Catena 170 (2018) xxx–xxx

Contents lists available at ScienceDirect

Catena

journal homepage: www.elsevier.com/locate/catena

Predicted 21st century climate variability in southeastern U.S. using downscaled CMIP5 and meta-analysis

Aavudai Anandhi[a,*], Chance Bentley[b]

[a] Biological Systems Engineering, Florida Agricultural and Mechanical University, Tallahassee, FL 32307, USA
[b] College of Agriculture and Food Science, Florida Agricultural and Mechanical University, Tallahassee, FL 32307, USA

A R T I C L E   I N F O

Keywords:
Conceptual framework
Scenario development
Scenario funnel
Coupled Model Intercomparison Project (CMIP5) datasets
Causal chains
Feedback loops
Climate change adaptation
Mitigation
Ecosystems functioning

A B S T R A C T

Trends and variability of the climate in the southeastern United States, including Alabama, Florida, Georgia, Mississippi, North Carolina, South Carolina, and Tennessee was studied for an array of future scenarios in the 21st century. The region is a biodiversity hotspot affected by more billion-dollar disasters than any other region in the country. Assessing the impacts of climate change in southeastern United States is important and often requires knowledge of plausible future climate change (e.g. scenarios of temperature and precipitation change). Although several methods are available in literature to develop plausible scenarios of the changes, there exists a usability gap [gap between what scientists understand as useful information and what users recognize as usable]. A novel conceptual framework that represents the plausible future climate change scenarios in southeastern United States was developed using information from meta-analysis and outputs from ~19 Coupled Model Intercomparison Project (CMIP5) Global Climate Models (GCMs) [data analysis] in the form of scenario funnels (represent the plausible trajectories of changes in climate). The systematic literature review provided 33 values of precipitation changes from 15 studies and 35 for temperature changes from 14 studies. In general, the meta-analysis revealed, the precipitation changes observed ranged from −30 to +35% and temperature changes between −2 °C to 6 °C by 2099. Fiftieth percentile of the GCMs predicts no precipitation change and an increase of 2.5 °C temperature in the region by 2099. Among the GCMs, 5th and 95th percentile of precipitation changes range between −40% to 110% and temperature changes between −2 °C to 6 °C by 2099. Finally, the usability of scenario information to stakeholders in various southeastern United States ecosystems and guidelines for developing causal chains and feedback loops with three levels of complexity were provided. They include utilizing the information from impact assessment studies, stakeholder's expertise and requirement as well as understanding the potential impacts in ecosystems (e.g. agroecosystems, coastal, wetland) by relating the structural components of an ecosystem, their interactions with each other, within and across ecosystems for improved management and sustainable use of their resources. These would improve understanding of ecosystem functioning for better management and sustainable use of resources. Although the methodology was demonstrated for southeastern United States, it could also be applicable to other regions of the world. However, the scenario funnels, potential impacts on ecosystems and causal chain/loops are subjective to the study region, availability of literature, the changes observed in the literature and data analyzed, the characteristics of the study region, the stakeholder and their requirement.

1. Introduction

The southeastern United States is a biodiversity hotspot (Cartwright and Wolfe, 2016) with the highest overall native richness of any temperate region in North America (north of Mexico) (Lynch et al., 2016). The region is considered the "wood basket" of the United States, producing about half of the country's timber supply. The southeastern United States is one of the major agricultural areas in the nation. It has an annual output of about $55 billion in agricultural production (about 17% of total annual agricultural production of the USA) and is a major contributor to the US economy (Mitra and Srivastava, 2016). Earlier studies observed, the region produced roughly one quarter of US agricultural crops, and additionally produced a large portion of the nation's fish, poultry, tobacco, oil, coal, and natural gas (Jones et al., 2001).

The southeastern United States receives ample rainfall throughout the year (Rose, 2009). Despite this, the region has experienced recurring droughts that have caused losses in agricultural productivity, prompted water use restrictions on municipal and irrigated waters uses,

* Corresponding author.
E-mail addresses: anandhi@famu.edu (A. Anandhi), chance.bentley@famu.edu (C. Bentley).

https://doi.org/10.1016/j.catena.2018.06.005
Received 4 December 2017; Received in revised form 27 April 2018; Accepted 4 June 2018

and induced interstate water conflicts (Mitra and Srivastava, 2016). This region is particularly vulnerable to a number of climate-driven events, including sea-level rise and catastrophic floods, drought, heat waves, winter storms, tropical cyclones, and tornadoes (Ingram et al., 2013), and has been affected by more billion-dollar disasters than any other region in the country (Carter et al., 2014). Furthermore, the southeastern United States often suffers from low surface water availability due to frequent occurrences of La Niña, which brings warm and dry conditions between the months of October and April (Mitra and Srivastava, 2016).

Climate change can impact ecosystems in many ways, from effects on species to phenology to wildfire dynamics (Cartwright and Wolfe, 2016). Assessing the potential vulnerability of ecosystems to future changes in climate is an important first step in prioritizing and planning for conservation (Costanza et al., 2016). Additionally, mitigation and adaptation are widely known as the two major responses to climate-driven events (Fu et al., 2016). Scenarios of changes in temperature and precipitation are useful climate information for developing these responses. One way to assess vulnerabilities and impacts, initially through a screening perspective and later with a more directed focus, is to pose plausible and scientifically credible future conditions, or scenarios, with regard to climate variables (Hall et al., 2016). Several methods are available in literature to develop plausible scenarios of changes in near-surface air surface temperature (here called temperature) and precipitation (Anandhi et al., 2008). This study used a novel conceptual framework to develop the scenarios from meta-analysis and data-analysis.

The goal of the study was to provide information to stakeholders while decreasing the usability gap [gap between what scientists understand as useful information and what users recognize as usable in their decision-making (Lemos et al., 2012)]. The specific objectives of this study were to (1) develop a novel conceptual framework that communicates the plausible future climate change scenarios in a region, (2) communicate the potential changes observed in a region (3) develop the causal chain/loops from scenarios and potential impacts for improved ecosystem functioning and informed decision making. The framework was applied to southeastern United States (Fig. 1a). For this the peer-reviewed studies on temperature and precipitation changes in southeastern United States were compiled and synthesized (referred as meta-analysis, Fig. 1b). Also from the Coupled Model Intercomparison Project (CMIP5) downscaled temperature and precipitation data changes were estimated for the region and scenario funnels were developed. Information provided in the scenario funnel is not meant to provide the actual magnitude, along with its timing, of future change; rather, the scenarios are intended to provide a range observed that can assist decision-makers and other stakeholders in making robust choices to manage their risks in the context of plausible future temperature and precipitation changes. The term stakeholders encompass a spectrum of professions and is broadly used to ensure inclusivity as to whom can utilize the methods/results used in this study. The scenario funnel and the data used in developing it would provide a resource for authors of the IPCC Assessment Report and the National Climate Assessment Report (NCA, https://nca2014.globalchange.gov/). NCA is a report submitted to the President and Congress of United States every four years on the status of climate change science and impacts. The NCA informs the nation about already observed changes, the current status of the climate, and anticipated trends for the future by integrating scientific information from multiple sources and sectors to highlight key findings and significant gaps in our knowledge.

2. Methodology

2.1. Definitions/descriptions of key terms

Meta-analysis is a systematic approach to identifying, appraising, synthesizing, and (if appropriate) combining the results of relevant studies to arrive at conclusions about a body of research have been applied with increasing frequency (Stroup et al., 2000). **Snowball sampling** is a tool used in meta-analysis where one accumulates literature sources extracting the relevant references of a known reliable source for use in the analysis, this step may be repeated multiple times until sufficient material is accumulated. **Systems thinking** focuses on understanding the relationships and feedbacks between the parts to understand the entire system (Anandhi, 2017; Caulfield and Maj, 2001), thereby providing a big picture of the system. Global climate models (GCMs) are mathematical formulations of the mechanisms that make up a climactic system (i.e. radiation, energy transfer by winds, formation of clouds, evaporation and precipitation of water, and transport of heat by ocean currents). An **indicator** can be defined as any variable that indicates the magnitude (e.g., mean seasonal temperature) or variability (e.g., standard deviation seasonal rainfall) of a parameter (Alessa et al., 2008), or the statistical relationship among variables (Anandhi, 2017; Gain et al., 2012). **Stakeholders** have been defined as, "individuals or groups with a vested interest in the outcome of a decision" or in the research project (DeLorme et al., 2016). Scenarios represent plausible descriptions of possible future climate states, that must be coherent, internally consistent, and used as planning and communication tools to explore uncertain futures (Berkhout et al., 2002). **Causal chains/loops:** a causal chain is an ordered sequence of events in which any one event in the chain causes the next. When an event in the chain causes an earlier event in the chain then the loop developed is referred to as causal loop. A **scenario** is a coherent, internally consistent and plausible description of a possible future state of the world. It is not a forecast; rather, each scenario is one alternative image of how the future can unfold (Mahmoud et al., 2009). The description of scenario funnel is explained in the next section, Fig. 1a and Anandhi et al. (2018).

