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CISTA-A: Conceptual model using indicators selected by systems thinking for adaptation strategies in a changing climate: Case study in agro-ecosystems

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ABSTRACT

Adapting our ecosystems to climate change for sustainable management requires an understanding of three broad interconnected systems: ecosystems, climate systems and adaptive management and planning systems. Multiple factors shape adaptive responses to a changing climate because of the complexities and multi-disciplinary nature of these three systems. In this study, the conceptual model CISTA-A (CISTA for Agro-ecosystems) is developed using Indicators that are identified as using a Systems Thinking approach to Adaptation. CISTA addresses questions concerning "how to adapt" our ecosystems to climate change and has three or more layers: A base (element) layer has abiotic/biotic information (e.g. ecological, agro-hydrological, and meteorological data). One or more components (intermediate) layer(s) have ecological, agro-hydrological, and climatological indicators (e.g. length of the growing season and growing degree days) that affect the ecosystem. Indicators are identified and estimated from an element layer. In the final layer, the translation of information from indicators to adaptation strategies (incremental systems and transformational adaptation) depends on the degree of change and the level of adaptation. CISTA can stand alone or combine with existing crop/integrated assessment models to develop quantitative adaptation strategies. The use of 23 indicators and 3 empirical tests in the agro-ecosystems (AS) of Kansas, USA demonstrate the application of CISTA-A.

1. Introduction

Adaptation is a key feature of sustainable ecological, social (Folke et al., 2005; Folke, 2006) and agricultural systems (Howden et al., 2007). Agricultural systems comprise a major portion of global land use. With growing recognition of the inevitability of climate change, adaptation in these systems has become a core element of climate policy and research (Berrang-Ford et al., 2015). The increasing focus on research and policy is concerned with responding to the unavoidable impacts of climate change (Thomsen et al., 2012) while utilizing the benefits of change. In addition, adaptation is a key factor that will shape the future severity of climate change impacts on food production (Lobell et al., 2008). Therefore, developing adaptation strategies to counteract impacts of climate change are in the forefront globally (IPCC, 2014) and nationally (Walthall, 2012). Numerous recent studies and publications have shifted the focus from "need to adapt" to "how to adapt" (Nabikolo et al., 2012). However, it is observed that the pace of adaptation to climate change and land use is still relatively modest, and awareness of available management options is low (Dilling et al., 2014; Preston et al., 2015).

Adaptation strategies are most often presented as options in the form of a shopping-list (e.g., earlier planting, new crop varieties), where people are asked to choose, among a selection of alternative practices, policies and/or technologies without any deeper consideration of the broader or systemic implications (Thomsen et al., 2012). The reasons for this approach may be due to: 1) Complexity in developing the strategies. Adger et al. (2005) reported that adaptation strategies are sensitive to spatial (farm, county, regional) and temporal (daily, monthly, annual, decadal) scales, with some strategies being more scale dependent than others. Understanding the complex systems is not well developed and is likely to remain so into the foreseeable future (Thomsen et al., 2012). In addition, adaptation strategies to changing land use and climate are sensitive to triggers or drivers of change (e.g. commodity prices) (Tompkins et al., 2005). 2) Multi-disciplinary nature of the ecosystems and its adaptive management. Understanding an ecosystem's multifaceted character requires information about its biophysi-

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cal, socio-economic and/or behavioral changes. The paths between information to actual adaptation strategies are not clearly defined and quantified. In addition, research on the consequences of climate change on sustainable ecological systems requires addressing deepening levels of system complexity that require a new suite of methodologies to cope with the added uncertainty that accompanies the addition of new, often non-linear, process knowledge (Easterling et al., 2007).

Effective adaptation depends on an understanding of projected climatic changes at geographic and temporal scales appropriate for the needed response (Anandhi et al., 2016). The complexity in developing the adaptation strategies, the multidisciplinary nature of adaptive management of ecosystems, and the knowledge gap existing in translating the biophysical information into adaptation strategies limit our understanding of "how to adapt" with regards to ecosystems. The objective of this study is to address some of these challenges and improve our understanding of "how to adapt" by translating the biophysical information into adaptation strategies. In this study, CISTA is a conceptual model developed to arrive at quantitative adaptation strategies in ecosystems. For the most part, the model's description and development are explained using biophysical elements. The novelty of the methodology is in the model's use of a systems approach in the conceptual model development. In CISTA-A, the additional A is added because the developed model is empirically tested in agro-ecosystems (AS) using three applications. These applications use available biophysical information to develop quantitative adaptation strategies to combat climate change and variability. Although the CISTA-A's application demonstrates the use of biophysical information in agro-ecosystems, CISTA can be applied to other ecosystems using ecological, economic, sociological and behavioral information (in addition to biophysical), which need consideration in adaptation to a changing and variable climate.

2. Material and methods

2.1. Key definitions and theory descriptions used in CISTA development

In this study, adaptation is defined as 'adjustment in ecosystem management in response to actual or expected climatic stimuli or their effects, which moderates harm or exploits beneficial opportunities' (IPCC, 2001). There are three levels of adaptation: 1) Incremental adaptation refers to changes in practices and technologies within an existing system (Kates et al., 2012). These are tactical choices requiring minimal financial investment, few cropping seasons for the mastery of associated managerial skills, and can be reversed from one cropping season to another (Leclère et al., 2014). 2) Systems adaptation are changes to an existing system, such as new crop types that are mapped against an increasing degree of change (Anandhi, 2016). 3) Transformational adaptation refers to the more radical end of a spectrum of change such as a change in land use. Adaptations become systemic and then transformational in proportion to their irreversibility, capital requirements, lifetime, and impact (Leclère et al., 2014).

A system is that which possesses a definite set of characteristics and elements, including input requirements, productivity, environmental impact, and economic return, but it is difficult to understand completely which system components are contributing to these outcomes (Allen et al., 2007). Complex systems are systems that involve the collective behavior of a large group of relatively simple elements or agents in which the interactions among elements are typically local and non–linear. Systems thinking focuses on the relationships between the parts forming a purposeful whole (Caulfield and Maj, 2001). Systems theory (Bertalanffy, 1968) states that complex, nonlinear systems function differently *in vivo* than a separate scrutiny of their component parts might indicate. Gödel's theorems postulate that there is inadequate information within a system to understand or predict its behavior (i.e., one needs to understand its external inputs). The Heisenberg principle states that science is approximate and subject to our method of questioning (Hopkins et al., 2011). An indicator is defined as any variable that represents either the magnitude of an element (e.g. average annual precipitation), the variability of an element (e.g. coefficient of variation for annual precipitation) or the statistical relationship among elements (Heink and Kowarik, 2010).

2.2. Summary of methods used to develop adaptation strategies

Traditionally, most studies on adaptations and strategy development use preselected adaptation strategies like a shopping list and do not show quantitative information regarding their selection. These studies can be broadly classified into three approaches (Fig. 1a and Section 4). One strategy uses the top-down approach (Approach 1, all solid lines in Fig. 1a). These studies usually pick a few preselected strategies based on experience and a review of the literature. Some of these strategies can be simple management scenarios, which are often used in model sensitivity analysis (e.g. planting a few weeks earlier/later to study its effect on crop yield, turning on and off the irrigation to study its effects on yield response). These preselected strategies in a changing climate are then applied to a combination of models (e.g. crop/economic/ecosystem), change scenarios (e.g. climate change/management) to study the effect of an adaptation strategy's response to agriculture (Anandhi et al., 2011; Rosenzweig et al., 2013; Waha et al., 2013a; Webber et al., 2015) and natural ecosystems (Tang et al., 2012). In this approach, only a few studies have quantified the methodology for developing preselected strategies from climate data (Waha et al., 2013b). While using these preselected strategies, the methodologies to arrive at the quantitative information on the strategy are often not clearly provided (e.g. how to choose the days for planting earlier/later). In the bottom-up approach (Approach 2, all dotted lines in Fig. 1a), information collected using surveys, questionnaires etc is provided by key decision makers in the ecosystems (e.g. producers, water managers, planners). This information is used to understand the needs of producers and to develop adaptation strategies (Dilling et al., 2014; Henstra and Vogel, 2014). For example, adaptation strategies are developed from the questionnaire to producers and decision makers. A hybrid approach that combines both modeling and surveys is an alternative (hybrid; Approach 3, dashed lines that combine Paths 1 and 2 in Fig. 1a) (Claessens et al., 2012; Waha et al., 2013a). Integrated assessment and modeling (IAM) is an example of this approach (Ewert et al., 2015). For example, sowing/planting information from the questionnaire are used to develop the adaptation strategies such as planting/harvest dates that are input into crop models to estimate the yield response (Waha et al., 2013a).

