mean, COV=Coefficient of Variation, RCP=Representative Concentration Pathway; NT=Near Term.

Fig. 6 Multi-Model Mean (MMM) change in precipitation (blue line, %), trend (black dashed line, %/yr), and uncertainty about the trend calculated by bootstrapping at 5% and 95% confidence levels (light blue shading, %/yr). Mean trend and confidence intervals based on bootstrapping and p-values based on a Mann-Kendall test are shown in the top right of the panels. (a) Annual mean RCP4.5. (b) Annual mean RCP8.5. (c) and (d) as in (a) and (b), but for November-January (NDJ). (e) and (f) as in (a) and (b) but for June-August (JJA). RCP=Representative Concentration Pathway.

Fig. 7 (a) Length of the wet season (LOWS) for near-term (NT) RCP4.5 minus historical in number of days. Brown indicates decreasing LOWS, and green indicates increasing LOWS. (b) as in (a) but for RCP8.5. (c) RCP4.5 robustness of the LOWS change (negative change only, %). (d) as in (c) but for RCP8.5. (e) Spatial mean accumulated precipitation anomaly (mm/day) for multi-model mean (MMM) RCP4.5 minus historical (blue), RCP8.5 minus historical (red), and RCP4.5 minus historical (gray). (f) Percent of