2.2. Conceptual framework of plausible future climate changes

The future climate is uncertain and unknown, so there can be a full range of possible trajectories of future climate change (Carpenter et al., 2006) often represented using scenarios. The conceptual framework developed in this study (Fig. 1a) combines 1) interpretation to the definition (previous section): scenarios are not forecasts or predictions, but instead, they provide a dynamic view of the future by exploring various trajectories of change that lead to a broadening range of plausible alternative futures in a form of scenario funnel (Mahmoud et al., 2009); 2) a modification of Carpenter et al.'s (2006) framework which was used to explain scenarios for ecosystem services; 3) the concepts of "There are known knowns. These are things we know that we know. There are known unknowns. That is to say, there are things that we now know we don't know. But there are also unknown unknowns. These are things we do not know we don't know" (Rumsfeld, 2002). In our developed conceptual framework, the possible full and unknown range of trajectories of future climate change is represented by the blue ellipse in Fig. 1a. Many published studies provide some useful ideas about how these trajectories might unfold in future. These studies have based their trajectories on observations from measurements, analysis of historical records, climate model simulations etc. These studies are collected and combined using meta-analysis, to provide a range of trajectories of future climate change represented by the magenta ellipse in Fig. 1a. We have GCM simulation data from virtually the entire international climate modeling community for a range of plausible futures. These GCM simulation data are analyzed to get a range of trajectories of future climate change represented by the green ellipse in Fig. 1a. The meta-analysis can be intended to synthesize the findings of change determined through their evaluation of evidence (confidence) while data-analysis could provide a probabilistic assessment of a variable or its change, or some well-defined outcome having occurred or occurring in the future (likelihood). Together, the circles of data-analysis and meta-analysis represent the information we have access to project the range

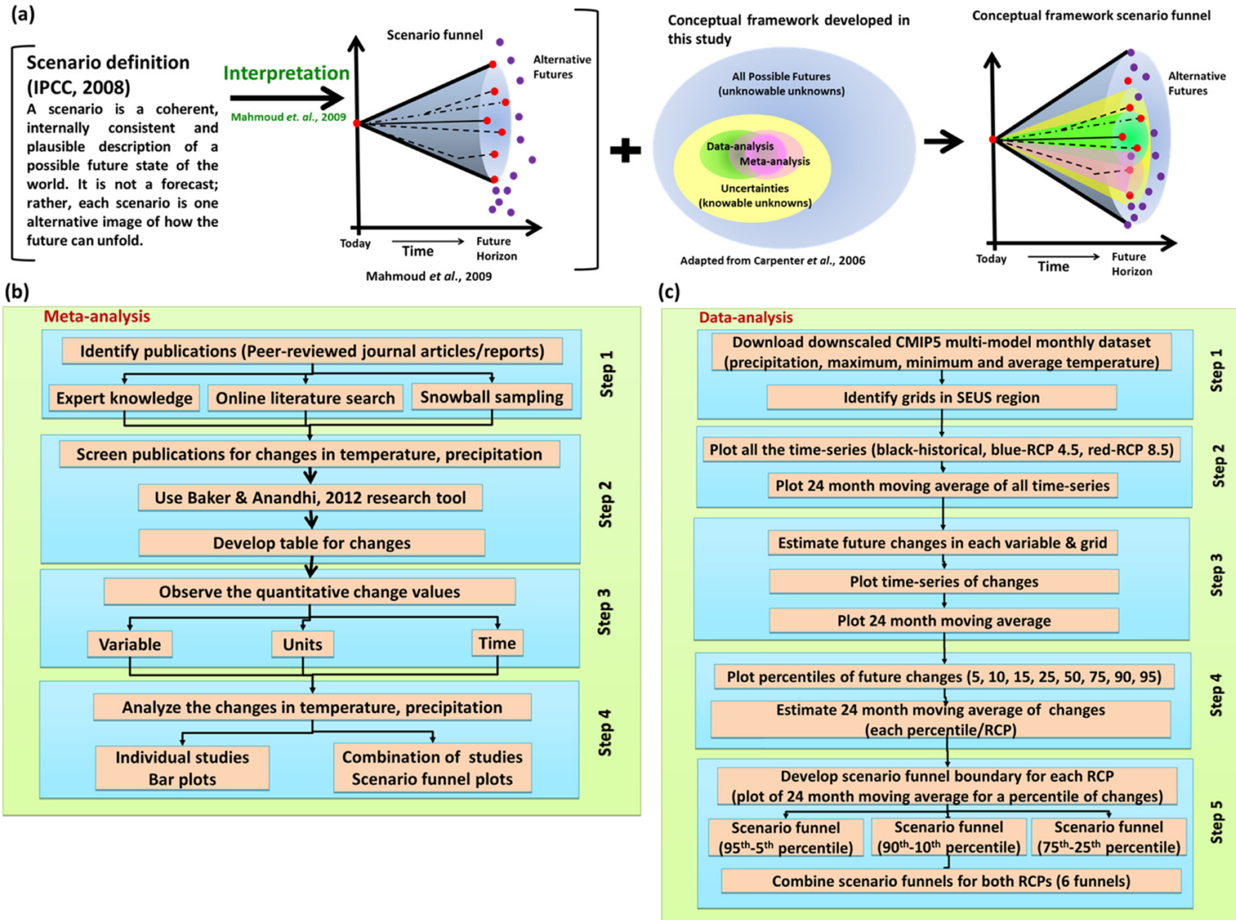

Fig. 1. (a) Conceptual framework used in this study could represent the plausible future climate change scenarios in southeastern United States. This was adapted from Carpenter et al. (2006). (b) Steps followed in developing scenario funnel from meta-analysis. (c) Steps followed in developing the scenario funnel from CMIP5 data. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

of trajectories of future climate change ("known knowns"). There can be an overlap in the two analyses. Around the circles is a yellow ellipse of uncertainty, the "known unknowns" that can be inferred from existing data-analysis and meta-analysis. These uncertainties can be described probabilistically and addressed through the conventional techniques of risk assessments. Example uncertainties are errors in model development and data collection, literature unintentionally missed out in the meta-analysis and multiple other methods and climate data sources to generate plausible future climate change scenarios. The blue space beyond the yellow ellipse represents the "unknown unknowns,". It represents the mysteries and surprises that have not yet been imagined (Carpenter et al., 2006; Smith, 2002) or unrecognized uncertainties of which we are unaware. An extreme, catastrophic, or dramatically surprising trajectory of future climate change is not an unknown unknown, if it had been envisioned but deemed too unlikely to occur. By definition, unknown unknowns are not known. Just because something is currently unknown does not mean that it is unknowable. The knowledge that unknown unknowns are probably "out there" can motivate the application of appropriate search strategies. Structural uncertainty arising from incomplete understanding of or competing conceptual frameworks for relevant systems and processes (Mastrandrea et al., 2010) can be an example. In the conceptual framework (Fig. 1a) of the plausible range of future climate change scenarios proposed in this study represents the logical progression from knowns to unknowns and divided into three parts. "Known knowns" are the range of possible trajectories, of climate change obtained from observed meteorological records, simulations from models such as GCMs. The rest of the possible trajectories range of future climate changes can be classified into two types of unknowns ("knowable unknown" and "unknowable unknown"). The first type "knowable unknown" is that we know, we don't know possible trajectories range of future climate (e.g. uncertainties in the knowns). The second type of unknown "unknowable unknown" are those possible trajectory range of future climate changes that we don't even know, we don't know. The stakeholders while using the possible trajectory range of future climate changes need be aware that the evidence they have may just represent the "known knowns" and/or "unknown knowns" and make appropriate choices. Thus, the conceptual framework (Fig. 1a) developed in this study could reduce the usability gap in one way by increasing awareness among stakeholders of the possible trajectories range of future climate changes available, and how their use of trajectories of future climate change in evidence based decision making. Our framework improves the usability gap in the literature and makes a significant practical contribution: it helps stakeholders diagnose the use of trajectories of future climate change in evidence based decision making, recognize and reduce the likelihood of "unknowable unknown" and thus deal more effectively with the otherwise unrecognized risks and opportunities.

2.3. Meta-analysis

In general, meta-analysis (pink ellipse in Fig. 1b), is a systematic approach to identifying, appraising, synthesizing, and (if appropriate) combining the results of relevant studies to arrive at conclusions about a body of research have been applied with increasing frequency (Stroup et al., 2000). The steps in the meta-analysis followed in the study were provided in Fig. 1b.

Step 1: Reviewed the available literature covering quantitative and qualitative climate change projections in terms of variables temperature and precipitation. Three rounds of screening and sampling was carried out. First, through author expert knowledge (collaborators, list of publications in Florida Climate Institute), then, an online literature search (Google Scholar, Web of Science), and finally, snowball sampling [i.e., using the references cited within confirmed studies of climate change, as well as subsequent references to those studies; Lynch et al., 2016].

Step 2: Identified studies with quantitative directional change projections in literature. We included only peer-reviewed studies conducted in southeastern United States or those which specifically references the region and published between 1999 and 2016. We limited our search to studies of directional changes in temperature and precipitation but did not require these studies to demonstrate a clear change (i.e., negative, positive and no change are all equally important). Research tool developed by Anandhi and Baker (2013) was used in synthesizing the studies into a table (Table 1a and 1b), in doing so simplifying multiple complex topics/information into a easier to understand form. This tool was developed to assist students in synthesizing copious amounts of literature to preserve energy and time.

Step 3: Sorted the changes in the studies for each variable (temperature and precipitation). For each variable, units of the changes were observed, and the start and end year changes were noted.