Generally, based on the timing of adaptation, approaches can be reactive or anticipatory; depending on the degree of spontaneity, the adaptations can be autonomous or planned (Smit et al., 2000). Adaptation strategies can be at three levels (described in Section 2.1) can overlap both conceptually and in practice, and can be pursued in any situation that depends in part on the type of decision being faced (Rickards and Howden, 2012). Some commonly preselected strategies at the different levels are new varieties, planting & harvest times (incremental adaptation), climate change ready crops, precision agriculture (systems adaptation), and transformation from land use or distribution change (transformational adaptation). Evidence suggests that conceptual models, tools, and methods developed by the research community have either not sufficiently evolved or have not been effectively delivered to guide

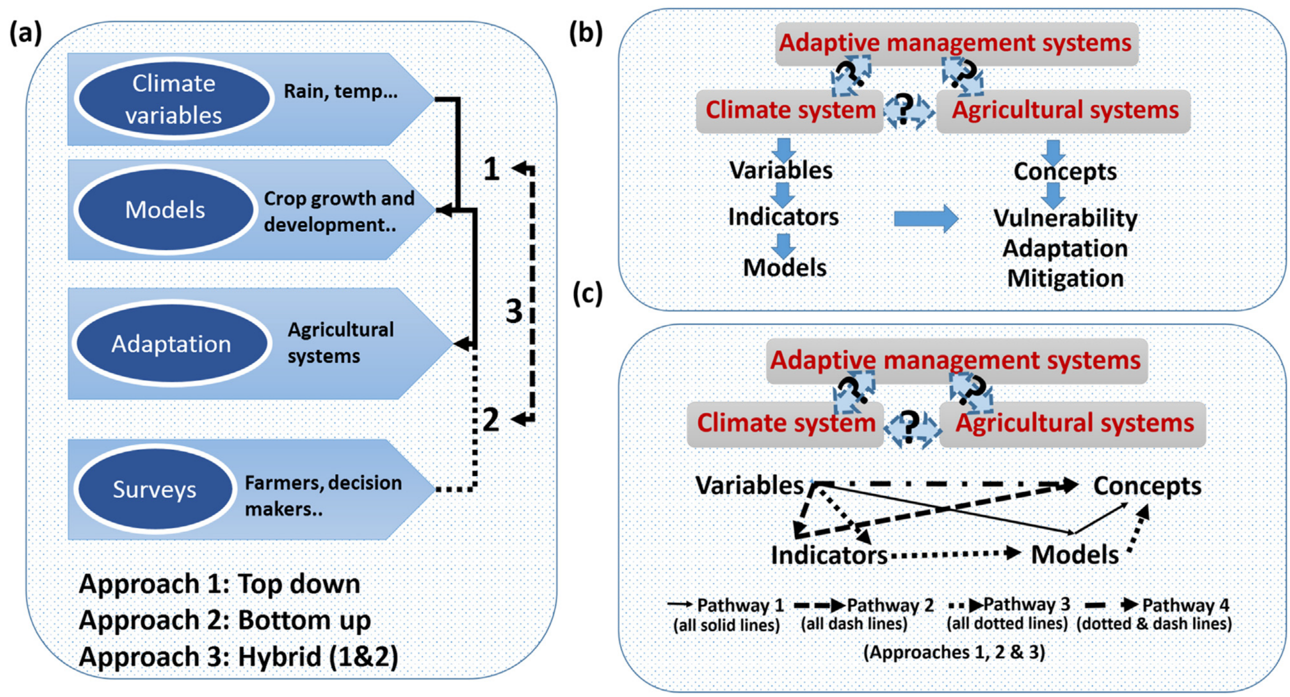

Fig. 1. Adapting the agricultural systems to variable and changing climate (a) Three approaches traditionally used in developing adaptation strategies, (b) Representing using systems approach the triple complexity, (c) Representing the complexity using approaches and pathways. The dashed-bordered arrows in (b) and (c) represent the inter-connectedness between the three systems. The solid bordered arrows in (b) represent the general information flow while translating variables to concepts such as vulnerability, adaptation, and mitigation. The first column of solid bordered arrows (left hand side) in (b) represents the climate systems and agricultural systems, while the second column of solid bordered arrows (right hand side) in (b) represents the adaptive management system. The information flow through solid bordered arrows in (1b) is divided into four pathways using 4 arrows types in (1c).

adaptation (Preston et al., 2015). It is important to note that although many studies have used one or more approaches and/or levels of adaptation, most of these studies do not provide a methodology to develop quantitative values for the preselected adaptation strategy based on commonly measured biophysical variables. The advantage of this study derives from the systems approach's ability to extract information about the functioning of complex systems to develop quantitative adaptation strategies that effectively guide adaptation.

2.3. Conceptual model framework development—overview for representing complexity

In order to quantify values for the preselected adaptation strategy, this study begins with a representation of the complex and multi-disciplinary nature of an ecosystem's adaptive management in relation to climate change and variability.

Here, the complex system is considered to be connected to three broad systems (represented using dashed-bordered two-way arrows in Fig. 1b and c) consisting of: 1) the complexity of the adaptation planning and management system, 2) the complexity of the ecosystems (e.g. AS-agricultural systems) and 3) the complexity of the climate systems (Fig. 1b). An example of this connection is the inter-annual, monthly and daily distribution of climate variables (e.g., temperature, radiation, precipitation, water vapor pressure in the air and wind speed) affecting a number of physical, chemical and biological processes that drive the productivity of ecosystems (Easterling et al., 2007), and its services and management. Within the three broad systems, elements of ecological, biophysical, economic, sociological and behavioral systems need consideration for adaptation (Ratter, 2012). Examples of bio-physical elements are environment, soil characteristics, landscape positions, genetics, and ecology of plants and animals (Allen et al., 2007); examples of socio-economic and behavioral system elements are management practices and goals, human lifestyles, social constraints, economic opportunities, marketing strategies, and externalities such as energy supplies and costs, and the impact of farm policies (Allen et al., 2008).

In general, a systems thinking approach (explained in Section 2.1) addresses the system's complexity and multi-disciplinary nature (Fig. 1b). The climate system and AS, its variability, are represented using variables and/or indicators obtained from biotic and abiotic information which are measured, observed, or surveyed (e.g. temperature, rainfall, crop yield, farmer choice, growing season length). This is represented in the first column of solid bordered arrows (left hand side) in Fig. 1b. Adaptive management is represented using concepts (e.g. adaptation, vulnerability), which is represented in the second column of solid bordered arrows (right hand side) in Fig. 1b. Finally, the variables and/or indicators are translated to concepts (Fig. 1b). This translation uses four pathways (Fig. 1c). Traditional studies use Pathway 1 (all solid lines in Fig. 1c; variable-model-adaptation; top-down approach, for example climate scenarios-crop model-impact of climate change) and/or Pathway 4 (alternate dash and dotted line in Fig. 1c; variable-adaptation; bottom-up approach, for example farmer choice for adaptation strategy). While developing quantitative adaptation strategies for AS to adjust for climate change and variability use the CISTA-A model framework, two other potential pathways, which include indicators, are introduced in this study (Pathways 2 and 3, Fig. 1c). In Pathway 2 (all dash lines in Fig. 1c; variable-indicator-adaptation), the information from climate variables will be translated to adaptation strategies using indicators (e.g. temperature-last spring freeze-early sowing). In Pathway 3 (all dotted lines in Fig. 1c; variable-indicator-model-adaptation), the information from climate variables will be translated to adaptation strategies using indicators and models (e.g. temperature-last spring freeze-crop/IA models-early sowing). Pathways 2 and 3 are used in the conceptual model development and are elaborated further in Section 4.1. Integration of the developed conceptual model Pathways 1 and 3 is further discussed in Section 4.5.

Representing the three connected systems presents challenges common to complex systems. They are 1) processes in the system operate at a wide range of spatial and temporal scales with many multi-scale interactions; 2) emergent self-organization reveals large-scale non-linear properties that cannot be inferred from the behavior of the individual elements (Slingo et al., 2009); 3) multiple biophysical and socio-economic drivers interconnect; 4) direct and indirect factors and impetuses for change impact AS; and 5) systems have elements of chaos, where the system appears to be wandering, always exhibiting new and different behavior; but over time, a deeper order is exhibited (Allen et al., 2007). Quantifying issues enmeshed in multi-scaled connectivity are a fundamental characteristic of complex systems, and the process of quantifying function within this complexity is the fundamental objective of the systems approach (Hopkins et al., 2011).

Hard and soft thinking are two extremes of the systems thinking approach that can be used to build the CISTA-A model to translate variables/indicators to quantitative adaptation strategies. Hard system thinking views each base element of a complex system as objectively ascertained; building the system simply requires using the proper elements. The top-down approach is an example of the hard system (Fig. 1a). The hard system is based on deductive thinking that puts the problem solver in the role of an external party to the change effort, perceiving it through coded variables and indicators. Here, the systems have 'boundaries' in time and space (e.g. farm level, county level, watershed level), inputs (e.g. fertilizer, irrigation), and outputs (e.g. crop yield). In contrast, soft system thinking focuses on mindsets (e.g. perceptions to climate change, perceptions to adaptive management), with elements highly dependent on context and purpose. Here, the systems boundaries, inputs/outputs are often fuzzy. This approach tends to use a bottom-up approach (Fig. 1a). Combining both hard and soft thinking when selecting components (hybrid approach) can be challenging, but it provides support in explaining complex systems. Here, system complexity in the three connected systems is perceived as having clarity in inputs/outputs in certain aspects (hard thinking), while in others, the inputs/outputs are fuzzy (soft thinking). This will be dealt with by using one or more indicators to represent an element or combination of elements in the three connected systems.

