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# 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

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ABSTRACT

Water is an essential natural resource. Among many stressors, altered climate is exerting pressure on water resource systems, increasing its demand and creating a need for vulnerability assessments. The overall objective of this study was to develop a novel tool that can translate a theoretical concept (vulnerability of water resources (VWR)) to an operational framework mainly under altered temperature and precipitation, as well as for population change (smaller extent). The developed tool had three stages and utilized a novel systems thinking approach. Stage-1: Translating theoretical concept to characteristics identified from studies; Stage-2: Operationalizing characteristics to methodology in VWR; Stage-3: Utilizing the methodology for development of a conceptual modeling tool for VWR: WR-VISTA (Water Resource Vulnerability assessment conceptual model using Indicators selected by System's Thinking Approach). The specific novelties were: 1) The important characteristics in VWR were identified in Stage-1 (target system, system components, scale, level of detail, data source, frameworks, and indicator); 2) WR-VISTA combined two vulnerability assessments frameworks: the European's Driver–Pressure–State–Impact–Response framework (DPSIR) and the Intergovernmental Panel on Climate Change's framework (IPCC's); and 3) used systems thinking approaches in VWR for indicator selection. The developed application was demonstrated in Kansas (overlying the High Plains region/Ogallala Aquifer, considered the "breadbasket of the world"), using 26 indicators with intermediate level of detail. Our results indicate that the western part of the state is vulnerable from agricultural water use and the eastern part from urban water use. The developed tool can be easily replicated to other regions within and outside the US.


## 1. Introduction

Water is widely regarded as an essential natural resource (Vörösmarty et al., 2010) and a necessary resource for nearly all human activities (EEA, 2012). It can be viewed as a resource for domestic use, as an input for agricultural and industrial uses, a sustainer of ecosystems, as well as a hazard in the form of floods and drought (Brown et al., 2015). Water availability will be one of the constraints for crop production and food security (Kang et al., 2009). Understanding the water resource system and its exposure to stressors are vital to secure and increase world food production to feed its growing population (Anandhi et al., 2016b). Climate change and its consequences limit the adaptive capacity of water resource systems, making them vulnerable to such changes (Al-Kalbani et al., 2014). These systems are transformed through land cover change, urbanization, industrialization, and several man-made systems such as reservoirs, irrigation, and inter-basin water transfers that increase human access to water (Vörösmarty et al., 2010). Therefore, water resource systems have complex interactions with both social and ecological sub-systems (Gain et al., 2013). In addition to climatic change, other stressors such as increasing population, socio-economic growth, and associated land cover changes, have direct impacts on increasing water demands as well as vulnerability to the resource (Al-Kalbani et al., 2014). This study focuses on the vulnerability of water resources (VWR) to stressors such as changes and variability in temperature and precipitation to a large extent, and population change to a smaller extent.

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Vulnerability is a theoretical concept and difficult to be measured directly (Tonmoy et al., 2014). Making a theoretical concept operational consists of providing a method or procedures (an operation) for mapping it to observable concepts (Kim, 2015). The method or procedures are then called the operational definition, while in the case of vulnerability, the operational definition is called the methodology of a vulnerability assessment (Hinkel, 2011). The scientific information and knowledge in the methodology later become part of a process in a much broader decision-making system (Weaver et al., 2013) and modeling frameworks can be useful tools. Translating a theoretical concept VWR to an operational tool is very useful but not often clearly explained in most studies; this study attempts to provide a clear explanation.

In general, vulnerability assessments are complex given the multiple uses for the assessments, the multi-disciplinary nature of the problem, limited understanding, dynamic structure of vulnerability, scale issues, problems when devising vulnerability indicators (Adger et al., 2004), and it being a theoretical concept. Due to the complexity in vulnerability assessment and water resource systems (dual complexity), estimating the vulnerabilities of water resources (VWR) to climate change is challenging but very important (Gain et al., 2012). Previous works have used econometric methods (using survey information from questionnaires) or index-based methods (using indicators) for vulnerability assessments (Deressa et al., 2008). The index-based method is the most commonly used approach in VWR (Bär et al., 2015).

Our study identified several needs in VWR to a changing and variable climate. The needs were grouped into those related to indicators and those related to decision tools. Some needs related to indicators were:

- Experts need to provide indicator relevance for clear, unambiguous messages to be conveyed to users (decision- and policy-makers and also the public) (Hák et al., 2016);
- Most indicator studies do not incorporate multiple spatial and temporal scales (Malone and Engle, 2011); and
- There has been a need for indicator providers to develop and/or apply adequate approaches for strengthening the largely neglected indicators characteristic – relevance (Hák et al., 2016). Selected needs related to tools were:
- There is an important need to develop tools for water managers whose systems are vulnerable to climate change and variability to assist them with planning (Sharda and Srivastava, 2016);
- There is a growing demand among stakeholders across public and private institutions for spatially-explicit information regarding vulnerability to climate change at the local scale (Preston et al., 2011);
- While recognizing that extensive literature exists to represent the VWR using multiple systems (e.g., ecological, natural, biophysical, social, socio-ecological, or combinations) and multiple frameworks at various spatial and temporal scales, there still exists a need to synthesize the literature and develop tools within a decision-making framework; and
- There is a need to translate a theoretical concept VWR to an operational one for decision making.

Our study attempted to address several of these needs. The specific objective was to develop an innovative framework that translated the theoretical concept (VWR) to a tool useful for decision-making mainly under a changing and variable temperature and precipitation and population change to a smaller extent. This involved integration of characteristics in vulnerability assessments, water resources and stressors (e.g., climate change, population change); through indicators selected by systems thinking approaches.

The novelty was the translation of the theoretical concept (VWR) to a decision support tool by:

- Adaptation of Gallopín (2006) generic vulnerability framework for VWR,
- Modifying Bär et al. (2015) flowchart (developed for agricultural VWR to a generic framework for VWR) that integrated two important frameworks,
- Integrating two vulnerability assessments frameworks: European's Driver–Pressure–State–Impact–Response framework (DPSIR) and the Intergovernmental Panel on Climate Change's framework (IPCC's), and
- Modifying Anandhi et al. (2016b) framework, developed for a single component (exposure) of agricultural production to a changing/variable climate, to include multiple components in VWR (driver, pressure, state, impact, response, exposure, sensitivity, adaptive capacity, and processes).

The objective was carried out in three stages (Fig. 1). Stage-1: Translating theoretical concept to charateristics identified from literature (Fig. 2). Stage-2: Operationalizing charateristics to methodology in VWR (Fig. 3). Stage 3: Utilizing the methodology for development of a conceptual modeling tool for VWR: WR-VISTA (Water Resource Vulnerability assessment conceptual model using Indicators selected by System's Thinking Approach) that is useful in the decision making framework (Fig. 4). We hypothesize that 1) the developed tool using novel systems thinking approaches would support several stakeholders to select and highlight trends in indicators as well as simplify and communicate the complex and complicated information and phenomena within a decision-making framework; and 2) the compiled characteristics in vulnerability assessments from existing vulnerability assessments, WR-VISTA conceptualization as well as a discussion on the information related to using multiple indicators, scaling, normalization, weighting and aggregation methodology, and uncertainty would improve conceptualization of VWR assessments and tailor the developed tool for multiple stakeholders. The developed tool was demonstrated by application to a case study. The High Plains region (overlying the Ogallala Aquifer) was chosen in this study because it is one of the most productive agricultural regions and called the "breadbasket of the world" (Sanderson and Frey, 2014). Additionally, this study addresses an important need for assessment of the vulnerability of water resources in the region brought out by a previous study (Steward et al., 2013).

## 2. Descriptions of key terms and methodology

### 2.1. Definitions/descriptions of key terms used in this study

A **water resources system** is described as the "whole made from connected hydrologic, infrastructure, ecologic, and human processes that involve water" (Brown et al., 2015). **Vulnerability** is defined as "the degree to which the system is susceptible to and is unable to cope with adverse effects of change" (Adger, 2006). **Complex systems** involve the collective behavior of a large group of relatively simple elements or agents, in which the interactions among these elements typically are local and non-linear (Anandhi, 2017) or simply put, "the whole is more than the sum of its parts" (Ratter, 2012). **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. An **indicator** can be defined as any variable that indicates the magnitude (e.g., mean seasonal temperature) or variability (e.g., standard deviation

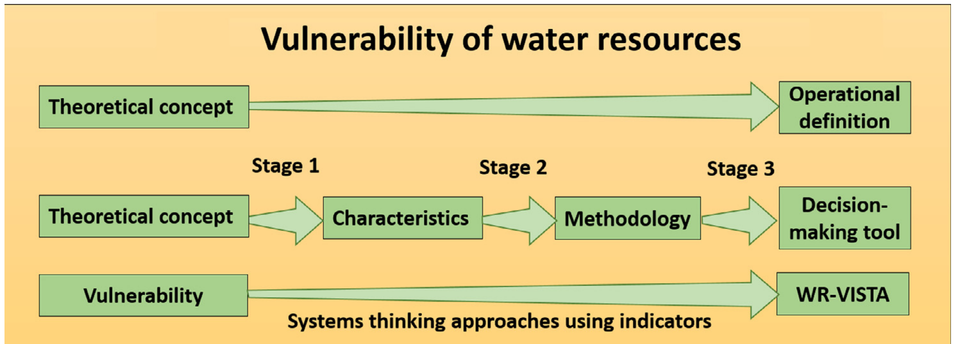


**Fig. 1.** Translating vulnerability in water resources from a theoretical concept to operational definition in three stages.