Step 4: Analyzed the changes of temperature and precipitation observed in the literature using bar plots and funnel plots. Bar plots provided the information about individual change values in temperature and precipitation for southeastern United States and the approximate range of values across studies, while the funnel plot provided the changes across the studies and change dates. Each quantitative change in temperature and precipitation from the studies (Tables 1a and 1b) are plotted in a bar plot. A study can have multiple values to represent the changes across multiple time-periods (e.g. up to 2050, up to 2100), data (e.g. one or more GCMs), seasons (e.g. summer, annual). Each bar is created for a value (x-axis) and the length of the bar represents the extent of change projected (y-axis) for a study with a time-period/season/source. Funnel plots were developed to show a range of plausible scenarios of future climate. These plots synthesize the findings of literature used in the meta-analysis portion of the study to determine a range of future climate. The funnel plot lines drawn from individual bars and lines were combined to form the scenario funnel (Fig. 2c and f). The x-axis represented the year and y-axis represented the change in temperature or precipitation. For each bar plot a line was drawn between two points: the start year with no change and end year with change in temperature or precipitation documented by the study (Fig. 2d and g). The length of the funnel represents the time and width of the funnel represents the level of change in temperature and precipitation. Studies with qualitative directional changes in temperature and precipitation were used in discussion. Seventeen publications were finally identified that directly characterized temperature and precipitation change in southeastern United States through three rounds of screening and sampling. The list is provided in

Table 1a
Percent change in precipitation observed from studies used meta-analysis.

Precipitation (P)	Time frame	Change found (%)	Reference
P annual	2001–2090	20	Jones et al. (2001)
P annual	2001–2090	−10	
P annual	2007–2050	6	Endale et al. (2014)
P fall and spring	2007–2050	5–20	
P winter and summer	2007–2050	−5 to −20	
P annual	1901–2000	20–30	
P heavy annual	1958–2007	15–20	
P fall	1901–2009	30	Greenberg et al. (2015)
P annual	2009–2100	−10 to −20	Kim and Grunwald (2016)
P heavy annual	1901–2009	22	McNulty et al. (2015)
P annual	2007–2091	7–9	Neubauer and Craft (2009)
P fall	2014–2100	10	Susaeta et al. (2016)
P winter	2014–2100	20	
P heavy	1900–1999	15	Groisman et al. (2001)
P heavy	1950–1993	15–30	Gershunov and Barnett (1998)
P annual	1900–1999	20–30	Greenland (2001)
P annual	1895–1997	10	
P annual	1895–2000	10	
P summer	1960–1995	−20	Mearns et al. (2003)
P spring	1960–1995	35	
P winter	1960–1995	20	
P summer	1960–1995	−30	
P spring	1960–1995	25	
P max daily	1996–2091	5–15	Wuebbles et al. (2014)
P max daily	1996–2091	10–25	
P annual	2007–2050	−2 to −4	Ingram et al. (2013)
P annual	2007–2050	6	
P annual	2007–2050	15	
P annual	2007–2050	−12	
P annual	2007–2050	6	
P heavy	1910–2000	26	Groisman et al. (2003)
P annual	1907–1998	16	Groisman et al. (2004)
P occurrence	1931–1996	−5	Kunkel et al., 1999

Table 1b
Changes in temperature observed from studies used in meta-analysis.

Temperature (T)	Time frame	Change found (°C)	Reference
T max summer	2001–2030	1.3	Jones et al. (2001)
T max winter	2001–2030	0.6	
T annual	2001–2030	1	
T annual	2001–2100	2.3	
T annual	2001–2030	1.7	
T annual	2001–2100	5.5	
T annual	2007–2100	2–10	Greenberg et al. (2015)
T annual	1970–2015	1	
T annual	1880–2016	1	Gutierrez and LePrevost (2016)
T annual	2007–2100	2–6	
T annual	2007–2100	1.5–5	Kim and Grunwald (2016)
T annual	2007–2090	3.2	Neubauer and Craft (2009)
T annual	2013–2100	1.5–3	Susaeta et al. (2016)
T annual	2001–2100	2.3	Flebbe et al. (2006)
T annual	2001–2100	5.5	
T annual	1949–1994	−0.09	Greenland (2001)
T annual	1895–2001	0.5	
T annual	1960–1995	3–4	Mulholland et al. (1997)
T annual	1960–1995	3–5	Mearns et al. (2003)
T annual	1900–1994	1–7	
T annual	1961–1990	−1 to −2	Soule (2005)
T annual	1961–1990	0.1	
T annual	1961–1990	0.18	
T annual	2013–2050	0.09	
Tmin	1996–2091	1–3	Wuebbles et al. (2014)
Tmax	1996–2091	1	
Tmin	1996–2091	3–10	
Tmax	1996–2091	3–7	
Tmax max	1950–2007	0 - -4	Grotjahn et al. (2016)
Tmax min	1950–2007	0–2	
Tmin max	1950–2007	0 to −4	
Tmin min	1950–2007	0–3	
T annual	1895–2007	−0.05	Rogers (2013)
T winter	1895–2007	−0.15	
T summer	1895–2007	−0.7	

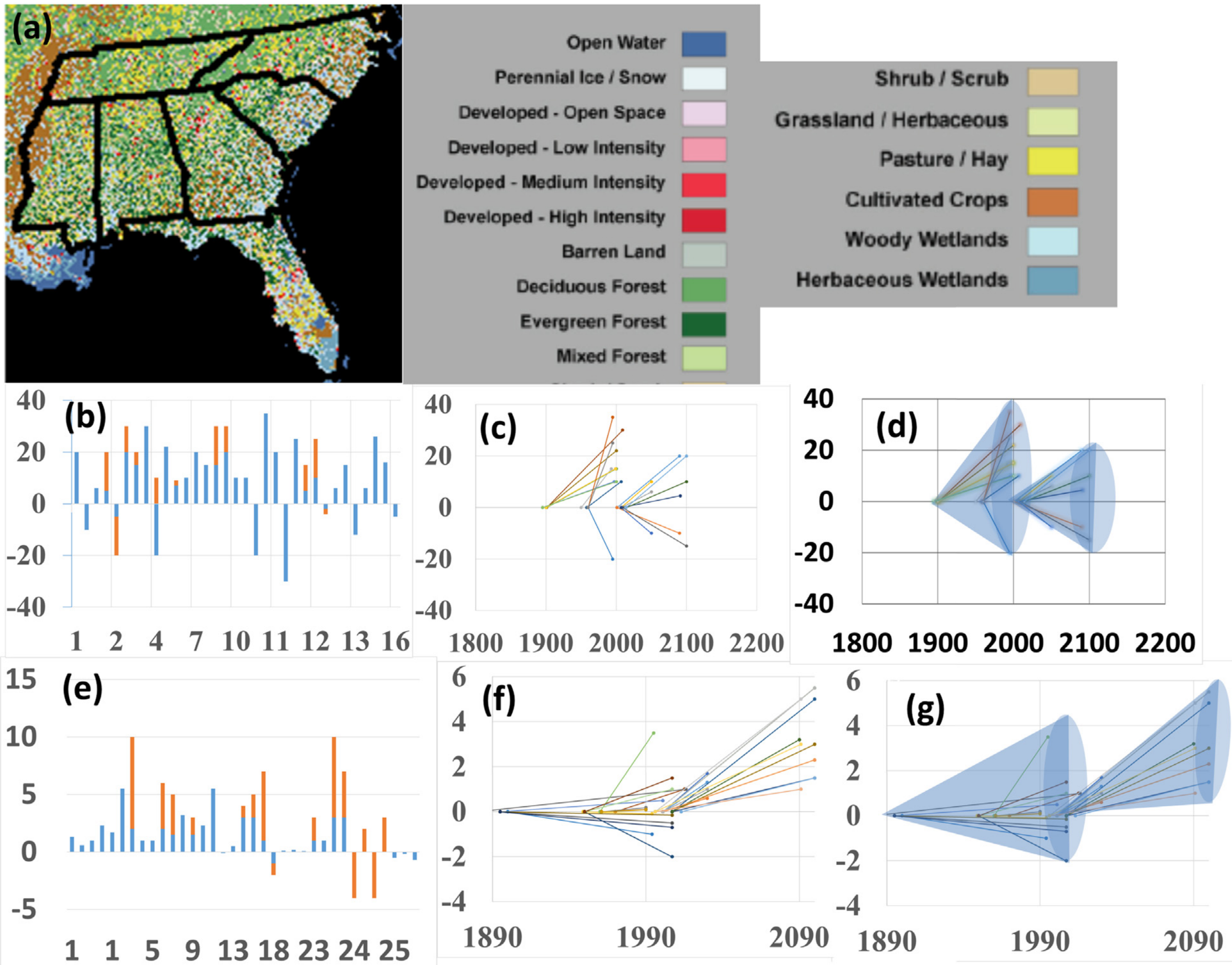

Fig. 2. (a) Land use/land cover Map of southeastern United States region used in data-analysis and some studies in meta-analysis. Land cover data from Homer et al. (2015). (b, c, d) Bar plots, scenario lines and funnel plots for precipitation change in percent (y-axis). (e, f, g) Bar plots, scenario lines and funnel plots for temperature change in °C (y-axis). X-axis in bar plots (b, e) were for individual values from studies. The values and references are provided in Table 1. In scenario lines and funnel plots they were years. In bar plots, blue bars represent values cited. In studies with ranges of change in precipitation and temperature, the ranges were plotted in orange in the bar plots. The midpoint of the range was used as end the point of scenario line. For example, a scenario line's end point for +2 °C to +10 °C change in temperature observed in bar plot, will be +6 °C. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Tables 1a and 1b.

2.4. Data-analysis

The steps in the data-analysis (green ellipse in Fig. 1b) followed in the study were provided in Fig. 1c. The various steps explain the scenario funnel developed from the downscaled data in the region (Fig. 3a top).