realizations depicting a positive (green) or negative (brown) change in accumulated precipitation for RCP4.5 (%). RCP=Representative Concentration Pathway.



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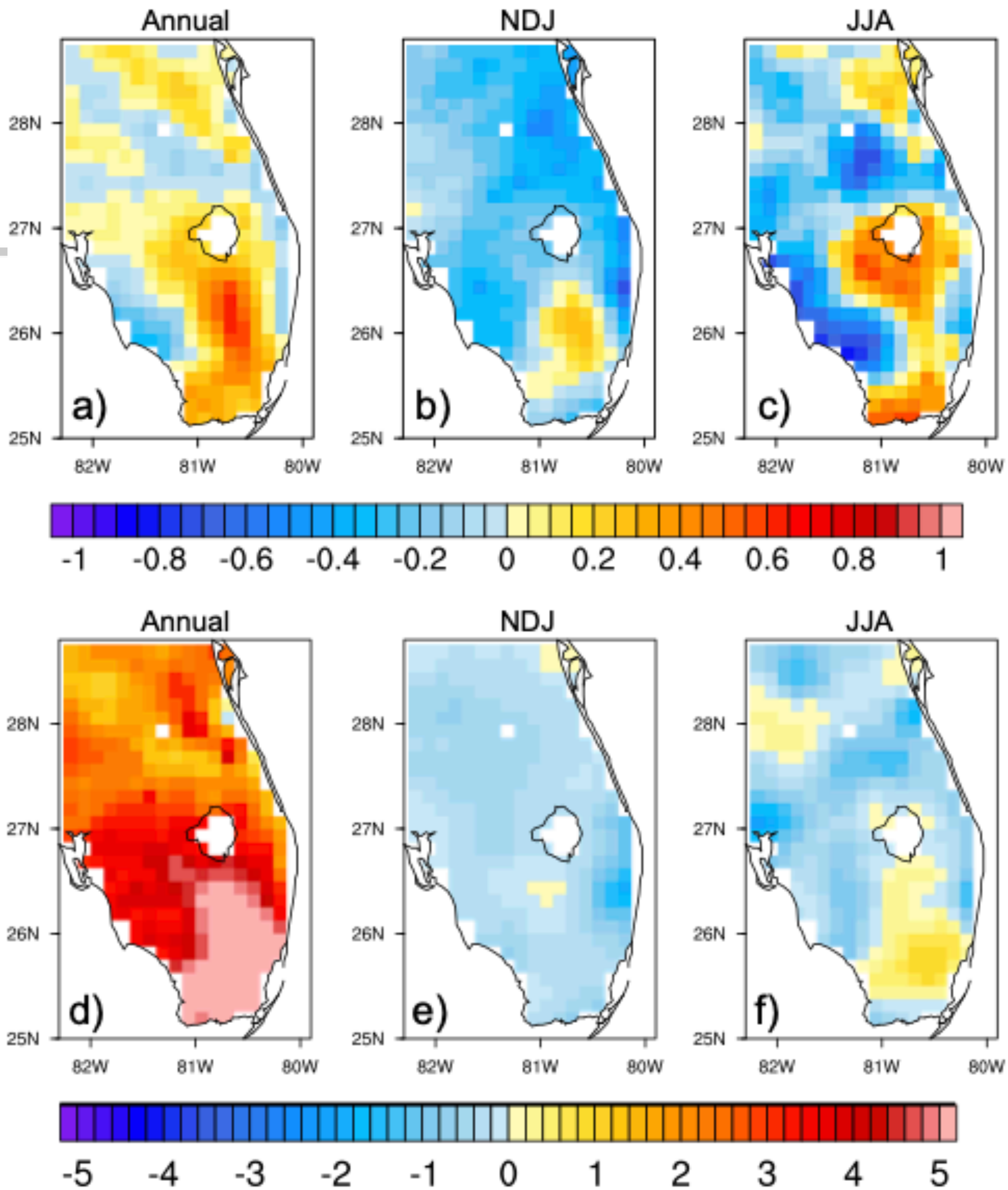

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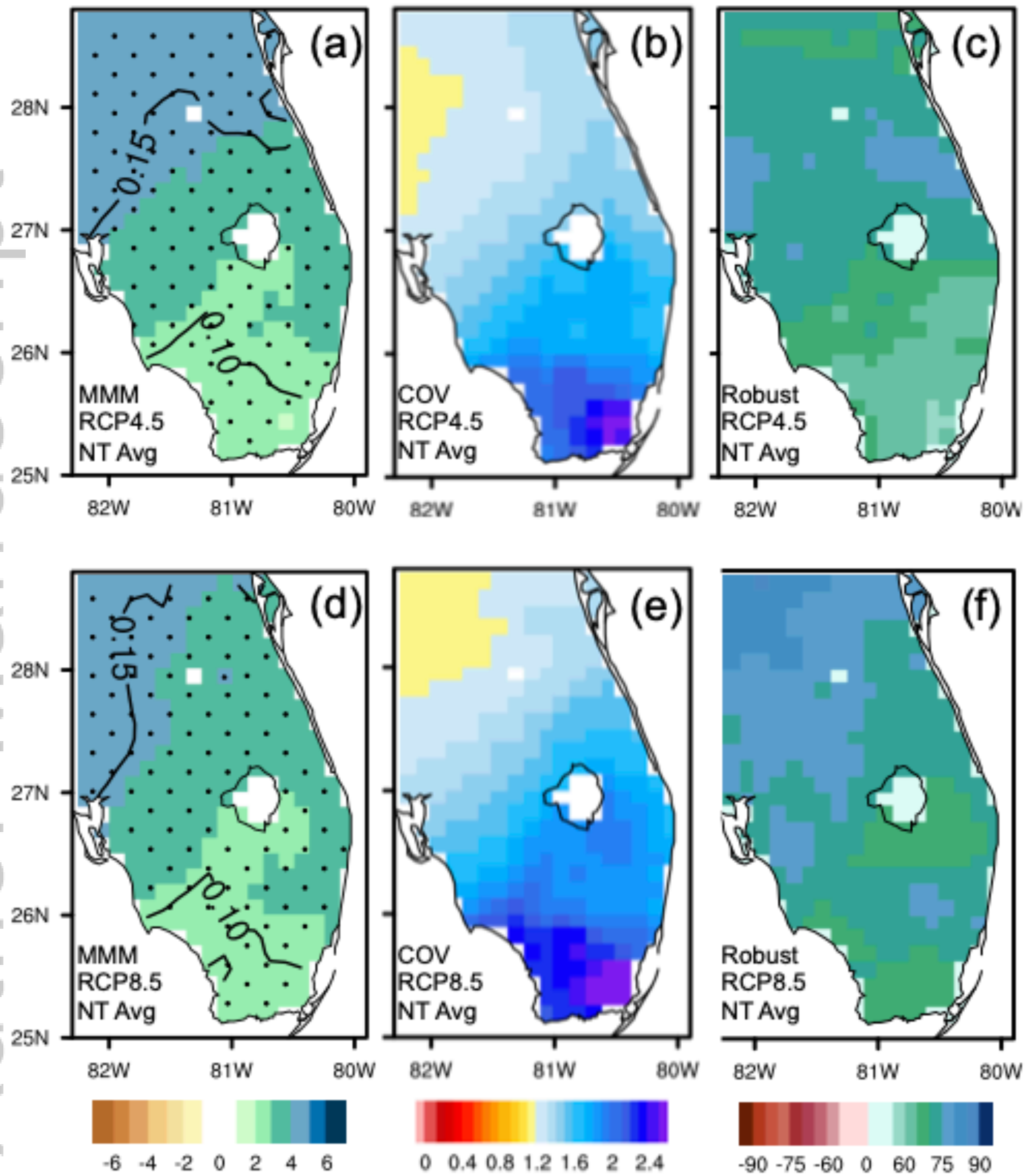

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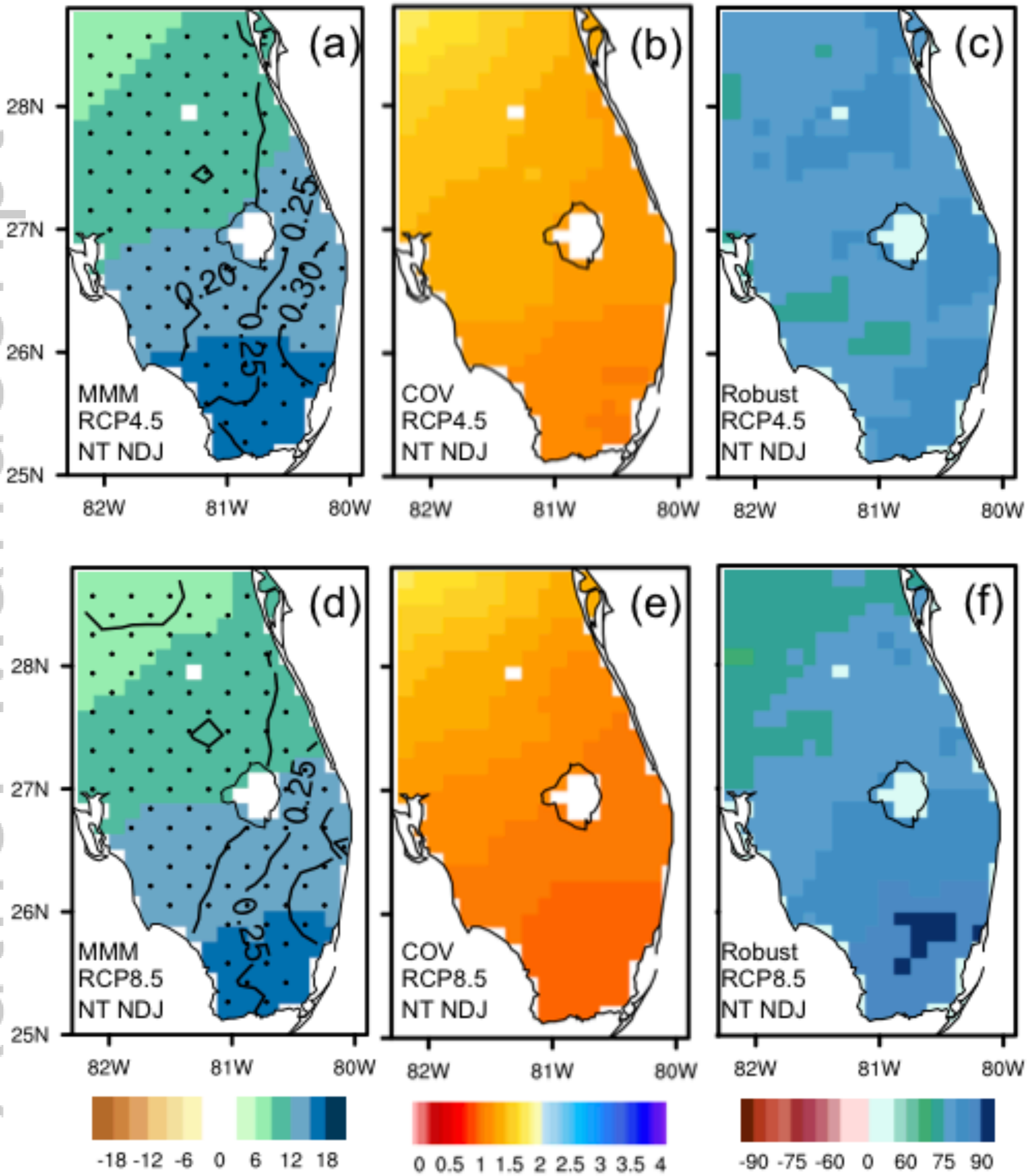