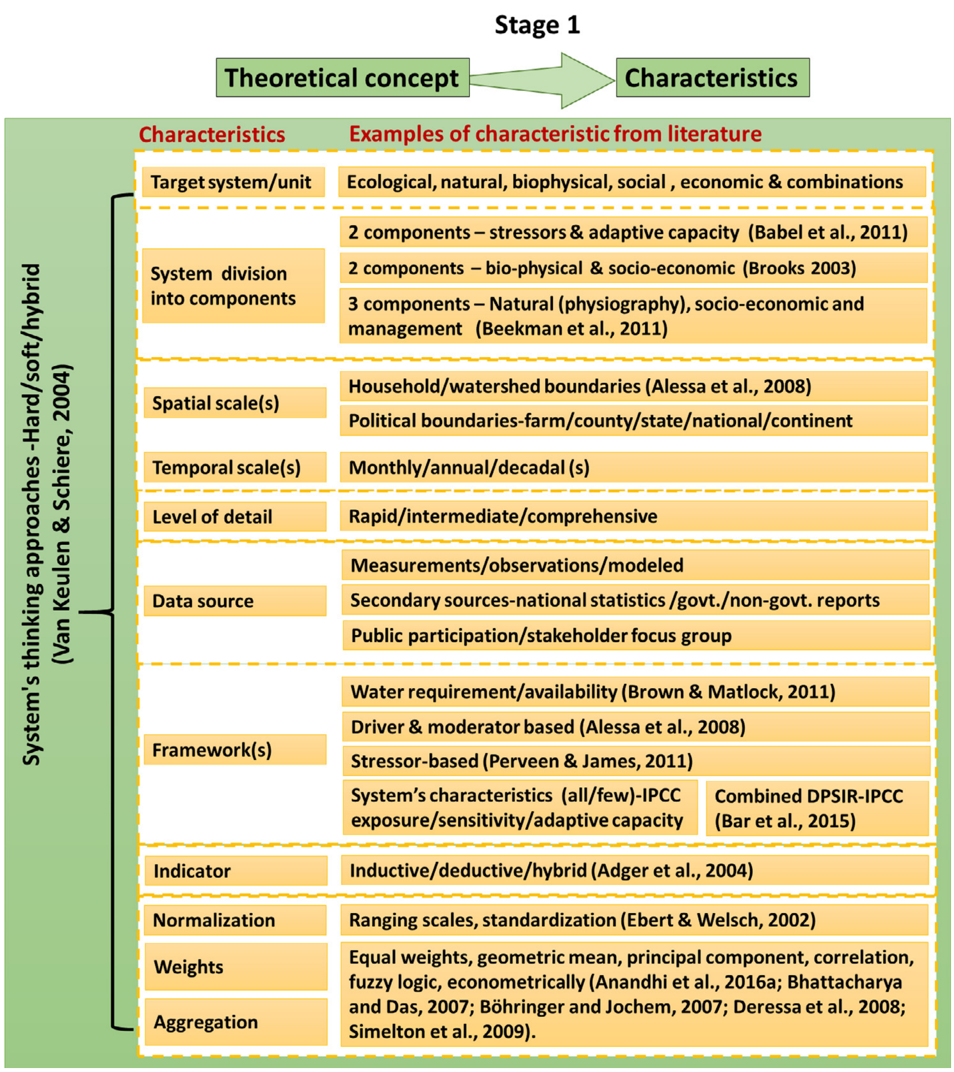


**Fig. 2.** Stage 1: Translating theoretical concept vulnerability to characteristics from literature for vulnerability of water resource system assessments.

seasonal rainfall) of a parameter, (Alessa et al., 2008), or the statistical relationship among variables (Anandhi, 2017; Gain et al., 2012). Finally, **stakeholders** have been defined as "individuals or groups with a vested interest in the outcome of a decision or the research project" (DeLorme et al., 2016). Food security is typically defined as "when all people at all times have access to sufficient, safe, nutritious food to maintain a healthy and active life" (Glamann et al., 2017).

### 2.2. Methodology

This study's objective was achieved in three stages (Fig. 1). Stage-1: Translating theoretical concept to charateristics identified from literature (Fig. 2). Stage-2: Operationalizing charateristics to methodology in VWR (Fig. 3). Stage 3: Development of a conceptual modeling tool for VWR in a changing climate: WR-VISTA (Fig. 4).

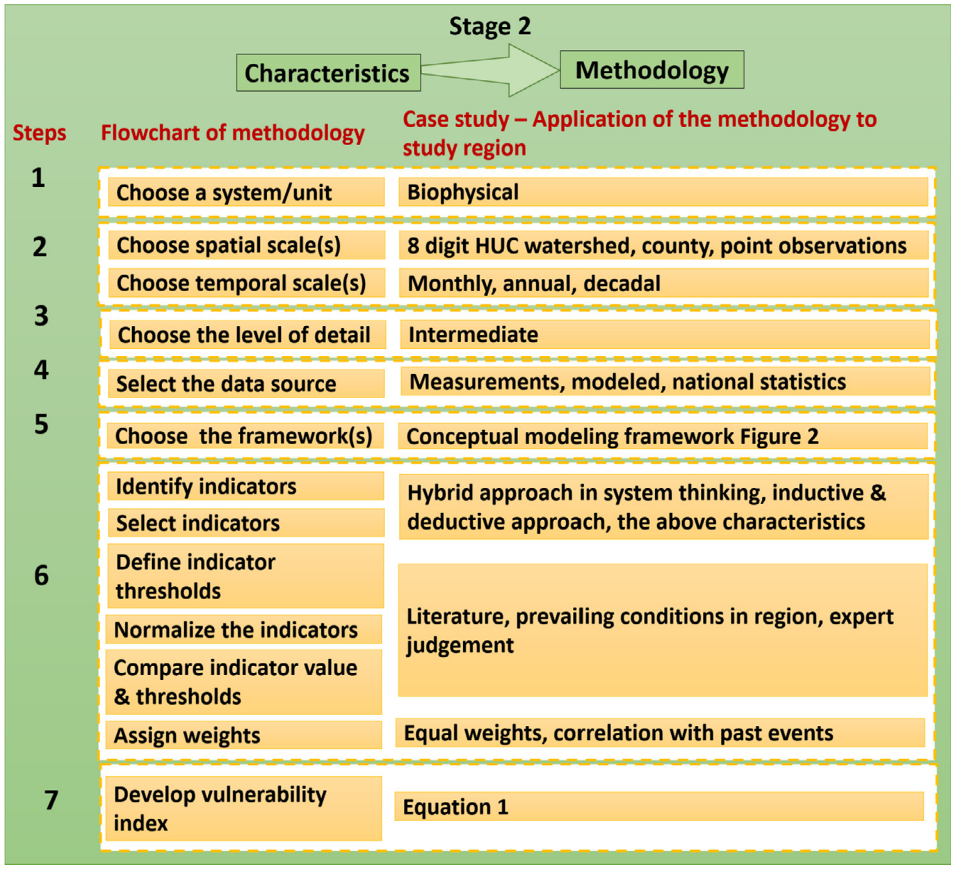


**Fig. 3.** Stage-2: Translating characteristics to the methodology for the vulnerability of water resource system assessments.

#### 2.2.1. Stage 1: Translating theoretical concept to characteristics in VWR

The studies on index-based methods for vulnerability of water resource assessments were synthesized by identifying the commonality in them (Fig. 2). They were also referred as steps, methods, procedures, and/or classification schemes in studies (Adger et al., 2004; Tonmoy et al., 2014). In this study, we referred to them as characteristics of the operational definition of VWR. The characteristics we observed from studies on vulnerability in general and VWR in particular were: target system, system components, scale, level of detail, data source, frameworks, indicators, normalization/weights/aggregation, etc. The characteristics were subjective. For example, the characteristic scale represented spatial/temporal scale and could be divided into two classification schemes (geographical scale and temporal scale) (Tonmoy et al., 2014).

**Target system:** We observed that in VWR, the target system is also referred to as knowledge domain (Tonmoy et al., 2014)), unit exposed, or system of reference (Gallopín, 2006). The target system could have an ecological, natural, biophysical, social, or socio-ecological perspective (Tonmoy et al., 2014). Some target systems can be more easily and clearly definable than others (Allen et al., 2007). Selected examples of target systems: Artic (Alessa et al., 2008; Ford and Smit, 2004) and agro-ecosystems (Bär et al., 2015).

**System components:** The target system was divided into one or more components (also referred to as parts) and the divisions varied with studies. For example, Babel et al. (2011) used two main components (represented as system's stressors and adaptive capacity); Brooks (2003) defined two components (bio-physical and social subsystems); Tonmoy et al. (2014) referred them as socio-ecological system (SES) classification scheme; Beekman et al. (2003) used three components (natural (physiography), socio-economic, and management). Components and target systems could be interchangeable.

**Scale:** There can be multiple spatial (also referred as geographical scale (Tonmoy et al., 2014)) and temporal scales. An example of spatial scales: household or political boundaries ranging from regional (farm or county level; (Babel et al., 2011; Pandey et al., 2011)) to global scales (national to continent levels), hydrology-based boundaries (Alessa et al., 2008), or based on ecoregions (Snelder and Biggs, 2002). The temporal scales could vary from monthly, annual, to decadal scales as well as at current and future time. Studies looking at social components seem to be more focused on current time while studies with biophysical in VWR focused on future scale (Tonmoy et al., 2014).