Step 1: Downloaded data for the southeastern United States region at a 1° × 1° grid scale. The region included the states of Alabama, Florida, Georgia, Mississippi, North Carolina, South Carolina, and Tennessee covers 98 grids (Fig. 2a). Downscaled CMIP5 multi-model monthly data measuring minimum, average, and maximum for temperature and precipitation was downloaded (http://gdo-dcp.ucllnl.org/downscaled_cmip_projections/). The Representative Concentration Pathways (RCPs) were used in the IPCC's Fifth Assessment Report to represent low-to-medium (RCP4.5) and high (RCP8.5) greenhouse gas emission trajectories over time (Susaeta et al., 2016). The RCPs provide plausible information about how the future may evolve with regards to energy and land use, emissions of greenhouse gases, and changes in socioeconomic and technological conditions (Van Vuuren et al., 2011). More details of the data can be obtained from Maurer et al. (2014). For each scenario, the time-series from 19 GCMs with some of them having multiple runs (up to 10) for all 98 grid points were used.

Step 2: Plotted multi-model monthly time series for the 98 grids for temperature and precipitation (Fig. 3a, g). Next a two-year (24 month) moving average was applied to the data to smoothen the projections.

Step 3: Estimated future changes in precipitation and temperature using Eqs. (1) and (2). The changes were plotted. A two-year (24 month) moving average was applied to the data to smoothen the projections.

Step 4: Estimated multi-model percentiles (5th, 10th, 25th, 50th 75th, 90th, 95th) of changes for each month from step 3. A two-year (24 month) moving average was applied to the percentiles to smoothen the projections.

Step 5: Developed three scenario funnel boundaries for each RCP. The first scenario funnel had time series of 5th and 95th percentile projections as its boundary, while the second and third funnel had 10th and 90th and 25th and 75th percentile values as its boundaries. Finally, the six funnels for each variable were

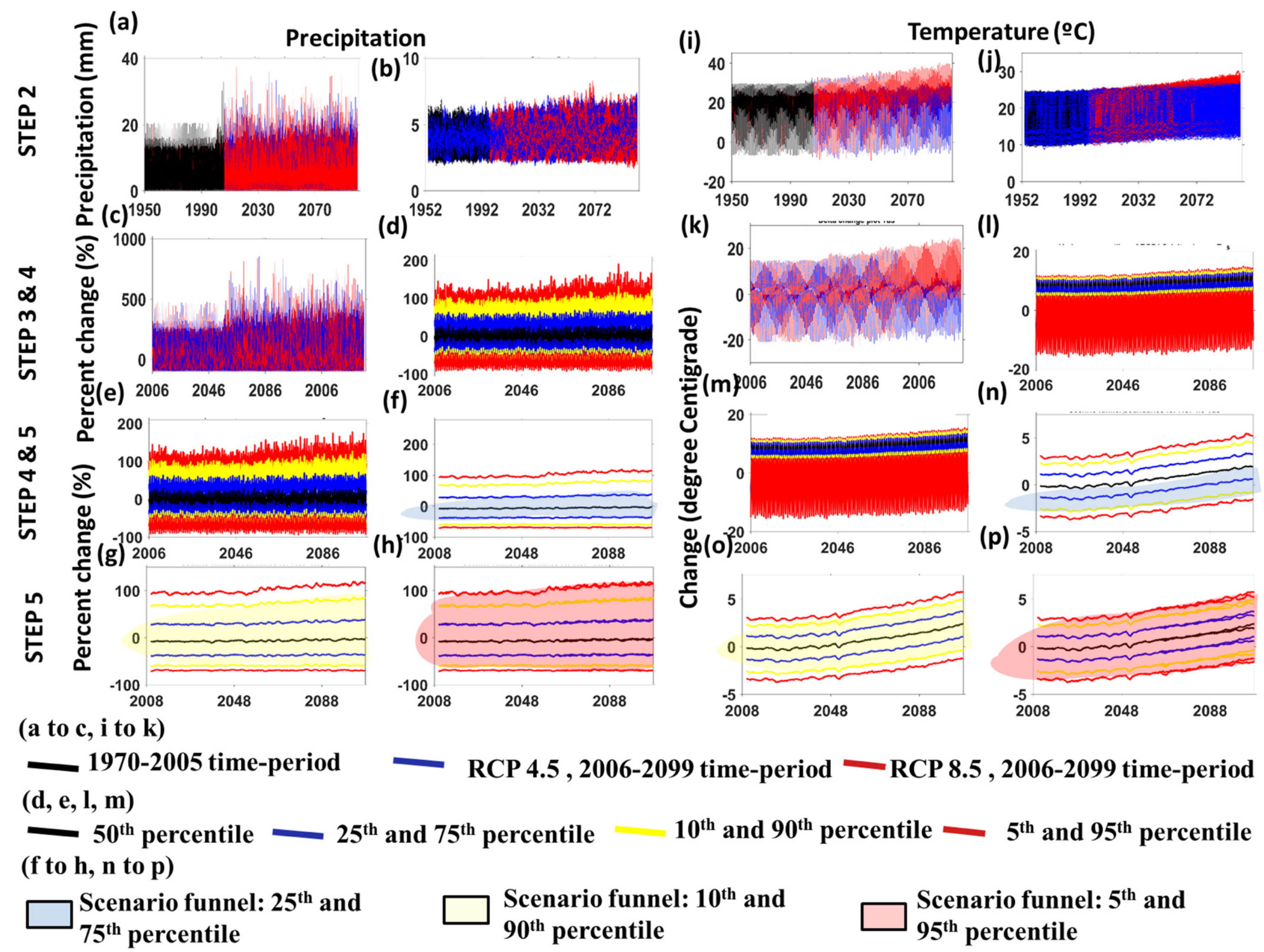

Fig. 3. The plot of various steps in developing the scenario funnel for precipitation (a to h) and temperature (*Tas*, i to p) by data-analysis, (a, i) time-series plot of raw precipitation and temperature data, (b, j) time-series plot of 24 month moving precipitation and temperature data, (b, j) time-series plot of 24 month moving average precipitation and temperature data, (c, k) time-series plot of delta change estimated for precipitation and temperature, (d, l) various percentile values for RCP 4.5 for precipitation and temperature (red: 5th, 95th; yellow:10th, 90th, blue: 25th, 75th, black: 50th percentiles), (e, m) various percentile values for RCP 8.5 for precipitation and temperature (red: 5th, 95th; yellow:10th, 90th, blue: 25th, 75th, black: 50th percentiles), (f, n) Developing scenario funnel boundaries for RCP 4.5 from 24 month moving average of the percentiles (red: 5th, 95th; yellow:10th, 90th, blue: 25th, 75th, black: 50th percentiles), (g, o) Developing scenario funnel boundaries for RCP 8.5 from 24 month moving average of the percentiles (red: 5th, 95th; yellow:10th, 90th, blue: 25th, 75th, black: 50th percentiles), (h, p) scenario funnels for precipitation and temperature. In a, b, c, i, j, k red and blue color represents the RCP 8.5 and RCP 4.5 respectively. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

combined.

$$\%change = \left(\frac{future\ value - historic\ base}{historic\ base}\right) * 100 \tag{1}$$

$$Degree\ change = future\ value - historic\ base \tag{2}$$

Step 6: Examined the spread of scenario funnel month. It informs us about the changes in the extremes (e.g. 5th and 95th percentiles), uncertainty and agreement between trend projections of GCMs.

2.5. Study region

Southeastern United States was the study region selected. The region has multiple unique ecosystems [e.g. urban, coastal, wetland, insular, forest, Fig. 2a Homer et al., 2015]. The boundary of southeastern United States differed among the studies used in the meta-analysis. These differences are discussed in more detail in Section 3.3. In the data-analysis of CMIP5 models, southeastern United States boundary included the states of Tennessee, North Carolina, South Carolina, Mississippi, Alabama, Georgia and Florida (Fig. 2a).

3. Results and discussion

3.1. Meta-analysis: pink ellipse in conceptual framework

The systematic literature review provided 33 values of precipitation changes from 15 studies (Table 1a) and 35 for temperature changes from 14 studies (Table 1b). In general, the meta-analysis revealed, the precipitation changes observed ranged from −30 to +35% (bar plots in Fig. 2b). Some studies showed a range of changes rather than a single value change. Mearns et al. (2003) observed that the highest precipitation change (35% increase) was observed in spring precipitation during the latter part of the 20th century. They observed largest decreases in precipitation (upto 30%) during the summer months. Endale et al. (2014) observed a 20% decrease in precipitation during the summer. In the studies, 8 of 33 change values projected a decrease in precipitation over the period. Among the 25 change values with increasing precipitation, projections over the 20th century tend to depict greater increases (14 out of 33 values) when compared to future projections (11 out of 33 studies).

Our meta-analysis of temperature changes using bar plots, scenario lines and funnels show much less variation among studies (Fig. 2e, f, g). Of the 35 values derived from literature 28 (80%) showed an increase in temperature. All the studies projecting future temperature showed an increase over their respective time frames, with a range of 1 to 5.5 °C increases. The 7 decreasing values all occurred during the 20th century, as it is well documented the area went through a cooling period over the latter half of the 20th century (Jones et al., 2001). Much like the precipitation studies, we can see a clear contrast of studies analyzing historic temperatures and projecting future temperatures. However, unlike precipitation projections, the highest changes occur in projections of annual temperatures and not seasonal temperatures, suggesting a more uniform change in seasonal temperature compared to precipitation. For both precipitation and temperature, a group of studies focused on future changes based on historical studies as well as future projections was observed. This study developed two future scenario funnels for each variable with historical changes and future changes (Fig. 2d, g). These two funnels can be combined to form a single funnel (not shown in figure). We found for temperature, the most commonly used unit of change was °C over time. The other units of change were °F (Carter et al., 2014), indexes that count days relative to a critical temperature threshold (Easterling, 2002; Ingram et al., 2013; Maloney et al., 2014). For precipitation, the unit was % change over time. Other measures for precipitation found include inches/decade (McNulty et al., 2015) and centimeters over time (Doublin and Grundstein, 2008). The units remained the same even though the time-period, seasonality and definition of southeastern United States varied.

