


Combining agriculture, social and climate indicators to classify vulnerable regions in the Indian semi-arid region

Rajesh Kalli ^{a,*} and Pradyot Ranjan Jena ^b

^a Presidency University, Bangalore, Itgalpur, Rajanakunte, Yelahanka, Bengaluru, Karnataka 560064

^b School of Management, National Institute of Technology Karnataka, Surathkal, Mangalore 575025, Karnataka, India

*Corresponding author. E-mail: rajukalli.nitk@gmail.com

 RK, 0000-0002-5537-8452; PRJ, 0000-0002-0674-3441

ABSTRACT

Climate change vulnerability is highly counter-productive for agriculture among the arid and semi-arid regions. The study constructs the agriculture vulnerability index for Karnataka, a south Indian state. The state has faced frequent climate-related shocks in the last decade. The district-wise vulnerability index is estimated using longitudinal data considering exposure, sensitivity and adaptive capacity as sub-indices. The results show that the districts in the north interior region of Karnataka are highly vulnerable to the climate change followed by the districts in the south interior and coastal regions. There is an urgent need to prioritize the most vulnerable districts while formulating the development policies to minimize the risk of climate change on agriculture. Specific technical knowledge and support need to be made available to the farmers for informative climate resilience action.

Key words: agriculture, climate change, semi-arid region, vulnerability index

HIGHLIGHTS

- We developed a framework to derive the vulnerability index considering the impacts of climate change.
- Three indices were calculated to estimate the overall vulnerability index.
- Exposure – sensitivity – adaptive capacity, which include agriculture, social and climate indicators, were used to build the vulnerability index for the state.

1. INTRODUCTION

The consequences of climate change is becoming an important area of research not only in natural sciences but also in social sciences. Over time, researchers have attempted to quantify the effect of climate change on various sectors such as agriculture, forests, ecosystems, human health, water and land (IPCC 2014). This quantification indicates that the climatic conditions and variations of the climate patterns on a longitudinal scale vary from country to country and region to region within the country. The tropic and sub-tropic regions are experiencing intense and longer droughts (Fu 2015). Similarly, uneven rainfall pattern is causing floods among the coastal regions. With the current trend in the emission of greenhouse gases, global temperature may rise between 2 and 4 °C in the next century (IPCC 2007, 2014), while the global surface temperature change is likely to exceed 1.5 °C by the end of this century (IPCC 2018). With uncertainty over the accuracy of the different estimates, the actual warming may be even larger over the next century. The increasing emission of harmful gases and environmental degradation will have a devastating impact on a human ecosystem. The countries around the world have pledged to mitigate the carbon footprints and commit to sustainable development, while adaptation is prioritized to fight against the climate change (Dimitrov 2016). To minimize the effect of climate shocks, policymakers need to be attuned with the information on vulnerable regions. The vulnerability concept is studied among different disciplines, from economics and anthropology to psychology and engineering (Fekete *et al.* 2014). Although the sense with which the term ‘vulnerability’ is used in the climate change assessment, the human–environment relationship holds a common element. The climate change vulnerability assessment was conceptualized in the 1990s (Downing 1991; Bohle *et al.* 1994; Adger 2006), and by the early-2000s to

This is an Open Access article distributed under the terms of the Creative Commons Attribution Licence (CC BY 4.0), which permits copying, adaptation and redistribution, provided the original work is properly cited (<http://creativecommons.org/licenses/by/4.0/>).

mid-2000s, a body of well-established literature can be found on the vulnerability assessment. These evaluations among different regions have led several international organizations and governments to derive several policy implications.

IPCC (2014) defines vulnerability as the 'propensity of a system, to be adversely affected'. The new framework proposed in IPCC (2014) represents sensitivity and adaptive capacity of the system as the source of vulnerability. IPCC (2014) represents sensitivity and adaptive capacity of the system as the source of vulnerability and the exposure is the external co-factor that indicates the region could be adversely affected. This concept is referred to as contextual vulnerability, where it answers the question 'vulnerability to what'? Vulnerability is a dynamic process, a continuous state that fluctuates between biophysical and social environments, that shapes a region's resilience to cope against the external risk possessed (O'Brien *et al.* 2007). The most prominent vulnerability concepts in climate change context are biophysical vulnerability (outcome vulnerability) and social vulnerability (contextual vulnerability); however, both concepts differ in their interpretation of vulnerability. The vulnerability assessment helps to understand why few regions and communities are vulnerable (or not vulnerable), emphasizes the dynamic and complex interactions between climate change and society and draws upon a rich and varied intellectual results. Adopting collaboration across disciplines and linking research to the practicality are essential realities for decision-making. The vulnerability assessment creates pathways for stakeholders to develop a suitable adaptation to reduce the risk associated with climate change. At the same time, analysing the climate change impact on different communities, sectors and geographical locations can lead to specific and highly resilient adaptive measures. This will further help to raise awareness and identify the key issues in different contexts and conditions. In this context, the present study focuses on identifying the vulnerable regions within the state of Karnataka.