**Level of detail:** VWR assessments could have multiple levels of detail. They could be based on study objective and resource availability (Beekman et al., 2003). The details in VWR could be classified into three tiers: rapid, intermediate, and comprehensive respectively.

**Data Sources:** Directly "measuring" vulnerability is particularly misleading and challenging (Hinkel, 2011) so data on proxy variables were used. The data used could be hydrologic, socio-economic, etc. Data could be from multiple sources such as: measured, observed, modeled, or from secondary sources (e.g., federal, state, and non-government organizations) as well as information obtained from public participation, and discussions with the stakeholder group (Gain et al., 2012).

**Frameworks for vulnerability assessments of water resources:** Multiple conceptual frameworks for VWR assessments exists to address the various aspects of the dual complexity of VWR, its multiple-uses and resource availability (Tonmoy et al., 2014). Selected frameworks were: stressor-based (Perveen and

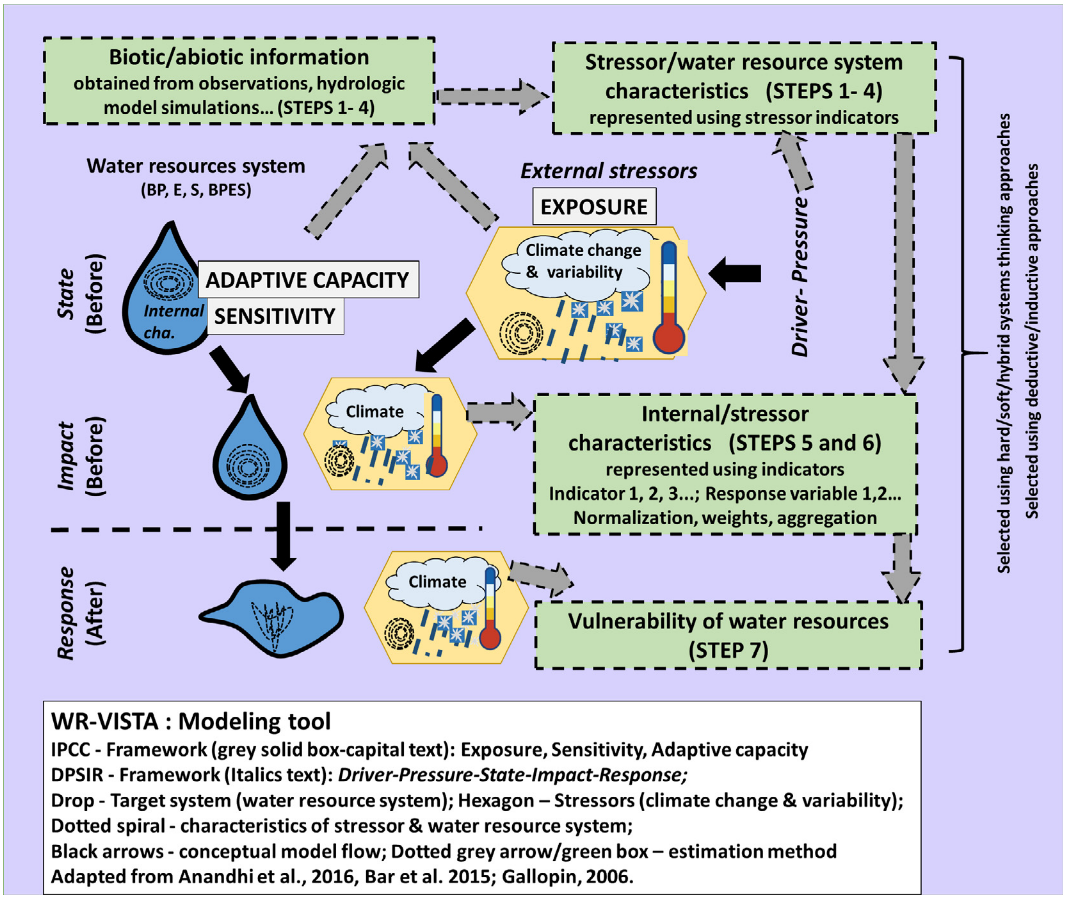


**Fig. 4.** Stage 3: Translating methodology to WR-VISTA (a decision making tool) for the vulnerability of water resource system assessments.

James, 2011), drivers and moderators-based (Alessa et al., 2008), requirement-availability-based (Brown and Matlock, 2011). Additional framework also include van der Vyver (2013) who estimated using stressors and expressed water stress using water poverty index; system characteristics-based defined by the IPCC (exposure-sensitivity-adaptive capacity), European's Driver–Pressure–State–Impact–Response (DPSIR) framework. Many studies used the parts of the frameworks or combined multiple frameworks (Gain et al., 2012). For example, Babel et al. (2011) used a framework with stressors and adaptive capacity while Hamouda et al. (2009) and Xia et al. (2016) focused on sensitivity and adaptive capacity. Ford and Smit (2004) focused on exposure and adaptive capacity while Brooks (2003) developed vulnerability as a function of exposure, sensitivity, and social vulnerability. Pandey et al. (2011) defined vulnerability as the ratio between water stress index (WSI) and adaptive capacity index (ACI) and Bär et al. (2015) combined DPSIR with the IPCC's framework. They observed that each of the frameworks had its advantages and disadvantages. Refer to Bär et al. (2015) for a more detailed explanation on some of these frameworks.

**Indicator selection in VWR:** There were several indicators used in vulnerability assessments. Their choice can be subjective to the study's goals and targets (Hinkel, 2011), the degree of response to changes (Perveen and James, 2011), etc. In general, indicators could be selected using deductive (framework based, or theory based or physical relationship based), inductive (statistical based), normative (based on value judgements), non-substantial argument (based only on data of the indicating variables) approaches (Adger et al., 2004; Hinkel, 2011), or their combination, referred as hybrid approaches. Detailed discussion of these approaches can be found in Adger et al. (2004), Hamouda et al. (2009), Gain et al. (2012), Hinkel (2011), Heink and Kowarik (2010), and Anandhi (2017). Many vulnerability studies do not clearly belong to either of the approaches. Each of the approaches have their own advantages and disadvantages.

**Normalization, weights and aggregation methods for VWR:** While constructing the vulnerability index using multiple indicators, scientifically sound methods for normalization, weighting (to specify the "correct" interrelationships), and aggregation (to get the "right" functional relationship) are important (Böhringer and Jochem, 2007). The normalization is to make data "comparable" when a variety of measurement units in which the indicator variables are expressed (Ebert and Welsch, 2004). They are carried out to avoid disproportionalities while combining multiple indicators. For example, Xia et al. (2016) used max-min normalization. The normalized indicators are aggregated using specific formulas and the indicators are assigned weights within the aggregation procedure.

*2.2.2. Stage-2: Characteristics to methodology development for VWR*

In this second stage, the eight characteristics identified and discussed in Stage-1 were translated to methodology (steps) for VWR (Fig. 3). To apply the methodology, characteristics of the flowchart (column 1, Fig. 3), namely the target system, the spatial and temporal scales, the level of detail, data sources, the framework, indicators, normalization, weights and aggregation methods, need to be identified. An example application of these characteristics for the Kansas study region was provided in column 2 of Fig. 3. The vulnerability index ($VI_i$) from time-series data (having $i$ time steps) was calculated using the ratio in Eq. (1).

$$VI_i = \frac{Average\ value\ of\ indicator\ for\ a\ period}{The\ actual\ value\ of\ indicator\ for\ a\ year} \quad (1)$$

$VI = 1$, indicated negligible vulnerability of the system to external stressors (e.g., climate change and variability). $VI$ deviating from 1 ($VI > 1$ or $VI < 1$) indicated a higher vulnerability of the system to external stressors. The wider the deviation from 1, the greater the stress.

#### 2.2.3. Stage 3: Methodology to conceptual modeling tool for VWR: WR-VISTA

In the novel conceptual model WR-VISTA (Fig. 4), the water drop represented the water resource systems (target system). E, BP, S, BPES represented the target's multiple dimensions (ecological (E), biophysical (BP), social (S), and/or their combinations (BPES)). Dotted spiral within the water drop represented the various internal characteristics (e.g., land-use and soil characteristics) and processes (e.g., runoff, vegetation growth, evapotranspiration (ET)) that described the target system's adaptive capacity (adjustment to stress) and sensitivity (response to stress). They could be divided into multiple components (e.g., water supply systems, water distribution systems) and span multiple spatial/temporal scales. For example, hydrological processes can span over larger areas with internationally shared rivers and aquifers to smaller scale watersheds, while human processes such as water treatment or delivery systems are usually limited to smaller areas of regulation and governance.

In the figure (Fig. 4), climate change was one of the external stressors represented as cloud, thunder, snow/heat. Other stressors such as increasing population, socio-economic growth, and associated land cover changes can also be considered. Depending on how the target system is viewed, climate change could be treated as a gradual, predictable, and continuous change in environmental conditions over time, or as the changing occurrence of discrete climatic extreme events such as droughts, heat waves, or floods (Butt et al., 2016). The external stressors were represented using driver-pressure characteristics. For example, precipitation characteristics such as quantity, magnitude, frequency, intensity, rate, seasonality, etc. which impact the water resource availability and supply at multiple spatio-temporal scales. These drivers (social, economic, environmental) exerted pressures on the target system, which in turn changed the target system's internal characteristics. As a consequence, the resulting impacts evoke responses (e.g., political actions or management measures) that can affect drivers, pressures, states, or impacts (Bär et al., 2015). For example, droughts and low flows in many areas of the US indicated that even small changes in drought severity and frequency would have a major impact on the various ecosystem services relating to water resource systems (e.g., drinking-water supplies) (Ford et al., 2011). The response of the target system to the impacts of external stressors was framed as the ability of the target system to adapt to change. Knowledge, power, and resources mediated the set of responses (e.g., political actions, management measures, and adaptation strategies). These involved the characteristics of the target system and stressors, the drivers of change and operators of the responses (e.g., policy makers, water managers).