Indicators characterize the drivers, processes, and connectedness in the three interrelated systems. Indicators are identified and selected to represent the complexity among and within the three systems namely: adaptation planning and management systems, agricultural systems, and climate systems (Anandhi et al., 2016). Using indicators is valuable for the following reasons: 1) indicators are powerful tools to communicate technical data in relatively simple terms that portray the interrelationships among climate and other physical and biological elements of the environment, to help reveal evidence of the discernible impacts of change (Kadir et al., 2013); 2) indices often provide important insights on the factors, processes, and structures that promote or constrain adaptive capacity; 3) the index-based approach is also valuable for monitoring trends and exploring conceptual frameworks (Luers et al., 2003; Deressa et al., 2008); and 4) indicators are useful in combining both hard and soft thinking systems approach. For example, sowing dates based on trends in last spring freeze indicator, which is estimated from measured low temperature data, is an instance of the hard thinking approach. Estimating sowing dates from rainfall and temperature data using fuzzy rule composed of three indicators, the 5-day cumulative rainfall amount, the number of wet-days, and the dry-spell length (Waongo et al., 2015) can be an example of combining both hard (5 day cumulative) and soft (fuzzy logic) thinking approaches. Sowing dates based on farmer perceptions of climate change (Akponikpè et al., 2010) is an example of the soft thinking approach. The adaptation strategies may also be based on a combination of factors such as the type of crop, stage of crop growth, region, soil type and water availability, and in some cases, the relationship between these factors can be dependent on perceptions (soft thinking). Also, while combining various components to explain the processes/drivers that are highly dependent on context and purpose (soft thinking), this will be dealt with by using one or more indicators to represent an element or combination of elements. Current studies use scientific methods and disciplinary specialization, which have provided us with an enormous database on the biotic and abiotic composition of systems, and often lack the systems large-scale interactions. The CISTA framework for AS (CISTA-A) is based on the fact that both hard and soft systems thinking use indicators that are useful in representing the triple complexity of the adaptive management of AS with regards to changing climate. The biophysical elements and methodology emphasized in this study can be applied to include other elements as well.

2.4. CISTA-A model description

CISTA-A, the novel conceptual model developed in this study for estimating quantitative adaptation strategy is summarized in Fig. 2. The developed model is empirically tested using three applications in agro-ecosystems in the next section.

CISTA-A consists of three or more layers namely:

2.4.1. Base (elements) layer

This layer consists of biotic/abiotic information such as ecological,—hydrological and climate variables that are observed/measured/surveyed. These are raw data on the various drivers and processes in the three inter-connected systems (AS, climate and adaptive planning and management). Examples include plant biomass, plant yield, rainfall, temperature, streamflow, irrigation information, and perceptions to adaptation.

2.4.2. Intermediate (Component) layer(s)

This layer consists of one or more intermediate layers. Each of these layers can have one or more indicators. Indicators are identified and selected using systems thinking approaches (described in the previous section). Indicators are estimated from variables in the base layer to represent and improve understanding of the complexity of the drivers and processes in the ecosystem. This improved understanding provides information to develop quantitative adaptation strategies. Examples include agro-ecological, eco-hydrological and climatological indicators that affect AS.

2.4.3. End (adaptation) layer

In this layer, quantitative adaptation strategies for various levels of adaptation (incremental, systems, and transformational adaptation) are developed from the estimated indicators.

In general, the layers and intermediate layers in CISTA-A can operate on a wide range of spatial and temporal scales with many multiscale interactions. In this conceptual model, the first (base) layer is the "elements". They are the data that supports the understanding of the various drivers and processes in the three inter-connected systems (AS, climate and adaptive planning and management). In cases when adaptations are targeted to specific climate variables or weather events (e.g. rainfall, temperature, extreme heat, drought) these variables then become the base layer if measurements/observations exist. Variable and changing climate is the main driver considered in this study, and some other drivers are discussed in Section 4. Processes in the AS include plant growth and development, water uptake, evapotranspiration, nutrient management, runoff, precipitation. These drivers of

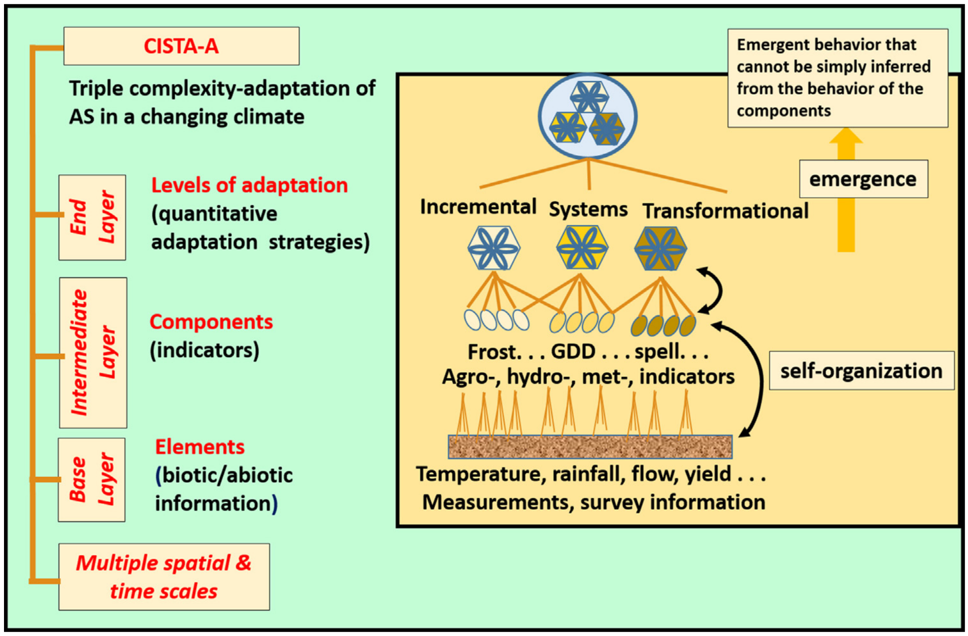

Fig. 2. CISTA-A developed in this study to represent the triple complexity in adaptation of agricultural systems to variable and changing climate. Adapted from Slingo et al. (2009).

change and processes require the incorporation of data on multiple spatio-temporal scales, which are often hampered by a lack of spatially explicit data and by methodological difficulties in linking the data. This base layer possesses abiotic and biotic information on agricultural, climate, and adaptive management systems that are already available in the form of measurements and observations or surveyed information. Example sources of data can be individual station (meteorological/hydrological/crop performance tests) or regional data. Examples of variables are air temperature through any particular day, including daily maximum and minimum temperature, and related weather and physiological variables. These elements can be provided in the form of a time series (e.g. rainfall, temperatures, land use/land cover, yield etc.) or limited-time information (e.g. collected from surveys or interviews from important AS stakeholders). The elements selected depend on the availability of data, the type of driver/process in question, and its relation to the three systems (AS, climate and adaptive planning and management systems).

There may be multiple intermediate layers called “component layers”. The component layer(s), the heart of the model, are made of indicators that translate observed information from the base layer to concepts in CISTA. This will be constructed from the information provided from the base layer in order to accommodate the varying complexity of the processes in the three systems and their respective levels of adaptation strategy. For example, a less complex process or a simple adaptation strategy can be represented using a single component layer with one or more indicators while a more complex process/adaptation strategy may need multiple component layers, with each layer having one or more indicators. The component layer integrates the various concepts of complex systems in the adaptive management of AS in response to climate change and variability. The underlying assumption is that each component of a complex system has underlying properties that can be objectively ascertained, whose component properties are highly dependent on context and purpose (Magoulas et al., 2012). Building the system requires using the proper components; this is accomplished with indicators in the component layer. The indicators are selected using deductive (theory based or physical relationship based) and inductive (statistical based) approaches (Adger et al., 2004b).

This layer in CISTA is mainly the identification and estimation of indicators. Indicators are identified by how they 1) represent the drivers, processes and portray connectedness in the three interrelated systems to help reveal evidence of the discernible impacts of climate change and variability; 2) overcome some of the challenges in complex systems namely, revealing new and different behaviors than separate scrutiny of the base elements used to estimate them; 3) exhibit non-linear properties that cannot be inferred from the behavior of the individual base elements; 4) improve understanding or predicting the system’s behavior using inadequate information within a system to understand or predict its behavior by understanding its external inputs; 5) often provide important insights on the factors, processes, and structures that promote or constrain adaptive capacity; 6) can be estimated at a wide range of spatial and temporal scales with many multi-scale interactions. Hamouda et al. (2009) categorized the indicators into hydro-physical and socio-economic or political in nature. An elaborate discussion on indicators can be found in Heink and Kowarik (2010). The choice of indicators can be specific to either an agro-ecosystem, climate system, or be adaptive-management specific, region–specific, or a combination of the above. They are selected using deductive (theory based or physical relationship based) and inductive (statistical based) approaches (Adger et al., 2004a). The deductive approach involves; 1) understanding the phenomenon and the main processes involved; 2) identifying the main processes to be included in the study and how they are related; and 3) selecting the best possible indicators for these processes, thereby assigning values and weights based on their degree of affect.