Vulnerability to climate change or natural hazards is commonly assessed in several sectors (tourism, energy and finance), including agriculture (Moore 2010; Wan *et al.* 2011; Monterroso *et al.* 2014; Hong *et al.* 2019). Though researchers have contributed vast amounts of literature assessing the vulnerability of regions, conservative methodology indicates a drawback and the dynamics of climate drivers and society are unevenly accounted for (Sridevi *et al.* 2014; Kumar *et al.* 2016a, 2016b; Raju *et al.* 2017; Singh *et al.* 2017). Interactive mapping is found to be limited among the past studies, mapping help to select, categorize and weight-relevant indicators of vulnerability (Wiréhn 2018; Neset *et al.* 2019). As discussed earlier, considering the biophysical and socio-economic indicators at the regional scale are required to frame effective climate adaptation strategies (Steiner *et al.* 2018). Furthermore, a clear gap can be found in understanding the vulnerability through integrated multiple-level assessments (Shukla *et al.* 2018), which includes longitudinal scale and varied indicators from different disciplines. The shortcomings of vulnerability assessment in the past literature privileged climate factors over social factors. However, recent studies have attempted to account the socio-economic indicators (Kumar *et al.* 2014; Monterroso *et al.* 2014). Additionally, both climate and social indicators or the system to which vulnerability is measured need to be evaluated in the dynamic approach rather static. The longitudinal data analysis will provide more information while assessing vulnerability. For example, farmers adapt different cropping patterns based upon change in climate patterns, and thus, researchers have to capture the shift in agriculture practices over time. For example, Raju *et al.* (2017) and Kumar *et al.* (2014) employed indicators at cross-section (static) rather than longitudinal. Studies measuring vulnerability with 1-year cross-section data may have less importance for policy response. Furthermore, the common challenge in assessing vulnerability is the broad indicator-based approach. There are several critiques regarding the indicators used in the past studies, which fail to capture the motivation of study, and manifest an inability to address vulnerability (Ford *et al.* 2018). For example, the average of the climate indicators does not capture the frequency and intensity of the extreme events. Similarly, Raju *et al.* (2017) employed an area under commercial crops, which neither indicate the region's sensitivity nor the adaptive nature of the region. Commercial crop cultivation depends on the topography characteristics of a particular region and additional capital requirement, which may not be a proxy for adaptation in agriculture. Moreover, regions of agricultural vulnerability focus primarily on major food crops as they constitute a larger part of cultivation. A holistic approach has to be adopted in identifying and defining the indicator while assessing vulnerability. Furthermore, a large-scale or countrywide assessment fails to capture the sub-national spatial scales and social differences among the local communities (Cutter *et al.* 2012). In India, for example, different topographic features, cultivation of crops differs with the regions' climate, and government incentives and schemes also vary among the states. The vulnerability analysis combining the social environment with climate variables will be critical in the development of better future projections.

The present study examined each of the concerns discussed above and adopts significant changes in the vulnerability assessment literature for policy formulation. Detailed information on the construction of variables is discussed in Section 4. The present study makes several contributions to the vulnerability assessment literature. First, the primary objective of

the study is to identify the districts that are agriculture-vulnerable in the context of climate change for the policy response and further to employ the relevant indicators by addressing the challenges from the past studies to derive the vulnerability. Based on the final vulnerability outcome – the study recommends possible adaptation among the regions employed in the study. The scope of the study is limited to a region to understand the dynamics between climate change and the agriculture sector, as the similar government policy and the community adaptation can be found in the region.