The thick arrows in Fig. 4 represented the overall flow direction of processes in WR-VSTA as well as the direction of movement of time in the figure. The dotted arrows and flowchart in Fig. 4 represented the synthesized flowchart incorporated in the conceptual framework (detailed methodology is provided in Section 4). The observed/modeled biotic and abiotic information were used to represent the water resource system's (target system) and the stressors. The target system's internal characteristics (adaptive capacity and sensitivity) and processes as well its stressor characteristics (driver-pressure) were represented using indicators identified in the conceptual model using systems thinking approaches.

## 3. Study region and data used

### 3.1. Study region

The developed WR-VISTA model was applied to a case study in Kansas, which is comprised of 105 counties (Fig. S1 in the supplementary material). The region is important in many ways. The region has the second-highest cropland acreage in the US (Anandhi et al., 2013a). The study region is part of the "breadbasket of the world," or the "grain basket of the United States" (Anandhi, 2016), and has some of the most productive agricultural lands in the country. The corn production land in Kansas over-lies the High Plains (Ogallala) Aquifer, and the Kansas portion has one of the steepest water-level declines in the aquifer (Sanderson and Frey, 2014). The High Plains Aquifer is the largest aquifer in the US, supplying 70% of the total groundwater and providing 30% of the irrigated water to the country (Zhang et al., 2016). Additionally, Kansas has the highest decrease in ground water level in the aquifer. Declining water levels in the aquifer affect the agricultural production in the region (Steward et al., 2013), national food production, and impact the nation's food security. Previous studies have indicated changes in the last spring freeze, first fall freeze, growing season, plant phenology, warm/cold/wet/dry spells, plant failure temperatures, and extreme rainfall in the region (Anandhi, 2016; Anandhi and Blocksome, 2017; Anandhi et al., 2013a; Rahmani et al., 2015; Rahmani et al., 2014). Additionally, exposure of the agricultural production in the region to these changes can amplify the vulnerability of hydrological systems (Anandhi et al., 2016b).

### 3.2. Data used

Water resource systems have distinct spatial, temporal, and physical characteristics because of its complexity and multidisciplinary nature. For example, the spatial management of these systems involves many stakeholder collaborations (e.g., policy makers, researchers, citizens, producers) at different levels of action (Murgue et al., 2015). Therefore, data collection at common temporal and spatial scales is a big challenge (Khan et al., 2017). Multiple spatial (e.g., point, watershed scale) and temporal scales (e.g., daily, annual scale) data were used. Additionally, these data were from multiple sources such as measurements (e.g., temperature), modeled (e.g., evapotranspiration), and secondary sources (e.g., Kansas Department of Agriculture). The details of the data used in the case study were provided in Table 1.

## 4. Results

### 4.1. Application to the case study in stages 1 and 2

Translating the theoretical concept to the operational tool for VWR in three stages is demonstrated in the Kansas region of the Ogallala Aquifer (High Plains Aquifer). In Stage 1, eight characteristics were selected for translation. They were target system, system components, scale, level of detail, data source, frameworks, indicators, and methods for normalization/weights/ aggregation.

For the application, six steps were used in Stage-2 for operationalizing charateristics to methodology in VWR (Column 2 of Fig. 3). In this study, the water resources system was the chosen target system with mainly biophysical components. The data was at several spatial and temporal scales. For example, streamflow and ET were at 8-digit hydrologic unit code (HUC) spatial scale,

**Table 1**
The details of the data used in the case study.

| Variable name | Spatial scale (Temporal scale) | Data source |
|---|---|---|
| Precipitation, air temperatures (maximum and minimum) | Point, 26 weather stations data (Daily). Details in Fig. S1, Table S1, Anandhi, et al. (2016a), and Anandhi et al. (2013a) | Measured data from High Plains Regional Climate Center's (HPRCC) website (Fig. S1, Table S1) |
| Evapotranspiration (ET), runoff | 8-Digit HUC-Hydrologic Unit Code, 90 HUC for Kansas, (Annual) | Modeled from Soil and Water Assessment Tool (SWAT) Kannan et al. (2013) |
| Stream flow | Point, Model setup, calibration and validation during 1960–1965, 1951–1980, and 1971–2000 respectively | Measured data from 5951 and 54 USGS gauging stations, respectively |
| ET | 8-Digit HUC-Hydrologic Unit Code annual ET for the period 1971–2000 is compared to corresponding published estimates | Based on a water balance method with a combined land cover and climate regression equation (Sanford and Selnick, 2013) |
| Topography | Gridded-input to SWAT model (one time) | National Elevation Dataset |
| Land cover | Gridded- input to SWAT (one time) | National Land Cover Data |
| Soil | Gridded-input to SWAT (one time) | STATSGO soil databases |
| Area | County-wise (one time) | Kansas Statistical Abstract (http://ipsr.ku.edu/ksdata/) |
| Population | County-wise data for the period 1980–2012 (annual) | Kansas Statistical Abstract (http://ipsr.ku.edu/ksdata/) |
| Water use, acres irrigated | County-wise data for the period 1980–2012 (annual) | Kansas Department of Agriculture – http://agriculture.ks.gov/docs/default-source/dwr-water-appropriation-documents/2011_irrigation-water-use.pdf?sfvrsn=2 |
| Standard Precipitation Indexes (SPI) | Nine climate divisions in Kansas from 1895 to 2012 (1-, 3-, 6-, 9-, 12-, and 24-month referred as SPI 1, SPI 3, SPI 6, SPI 9, SPI 12, SPI 24) | Estimated from precipitation downloaded from (ftp://ftp.ncdc.noaa.gov/pub/data/cirs/climdiv/)(Anandhi and Knapp, 2016) |

precipitation was the station data at point scale at daily time steps, and population data were at county level and annual scale. The case study was at an intermediate level of detail using data from several sources (e.g., measurements, modeled information, and secondary statistics (Table 1). The WR-VISTA framework was used to select 26 indicators. The indicators were selected using a hybrid approach (more details in Section 4.3). Normalization was carried by averaging and aggregated using equal weight and correlation with historical events.

### 4.2. Hydrologic model calibration and validation results

In the absence of observed/measured information on multiple components (biophysical/social/economic/combinations), model simulations were used. In this application, runoff/ET was estimated using the SWAT model and the plant growth stage was simulated using the heat unit model (Anandhi, 2016). The SWAT model calibration and validation were carried out on annual average runoff (1965–1985) and annual average actual ET (1971–2000). The results were aggregated from the model at the 8-digit HUC level for a comparison with the observations. Statistical measures such as mean, standard deviation, coefficient of determination ($R^2$), and Nash-Sutcliffe prediction efficiency (NSE) (Nash and Sutcliffe, 1970), percent bias (PBIAS) (Gupta et al., 1999), and RSR (Legates and McCabe, 1999) were used to evaluate the model performance of predicting annual runoff and annual actual ET. If the $R^2$ and NSE values were less than or very close to zero, the model prediction is considered unacceptable or poor. If the values are 1.0, then the model prediction is perfect. Values greater than 0.6 for $R^2$ and greater than 0.5 for NSE, less than ±25% for PBIAS, and less than 0.7 for RSR were considered acceptable for flow (Moriasi et al., 2007; Santhi et al., 2001). The validation of the SWAT model was carried out using the guidelines of Biondi et al. (2012). There was a close correlation between the model-predicted annual runoff and the observations except for a few 8-digit HUCs. This was evident from the patterns of predicted and observed annual runoff as well as the model performance evaluation statistics (NSE, $R^2$, PBIAS, and RSR) presented in Fig. 5. Except NSE and RSR, all of the other model performance evaluation measures suggest an acceptable quality of modeled ET with respect to observations. In summary, the quality of model estimated annual average runoff and ET values appear reasonable and acceptable.

### 4.3. Application of WR-VISTA (Stage 3) for identification of indicators in the case study

Utilizing the WR-VISTA (conceptual modeling tool), 26 indicators were selected in the case study for VWR to stressors which largely represented changes and variability in temperature and precipitation, and to a smaller extent on population change (Table 2). The application of systems thinking approaches in their selection for the development of WR-VISTA is given below. The water resources system (target system) in Kansas includes bio-geo-physical processes (e.g., elements of the hydrologic cycle: runoff, evapotranspiration, precipitation; ecosystem functioning) and human processes (e.g., human decisions and actions regarding irrigation with the declining groundwater levels in the Ogallala Aquifer). Runoff, evaporation, evapotranspiration, and ground water recharge could be some examples of hydrological processes; vegetation growth and development could be examples of the ecological process, while those for internal characteristics could be land-use and soil characteristics. These processes could span over the entire state with a shared hydrology of rivers (e.g., Kansas River) and aquifers (e.g., Ogallala) shared across neighboring states (e.g., Colorado, Nebraska); human processes such as regarding increasing water demands and declining water supply are usually limited to smaller areas of regulation and governance (e.g., county level, groundwater management district 1, 3, and 4 levels). Some of the processes could vary across the water cycles from a larger scale to smaller scales. Water resource systems in this study were examined from biophysical (BP) dimensions. Each of these dimensions in the water resource system could be divided into individual parts. Some examples include water supply systems and water distribution systems for agricultural and urban water use.