An inductive approach involves a ‘hoovering’ of potentially relevant indicators and selecting indicators based on significant statistical relationships or local experience, which are then used to build a model. The inductive approach needs a benchmark against which indicators are tested. One or more proxy variable for adaptation are used as the benchmark. For example, agricultural yields or economic feasibility have been used as a proxy variable in adaptation studies (Claessens et al., 2012). Water-use efficiency has been

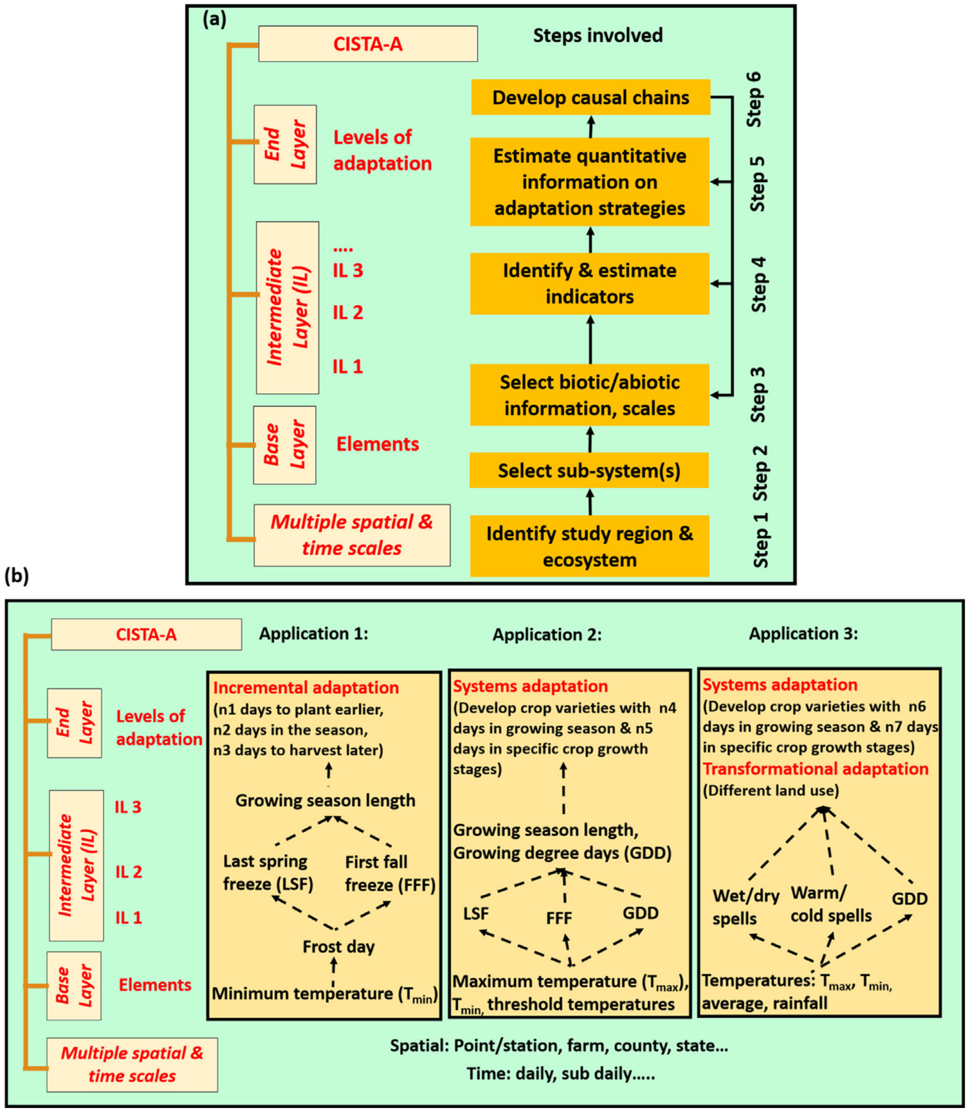

Fig. 3. (a) Steps followed in developing quantitative adaptation strategies. (b) Applications of the conceptual model developed in this study. The first two applications has two layers in the intermediate layer (IL) and provides quantitative information for incremental and systems adaptation. The third application has a single IL and provides quantitative information for two levels of adaptation. In (a) n1, n2, n3. . .n7 represents the number of days for various adaptations.

used as a proxy variable for adaptation studies. When there are not many quantifiable elements of adaptability, a deductive approach for indicator selection is recommended. When such data is available, deductive and inductive approaches for indicator selection is recommended. In this study, the deductive approach for indicator selection was used. The identified indicators are shortlisted based on their application and data availability.

The last (end) layer in CISTA-A translates the information from indicators in the component layer to quantitative information needed for developing one or more adaptation strategies in AS to adjust for climate change and variability. Depending on the degree of change and the benefit from adaptation, the adaptation strategy in the end layer may be for different levels of adaptation, namely incremental, systems and transformation. These strategies may be scale dependent. The information from this layer will be useful for general policy options (e.g. investment in irrigation, other natural resource conservation) and scientists (such as crop breeders). It provides the stakeholders with useful information regarding decision making, while increasing their adaptive capacity in terms of climate change and variability.

2.5. *Steps to apply CISTA*

The various steps to develop quantitative adaptation strategies using CISTA, and developed in this application, are given below and summarized in figure (Fig. 3). Steps 3–6 can be iterative.

2.5.1. *Step 1*

Identify the study region and the ecosystem (e.g. agro-ecosystem, urban ecosystem, forest ecosystem) for which you would like to develop quantitative adaptation strategies. In this study, the agro-ecosystem is chosen, so the conceptual model is named CISTA-A. The other two interconnected systems are climate system and adaptive management systems.

2.5.2. *Step 2*

Select one or more sub-systems to focus on within these three broad systems (e.g. biophysical, ecological, economic, sociological, behavioral systems). Align them with goals and objectives of the adaptation project. All elements are equally important and need consideration in the adaptation; however, due to resource constrains, only a few are often selected.

2.5.3. Step 3

Build the base layer in CISTA. Identify the biotic and abiotic information available that represents the ecosystems and their interconnectedness for the study region (e.g. time-series of climate information, survey information on stakeholder preferences and perceptions). The spatial scale and temporal scale of the various available information are identified.

2.5.4. Step 4

Build the component layer in CISTA. This requires the identification and estimation of indicators using systems approach. Depending on the selected indicators, there can be one or more component layers. Information in the previous steps and model development (Section 2) are useful while identifying the indicators. Next, estimate the indicator from the available information. The relationship between the element(s) and indicator(s) can either be the magnitude of an element, the variability of an element, or the statistical relationship among elements. Indicators estimated from the elements layer use data (time-series of variables) from observations (in the historical time-periods) and/or future projections model simulations.

2.5.5. Step 5

Build the end layer in CISTA. Here the information from the indicators are translated into quantitative information on different adaptation strategies in multiple layers. The quantitative information on different adaptation strategies can be scale dependent. The dependency is contingent on the spatial and temporal scale of the biotic and abiotic information of the chosen indicators.

2.5.6. Step 6

Develop causal chain diagrams. These diagrams display the behavior of cause and effect from the systems standpoint in developing adaptation strategies. They represent the connectedness between the inputs layer, layer(s) in the component layer, and the end layer using causal relationships. These diagrams simply convert the complexity in AS, climate and adaptive planning, and management systems into simple, easily understood quantitative strategies. If need be, these diagrams can be used to revisit steps 3–5.

3. Results

In this section, the CISTA-A is empirically tested to develop quantitative adaptation strategies to combat the negative impacts of climate change and variability (Fig. 4). The causal chains diagrams are in Fig. 5.

3.1. CISTA-A: application 1 to develop incremental adaptation strategies

In this application, CISTA-A is empirically tested by developing three quantitative incremental adaptation strategies to combat the negative impacts of climate change and variability, namely, the number of days to plant earlier/later; the number of days to harvest earlier/later, and the length of crop varieties to select for growth.

3.1.1. Step 1

The state of Kansas is the study region, and a sorghum/corn producing agro-ecosystem is the selected ecosystem.

3.1.2. Step 2

Biophysical elements are the main focus for the three interconnected systems—agro-ecosystem, climate system, and adaptive management system. Plant variety, type, growth, development and yield; land conditions and type; growing season; temperature; rainfall, and agricultural practices are some examples of biophysical elements.

3.1.3. Step 3

In the base layer, 100 years daily minimum temperatures (Tmin) from 23 weather stations spread across Kansas provide the abiotic information. The biotic information from sorghum plant yields and years in which the sorghum yield was stressed due to climate parameters was observed in the performance tests.

3.1.4. Step 4

In the component layer, four indicators are selected. They are frost day (FD), last spring freeze (LSF), first fall freeze (FFF), and length of growing season (GSL), which represent the biophysical elements of the three systems. A frost day was defined as a day with Tmin < 0 °C. LSF is the last day in March through May with Tmin < 0 °C while, FFF is the first day in September through November with Tmin < 0 °C. GSL is the number of days between the LSF and the FFF of the same year. There will be three intermediate component layers. The first intermediate layer has one indicator estimated from Tmin. The second intermediate layer has two indicators: last spring freeze and first fall freeze estimated from the first layer. The third intermediate layer, the growing season length, is estimated from the indicators in the second component layer. The four indicators are estimated for 100 years, at 23 weather stations (point location spatial scale). More details on the four indicators can be obtained from Anandhi et al. (2013a).