3.2. Data-analysis: green ellipse in conceptual framework

The changes in temperature and precipitation observed in our data-analysis complement the meta-analysis and provide the likelihood of changes observed from CMIP5 GCM simulations in southeastern United States. Fiftieth percentile of the GCMs predicts no precipitation change and an increase of 2.5 °C temperature in the region by 2099. The GCMs predictions of increase in temperature by 2099 are more consistent than precipitation change. Up to 110% precipitation change was observed as the 95th percentile change in the region, while the changes are 90% and 40% for 90th and 75th percentiles respectively by 2099. Negative precipitation changes (−75%, −60% and − 40%) was observed by 5th, 10th and 25th percentile of the models by 2099. A high of 5 to 6 °C temperature increase was observed as the 95th percentile in the region, while the changes are in the range of +4 to +5 °C and + 3 to +4 °C for 90th and 75th percentiles respectively by 2099. Smaller temperature changes (up to +2.5 °C) were observed for 5th, 10th and 25th percentile of the models by 2099. The changes in RCP 4.5 and RCP 8.5 are quite similar. This can be observed from the overlap of scenario funnel boundaries between RCP 4.5 and RCP 8.5 (for each red, blue and yellow funnel boundaries) with RCP 8.5 showing a slightly more variability (1 to 3% difference for precipitation and 0.1 to 0.2 °C for temperature as estimated from values) than RCP 4.5. These variability among RCP's could also be observed from the concentric funnel boundary (e.g. red: 5th and 95th) of RCP 4.5 is inside the RCP 8.5. From the changes observed among the GCMs, the precipitation change has an interquartile range of ± 40%, while the temperature has interquartile range of 5 to 6 °C.

3.3. Uncertainties: yellow ellipse in conceptual framework

A variety of uncertainties, including those associated with human behaviors, limit the predictive capabilities of climate-related sciences (Hall et al., 2016). Some of these are knowable unknowns, while others are unknowable unknowns. While comparing studies for southeastern United States, the spatial boundaries, the temporal scale (time-period and time-scale), data sources are important. Accommodating these variabilities can lead to uncertainties.

The variation of southeastern United States boundaries among studies could also result in the variability and uncertainty in the projected changes in temperature and precipitation because some states can have a different change than others. Our changes using data-analysis covered seven states for southeastern United States (Tennessee, North Carolina, South Carolina, Mississippi, Alabama, Georgia and Florida). These seven states were also used by Selman and Misra (2016) and Alexandrov and Hoogenboom (2000) in their studies on southeastern United States. Some studies had different seven states for southeastern United States. For example, Soule (2005) considered Virginia, instead of Tennessee, the rest being the same. Some studies had smaller area in southeastern United States, while some studies on southeastern United States covered a larger area. For example Fraisse et al. (2006) considered three states (Alabama, Georgia and Florida), while Williams (2016) defined southeastern United States to include five states (Alabama, Florida, Georgia, North Carolina, and South Carolina). Some included Louisiana and Arkansas in addition to the seven states we considered (Mitra and Srivastava, 2016). Some studies included eleven states: Kentucky, Virginia, Louisiana and Arkansas in addition to the seven states we used in the study (Carter et al., 2014; McNulty et al., 2015) while Ingram et al. (2013) in the NCA defined southeastern United States includes Puerto-Rico and Virgin Islands in addition to the eleven states.

The variation in the time-scales of the studies could also have caused the variability in the changes documented by the studies. The scales varied from annual time-scale (Carter et al., 2014; Ingram et al., 2013; Jones et al., 2001), seasonal (Maloney et al., 2014; McNulty et al., 2015), to monthly scales. The two funnels are for the two time-periods. The way the funnels are combined could also cause uncertainties in the future scenarios. Additionally, the data sources in these studies were from either historical observed data (Groisman et al., 2003; Soule, 2005), historical and future time-period modeled data for multiple temporal scales (Greenland, 2001; Jones et al., 2001) etc. The range of percent change in precipitation (e.g. −75 to 110% represented by red funnel) and temperature change (upto +6 °C represented by red funnel) observed from different scenario funnels obtained from data-analysis represent the variability among GCM model simulations.

Southeastern United States is somewhat anomalous in climate change research as most analyses show this area did not warm significantly during the twentieth century (Soule, 2005). The importance of convective precipitation in southeastern United States; the complexity of the moisture sources for precipitation (Gulf of Mexico and the Atlantic Ocean); the location and strength of the Bermuda high; the location and strength of the nocturnal jet; and the importance of contributions to precipitation from hurricanes along the coast in late summer are some factors that make reproduction of the climatology of the region often challenging to model (Mearns et al., 2003). Additionally, precipitation is difficult to measure with confidence. Only a few decades of reliable data are available, internal variability in these short record lengths may contribute to the uncertainties and limit the applicability of the observational data to better understand anthropogenic climate change (Kramer and Soden, 2016). Studying the direct effects of climate change on southeastern ecosystems (e.g. inland fishes) can be challenging: given the interactive nature of climatic and anthropogenic pressures and the rarity of unperturbed reference systems (Lynch et al., 2016); complexities and multidisciplinary nature of these ecosystems (Anandhi, 2017).

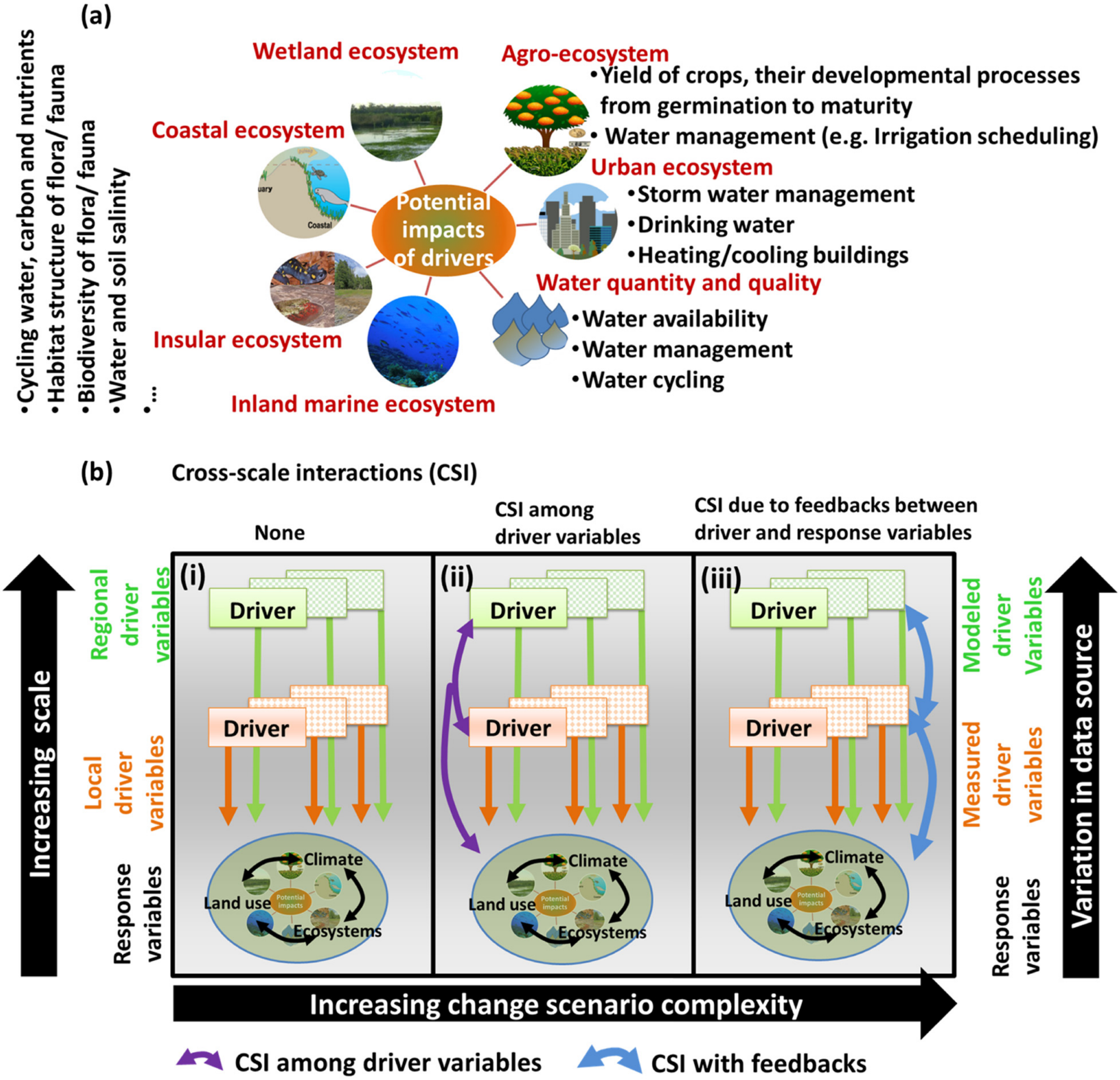

Fig. 4. (a) Potential impacts of drivers (changes in temperature and precipitation in southeastern United States) and (b) The conceptual description of the causal chains and feedback loops between the driver variables (e.g. precipitation and temperature) and response variables (e.g. impacts in Fig. 4a). They can range - from (i) simple to (ii and iii) more complex. The "response variables" are the impacts in various ecosystems. The "local driver variables" (orange boxes) are the variables at point scale, while the "regional driver variables" (green boxes) are the variables at coarser scale (hydrological or ecosystem or political boundary). The green and orange arrows depict one-way effect of regional and local driver variables, respectively on the response variable. The climate variables and the ecological indicators are the driver variables, while the response variables are the various impacts in ecosystems. Figure (b) is adapted from Soranno et al. (2014). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

3.4. Application of scenario funnels for assessment of potential impacts in the region

The ranges of changes observed from scenario funnels in meta-analysis and data-analysis are useful for effective conservation and management of ecosystems- especially in the face of climate-change (Costanza et al., 2016) and communicating the uncertainties in the decision making process. The impacts of both increasing and decreasing changes in temperature and precipitation on various ecosystems and water resources in southeastern United States were briefly summarized in Fig. 4a and discussed in this section.