In the WR-VISTA, runoff, evapotranspiration, stages of plant growth and development, and water resource variability (WRV) were some of the internal processes chosen in the target system. We used both inductive and deductive approaches to identify these indicators that represented internal characteristics of the water resource system. Vegetation plays an import role in the water resource system. Growing degree-days was the indicator used to represent plant growth and development, while other indicators such as runoff and evapotranspiration represent the hydrological components of the water cycle. The internal characteristics and processes of the water resource systems were represented using

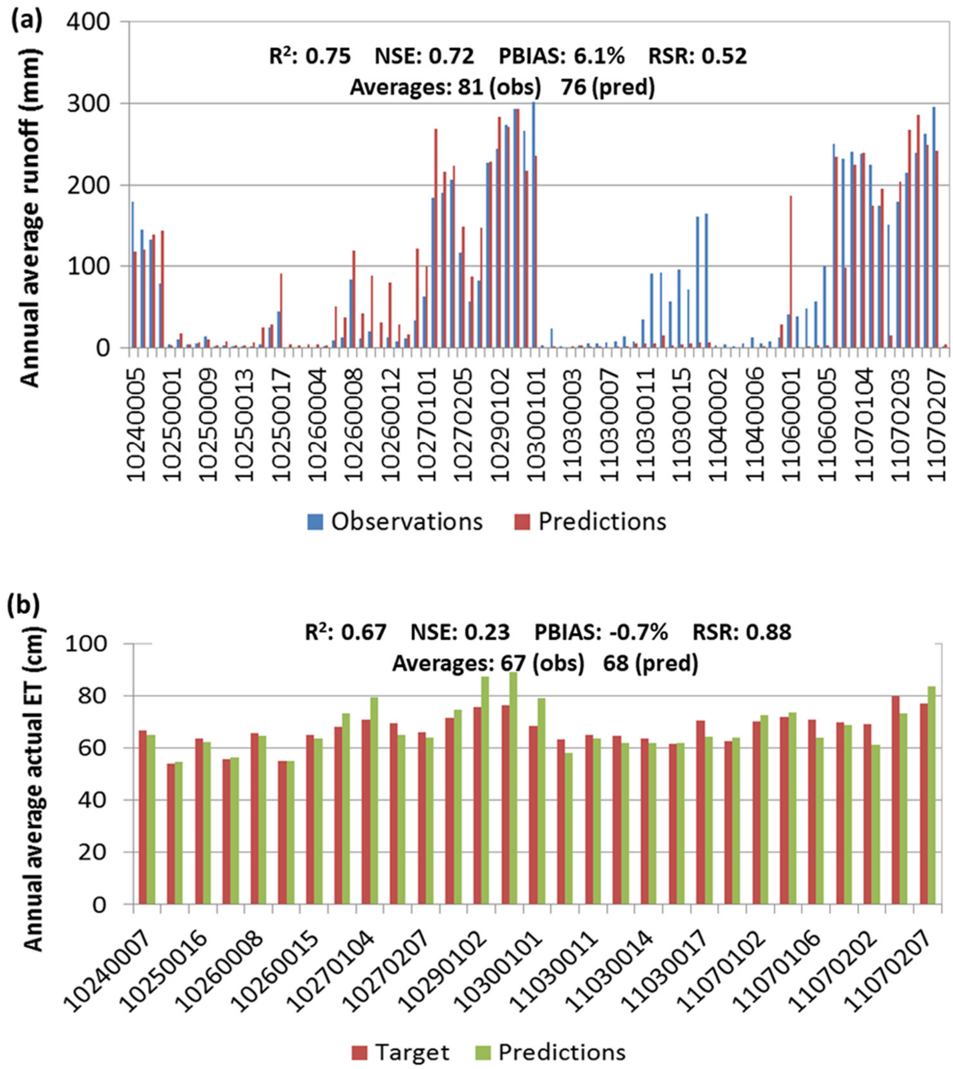


**Fig. 5.** (a) Annual average runoff of 8-digit HUCs in Kansas (NSE: Nash and Sutcliffe Efficiency; $R^2$: Coefficient of determination; PBIAS: Percent BIAS; RSR: Root Mean Square Error (RMSE)-observations standard deviation ratio. (b) Annual average actual ET of 8-digit HUCs in Kansas (Note: The ET comparison was possible for 29/90 HUCs only).

adaptive capacity (adjustment to stress) and sensitivity (response to stress).

To represent the sensitivity of the water resource system to climate change and variability stressor, the changes in the target system characteristics (runoff and evapotranspiration) across time were correlated with the changes in the indicators to represent the response of the target system to external stress (Fig. 6). WRV over a period of years determines the reliability of annual available water resources (Table S2 in the supplementary material). WRV was expressed in percentages. Variability in rainfall is a key parameter related to agricultural production and water management (Devineni et al., 2013) in managed and natural ecosystems. To identify the long-term variation of water resources, we used the county level coefficient of variation of annual precipitation (CV) during the 2000–2012 period. Water resources scarcity (WRS) indicator (equation in the supplementary material), or social water stress, is the average water available per year per person (Perveen and James, 2011). The water scarcity threshold is subjective to the region, society, and its affordability. The highest vulnerability had a maximum value of water stress (=1). The county-level per capita water availability for the period of 1985–2010 was calculated. It is the total water use (both from fresh and saline water sources) divided by the population. The irrigation coverage represented the extent of water resources used for irrigation. A high value indicated more dependence on irrigation and a low value indicated a lower dependence. The sensitivity of the water resources system is affected by population density and the area cultivated that is dependent on water resources. Land use patterns that maintain the integrity of watersheds have a significant influence on surface water resources (Price et al., 2011) and have interactions with drought (Xia et al., 2016).

Vulnerable groups are more exposed and less capable of adapting to stressors due to limited infrastructure and inputs (McDowell and Hess, 2012). For example, smallholder farmers are often considered particularly vulnerable to climate-related food insecurity, such as exposure to drought, than more commercial farmers who have higher adaptive capacity from that exposure using irrigation, narrow yield, etc. Adaptive capacity is necessary to convert natural and social resources into useful adaptation strategies (Briske et al., 2015). For example, changes in frost indicators (first fall freeze, last spring freeze) are useful to develop incremental adaptation strategies such as planting earlier/harvesting later or systems adaptation such as different crop variety. Trends in growing degree-days (GDD) are useful to develop adaptation strategies such as irrigation amount and timing, water management, and selecting crop varieties. Changes in drought (e.g. SPI index) and crop growth (GDD)

**Table 2**
Indicators range observed in the study.

| S.N | Indicator name | Range in values |
|---|---|---|
| 1 | Water resources variation (WRV) | 0.3–0.96 |
| 2 | Irrigation coverage | 0.0–2.25 |
| 3 | Water resources scarcity (WRS) | 0.35–1.0 |
| 4 | Population density | 0.05–34.0 |
| 5 | Average population change | −4.0 to 7.2 |
| 6 | Average annual precipitation (RF) | 411–1006 mm |
| 7 | Average annual runoff | 11–300 mm |
| 8 | Average annual evapotranspiration (ET) | 400–806 mm |
| 9 | Wet Spell Length (WetSL) | 0.8–1.6 |
| 10 | Average WetSL (AvWetSL) | 0.9–1.2 |
| 11 | Maximum Consecutive Wet Days (MaxWetSL) | 0.7–1.6 |
| 12 | Dry Spell Length (DrySL) | 0.95–1.1 |
| 13 | Average Dry Spell Length (AvDrySL) | 0.75–1.2 |
| 14 | Maximum Consecutive Dry Days (MaxDrySL) | 0.75–1.5 |
| 15 | Warm Spell Days (WarmSL) | 0.50–2.5 |
| 16 | Average Warm Spell Days (AvWarmSL) | 0.50–1.5 |
| 17 | Maximum Warm Spell Days (MaxWarmSL) | 0.50–2.5 |
| 18 | Cold Spell Days (ColdSL) | 0.50–2.5 |
| 19 | Average Cold Spell Days (AvColdSL) | 0.90–1.5 |
| 20 | No. of coldSL | 0.50–2.0 |
| 21 | Maximum Cold Spell Days (AvColdSL) | 0.75–2.0 |
| 22 | Average Maximum temperature (Tmax) | 0.99–1.01 |
| 23 | Average Minimum temperature (Tmix) | 0.99–1.01 |
| 24 | Average temperature (Tave) | 0.99–1.01 |
| 25 | Standard precipitation index (SPI) – 3, 9 and 24 months | −1.0 to 1.5 |
| 26 | Average precipitation (Pptn) | 0.75–2.0 |

*Note:* Details about rows 1–8 can be found in Table S2, Figs. 6 and S3; the values in rows 9–26 is a ratio calculated using Eq. (1) and represented in Fig. S2.

will support water management. More information in translating these indicators to adaptation strategies in agro-ecosystems and water management can be obtained from Anandhi (2017) and Steiner et al. (2017). For an application, the indicators described in this study can be used as a model by stakeholders (e.g., farmers, water managers, and decision-makers) or a completely a new set of indicators can be selected using WR-VISTA framework.