3.1.5. Step 5

In the end layer, the time-series of the four indicators were plotted and the changes observed (Fig. 4a). Also, the long term (100+ years) and short term (30 years) linear trend lines were developed and studied. The probability of occurrence of the indices was analyzed at 5%, 25%, 50%, 75%, and 95% for both long term and short term trends. The results of the long term trend show that a general increase in Tmin from 1900 through 2009 caused a decrease in the number of frost days. LSF and FFF occurred earlier and later than normal in the year, respectively, thereby resulting in an increase in GSL. Based on the long-term records in most stations, LSF occurred earlier by 0.1–1.9 days/decade (n1); FFF occurred later by 0.2–0.9 days/decade (n2), and GSL was longer by 0.1–2.5 days/decade (n3). Not all results from the 23 stations were used here, and only a majority of the stations with earlier LSF trends, later FFF trends, and longer GSL trends were taken. Based on the trends of the indicators, three adaptation strategies can be developed, namely, planting earlier; harvesting later, and selecting a crop variety with a different growing length. The planting earlier/harvesting later can be either for the same or a different crop variety. The value of the trend lines can provide a quantitative measure for the number of days to planting earlier (1–19 days earlier- n1); harvesting later (2–9 days later- n2) and the length of the crop variety longer by 1–25 days (n3). n1, n2 and n3 values are subjective to the time-period for which the analysis is carried out (historical or future time-periods). Fig. 5a illustrates the causal loops developed using frost indicators to describe the connectedness.

3.2. CISTA-A: application 2 to develop systems adaptation strategies

In this application, the CISTA-A is empirically tested by developing two quantitative systems adaptation strategies to combat

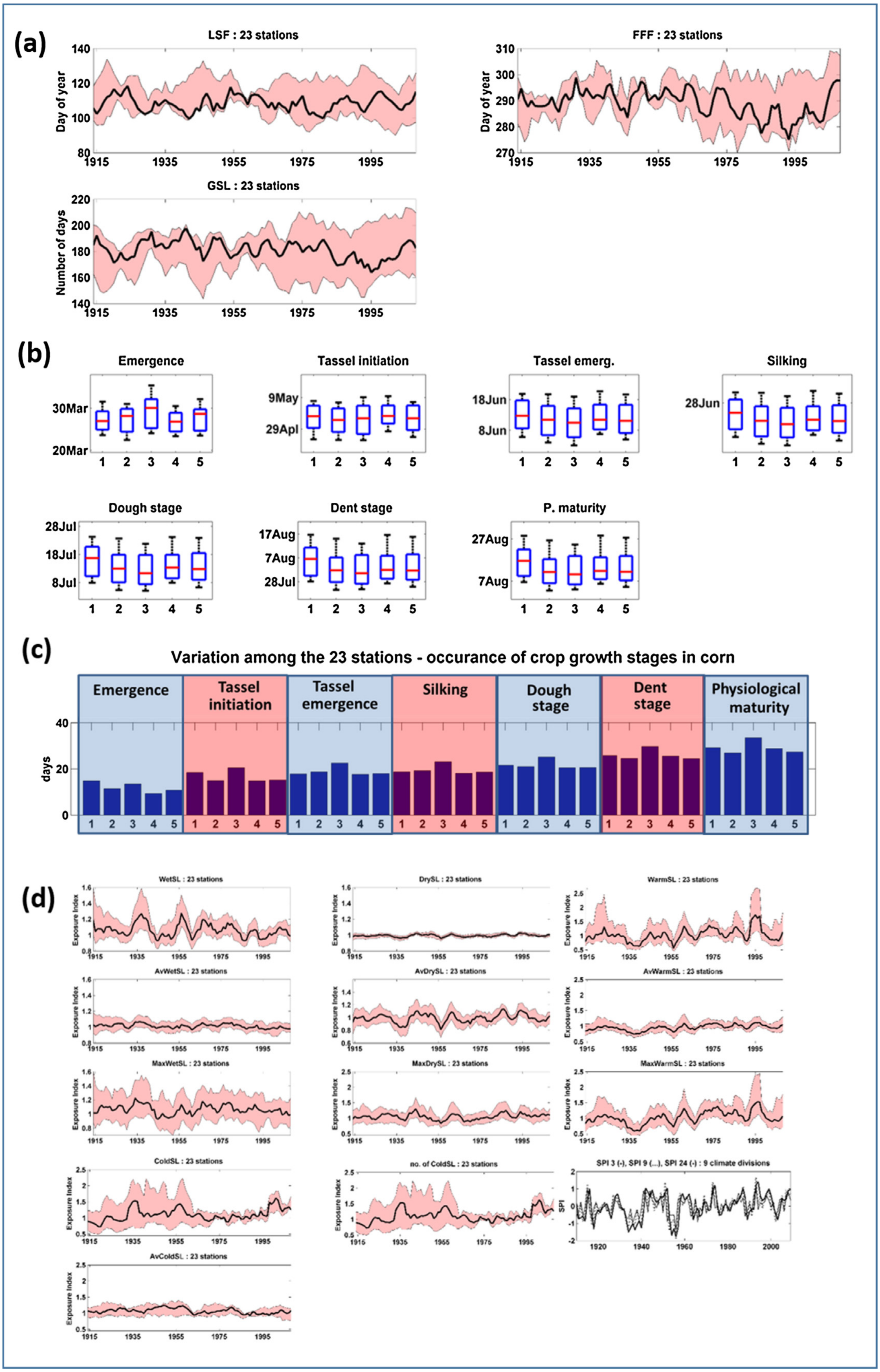

Fig. 4. Spatio-temporal changes in the selected indicators used in the development of quantitative adaptation strategies in the three empirical tests (a – Application 1; a,b–Application 2; b,c Application 3). In the figure, the red portion represents the spread of the indicator values across the 23 stations. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.).

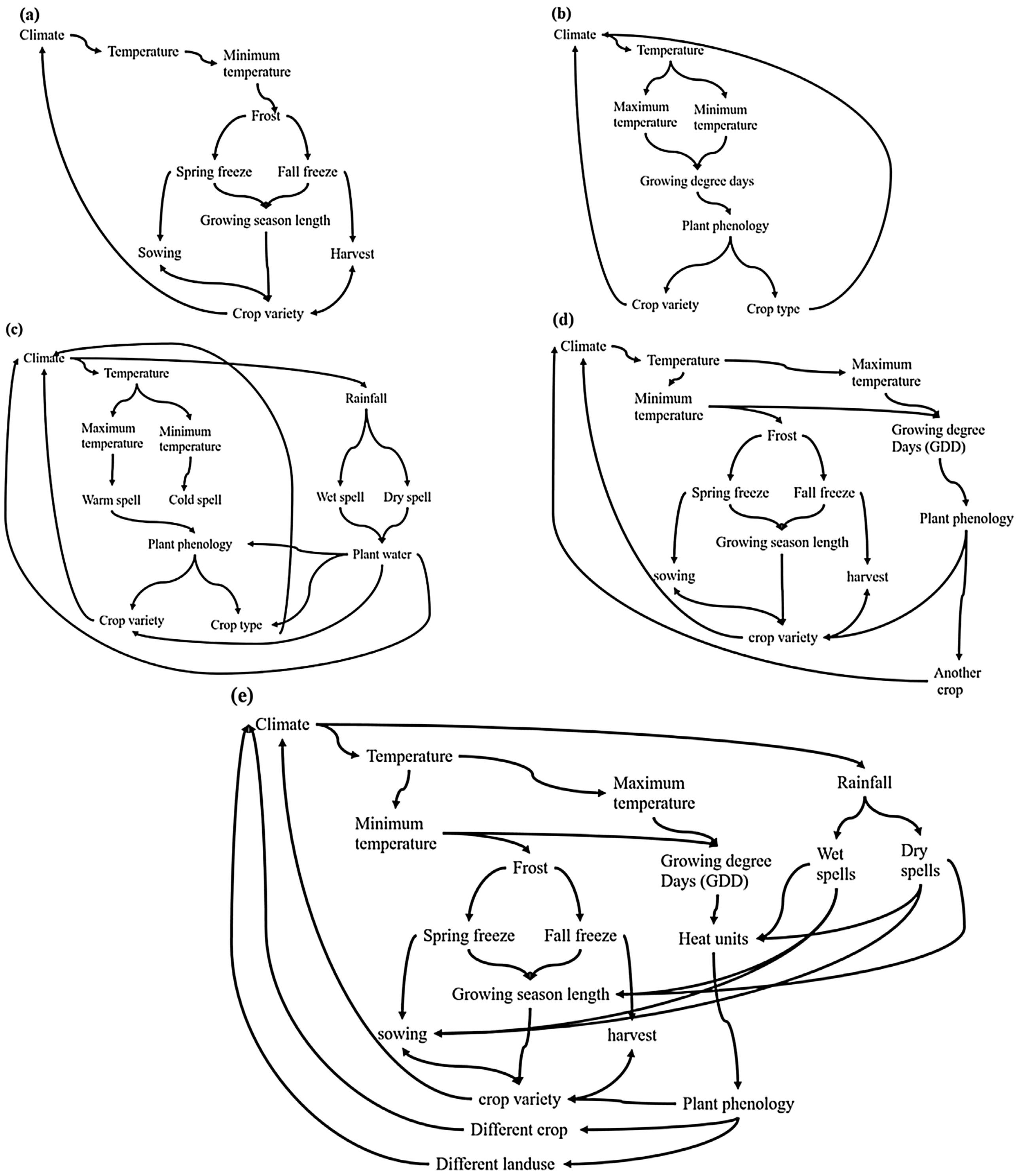

Fig. 5. (a) Causal chain diagram for frost indicators (Application 1). (b) Causal chain diagram for GDD indicator. (c) Causal chain diagram for spell indicators (d) Causal chain diagram for Application 2 (combining a and b). (e) Causal chain diagram for Application 3 (combining frost, GDD and spell indicators).

climate change and variability, namely, to develop crop varieties with a quantified growing season days and to develop crop varieties with approximate days in each of the crop growth stages.