The temperature and precipitation change (drivers) play critical roles in water resources management, plant, insect and animal growth. Specifically, the changes impacts ecosystems in many ways, from its effects on species to phenology to wildfire dynamics (Costanza et al., 2016) and influences the components of hydrologic cycle. Climate variability induced stresses on water resources combined with an ever-growing population with increasing need for irrigated agriculture puts stress on freshwater bodies such as lakes, streams, and aquifers and increased demand for water consumption (Singh et al., 2016). The southeastern United States is one of the USA agricultural areas with high heterogeneity of crop production (Ingram et al., 2013). In plants, temperature affects and drives most developmental processes, starting as early as the germination process immediately after planting, and as late as the ripening process during physiological maturity (Alexandrov and Hoogenboom, 2000). The precipitation changes drive and affect irrigation scheduling and combined with temperature changes impact water management. Stakeholders in agro-ecosystems could utilize the information from scenario funnels for improved management and sustainable use of their resources for increased yield and greater economic return.

Some of the wetland ecosystems found in southeastern United States are unique to the region. In these wetland (lands transitional between terrestrial and aquatic systems where the water table is usually at or near the surface or the land is covered by shallow water) ecosystems, changes in temperature and precipitation could impact various ecosystems functions. For example: Decreased precipitation reduces freshwater discharge and water table. Evapotranspiration in wetlands can be classified into a two stages, first stage (wet) and second stage (dry) based on soil water availability (Drexler et al., 2004). When the wetlands are inundated, evapotranspiration occurs at the first stage evapotranspiration rate. First stage evapotranspiration (also called potential evaporation) is well understood and has been modeled. In this stage, evaporation has adequate water near the surface such that the evaporation rate is limited by available energy. Second stage evaporation occurs during drying soil conditions when the evaporation rate is limited by the available soil water coupled with the available energy. Depending on the stage, the changes in temperature's and precipitation's impact on evapotranspiration could vary (Drexler et al., 2004). In wetlands, increases in temperature, elevate the salinity of estuarine waters and desiccate otherwise moist wetland soils. The drier climate conditions (decreased precipitation or increased temperatures) could lead to a drier wetland landscape, a change in land-use (e.g. shrub encroachment) which could substantially impact wetland carbon and water cycling, which can compromise conservation and water management objectives (Budny and Benscoter, 2016). During drier conditions waterlogged marsh soils can dry and oxidize, causing increased porewater salinity, acid and heavy-metal concentrations around certain plant roots causing die-offs—largely denuded mudflats when they reach critical limits (Angelini et al., 2016). Stakeholders in wetland ecosystems could utilize the information from scenario funnel to protect and manage the wetland sustainably.

In certain urban ecosystems in southeastern United States, a 20% increase in rainfall increased the runoff by 47%, increased the loads of different pollutants in the waterbodies by around 50% (Abdul-Aziz and Al-Amin, 2016). Certain cities in coastal cities in southeastern United States are ranked as the most vulnerable regions to climate extremes globally (Fu et al., 2016). It is projected that by 2025 five out of eight people will be living under water scarce conditions (Singh et al., 2016). Stakeholders in urban ecosystems could utilize the information from scenario funnels for sustainable development to meet the demands of the growing population in the urban areas.

Over half of US population resides on 17% of coastal regions and this population is projected to increase by 25% in the next 25 years (Scavia et al., 2002). Humans, flora and fauna are severely impacted by climate changes. For example, the coastline (e.g. in Florida) is important for various species of sea turtles that have various ecological roles, including: nutrient cycling (crucial for the coastal ecosystem); maintenance of sea grass beds, coral reefs, and beach dunes; and contribute in generating tourism activities, yielding great economic benefits (Hamed et al., 2016). They observed climate change impacts their habitat having social, ecological, and economical consequences that cannot be accurately measured using traditional market valuation techniques. The decreased precipitation reduces freshwater discharge, increases evapotranspiration, elevate the salinity of estuarine waters and soils (stressors) and often act together with disease outbreaks causing widespread mortality of dominant plants and reef-building fauna, resulting in declining ecosystem states (e.g. defined by habitat structure, biodiversity and ecosystem functioning) (Angelini et al., 2016). Utilizing, the information from scenario funnels, the stakeholders in coastal ecosystems could mitigate the shifts to undesirable ecosystem states also to identify the mechanisms that facilitate recovery and bolster resilience to these stressors.

3.5. Application of scenario funnels for potential development of causal chains and feedback loops

The information from scenario funnel will likely improve our understanding of the key drivers of ecosystem dynamics, their biotic and abiotic interactions, and their sensitivities to human alteration (Fig. 4b). Some of these drivers, their interactions and sensitivities were briefly discussed in previous paragraphs. It can be used to develop causal chains and feedback linking non-uniform changes and ecosystem functions. The scales in the figure refer to both spatial and temporal scales. The driver variables use several spatial scales (e.g. point and regional) and temporal scales (e.g. daily, monthly, seasonal, and annual). Variation in both temporal and spatial scales and data sources are arrayed along a gradient of scenario complexity. Initially, driver variables will be grouped into appropriate scales, and three groups of causal chains and feedback could be identified (Fig. 4b i, ii, and iii). Group 1 scenarios (Fig. 4bi) have the least complexity. Only unidirectional interactions between driver variables from broader to a finer scale will be represented (Fig. 4b, green and orange arrows). Group 2 scenarios (Fig. 4bii) have medium complexity; when driver variables interact across scales, more complex relationships occur, and the driver variable at different scales influences the response variable (Fig. 4b, purple, one-way arrows between driver and response variables). Group 3 scenarios (Fig. 4biii) are the most complex, and here the most complex relationships could be mapped. The driver variables interact across scales along with feedback from the response variables (blue, two-way arrows connecting driver and response variables). Thus, the ecosystem functions influenced by interactions could be documented by stakeholders. This approach is iterative; interactions can be refined, or new relationships added during subsequent iterations. These include documenting uncertainties in the interactions. If the stakeholders observe no change in the future ecosystem functions, then they could identify other ecological indicators, ecosystem processes and scenario generation methods that are dampening the relationship exhibited by the driver and response variables. The better identification of causal chains and feedbacks underlying the changes in driver variables play an important role in developing sound policy and management strategies. This will help identify ecosystems and regions vulnerability to climate changes that might need stronger protection or a different management approaches (Anandhi, 2017; Anandhi and Kannan, 2018).

3.6. Reducing the usability gap in this study

The three ways the study supports reducing the usability gap (summarized in Fig. 5) were by: 1) Developing a novel conceptual framework scenario funnel that can help stakeholders diagnose the use of trajectories of future changes in temperature and precipitation in evidence based decision making, recognize and reduce the likelihood of “unknowable unknown” and thus deal more effectively with the otherwise unrecognized risks and opportunities; 2) Communicating changes to potential stakeholders the range of known changes in temperature and precipitation that can be expected in the study region so they use it for effective conservation and management of ecosystems-especially in the face of change and communicating the uncertainties in the decision making process; 3) Development of three groups of causal chains and feedback loops of varying complexity that could be identified from scenario funnel, existing impacts in literature and potential stakeholders. This will likely improve our understanding of the key drivers of ecosystem dynamics, their biotic and abiotic interactions, their sensitivities to human alteration and play an important role in developing sound policy and management strategies. Although the application of the developed methodology was demonstrated for southeastern United States, it could also be applicable to other regions of the world. To be considered for other regions the methodology for the conceptual framework scenario funnel and data-analysis remain the same. However, the size and number of scenario funnels (broader/