Temperature and precipitation change and, to a smaller extent, population change were the external stressors considered in this study. Given the uncertainty of the future climate (and other changes), consideration for enhancing the robustness of such a decision is warranted. We used the hybrid approach for the indicator selection. Climate was represented using variables such as precipitation and temperature, while the population was represented using the number of people. For example, changes in rainfall and temperature characteristics (stressor characteristics) impact water resource systems and its internal characteristics and processes. As a consequence, the resulting impacts evoke responses (e.g., political actions or management measures) that can affect drivers, pressures, states, or impacts (Bär et al., 2015). Climatic processes drive the water resource system processes (e.g., hydrological cycle, water temperature) (Snelder and Biggs, 2002). We incorporated the mean and extreme climate, its variability and relevant hydrological elements, for ecosystem functioning information. The coefficient of variation of precipitation, variability in drought, mean and extreme precipitation and temperature, duration of spells (wet/dry/warm/cold), growing season length, population density and change, and proportion of cultivated area dependent on irrigation were some of the indicators selected in this study (Fig. 6, defined in Table S2, Figs. S2 and S3 in the supplementary material). They were chosen to represent the variations in stressor characteristics, the magnitude of the pressure, and intensity of the drivers of water resource system processes. Many of these indicators represented the stresses of extreme climate impacting land-use (e.g., agriculture, irrigation), water use (e.g., irrigation), and processes in water cycle (e.g., ET, runoff). Some of these indicators represented the variability in precipitation, a key parameter related to runoff, agricultural production, and water management (Devineni et al., 2013) while others represented the prolonged periods with precipitation and temperature extremes (e.g., wet/dry spells, frost). These have many ecological and hydrological consequences such as implications on the water cycle, changes in the growing season, crop growth and yield, milk production in livestock, and reproductive capabilities of farm animals (Anandhi, et al., 2016a). Changes in frost indices impact the hydrological and energy cycles by changing the patterns in ET and streamflow, and the frequency of drought (Anandhi et al., 2013b). Changes in precipitation and ET may cause annual runoff to change. Additionally, changes in temperature are expected to change the hydrology of the region by decreasing the precipitation falling as snow, shifting the timing of snowmelt, and the streamflow resulting from snow-melt to occur earlier in the spring or in late winter, which eventually changes the magnitude of streamflow. Warming and drying are expected to modify vegetation composition and land-surface cover, including an increase in the density and cover of woody plants in the region (Briske et al., 2015). Very few indicators representing the social unit are chosen in this study. The density of population is one of them. It is the number of people per square mile and represented the population centers in Kansas (indirectly the land-use). A higher value indicated the presence of a relatively bigger city and a lower value indicated a rural setting. An index of the cultivated area under irrigation was developed to identify the dependence of agriculture on water resources.

### 4.4. Vulnerability results estimated in the case study using the developed tool

Our results indicate that vulnerability components in the WR-VISTA model (exposure, driver, pressure, stressors, sensitivity, adaptive capacity, state, impact, and response) are not static but change over time and space. These changes were translated to changes in the vulnerability indicators and observed from the red shaded portion obtained from the time-series in Fig. 6 and synthesized in Table 2. The correlation of the indicators to the region runoff and evapotranspiration for the period 1971–2000 were plotted in Fig. S3 in supplementary material, while the spatial variation were potted at a county level in Fig. 6. Time-series of the indices estimated in the study using Eq. (1) and the indicator description provided in Table S2 in the supplementary material. Mean values of selected indicators obtained from 105 counties in Kansas are discussed in this section as spatial plots (Fig. 6).

Understanding adaptation to multiple stressors allows us to address the complexity of vulnerability (McDowell and Hess, 2012). From the time-series plot of the exposure indicators across Kansas, we observed the degree of stress varied with the indicator and time-period. In Fig. S2 in supplementary material, a greater spread of the shaded portion indicated greater spatial variability. The hills and valleys in the plot indicated higher vulnerability of the indicators. The higher the peaks of the hills and valleys, the greater the vulnerability (observed by higher deviation of the index from 1). For example, in Kansas, the 1930s and 1950s had high vulnerability and served as benchmarks for severe, climate-stressed periods although the spatial dimensions of both the 1930s' and 1950s' droughts were different. The vulnerability varied with the indicator as seen by the different y-axis in the sub-plots. Indicators that represent the mean stressor and target system characteristics (e.g., average annual precipitation (Pptn), maximum, minimum, and average temperature (Tmax, Tmin, Tave) have smaller vulnerability indices when compared to the indicators representing extremes.

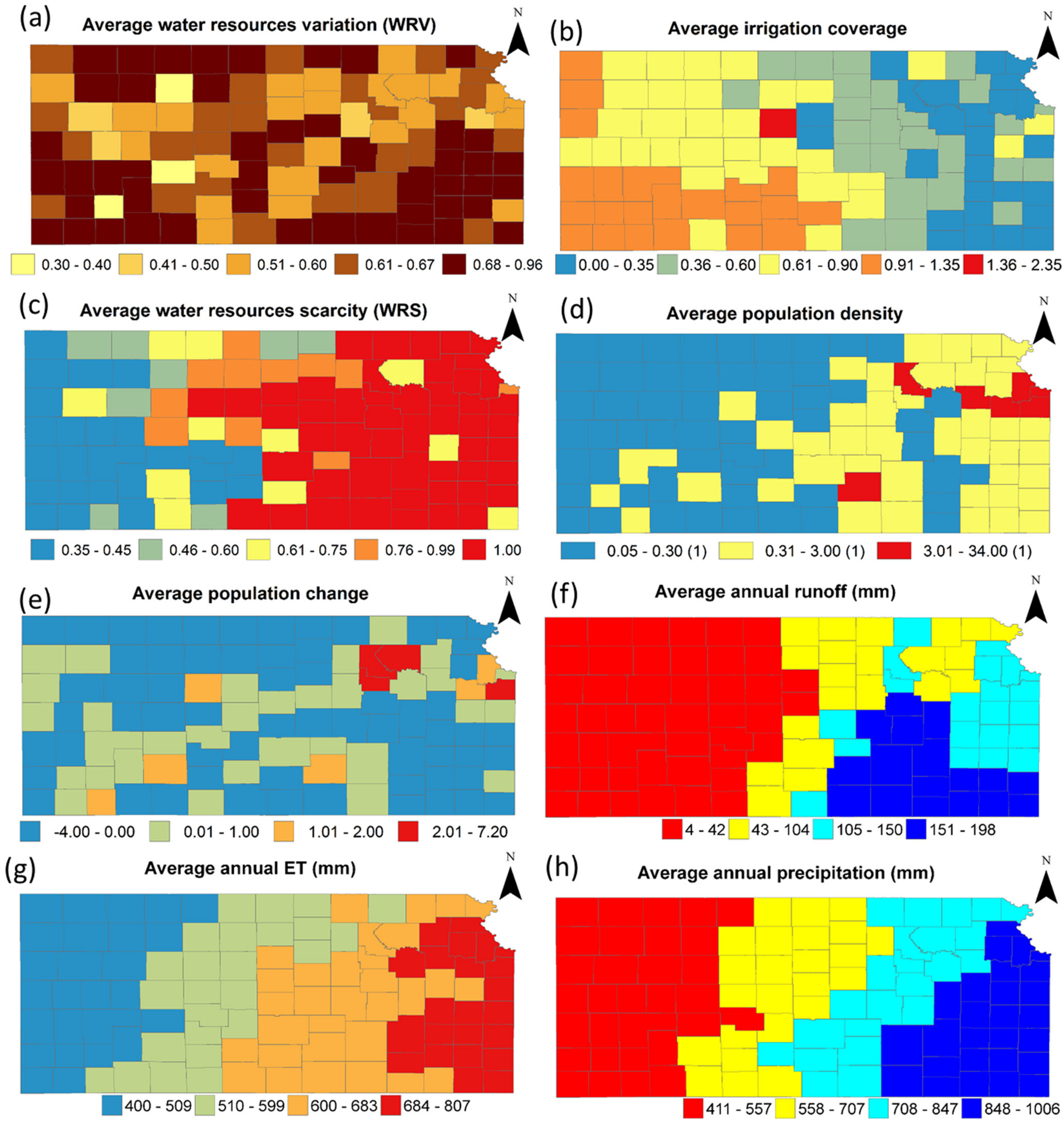


**Fig. 6.** County-wise variability in the indicators selected to represent the VWR in Kansas. In Figures f and h, low values are represented by a red color while in the rest of the plots, red represents high value. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

The sensitivity of the indicators to evapotranspiration and runoff also varied with indicators. No one indicator showed a strong sensitivity to evapotranspiration and runoff. This was observed from a five-year moving average of the time series plot of evapotranspiration and runoff for the 1971–2000 time-period were shown for the various indicators selected in this study (Fig. S3 in supplementary material). The shaded portion in the figure represents the 95th and 5th percentile values of the indicators in each year. The solid, bold, black line in the middle of the shaded portion represents the median value for each year. In this study, the simple probabilistic approach (95th and 5th percentile values) was used to represent the sensitivity. The results can be more reliable if more advanced uncertainty analysis methods are used (Biondi et al., 2012). Similarly, observed values of streamflow/ evapotranspiration at the location of the stressors can provide more reliable sensitivity results.