2. STUDY AREA

The importance of this study can be realized in the context of recent severe drought in many parts of India, especially in Karnataka. The state has the second largest arid and semi-arid regions in the country after Rajasthan (Biradar & Sridhar 2009; Anandhi 2010). Several episodes of high-intensity drought and significant variation in monsoon rainfall have been observed in Karnataka (Guhathakurta *et al.* 2015). Agriculture in Karnataka is highly dependent on the monsoon rainfall; a 26.5% area is irrigated while the remaining depends on rain-fed cultivation (Bhende 2013). Reliance on monsoon for agriculture and significant variation in climate make it a highly vulnerable state. The state has a varied topographical character ranging from coastal plains to gentle slopes and the heights of the Western Ghats. The Karnataka state is at present divided into 30 administrative districts. However, as per the census report 1991, the state had 20 districts. The newly carved out districts have been allotted back to the respective districts to which they previously belonged.

3. ANALYTICAL FRAMEWORK

The definition of the IPCC specifically highlights three components of vulnerability in the climate change context: exposure, sensitivity and adaptive capacity. This implies that a region is vulnerable if it is exposed and sensitive to the change in climate patterns. On the contrary, a region is less vulnerable if it is less exposed, less sensitive or has a strong adaptive capacity. The general framework of vulnerability assessment is broadly classified into three sub-indices (exposure, sensitivity and adaptive capacity) (IPCC 2007; Sridevi *et al.* 2014; Kumar *et al.* 2016a, 2016b; Raju *et al.* 2017; Singh *et al.* 2017). The study employs the similar empirical framework of broad sub-indices and addresses some of the concerns, which act as the limitation among the past studies. Ford *et al.* (2018) raised several concerns from the choice of indicator to the cross-disciplinary approach. Based on the concerns raised, the present study focuses on three dimensions to overcome the challenges from the previous studies. First, prioritizing social factors rather than climate factors, we employ major non-climatic drivers that are important in evaluating the climate change vulnerability to the agriculture sector. Second, past vulnerability research neglects the dynamic approach and presented the static understanding of the interactions between the field of study and climate indicators. With evolving changes in the climate and external environment, the sensitive environment of the region adapts to the changing scenario. Thus, vulnerability studies should focus on longitudinal data rather than evaluating with cross-section data. Third, the choice of indicator and the misspecification of vulnerability concept manifest inability to address the regions' vulnerability. For example, the literacy rate considered in the past studies includes urban communities (Sridevi *et al.* 2014; Kumar *et al.* 2016a, 2016b; Raju *et al.* 2017). This inclusion sometimes renders the results biased as the agriculture is part of rural economy. To overcome the concern, we employ the rural literacy rate that captures the interaction. Furthermore, several studies have employed the average of climate indicators (rainfall and temperature), while based on the topography, climate varies. For example, the coastal region receives higher rainfall when compared with arid or semi-arid region. Though it represents the average climate of the region, adopting this will result in irrelevant characteristics of the region. Thus, the studies must employ variation in the climate which resembles the variability in the climate patterns. The additional measure to be considered is to employ the indicators that resemble regional characteristics (cyclones, frost occurrence, etc.), and the repeatability of similar indicators in different dimensions must be avoided.

3.1. Exposure

Exposure is defined as the degree of change in the ecosystem that affects the region, system, sector or a group. Exposure refers to the presence of people, means of livelihood support, species or ecosystems, infrastructure or economic, social or cultural assets in places that could be adversely affected by climate change (IPCC 2014). In the context of climate change vulnerability to the agriculture sector, 'exposure' can be defined as the degree to which agricultural productivity is affected by significant external characteristics. The most influencing external characteristic that affects the agricultural productivity is climate (rainfall and temperature). In general, rainfall is the key climate indicator that affects cultivation. Higher rainfall variability will indicate the vulnerability of region; however, districts with low average rainfall coupled with higher variation are extremely

vulnerable. Similarly, rise in temperature alters the photosynthetic rate and inhibits plant growth, which, in turn, decreases the total agriculture production. In arid regions, where higher temperature pre-exists, a small rise in temperature will have a stronger negative impact on plant growth (Kalli & Jena 2020). To represent the climate change of the region, we used six indicators to construct the exposure sub-index – two indicators of rainfall and four indicators of temperature. The classification of the time period of climate indicator is based on the cropping pattern. Two major rainfall season and four seasonal temperature indicators were classified. The variability of rainfall in kharif and rabi seasons was estimated using the coefficient of variation (CV) (also referred to as relative standard deviation). In the case of temperature, the standard deviation of maximum temperature in the kharif season (June to September), the rabi season (October to December), the post-rabi season (January and February) and the summer season (March to May) was estimated to construct the exposure index.