3.2.1. Steps 1 & 2

Same as application 1.

3.2.2. Step 3

In the base layer, 100 years of daily minimum and maximum temperatures (Tmin, Tmax) from 23 weather stations spread across Kansas, threshold or base temperature of plants grown in the region, are the abiotic information. The three sources of biotic information are sorghum plant yield, heat units that relate temperature to plant phenology, and years in which sorghum yield was stressed due to climate parameters observed in the performance tests.

3.2.3. Step 4

In the component layer, five indicators are selected. They are FD, LSF, FFF, GSL and growing degree-days (GDD), which represent the biophysical elements of the three systems. There will be three intermediate component layers. First, the intermediate layer has two indicators: FD estimated from Tmin and GDD estimated from Tmax and Tmin. Two indicators (LSF, FFF) are estimated in the second intermediate layer, both from Tmin. The third component layer, GSL, is estimated from LSF and FFF. The procedure for estimating the LSF, FFF, and GSL are given in the previous section. GDD indicators relate the growth and development of plants to temperature and assumes that plant growth does not progress beyond or below threshold temperatures. In this study, thresholds are 10 °C (50 °F) and 30 °C (86 °F). Temperatures above the upper threshold temperature affect plant photosynthesis and stomatal conductance (Bussel et al., 2015). At these high temperatures, plant roots have greater difficulty taking in water fast enough to keep the plant growing at full speed (Boryan et al., 2011; Anandhi, 2016). GDD is calculated using Eqs. (1–3) and assumes that the GDD required to complete a given growth stage is constant for a crop variety, regardless of the temperatures experienced.

$$GDD = [T_{max} + T_{min}]/2 - T_{base} \tag{1}$$

$$T_{\max} = \begin{cases} T_{\max} & 30^{\circ}\mathrm{C} > T_{\max} > T_{base} \\ 30^{\circ}\mathrm{C} & T_{\max} \geq 30^{\circ}\mathrm{C} \\ T_{base} & T_{\max} \leq T_{base} \end{cases} \tag{2}$$

$$T_{\min} = \begin{cases} T_{\min} & 30^{\circ}\mathrm{C} > T_{\min} > T_{base} \\ 30^{\circ}\mathrm{C} & T_{\min} \geq 30^{\circ}\mathrm{C} \\ T_{base} & T_{\min} \leq T_{base} \end{cases} \tag{3}$$

3.2.4. Step 5

In the end layer, time-series of the four indicators were plotted and the changes observed (Fig. 4). Results of the 100 year linear trend show that all seven crop stages, except the tassel initiation occurred earlier by ~10days/100 years, while the tassel initiation stage occurred later by ~10 day/100 years. Combining these trends with the trends in LSF, FFF, GSL provides information for additional adaptation strategies (planting earlier, harvesting later, and selecting a crop variety discussed in the earlier section). Additionally, they provide information for systems adaptation – to develop crop varieties with longer/shorter growing season days, to develop crop varieties with approximate days in each of the crop growth stages. The value of the trend lines and the variability can provide quantitative measures for the number of days in each stages (Fig. 4b,c). Definitions of thresholds/heat units required to reach a particular crop growth stage are subjective with regard to the plant/ecosystem and may vary with application. The system boundary: spatial scales examples can be individual farm/county level/state level; temporal scale examples can be 100 year trends with at least daily time-scale temperature information. The causal loops are developed using the GDD indicator (Fig. 5b), and for this application (Fig. 5d), by combining frost and GDD causal loops (Figs. a,b).

3.3. CISTA-A: application 3 to develop water management adaptation strategies

In this application, CISTA-A is empirically tested by developing one quantitative systems adaptation strategy and another transformational adaptation strategy to combat climate change and variability namely, to develop crop varieties that are drought tolerant or to provide additional irrigation (systems adaptation) and different land-use (transformational adaptation).

3.3.1. Steps 1 & 2

Same as applications 1 & 2.

3.3.2. Step 3

In the base layer, 100 years of daily rainfall, with minimum, maximum, and average temperatures (Tmin, Tmax, Tave) from 23 weather stations spread across Kansas provide the abiotic information. The biotic information is defined as a wet day impacting water requirement by plants and irrigation scheduling as well as heat units to relating temperature to plant phenology.

3.3.3. Step 4

In the component layer, nineteen indicators are selected. There will be one component layer. Eighteen of these indicators represent wet/dry/warm/cold spells, and GDD is the other indicator (explanation in earlier section). Extended periods with excessive or no rainfall or high or low temperatures have important implications for the water cycle, which can stress ecosystems, and be detrimental to the economy of a region. They have an impact on plant growth, development and crop yield and changes in growing season. Spells represent these extended periods. Changes in temperature spells will most likely force changes in the hydrology of the region by decreasing the proportion of precipitation falling as snow, shifting the timing of snowmelt, and causing snowmelt-supplemented streamflow events to occur earlier in the spring or in late winter, which change the magnitude of streamflow. Among these indicators, 4 represent wet spells [wet spell length (WetSL), the average wet spell length (AvWetSL), maximum wet spell length (MaxWetSL), and the number of wet spells (no. of wetSL)]; 4 for dry spells [dry spell length (DrySL); average dry spell length (AvDrySL); maximum dry spell length (MaxDrySL); number of dry spells (no. of drySL)]; 5 for warm spells [warm spell length (WarmSL); the average warm spell length (AvWarmSL); the maximum warm spell length (MaxWarmSL); the warm spell duration index (WarmSDI);the number of warm spells (no. of warmSL)], and 5 are for cold spells [cold spell length (ColdSL); the average cold spell length (AvColdSL); the maximum cold spell length (MaxColdSL); the cold spell duration index (ColdSDI); the number of cold spells (no. of coldSL)]. The definitions of these indicators are provided in Table 1. More information on the indicators can be obtained from Anandhi et al. (2016):

3.3.4. Step 5

In the end layer, the time-series of the four indicators were plotted and the changes observed (Fig. 4b,c,d). Results from ~100 year analysis indicate, that in general, Kansas has 57–64 days/year in a wet spell, 302–309 days/year in a dry spell, and ~47 days/year in each warm and cold spell. The average length of a wet/dry spell is ~1.5 days, while the warm/cold spells are for 2 days. The maximum length of a wet spell is ~4.4 days. A dry spell is ~35 days, and warm/cold spells are ~ 6 days. The general trends in the ~100 year analysis indicate the number of wet days is increasing annually. Interestingly, the warm days during the winter are increasing with an overall decrease of days in the warm and cold spells. Overlaying the changes in spell indicators with the days in each crop growth stage would help us identify the number of spells in each crop growth stage. Adding the trends in spell indicators will help predict whether there will be more wet or dry spells in each critical crop growth stage (e.g. flowering stage, grain filling stage). This will provide quantitative information to questions such as: Will plants require more or less water? Is it necessary to substitute excess water for irrigation or drain excess water? If there is a need for more water, is it provided through irrigation or by growing crop varieties that are drought tolerant (systems adaptation)? Is a different land-use (transformational adaptation) chosen because the water requirement cannot be met or developing crop varieties are not

Table 1
Definitions of spell indicators.

Acronyms	Description
Wet Spell Length (WetSL)	Count of number of consecutive days where daily *Precipitation* $\geq 1mm$ in the time period
Average Wet Spell Length (AvWetSL)	Average of WetSL in the time period
Maximum Consecutive Wet Days (MaxWetSL)	Maximum number of consecutive days with *Precipitation* $\geq 1mm$
No. of wetSL	Count of the number of wet spells
Dry Spell Length (DrySL)	Count of consecutive days where *Precipitation* $< 1mm$ in the time period
Average Dry Spell Length (AvDrySL)	Average of DrySL in the time period
Maximum Consecutive Dry Days (MaxDrySL)	Maximum number of consecutive days with *Precipitation* $< 1mm$
No. of drySL	Count of the number of dry spells
Warm Spell Days (WarmSL)	Count of consecutive days when Tmax > 90th percentile
Average Warm Spell Days (AvWarmSL)	Average of WarmSL in specific time period
Consecutive Warm Days (MaxWarmSL)	Maximum number of consecutive days when Tmax > 90th percentile
No. of warmSL	Count of the number of warm spells
Cold Spell Days (ColdSL)	Count of consecutive days when Tmin < 10th percentile
Average Cold Spell Days (AvColdSL)	Average of ColdSL in specific time period
Consecutive Cold Days (MaxColdSL)	Maximum number of consecutive days when Tmin < 10th percentile
No. of coldSL	Count of the number of cold spells

feasible. Transformational adaptation is considered to occur when ecological, economic, or social (including political) conditions make the existing system untenable (Park et al., 2012). The causal loops are developed using spell indicator (Fig. 5c) and for this application (Fig. 5e), by combining frost, GDD, and frost causal loops (Figs. a,b,c).