The WRV is provided in Fig. 6, and its variability is more in central Kansas. WRV (a function of the coefficient of rainfall), is a key parameter that represents agricultural production, its water management especially for rain fed agriculture. The western Kansas regions with higher WRV overlie the High Plains Aquifer and also have the highest market value for agriculture in the nation (Steward et al., 2013). Changes in precipitation and temperature observed in the region (Anandhi, 2016; Anandhi et al., 2013a;

Rahmani et al., 2014) would increase the WRV in the region. This, in turn, would increase the region's exposure to climate change. Ground water use for irrigation buffers the variability in precipitation for agriculture (Devineni et al., 2013) and domestic water use stresses the region's already declining ground water levels in the aquifer. The counties in western Kansas had a higher area under irrigation (Fig. 6b). Declining water levels was predicted to cut agricultural production in the region (Steward, 2014) thereby decreasing their adaptive capacity and increasing the VWR in the region.

The WRS map is provided in Fig. 6c and the scarcity was more in eastern Kansas when compared to western Kansas. In this study, WRS is a function of water availability and social water stress which in turn was a function of the population in the region. Counties in eastern Kansas had increased urbanization in the last few decades (Applegate et al., 2003) with a higher population density (Fig. 6d). No clear patterns in population change were observed (Fig. 6e). The WRS was higher in this part of Kansas even though they have higher rainfall and higher surface water availability when compared to the western part of the state.

## 5. Discussion

### 5.1. Indicator selection and systems thinking approaches

There is extensive literature on various indicators relating to the ecological, biophysical, socio-economic, and political dimensions that underlie VWR. Ecological/biophysical indicators measure impacts of water resource and use on the environmental domain, while the socioeconomic indicators measure fiscal or societal effects of water resource (Lane et al., 1999). System thinking approaches were used in this study to develop the tool (Figs. 1–4).

The introduction of systems thinking has had major benefits in the world of change and has also been a powerful stimulus to the development of an understanding of the natural systems allowing an integration of disciplines (Röling, 1997). While recognizing that extensive literature exists in applying systems thinking approaches to various applications (e.g., agriculture (Van Keulen and Schiere, 2004)), to the knowledge of the authors, hardly any studies have applied systems thinking to vulnerability assessments of water resources. In the past, Anandhi et al. (2016b) had used the systems thinking approach for one component of vulnerability (exposure) for a different target system (agriculture) than this study.

Hard and soft thinking are the two extremes of system thinking. The hard system thinking is based on deductive thinking, while soft system thinking focuses on mindsets (Van Keulen and Schiere, 2004) which are highly dependent on context and purpose. In hard thinking, the system is perceived with boundaries (e.g., time and space (Röling, 1997)), inputs and outputs, and using coded variables (e.g., indicators). Examples of spatial boundaries include political (county, state), hydrological (watershed, river basin), while decadal and annual could be temporal boundaries. An example of inputs could be rain, and outputs could be streamflow, evapotranspiration, etc. These approaches are used to characterize entities and areas concerned with alternatives and to assess the impacts of the alternatives by using indicators, for example, such as water volume withdrawn for irrigation. Hard thinking approaches provide quantitative and stable information, ensuring the saliency of inputs/outputs. In contrast, soft thinking approaches perceived the systems with highly fuzzy boundaries, inputs, and outputs (Röling, 1997). These approaches could be used for interacting with stakeholders and designing change options under investigation, which ensures the legitimacy of the process because it avoids the black box effect (Murgue et al., 2015). Examples could include perceptions of vulnerability, stress, exposure, etc. The fuzziness could be that each stakeholder understands the complex system according to his/her own interests, activities, and management strategies (Murgue et al., 2015). Therefore, combining both hard and soft thinking when selecting elements (hybrid approach) can be challenging, but it provides support in explaining the complexity of the system (Anandhi, 2017; Salerno et al., 2010).

### 5.2. Adaptation of the developed tool for multiple stakeholders

The study goals and objectives, the characteristics (Stage 1), methods (Stage-2) and indicator selection using WR-VISTA conceptualizations (Stage 3) depends on the water use, stakeholder requirement and their he resource availability. Our description of the assessment of VWR is presented in stepwise fashion, recognizing that various scientific and social processes will likely proceed simultaneously and many need to be repeated iteratively. While recognizing the existence of an extensive literature on various characteristics which underlined VWR for various stressors, there is subjectivity in selecting the eight characteristics from Stage 1 of this study. In this stage, the number of characteristics used in a study could be modified in a way that is beneficial to stakeholder and their water use (e.g., for domestic/agricultural/industrial use, used as a sustainer of ecosystems, or viewed as a hazard). Characteristics could be added, removed and/or split (e.g., scale to spatial and temporal scales).

In this study, we were interested in the application of the proposed framework for an intermediate level of detail using a few selected indicators for simplicity. In the future, by utilizing the 3-stage framework, a user/stakeholder could choose steps (Figs. 1–4) and indicators to develop the conceptual model. We believe that, depending on the available resources and the need, stakeholders are likely to adapt this tool, including the WR-VISTA model, for VWR assessment for various stressors. Depending on the study goals and objectives, the definitions of target system and components could be interchangeable. A target system could be a component of a larger system; at the same time, the component could be a system with smaller components. The choice of indicators for representation of the processes, and internal and external characteristics for these assessments could also vary. An elaborate discussion on indicators for ecology and environmental planning can be found in Heink and Kowarik (2010). Hamouda et al. (2009) categorized the indicators into hydro-physical indicators and socio-economic or political nature.

Depending on the availability of data and resources, the vulnerability assessments could be carried out at multiple levels of detail. For example, in the short term, changes in temperature had the potential to change plant water use via transpiration and evaporation, and hence, change the rainfall runoff ratio or groundwater recharge. In the longer term, changes in temperature could produce shifts in species distributions (e.g., a shift from deciduous to evergreen forests) which was likely to result in changed water use due to changed year-round transpiration and interception (Ford et al., 2011). Other hydrological models as well as crop and biogeochemical model outputs could be used to simulate processes and characteristics of the target system and its components. Additional indicators to represent the adaptive capacity that encompasses the ability to recognize and manage risk, plan and implement adaptation strategies, display financial and emotional flexibility (described in the section below), and even exhibit awareness of climate change and the need for adaptation could be added.

The current study did not include the comprehensive list of indicators that could be potentially used for the study region because the framework does not attempt to provide "optimal" solutions in the traditional decision, analytic sense. Instead, using only a few indicators in VWR at an intermediate level of detail, the approach was described. Identifying indicator(s) is an important component in VWR assessments. We recommend systems thinking approaches to identify region-specific indicators based on expert and local knowledge through discussion with stakeholders (e.g., water managers, extension specialists, etc.). Also, indicators could be selected based on a literature review or available data. Indicator identification exercise is difficult because each stakeholder understands this complex water resource system according to his/her interests, activities, and management strategies. For example, agricultural practices vary from an agricultural viewpoint, where they are the result of decisions of individual farming systems involved in socio-professional networks, while from the viewpoint of water managers, the practices are considered at the river basin level.

### 5.3. Adaptation of the developed tool for other stressors

Our description of the assessment of VWR is presented in stepwise fashion, recognizing that various other stressors will likely to impact them. The same procedure could be repeated iteratively or simultaneously for other indicators/stressors as well. With the emerging scientific consensus that the global population was likely to exceed 9 billion people by 2050 (Gerland et al., 2014), most of the increasing population will be in cities of the world. Urbanization and population growth can be potential stressors. In the context of climate change and other stressors, physical stressors may determine the physical quantity or quality of the water resource. However, the ability to benefit from such water depends on a broader set of abilities or access mechanisms such as technologies, landscape configurations, social capital, violence, or theft (McDowell and Hess, 2012). Some region-specific stressors are that the area under forests and wetlands can be used as the natural capacity parameter to indicate the ecosystem state. A higher value of the indicator indicates a more natural state or less human interventions, thus suggesting less vulnerable water resources system. Physical capacity can be represented using indicators such as the area covered by irrigation, with drinking water supply, or industrial use. The area covered with drinking water represents the percentage of the population with access to improved water supply. The industrial coverage indicates industrial development area with water supply. Higher coverage indicates better physical infrastructures and financial resources. The literacy rate and economically active population indicators are considered to represent the socio-economic capacity. A higher literacy rate suggests a relatively better awareness and ability to understand water-related issues. It may in due course steer the people to cope with a variety of water-related stresses and thereby increasing the adaptive capacity of the water resources system. The economically active population is another indicator (the age of working people). A higher economically active population reflects a higher flexibility to adapt to the new conditions/living patterns under increased stresses in the water resource system. This indicator is not used in this study due to a higher literacy rate in the region.

### 5.4. Potential uncertainties in WR-VISTA

Uncertainty in WR-VISTA can arise from many sources that can be grouped into three categories: model uncertainty, scenario uncertainty, and measurement uncertainty. Some model uncertainties arise due to insufficient knowledge, indicator fatigue, scoring framework, and weighing. Uncertainty due to insufficient knowledge arises when a few criteria were assessed due to limited knowledge about the abstract components or from assumptions or limitations of simplified models describing complex processes, such as the models describing future climate conditions or the algorithms describing components of water cycle-climate relationships. Studies have shown that changes in climate have important implications on the water availability; to understand the entire target system, it was necessary to examine the individual components and the interrelationships among them (Allen et al., 2007). The vulnerability indicators in the WR-VISTA model were used as one or more proxy variables to represent abstract components, namely exposure, driver, pressure, stressors, sensitivity, adaptive capacity, state, impact, and response. Depending on the stakeholder's judgment, the scope/location of the study, and the question to be answered, the indicators or sets of indicators in WR-VISTA would differ from study to study.