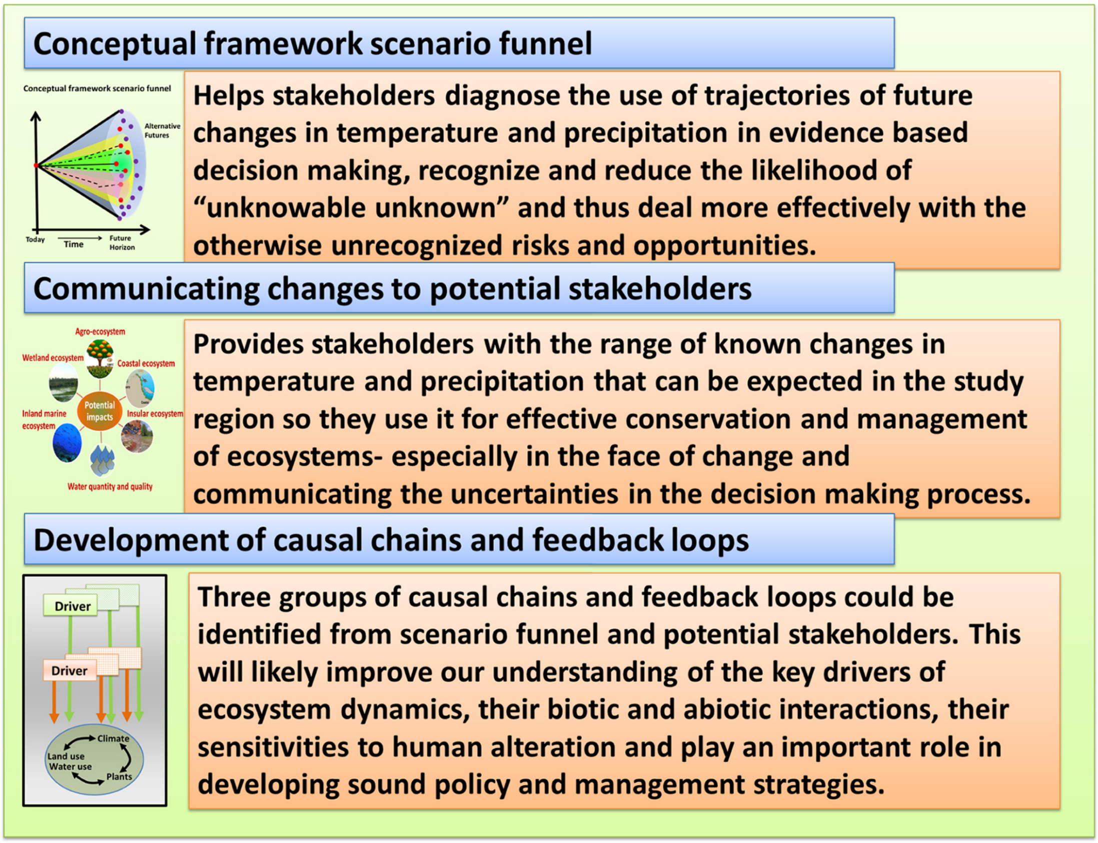

Fig. 5. Summary of ways the usability gap [gap between what scientists understand as useful information and what users recognize as usable in their decision-making process] was reduced in this study.

narrower) is subjective to the study region, availability of literature, the changes observed in the literature (e.g. meta-analysis might show higher or lower range studies) and data analyzed (e.g. higher/lower variability among GCMs). The complexity of causal chain(s) and loop(s) is subjective on the impact assessment literature (e.g. objective of study, inputs, outputs), the characteristics of the study region (e.g. coastal wetlands, cropland, hilly region), the stakeholder (e.g. scientist, producer, decision maker) and their requirement (e.g. preliminary analysis, sensitivity study).

4. Conclusion

Climate change can impact ecosystems in multiple ways. Assessing the potential vulnerability of ecosystems, its adaptation to future changes in climate, and mitigating the negative impacts of these changes are important steps in prioritizing and planning for conservation in a region. The objective of this study was to develop a novel conceptual framework for scenario development that reduces the usability gap [gap between what scientists understand as useful information and what users recognize as usable in their decision-making process]. The framework reduces the usability gap by communicating the plausible range of possible trajectories of changes in temperature and precipitation that has a logical progression from knowns to unknowns. The “known knowns” and “knowable unknown” in the possible trajectories of changes were represented in the framework from scenario funnels developed from meta-analysis (from literature) and data-analysis (10 GCMs, 2 future scenarios RCP 4.5/8.5). The stakeholders using the changes need be aware of “unknowable unknown” which are those possible trajectory range of future climate changes that we don't even know, we don't know. These will provide potential stakeholders the range of known changes that can be expected in the study region for informed conservation and management of ecosystems as well as communicating the uncertainties in the decision-making process.

The conceptual framework was applied for southeastern United States. The systematic literature review provided 33 values of precipitation changes from 15 studies and 35 for temperature changes from 14 studies. In general, the meta-analysis revealed, the precipitation changes observed ranged from −30 to +35% and temperature changes between −2 °C to 6 °C by 2099. Fiftieth percentile of the GCMs predicts no precipitation change and an increase of 2.5 °C temperature in the region by 2099. Among the GCMs, 5th and 95th percentile of precipitation changes range between −40% to 110% and temperature changes between −2 °C to 6 °C by 2099.

Stakeholders in various ecosystems and environment could utilize the information from scenario funnels to develop causal chains and loops to understand potential impacts such as in various ecosystems by relating the structural components of an ecosystem (e.g. vegetation, water, soil, atmosphere and biota) and how they interact with each other, within ecosystems and across ecosystems from impact assessment studies, stakeholder expertise and requirement. Some examples of how the information can provide improved understanding of ecosystem functioning are: (a) in agro-ecosystems they could be used for improved management and sustainable use of their resources for increased yield and greater economic return, (b) in wetland ecosystems the information can be used to protect and manage the wetland sustainably, (c) in urban ecosystems the information can be utilized for sustainable development to meet the demands of the growing population in the urban areas, (d) in coastal ecosystems could be used to mitigate the shifts to undesirable ecosystem states as well as to identify the mechanisms that facilitate recovery and bolster resilience to stressors (e.g. caused by precipitation and temperature changes and variability).

The scenario information provided in the scenario funnel was not meant to provide a single value along with its timing of future change;

rather, the scenarios were intended to assist decision-makers and others in making robust choices to manage their risks in the context of plausible future ranges of temperature and precipitation changes. The implications highlighted in this study represent only a possibility of potential outcomes of a continually changing climate, and by no means implies the absolute occurrence of these events. Caution should be exercised in using the scenario information to design specific responses to the changes in temperature and precipitation for implementation at the site level. Combining the scenarios with models (e.g. hydrodynamical, ecological models) and field observations to develop specific causal chains and feedback loops that improve our understanding of ecosystem functioning at various levels of complexity is differed for future.

Acknowledgements

This material is based upon work partially supported by the National Science Foundation under Grant No. 1735235 awarded as part of the National Science Foundation Research Traineeship, USDA-NIFA capacity building grant 2017-38821-26405, USDA-NIFA Evans-Allen Project, Grant 11979180/2016-01711, USDA-NIFA grant No. 2018-68002-27920 and Department of Energy Minority Serving Institution Partnership Program (MSIPP) managed by the Savannah River National Laboratory under SRNS contract DE-AC09-08SR22470. Drs. Magee's, Mbuya's and Milla's support and discussion during the initial stages of the research are also acknowledged. Mr. Medley's support with land cover map is acknowledged. Additionally, Ms. Hudson's support with editing the initial document is acknowledged. The authors express their gratitude to the three anonymous reviewers for their constructive comments and suggestions on the earlier draft of the paper.

References

Abdul-Aziz, O.I., Al-Amin, S., 2016. Climate, land use and hydrologic sensitivities of stormwater quantity and quality in a complex coastal-urban watershed. Urban Water J. 13 (3), 302–320.

Alessa, L., et al., 2008. The arctic water resource vulnerability index: an integrated assessment tool for community resilience and vulnerability with respect to freshwater. Environ. Manag. 42 (3), 523–541.

Alexandrov, V.A., Hoogenboom, G., 2000. Vulnerability and adaptation assessments of agriculturalcrops under climate change in the southeastern USA. Theor. Appl. Climatol. 67 (1), 45–63.

Anandhi, A., 2017. CISTA-A: conceptual model using indicators selected by systems thinking for adaptation strategies in a changing climate: case study in agro-ecosystems. Ecol. Model. 345, 41–55.

Anandhi, A., Baker, L.M., 2013. Undergraduate research: eliminating the drinking from the firehouse effect. N. Am. Coll. Teach. Agric. J. 57 (2), 85–86.

Anandhi, A., Kannan, N., 2018. Vulnerability assessment of water resources - translating a theoretical concept to an operational framework using systems thinking approach in a changing climate: case study in Ogallala Aquifer. J. Hydrol. 557, 460–474.

Anandhi, A., Srinivas, V., Nanjundiah, R.S., Nagesh Kumar, D., 2008. Downscaling precipitation to river basin in India for IPCC SRES scenarios using support vector machine. Int. J. Climatol. 28 (3), 401–420.

Anandhi, A., Sharma, A., Sylvester, S., 2018. Can meta-analysis be used as a decision making tool for developing scenarios and causal chains? - Case study in Florida. Ecohydrology (in press).

Angelini, C., et al., 2016. A keystone mutualism underpins resilience of a coastal ecosystem to drought. Nat. Commun. 7, 12473.

Berkhout, F., Hertin, J., Jordan, A., 2002. Socio-economic futures in climate change impact assessment: using scenarios as 'learning machines'. Glob. Environ. Chang. 12 (2), 83–95.

Budny, M.L., Benscoter, B.W., 2016. Shrub encroachment increases transpiration water loss from a subtropical wetland. Wetlands 36 (4), 631–638.

Carpenter, S., Bennett, E., Peterson, G., 2006. Scenarios for ecosystem services: an overview. Ecol. Soc. 11 (1).

Carter, L.M., et al., 2014. Ch. 17: southeast and the Caribbean. Climate change impacts in the United States. In: Melillo, J.M., Richmond, Terese (.T.C.)., Yohe, G.W. (Eds.), The Third National Climate Assessment. U.S. Global Change Research Program, pp. 396–417. http://dx.doi.org/10.7930/J0NP22CB.

Cartwright, J.M., Wolfe, W.J., 2016. Insular Ecosystems of the Southeastern United States—A Regional Synthesis to Support Biodiversity Conservation in a Changing Climate. 1828, Reston, VA.

Caulfield, C.W., Maj, S.P., 2001. A case for systems thinking and system dynamics. In: Systems, Man, and Cybernetics, 2001 IEEE International Conference on. IEEE, pp. 2793–2798.

Costanza, J., et al., 2016. Assessing Climate-sensitive Ecosystems in the Southeastern United States. 2016–1073, Reston, VA.

DeLorme, D.E., Kidwell, D., Hagen, S.C., Stephens, S.H., 2016. Developing and managing transdisciplinary and transformative research on the coastal dynamics of sea level rise: experiences and lessons learned. Earth's Future 4 (5), 194–209.