4. Discussion

The application of CISTA-A to crop/IA models and the developed causal loop diagrams are discussed in this section. The approaches and pathways briefly explained in earlier sections (Sections 2.2 and 2.3; Fig. 1) are also discussed here.

4.1. Complexity and multidisciplinary nature of the three systems

Multiple factors shape adaptive responses to a changing climate (Bartels et al., 2013) because of the complexities and multidisciplinary nature of the three interconnected systems (AS, climate system and adaptive management and planning systems). Sustainable management of the resources in these systems (i.e. acknowledging and balancing social, economic, and environmental aspects) requires information that considers the spatially and temporally varying nature of the resources and their linkages to society and environment (Perveen and James, 2011). Understanding these complex systems is not well developed and is likely to remain so into the foreseeable future; therefore, the consequences (i.e., predictability) of adaptation initiatives remain difficult to determine over the extended time scales required by sustainability (Thomsen et al., 2012). The lack of addressing adaptation in many studies and the conceptual inability to disentangle the different elements in adaptation, as well as their complex interaction across different drivers, are substantially hampering the scientific understanding of climate change impacts in managed ecosystems. Additionally, there is evidence that the conceptual models, tools, and methods developed by the research community have either not sufficiently evolved or effectively delivered to guide adaptation (Preston et al., 2015). Effective decision support systems must be built on our deep understanding of the complexities and nature of these systems. A deeper understanding of these systems can arise by using multiple intermediate layers in the component or from multiple indicators. In addition, understanding what motivates stakeholder awareness and action can shape the choice of indicators.

Adequate assessment of climate change for adaptive management in AS requires analysis of numerous biophysical and socio-economic drivers and processes to understand the triple complexity. This requires an analysis of numerous variables and data. The drivers and their interactions are complex, non-linear, and constantly changing (gradual and/or drastic) (Folke et al., 2002). Other drivers include declining per-capita land and water, increasing population and food demand, urban sprawl into forest and agricultural land, increased opportunities/needs for urban agricultural systems, conversion from irrigated crops to rain fed crops or grasslands, Conservation Reserve Program conversion to cropping, encroachment of woody species into grasslands, and economic development. CISTA-A developed in this study uses systems thinking approaches using indicators (Fig. 6a).

4.2. Causal loops developed with CISTA-A

Causal loop diagrams are used to represent the multidisciplinary nature and complexity of adaptation strategies (Fig. 5). These diagrams show the connectedness between the systems, using the various layers in CISTA-A. It can be observed from the causal loop diagram that frost indicators can represent multiple elements such as climate, minimum temperature, season, management practices (harvest, sowing) and crop variety (Fig. 5a). GDD is a single indicator that can represent elements such as climate, minimum and maximum temperature, plant phenology, management practices (duration of each crop development stage), crop variety and type (Fig. 5b). Spell indicators can represent elements, climate, rainfall, minimum and maximum temperature, plant phenology, plant water, management practices (crop stressed by temperature, water), crop variety and type (Fig. 5c). The loop diagrams become more and more complex when multiple indicators and component layers are added (Fig. 5d,e). If all the 23 indicators are used, the causal loop become more complicated (Fig. 5e). The causal diagrams in Fig. 5 are selective because they do not represent the full range of feedback loops responsible for the development of adaptation strategy over time. Stakeholder, socio-economic, and behavioral change information are not included in the diagram. For example, sowing dates are estimated using multiple ways and variables collected from various sources. In this study, sowing dates can be estimated from the minimum temperature based on last spring freeze indicator (Fig. 5a) and in combination with the wet/dry spell indicators (Fig. 5e) using temperature and rainfall data. Waongo et al. (2015) also estimated sowing dates from rainfall and temperature data using the fuzzy rule composed of three indicators: the 5-day cumulative rainfall amount, the number of wet-days, and the dry-spell length. Waha et al. (2013a) used household surveys to determine sowing dates. Each of these methods has its own advantages and disadvantages. Depending on the information available, each of these variables/indicators can be used in CISTA-A to estimate sowing dates.

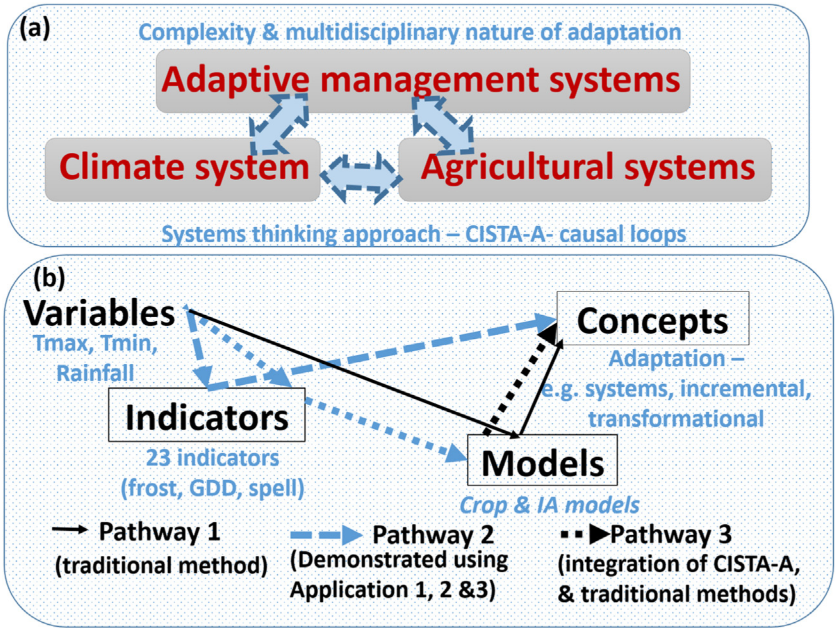

Fig. 6. a) Representing complexity and multidisciplinary nature of adaptation. b) integrating CISTA-A with crop and IA models (Pathway 3). The blue lines (lighter shade lines) in the figure represent CISTA-A and is in two of the four pathways (Pathways 2 and 3). Crop and IA models are in two of the four pathways (Pathways 1 and 3). Fig. 1c has all the four Pathways. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

4.3. Other potential bio-physical variables in the base layer for CISTA-A

In this study, we used measured bio-physical variables, temperature and rainfall in the base (element) layer. Other input variables can also be used in the base (element) layer of CISTA-A. These variables can be measured, modeled and/or collected through stakeholder surveys. Depending on how the variables are collected, CISTA-A can fall into either of the three approaches shown in Fig. 1a. When measured and modeled, bio-physical variables are used, and then CISTA-A uses Approach-1 (top-down approach, Fig. 1a). If variables are obtained from the survey, then CISTA-A uses Approach-2 (bottom-up approach). When the combination of measured, modeled, and survey variables are used in CISTA, then it is Approach-3 (hybrid approach). The other potential climate variables observed can be land surface temperature, relative humidity, wind speed, shortwave radiation at the surface, including cloud cover effects, precipitation type, amount, and distribution. In the absence of measured variables, some of these variables can be simulated using models. Solar radiation and evapotranspiration (ET) are examples of modeled variables. Some potential variables, summarized by Kersebaum et al. (2015) for crop models (e.g. meteorological data, agronomic management, soil data, initial values, previous crop, topography, phenology, crop growth variables) can be used in CISTA-A's base layer. Additional variables can be National Elevation Dataset at 30 m resolution (Gesch et al., 2002); Soil Survey Geographic (SSURGO) database; National Land Cover Dataset (Jin et al., 2013); Crop Data Layer (Boryan et al., 2011); watershed boundaries (Watershed Boundary Dataset http://datagateway.nrcs.usda.gov), Agricultural Census Data, Farm Ranch and Irrigation Survey, National Climate Data Center (NCDC) (http://www.ncdc.noaa.gov), and streamflow from U.S. Geological Survey (USGS).

4.4. Other potential indicators in component layer for CISTA-A

This study used 23 indicators (4 frost indicators, 1 GDD, 18 spell indicators) in CISTA-A. The component layer has multiple layers. Each layer can have one (e.g. GDD) or a group of indicators (e.g frost indicators) to represent one or more processes/elements of the three systems (AS, climate, and adaptive management systems). Although this study demonstrates the developed CISTA-A using climate information to estimate climatological, bio-physical and ecological indicators to link the three systems (discussed in next section). CISTA-A can be applied to other important economic, sociological, and behavioral system elements that need consideration in adaptation. These choices would depend on the user and the application for which CISTA will be used. Additionally, there are numerous other agro-, hydro-, ecological, meteorological and socio-economic indicators available in the literature to represent the three systems (Anandhi et al., 2013a; Anandhi et al., 2013b; Pradhanang et al., 2013; Anandhi, 2016). The indicators used in this study are measured climate variables. However, indicators can be estimated from other sources such as modeled variables (e.g. plant water uptake from modeled ET, plant water use from modeled hydrology, crop-specific indicators from modeled crop growth and development), stakeholder survey information (e.g. sowing dates). Additionally, in CISTA-A, an adaptation strategy can be reached in multiple ways by using one or more indicators or combinations of indicators (e.g. sowing dates Fig. 5a,e), and methods that combine these multiple indicators (e.g. averaging, fuzzy logic). This study recommends choosing appropriate indicators and a number of intermediate layers using systems thinking approaches to improve the understanding of the complexity and multidisciplinary nature of the system, and to arrive at quantitative adaptation strategies.