The model can accommodate different units of analysis. If not adequately integrated, it will result in "indicator fatigue". This is due to missing of important variables, co-linearity, lack of accounting for interactions/feedbacks, situation-specific normative judgments of researchers and users knowledge (Malone and Engle, 2011). The scoring uncertainty occurs when an expert feels that more than one value is equally likely to represent the vulnerability of the target system and weighting uncertainty occurs when one or two criteria contribute disproportionately to the vulnerability or value score (Reece and Noss, 2014) for a component.

Weighting is to specify the "correct" interrelationships (Böhringer and Jochem, 2007) to appropriate parameters. This study did not weigh constituent indicators differently because it was difficult to determine the order of importance of constituent indicators and parameters. For example, we had difficulty determining if precipitation change is more important than surface water change in VWR assessments. Equal weight method is recommended for applications where there is no sufficient expert knowledge or information on indicators. While using equal weight method, use caution because the vulnerability index can be highly influenced by dominating indicators (Anandhi, 2016). In the past, different indicators have been weighted differently, with some indicators given greater importance than others (Baettig et al., 2007). Previously, weights were assigned using expert judgment or statistical analysis such as geometric mean, principal component, correlation, fuzzy logic, or econometrically (Anandhi et al., 2016b; Bhattacharya and Das, 2007; Böhringer and Jochem, 2007; Deressa et al., 2008; Simelton et al., 2009).

Aggregation is to get the "right" functional relationship (Böhringer and Jochem, 2007). The functional relationship could involve known scientific relationships among variables (e.g., hydrological models, growing degree-days indicator to represent plant growth stage and its water use); experts could be consulted in a rather open discussion process, and statistical relationships among variables. Choosing normalization methods and weightings will, in general, be associated with subjective judgments (Böhringer and Jochem, 2007). Some of the selected indicators may require the definition of thresholds (see Section 4.2). The thresholds or values indicated acceptable conditions and standards. They provided a measure on whether or not the indicators contributed significantly to vulnerability. The critical values of some indicators proposed in the literature (Falkenmark and Widstrand, 1992) can be used, while others need to be estimated based on the prevailing conditions in the study area.

Uncertainty in how we are defining the target system and its components because the terms target system and components can be interchangeable. A target system could be a component of a larger system; at the same time, the component could be a system with smaller components. The choice of indicators in WR-VISTA could be region specific (more details in the next subsection). The estimated indicators (from observed and modeled biotic and abiotic information) were aggregated using Eq. (1) for determining VWR in WR-VISTA. Incorporating mean and extreme climate, its variability and relevant bio-geo-physical processes, relevant hydrological elements, ecosystem functioning information, and human processes are useful but complicated. Omitting them will almost certainly lead to incomplete understanding and should be taken up or addressed in comprehensive vulnerability analyses (Butt et al., 2016).

Scenario uncertainty arose when the indicators were chosen to attempt to capture the range of uncertainty in vulnerability assessments in space and time, although the true range of the uncertainty remains unknown. These indicated how vulnerable current conditions are and future conditions might be. The variation in the indicators provide a range of scenarios and presents the stakeholders with difficult choices. For example, the ranges might include one scenario where no action is necessary and another where very costly investments are necessary. Planning for either of the above mentioned sceanarios could result in considerable potential regrets. Given the limited resources typically associated with addressing some of the extreme case scenarios, a water manager is unlikely to be comfortable committing resources by a single or small number of scenarios (Brown et al., 2012).

Measurement uncertainty arises from imprecision or errors in obtaining data, and can occur when geographic coordinates of observations are recorded or transcribed incorrectly, or alternative climate datasets use different weather stations, time periods, and interpolation techniques to create climate maps (Watling et al., 2015). Use of uncertainty and sensitivity analysis can assist in identifying the gaps and check the robustness, thereby further enhancing the transparency and credibility of the tool (Singh et al., 2012).

### 5.5. Water resource vulnerability and societal impacts

Vulnerability assessments on water resources are powerful analytical tools for describing states of risk, powerlessness, the marginality of systems, and for guiding actions to enhance prosperity through mitigation of risk (Adger, 2006) against various stressors. Besides, they show where unsustainability may be the most likely (Bär et al., 2015). These assessments can provide decision makers with credible and transparent parameters to identify priority needs and justify their actions (Harley et al., 2008). They provide planners with insights on focus areas to reduce the system's vulnerability (Hamouda et al., 2009) and options to formulate new water resource management policies as well as evaluate, modify, and improve existing ones (Babel et al., 2011; UNEP, 2011). These assessments support building internal linkages of water resource vulnerability and adaptation (Allan et al., 2013) which are critical for management of aquifer sustainability in light of potential global climate change (Gurdak et al., 2007).

Agriculture is the largest single user of water with about 75% of the world's freshwater being currently used for irrigation (Qadir et al., 2007). This leads to an intrinsic relationship between the renewable water resources and the capacity for food production (Yang et al., 2003). Water availability is one of the main limiting factors for food production (Kang et al., 2009). With a world population that is expected to grow from current level to about 6.9–9.2 billion by 2050, as well as changing lifestyles and consumption patterns, global demand for food is projected to increase by 70–110% by 2050 (Delzeit et al., 2017). Future projections of increasing population as well as the changes in the crop's growing season length (due to increasing minimum temperature) would exacerbate the existing demand for water. Together, they will create unprecedented stress on water and food demand and supply, thus impacting food security. VWR will describe states of risk of food and water systems in an altered climate. They will support the identification of these systems' powerlessness as well as guide actions that enhance prosperity through risk mitigation against various stressors. Therefore, understanding the water resource system and its vulnerability to stressors such as changing temperature and precipitation are vital to secure and increase world food production to feed its growing population (Anandhi, 2016).

We deliberately provide only cursory treatment of the social and policy challenges inherent in gaining the adoption and implementation of VWR assessments. We expect that other authors with expertise in water policy and the social sciences will offer their perspectives on the need and challenges associated with effectively implementing our methodology in a variety of social and governance contexts.

Vulnerability is a dynamic phenomenon with dynamic processes (biophysical, economical, social, and combinations) that shape local conditions. Also, the ability of the water resource system to cope is also dynamic. Measuring vulnerability is also a challenge because it is often not a directly observable phenomenon and so the VWR assessments are difficult to validate. It is also a difficult, complex concept with inherent difficulties for quantifying it. Therefore, proxy variables or indicators were used in VWR assessment or modeling and are often used in environmental and social studies. The symbolic representation of VWR framework developed in this study can be useful in developing desirable proxy indicators. Given the uncertainty of future climate (and other) changes, consideration for enhancing the robustness of such a decision is warranted.

## 6. Conclusion

Water, is critical for human survival everywhere, but especially in the study region, the High Plains region (overlying the Ogallala Aquifer) because it is considered one of the most productive agricultural regions, the "breadbasket of the world." Increasing demand on the limited resource of water can make it vulnerable to climate and land cover changes, thereby creating a need for vulnerability assessments. The overall goal and objective of this study was to develop tools to address stakeholders need for assessment of vulnerability of water resources to climate change and variability. The tool could assist them with planning and decision making. Decision support is hard, not only because long-term prediction is hard, but also because creating decision-relevant processes from available information is hard. This was carried out in three stages using indicators selected by novel systems thinking approaches. Stage 1: Translating theoretical concept to charateristics identified from literature; Stage-2: Operationalizing charateristics to methodology in VWR; Stage 3: Utilizing the methodology for development of a conceptual modeling tool for VWR: WR-VISTA (Water Resource Vulnerability assessment conceptual model using Indicators selected by System's Thinking Approach) useful in decision making framework.

The WR-VISTA model was developed in one of the three stages and presented in this study. The development of WR-VISTA utilized the several important characteristics of VWR synthesized in this study from the literature review (Fig. 2). We adapted Gallopín (2006) generic framework of vulnerability for water resources system. Additionally, we modified Bär et al. (2015) flowchart (originally developed for agricultural water resources vulnerability combining DPSIR-IPCC frameworks) to the generic framework, and Anandhi et al. (2016b) framework originally developed for a single component (exposure) of agricultural production to changing/variable climate to include multiple components. The novelty of the theoretical framework in WR-VISTA is the representation of multiple components (driver, pressure, state, impact, response, exposure, sensitivity, adaptive capacity, and processes) using indicators to explain the critical elements of VWR. The application of the study region is important because it overlies the High Plains Aquifer, which supplies 30% of the nation's irrigated groundwater and produces agricultural products worth $35 billion market value.

We selected and estimated 26 indicators to study the VWR in Kansas. Our results showed in a changing environment an increased vulnerability in the western part of the state for agriculture, while in the eastern part, an increased vulnerability was observed for urban water use. The indicators used in this study demonstrate the framework and may/may not be suitable for all applications of VWR. The WR-VISTA framework can be applied by multiple stakeholders to identify indicators for VWR assessments. The framework does not attempt to provide "optimal" solutions in the traditional decision analytic sense. Instead, the approach identifies the best decision conditional on the weight of the indicator-based evidence. Using a more sophisticated approach for assigning the weights and including multiple socio-economic indicators, which measure fiscal or societal effects of water resource for VWR, differs for future work. The changes in future climate projections from global climate models can be applied to estimate the change in VWR and are deferred for future work.

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## Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.jhydrol.2017.11.032.

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