Doublin, J.K., Grundstein, A.J., 2008. Warm-season soil-moisture deficits in the southern United States. Phys. Geogr. 29 (1), 3–18.

Drexler, J.Z., Snyder, R.L., Spano, D., Paw, U., Tha, K., 2004. A review of models and micrometeorological methods used to estimate wetland evapotranspiration. Hydrol. Process. 18 (11), 2071–2101.

Easterling, D.R., 2002. Recent changes in frost days and the frost-free season in the United States. Bull. Am. Meteorol. Soc. 83 (9), 1327–1332.

Endale, D.M., Bosch, D.D., Potter, T.L., Strickland, T.C., 2014. Sediment loss and runoff from cropland in a Southeast Atlantic Coastal Plain landscape. Trans. ASABE 57 (6), 1611–1626.

Flebbe, P.A., Roghair, L.D., Bruggink, J.L., 2006. Spatial modeling to project southern Appalachian trout distribution in a warmer climate. Trans. Am. Fish. Soc. 135 (5), 1371–1382.

Fraisse, C., et al., 2006. AgClimate: a climate forecast information system for agricultural risk management in the southeastern USA. Comput. Electron. Agric. 53 (1), 13–27.

Fu, X., Gomaa, M., Deng, Y., Peng, Z.-R., 2016. Adaptation planning for sea level rise: a study of US coastal cities. J. Environ. Plan. Manag. 1–17.

Gain, A.K., Giupponi, C., Renaud, F.G., 2012. Climate change adaptation and vulnerability assessment of water resources systems in developing countries: a generalized framework and a feasibility study in Bangladesh. WaterSA 4 (2), 345–366.

Gershunov, A., Barnett, T.P., 1998. ENSO influence on intraseasonal extreme rainfall and temperature frequencies in the contiguous United States: observations and model results. J. Clim. 11 (7), 1575–1586.

Greenberg, C., Goodrick, S., Austin, J., Parresol, B., 2015. Hydroregime prediction models for ephemeral groundwater-driven sinkhole wetlands: a planning tool for climate change and amphibian conservation. Wetlands 35 (5), 899–911.

Greenland, D., 2001. Multiyear variation of temperature and precipitation in the coastal states of the southeastern United States. Southeast. Geogr. 41 (1), 36–52.

Groisman, P.Y., Knight, R.W., Karl, T.R., 2001. Heavy precipitation and high streamflow in the contiguous United States: trends in the twentieth century. Bull. Am. Meteorol. Soc. 82 (2), 219–246.

Groisman, P.Y., et al., 2003. Contemporary climate changes in high latitudes of the Northern Hemisphere: daily time resolution. In: 14th Symposium on Global Change and Climate Variations, Proc. 14th AMS Symp. on Global Change and Climate Variations (CD ROM With Proc. Ann. Mtg of the American Meteorological Society) Long Beach, CA, Feb. 2003, pp. 9–13.

Groisman, P.Y., et al., 2004. Contemporary changes of the hydrological cycle over the contiguous United States: trends derived from in situ observations. J. Hydrometeorol. 5 (1), 64–85.

Grotjahn, R., et al., 2016. North American extreme temperature events and related large scale meteorological patterns: a review of statistical methods, dynamics, modeling, and trends. Clim. Dyn. 46 (3–4), 1151–1184.

Gutierrez, K.S., LePrevost, C.E., 2016. Climate justice in rural southeastern United States: a review of climate change impacts and effects on human health. Int. J. Environ. Res. Public Health 13 (2), 189.

Hall, J., et al., 2016. Regional Sea Level Scenarios for Coastal Risk Management: Managing the Uncertainty of Future Sea Level Change and Extreme Water Levels for Department of Defense Coastal Sites Worldwide. US Department of Defense, Strategic Environmental Research and Development Program, Washington, DC Online at. www.serdp-estcp.org/News-and-Events/News-Announcements/Program-News/DoD-Report-on-Regional-Sea-Level-Scenarios, Accessed date: 25 May 2016.

Hamed, A., et al., 2016. How much are Floridians willing to pay for protecting sea turtles from sea level rise? Environ. Manag. 57 (1), 176–188.

Homer, C.G., et al., 2015. Completion of the 2011 National Land Cover Database for the conterminous United States - representing a decade of land cover change information. Photogramm. Eng. Remote. Sens. 81 (5), 345–354.

Ingram, K.T., Dow, K., Carter, L., Anderson, J., 2013. Climate of the Southeast United States: Variability, Change, Impacts, and Vulnerability. Inland Press.

Jones, J., et al., 2001. Potential consequences of climate variability and change for the southeastern United States. In: Climate Change Impacts on the United States-Foundation Report: The Potential Consequences of Climate Variability and Change. 137.

Kim, J., Grunwald, S., 2016. Assessment of carbon stocks in the topsoil using random forest and remote sensing images. J. Environ. Qual. 45 (6), 1910–1918.

Kramer, R.J., Soden, B.J., 2016. The sensitivity of the hydrological cycle to internal climate variability versus anthropogenic climate change. J. Clim. 29 (10), 3661–3673.

Kunkel, K.E., Andsager, K., Easterling, D.R., 1999. Long-term trends in extreme precipitation events over the conterminous United States and Canada. J. Clim. 12 (8), 2515–2527.

Lemos, M.C., Kirchhoff, C.J., Ramprasad, V., 2012. Narrowing the climate information usability gap. Nat. Clim. Chang. 2 (11), 789–794.

Lynch, A.J., et al., 2016. Climate change effects on North American inland fish populations and assemblages. Fisheries 41 (7), 346–361.

Mahmoud, M., et al., 2009. A formal framework for scenario development in support of environmental decision-making. Environ. Model. Softw. 24 (7), 798–808.

Maloney, E.D., et al., 2014. North American climate in CMIP5 experiments: part III: assessment of twenty-first-century projections. J. Clim. 27 (6), 2230–2270.

Mastrandrea, M.D., et al., 2010. Guidance Note for Lead Authors of the IPCC Fifth Assessment Report on Consistent Treatment of Uncertainties.

Maurer, E., et al., 2014. An enhanced archive facilitating climate impacts and adaptation analysis. Bull. Am. Meteorol. Soc. 95 (7), 1011–1019.

McNulty, S., et al., 2015. Southeast regional climate hub assessment of climate change vulnerability and adaptation and mitigation strategies. Agric. Res. Serv. 2015, 1–61.
Mearns, L., Giorgi, F., McDaniel, L., Shields, C., 2003. Climate scenarios for the south-eastern US based on GCM and regional model simulations. In: Issues in the Impacts of Climate Variability and Change on Agriculture. Springer, pp. 7–35.
Mitra, S., Srivastava, P., 2016. Spatiotemporal variability of meteorological droughts in southeastern USA. Nat. Hazards 1–32.
Mulholland, P.J., et al., 1997. Effects of climate change on freshwater ecosystems of the south-eastern United States and the Gulf Coast of Mexico. Hydrol. Process. 11 (8), 949–970.
Neubauer, S.C., Craft, C.B., 2009. In: Barendregt, Aat, Whigham, Dennis, Baldwin, Andrew (Eds.), Global Change and Tidal Freshwater Wetlands: Scenarios and Impacts. Tidal Freshwater Wetlands. Backhuys Publishers, Leiden, pp. 353–366.
Rogers, J.C., 2013. The 20th century cooling trend over the southeastern United States. Clim. Dyn. 40 (1–2), 341–352.
Rose, S., 2009. Rainfall–runoff trends in the south-eastern USA: 1938–2005. Hydrol. Process. 23 (8), 1105–1118.
Rumsfeld, D., 2002. Donald Rumsfeld. (Former United States Secretary of Defence).
Scavia, D., et al., 2002. Climate change impacts on US coastal and marine ecosystems. Estuaries 25 (2), 149–164.
Selman, C., Misra, V., 2016. The impact of an extreme case of irrigation on the south-eastern United States climate. Clim. Dyn. 48 (3–4), 1309–1327.
Singh, S., Srivastava, P., Mitra, S., Abebe, A., 2016. Climate variability and irrigation impacts on streamflows in aKarst watershed—a systematic evaluation. J. Hydrol. Reg. Stud. 8, 274–286.
Smith, L.A., 2002. What might we learn from climate forecasts? Proc. Natl. Acad. Sci. 99 (Suppl. 1), 2487–2492.
Soranno, P.A., et al., 2014. Cross-scale interactions: quantifying multi-scaled cause-effect relationships in macrosystems. Front. Ecol. Environ. 12 (1), 65–73.
Soule, P.T., 2005. A comparison of 30-yr climatic temperature normals for the south-eastern United States. Southeast. Geogr. 45 (1), 16–24.
Stroup, D.F., et al., 2000. Meta-analysis of observational studies in epidemiology: a proposal for reporting. JAMA 283 (15), 2008–2012.
Susaeta, A., Adams, D.C., Carter, D.R., Dwivedi, P., 2016. Climate change and ecosystem services output efficiency in southern loblolly pine forests. Environ. Manag. 58 (3), 417–430.
Van Vuuren, D.P., et al., 2011. The representative concentration pathways: an overview. Clim. Chang. 109 (1–2), 5.
Williams, M.D.A., 2016. Characterizing Multi-decadal Temperature Variability in the Southeastern United States. Unpublished Master of Science, Florida State University, Retrieved from Retrieved from FSU Dissertations and Theses database. (etd-06152010-160249) database, assessed on 19 April, 2018 in. http://diginole.lib.fsu.edu/islandora/object/fsu%3A253904/.
Wuebbles, D., et al., 2014. CMIP5 climate model analyses: climate extremes in the United States. Bull. Am. Meteorol. Soc. 95 (4), 571–583.