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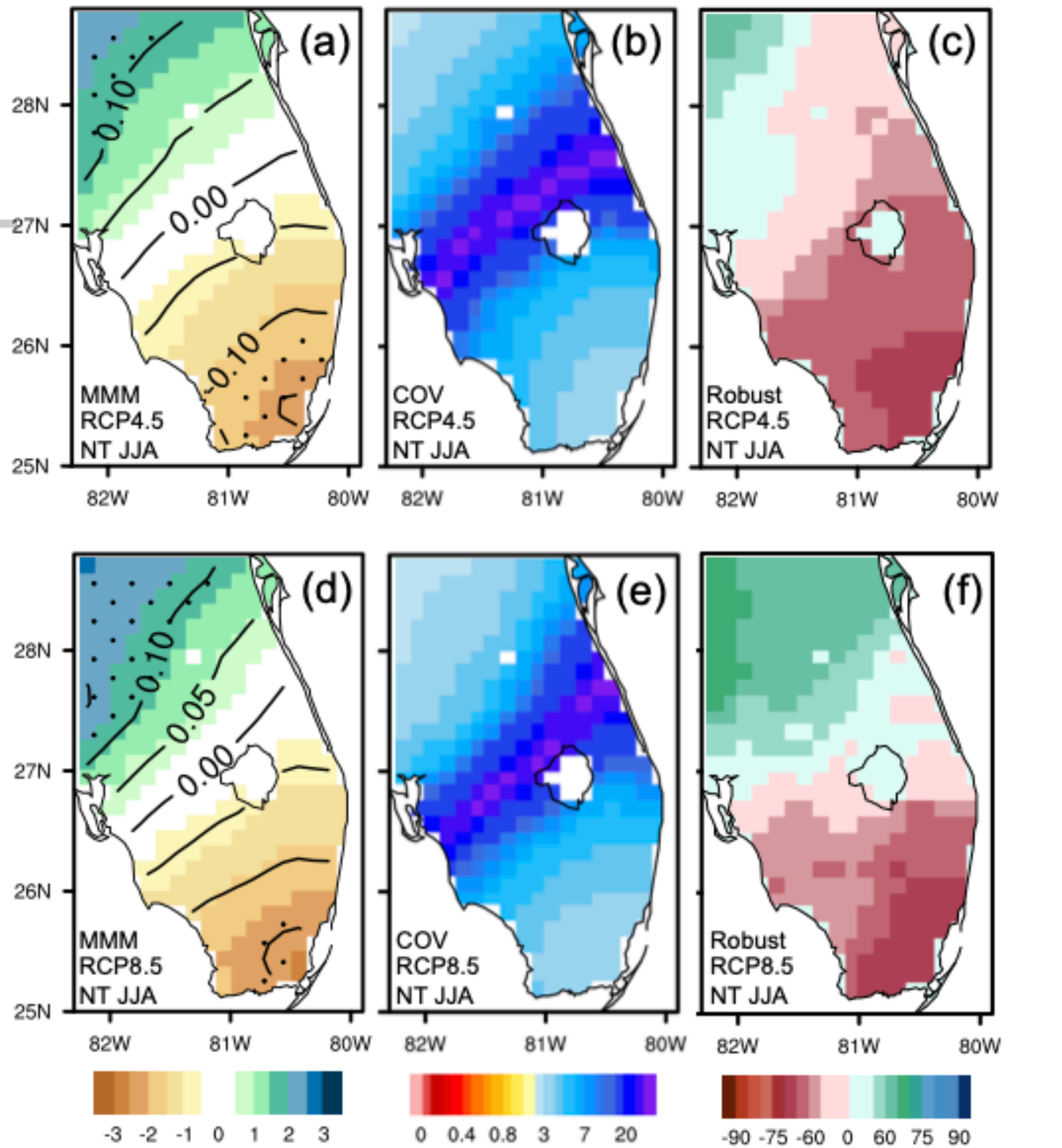

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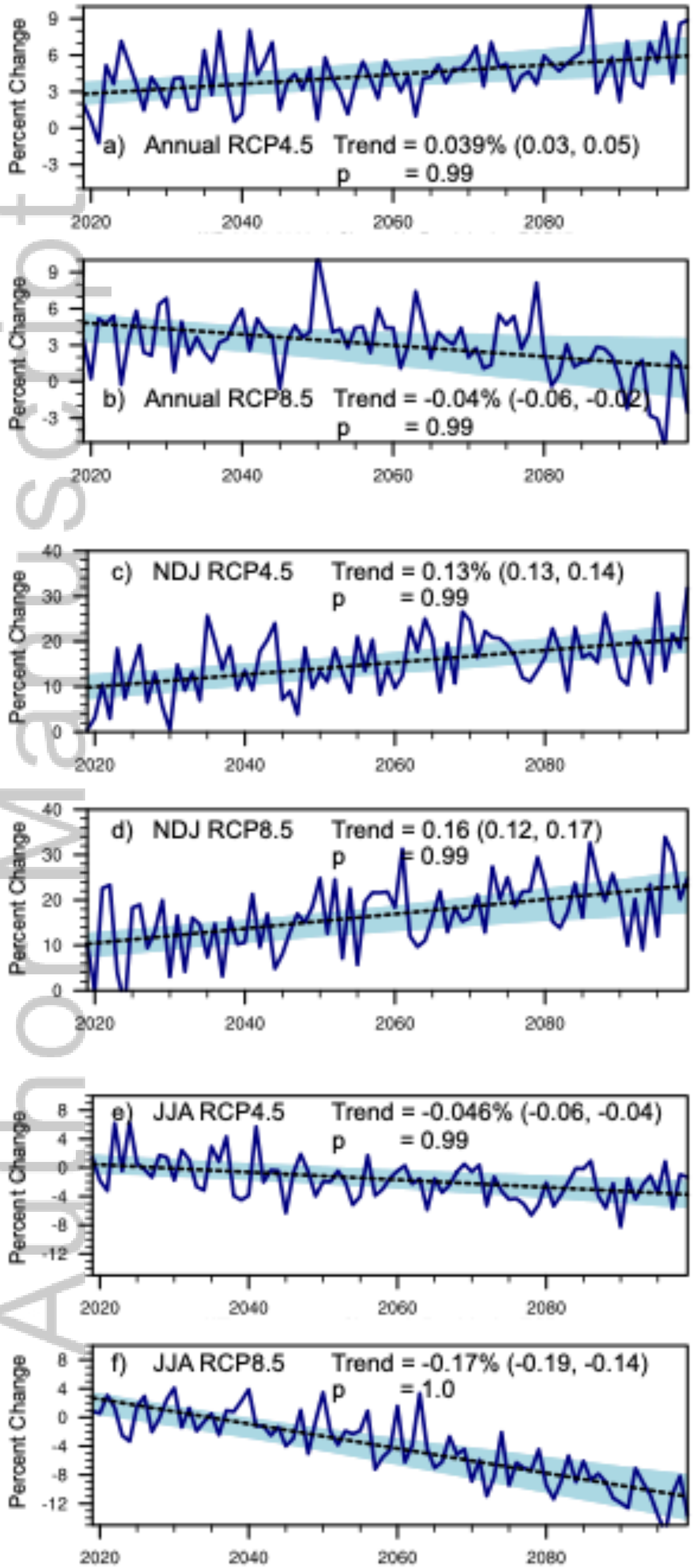

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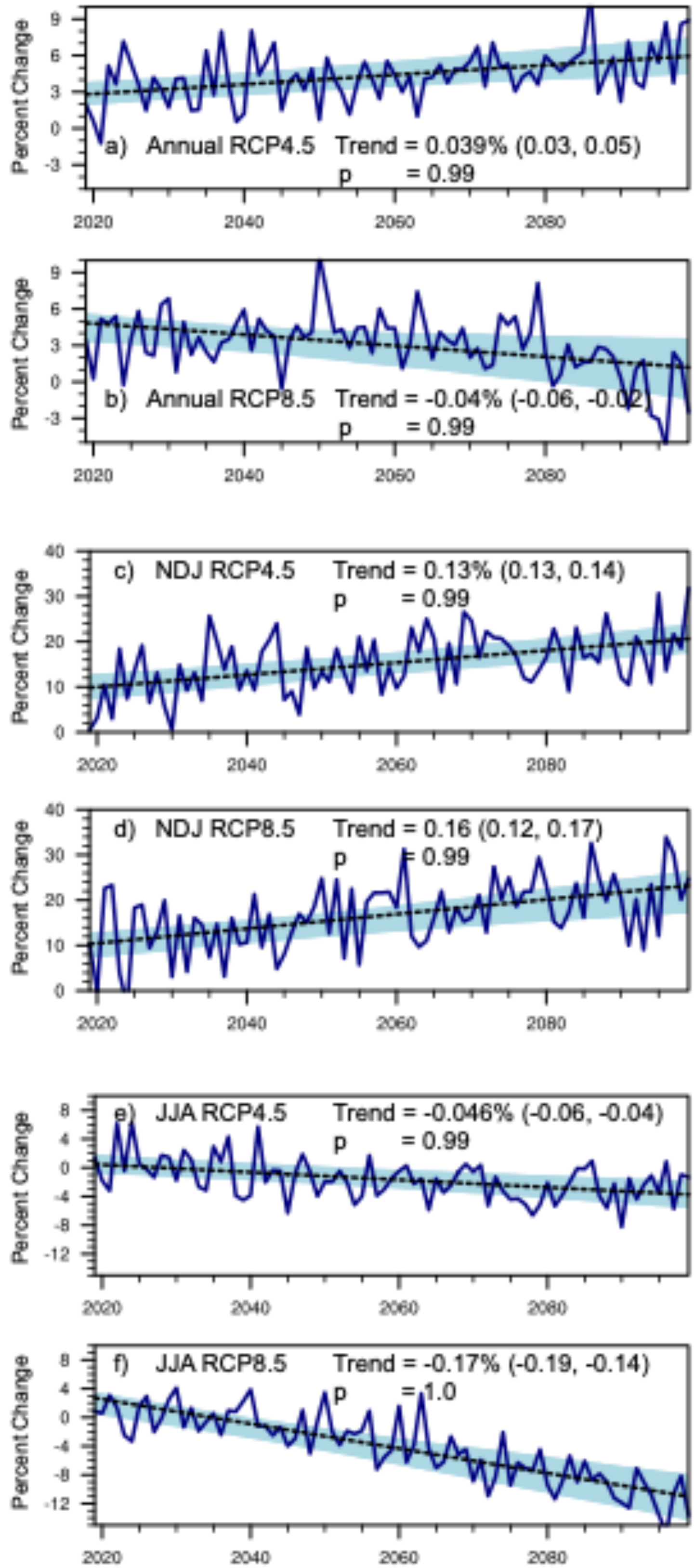

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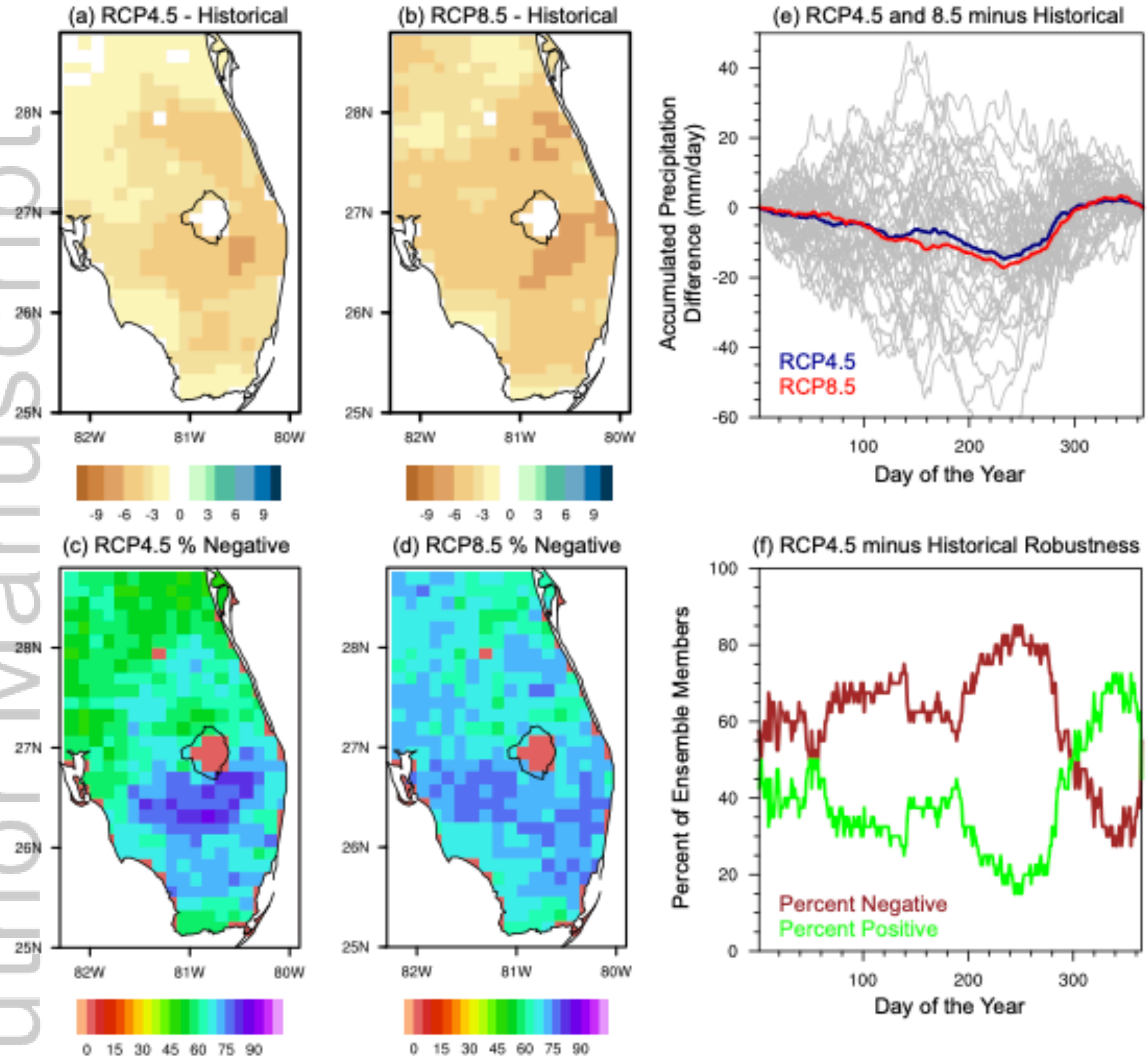

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Assessment of uncertainty in multi-model means of downscaled south Florida precipitation for projected (2019-2099) climate

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Abstract

South Florida resource management, particularly the Everglades restoration effort, is beginning to consider projections of precipitation from multiple climate models for decision-making. For 2019‒45, there is a likely increase in south Florida annual mean precipitation owing to a likely to very likely increase in dry season (November, December, January) precipitation, while wet season (June, July, August) shows a more likely than not decrease in southern precipitation and increase in northern precipitation.