4.5. Integrating the results into crop models and integrated assessment and modeling (IAM) for climate change adaptation

Crop models and integrated assessment and modeling (IAM) are the primary tools available to assess the impacts of climate change and other drivers on crop productivity. As well, they are suitable for informing climate change adaptation decisions (Webber et al., 2015). They summarized crop models used in adaptation studies: 1) to test the robustness of the farmer's change to future climate scenarios; 2) as tools in farmer organizations to build farmer capacity, minimize risk, and empower farmers; 3) to link with other models to widen the scope of potential impacts, adaptations, and constraints; 4) to probe the interactions of cropping systems with other systems; and 5) to evaluate various indicators of resilience. Presently, a range of crop models is available with differing degrees of model complexity and emphasis on different research questions, crops, and regions (Ewert et al., 2015). Different models applied to the same dataset were able to satisfactorily simulate a specific target variable, but they showed considerable differences in the quantification of different underlying processes (Kersebaum et al., 2015). Many reviewed crop modeling studies investigating climate change adaptation currently do not capture many of these drivers, adaptations nor constraints (Webber et al., 2015). The complexity of climate change impacts and adaptations for managing climate risks and improving food production calls for more integrated modeling and quantitative assessment approaches that go beyond the sole biophysical aspects of crop and cropping systems (Ewert et al., 2015). This has resulted in a number of IAM frameworks (Approach 3, Fig. 1a, Section 2.2). One of the greatest benefits of linking crop models across disciplines and in IAM frameworks is that they provide a platform that brings specialists and stakeholders from diverse backgrounds together to assess climate change adaptation options (Webber et al., 2015). IAM uses survey, experimental and modeled data that are typically available, combined with future socio-economic scenarios based on new scenario pathway concepts being developed by the climate change and impact assessment modeling communities (Claessens et al., 2012).

CISTA-A is not a substitute for crop and IAM models. Crop and IAM models are used in two of the four Pathways (Pathways 1 and 3; Figs. 1c and 6b) to generate adaptation decisions. Similarly, CISTA-A is used in two of the four Pathways (Pathways 2 and 3; Figs. 1c and 6b) to generate adaptation decisions. In Pathway 3, results of CISTA-A are input into crop and IAM models to generate adaptation decisions. The blue color (lighter) lines in Fig. 6b show CISTA-A, with and without crop and IAM models.

4.6. CISTA-A – uncertainties in the developed strategies

The flexibility in the choice of indicators and intermediate layers can be a boon and bane for the CISTA-A model developed in the study. Choices of indicators based on systems thinking approaches can provide different quantitative adaption options for decision making (farmers, policy makers etc.), as discussed in Section 4.2. example, application 3 demonstrated in this study (Section 3.3, Fig. 3) can provide a value for the number of days for the crop to emerge, but the spell indicator can give a different value based on rainfall (moisture availability) or from household surveys (Waha et al., 2013a). If multiple indicators are used, then the sowing date is subjective to the aggregation method, e.g. fuzzy logic (Waongo et al., 2015). In this study, the quantitative values in the adaptation strategies are probabilistic values because of the inter-annual variability of the indicator values. For example, the last spring freeze indicator can be different each year, and the trends vary depending on the method used to estimate the trend; the time-period in the estimations and single/multiple station information (spatial scale) is used. In this study, 100 year historical trends are used to demonstrate the application of CISTA under the assumption that the trends extend into the future too. This may not be the case. The other option is using future climate simulations from various global climate models (GCMs) to derive the indicators, as well as their future trends, to obtain n1, n2 and n3. Definitions of indicators and trend values are subjective with regard to the crop/agro-ecosystem and may vary with application. Given the variability in climatic parameters from year to year, large variations of seasonal rainfall, the impact that rainfall amounts and distribution will have on the adaptation strategies developed, it is important that alternative approaches to more detailed climate-induced risk analyses should be evaluated and management recommendations be made to mitigate the extent of risk (Dixit and Telleria, 2015).

The pitfall of the CISTA-A model framework is that the model may be affected by the chosen indicators to represent the complexity and multidisciplinary nature of the systems, their spatial and temporal scales, the multi-scale interactions among components and the methods used to aggregate. In addition field experimental datasets are usually not recorded for modeling purposes, their level of detail, quality of records, variables considered as well as their number of spatial and temporal replicates vary enormously (Kersebaum et al., 2015). These pitfalls can to some extent be overcome by determining a spatial resolution prior to developing the adaptation strategies (Zhao et al., 2015). Although the dilemma in compromising between different demands will exist, a fine spatial resolution demands an extensive computation load for input data and output analysis. A coarse spatial resolution could result in the loss of spatial detail in variability (Zhao et al., 2015). In an ideal world, data on the processes occurring in the three systems (AS, climate and adaptive planning, and management), would be available with the same spatial resolution as the drivers influencing those processes. However, data are often on different spatial and temporal resolutions, and this has a great impact on the results of quantitative adaptation strategies. There is need to understand how indicators are affected by spatial and temporal scales (Perveen and James, 2011). The scale of the input information (elements), indicators (components), and level of adaptation are important. Bias in crop yield simulations are observed when the larger scale simulations (e.g. regional, national, continental) use inputs such as soil and climate data, generated at low resolution via averaging and sampling by area (Zhao et al., 2015; Hoffmann et al., 2016). Here, a scaling effect is observed when coarsening resolution (i.e., aggregating small areas into larger ones, smaller time-scales into larger ones) and averaging the variables over each aggregation. This may result in stronger correlation between the studied variables and the loss of degrees of freedom and variance. Bussel et al. (2015) provides a methodology for scaling and zoning phenological development using growing degree days (GDD), sowing and harvest dates from point scale to global scales. These indicators and inputs are useful for selecting crop varieties and management operations (adaptation strategies) used to combat the negative impacts of climate change. In their methodology, the authors aggregated the data with multiple zoning areas (unit of analysis different from the unit of data). For example, the unit of analysis in the study was at global scale. The crop area at $5' \times 5'$ gridscale was aggregated to $30' \times 30'$ gridscale, obtained from harvest/sowing dates from monthly data. Local phenological parameters were aggregated from local scale to regions with no data. The impact of spatial resolution, data aggregation and spatial heterogeneity of weather data on simulations of crop yields, and guidelines for choosing a proper spatial resolution for simulations of crop yields at regional scale can be found in Zhao et al. (2015). Similar to the scaling effect, the zoning effect also causes differences in variance and correlation when comparing two different zonings of the same data. Relationships between variables can even switch from positive to negative when different units of analysis are used (Salmivaara et al., 2015). Scaling and zoning affects two such examples in the problem of ecological fallacy, which occurs if a researcher draws conclusions about a system on one scale based on results obtained at another scale (i.e., cross-scale inference) (Salmivaara et al., 2015). This phenomenon is particularly relevant if policies and decisions are made at scales defined by administrative units, while data and estimated indicators may be at other scales. In addition, to the scaling and zoning effects, the geographical context and the type of ecosystem are important determinants of the range of adaptation strategies. These disadvantages are present in all four pathways, as well as in the crop models and IAM. It is beyond the scope of this study to address the question of ecological fallacy in the developed conceptual model and is deferred for a future study.

5. Conclusions

Developing adaptation strategies to utilize the benefits of change and to reduce the negative impacts of change in climate are in the forefront globally and nationally, increasing the need for developing strategies to address questions on "how to adapt." There is evidence that the conceptual models, tools, and methods developed by the research community have either not been sufficiently evolved or have not been effectively delivered to guide adaptation (Preston et al., 2015). To address this need, this study synthesized the existing methodologies to develop adaptation strategies into four Pathway (Fig. 1c). Additionally, CISTA-A, a conceptual model using the system's approach for adaptation in Agro-ecosystems is developed. The applications of CISTA-A in the four pathways and its integration with crop and integrated assessment models are also discussed (Fig. 6b).

CISTA (Fig. 2) has three main layers (multiple intermediate layers) to help understand the triple complexity of the adaptive management of AS to climate change. The model consists of a base layer (elements), which has agro-ecological, agro-hydrological and meteorological data. Examples of elements include yield, rainfall, temperature, streamflow, irrigation information etc. and a component layer (indicators) with one or more intermediate layers. Examples of indicators are agro-ecological, agro-hydrological, and climatological indicators that affect AS, which are identified and estimated from the element layer. In the end (final) layer, depending on the degree of change and the level of adaptation, the information from indicators is translated into adaptation strategies (incremental, systems and transformational adaptation).

The CISTA-A model is demonstrated by representing the complexity and multidisciplinary nature of the three systems (agricultural systems, climate systems and adaptive management systems) using three applications. These applications use biotic/abiotic information (e.g temperature/rainfall/plant development stages) and 23 indicators to arrive at the adaptation strategies. It should be noted that these systems are extremely complex and dynamic and understanding them is always likely to be limited (Thomsen et al., 2012). Therefore, one is unlikely to have access to all information to be able to anticipate all the indicators with accuracy over multiple spatial and temporal scales, or all the anticipated adaptation strategies. It is beyond the scope of this study to address the question of ecological fallacy in the developed conceptual model and is deffered for a future study. Explanations for quantitative adaptation strategies described in this paper do not include measures that express the ability of a society to recover from shortages, such as economic, educational, or demographic variables that could facilitate alternative strategies. Yet, the indicators examined here are conventional measures and may be applicable to alternative ecosystems.

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