3.2. Sensitivity

Sensitivity is defined as the degree to which a region is modified or affected by an internal or external disturbance or the set of disturbances. Four indicators under the sensitivity index that reflect the agriculture environment were adopted that are highly sensitive to climate change. Agricultural labourers and cultivators are the two categories of working population that are directly dependent on agriculture. Agricultural labourers are the prime victims of crop failure, where it affects their livelihood and leads to migration to urban areas. Cultivators are the other set of individuals that are dependent on agriculture and allied activities. Counting labourers and cultivators as two different indicators provides more insights into the region, where the region with a large proportionate of agriculture labourers indicates less economic diversification. In terms of physical environment, two indicators – net sown area and rain-fed area – were adopted. Districts with a relatively larger portion of land under cultivation are highly sensitive to climate change. Furthermore, rain-fed agro-ecologies are prone to high climate risk. In general, the area under rain-fed agriculture, mainly in arid regions, experiences frequent droughts and is also considered to have poor infrastructure (Wani *et al.* 2009). The sensitivity of rain-fed agriculture can be realized by the fact that even a decrease of one standard deviation from the mean annual rainfall often leads to a complete crop failure.

3.3. Adaptive capacity

Exposure and sensitivity describe the potential impact of climate change on a region. However, even though the region may be considered as highly exposed and/or sensitive to climate change, it does not necessarily indicate that it is vulnerable. The IPCC defines adaptive capacity as ‘the ability (or potential) of a system to adjust successfully to climate change (including climate variability and extremes) to: (i) moderate potential damages; (ii) to take advantage of opportunities; and/or (iii) to cope with the consequences’ (IPCC 2007). The capacity of a household to cope with climate risks depends to some degree on the environment of the community (Yohe & Tol 2002; Smit & Pilifosova 2003). Past studies have emphasized socio-economic determinants of adaptive capacity (like, for example, education, income and health), whereas other determinants like adaptation related to agriculture have been neglected.

The adaptive capacity sub-index has been constructed with well-versed indicators to capture the adaptation behaviour of farmers. Agriculture gross domestic product (GDP) was considered as an indicator, which represents the monetary value of agriculture production and indicates the value created from cash crops and other allied activities. Education is a key dimension for adaptation, which reflects the wellbeing and consciousness within the society. Literacy is the most widely used indicator, which in turn shows the drivers of adaptation among the farmers (Wood *et al.* 2014). Past studies include the overall literacy rate that includes both urban and rural populations. The agriculture is an integral part of the rural economy; the present study adopts the rural literacy rate as an indicator rather than employing the overall district literacy rate. Effective utilization of agricultural land indicates the supporting external environment to capture this cropping intensity, and crop diversification was adopted. Cropping intensity implies higher productivity per unit of arable land during one agricultural year (Varadan & Kumar 2015). Crop diversification indicates the diversity in the cultivation of more than one variety of crop in the given area (Varadan & Kumar 2015). Crop diversification reduces the risk of depending on a single crop, and cropping intensity measures the intensity of land utilization. Gross cropped area was used, where it indicates the use of farmland more than once in a year. The well-known adaptation to reduce the climate change impact on agriculture is irrigation. In this case, irrigation was measured in two different indicators. The first one is the growth in the irrigated area where growth in the irrigation resembles the region’s adaptation over the period of time. The second one is the source of irrigation that represents the source of water that is supplied to farmland. Canal irrigation and bore-well irrigation were considered, which are the major sources of irrigation in the state.

4. DATA SOURCE AND VARIABLE CONSTRUCTION

4.1. Exposure

The key climate indicators used in the study include temperature and rainfall. The information on the temperature and rainfall was obtained from the India Meteorological Department. A fine gridded dataset of $0.25^\circ \times 0.25^\circ$ for rainfall and of $1^\circ \times 1^\circ$ for temperature was interpolated from unevenly distributed station-wise data using the Shepard interpolation method (Srivastava *et al.* 2009; Pai *et al.* 2015). From the gridded dataset, daily data on rainfall and temperature were extracted for the state of Karnataka. Later, the grid points were categorized and assigned for each district based on the boundaries within the state of Karnataka. To derive district-wise observation, we extracted daily grid-wise data for each district for 21 years (1992–2012). For rainfall, the grid points within the district boundaries were averaged daily and then summed up for all the seasons. Meanwhile for temperature, the grid scale was larger; hence, similar grid observation was applied for the three districts in the southern region due to a smaller geographical area of the districts. The table indicating grid of each district is presented in table 1.1 in the Appendix. The study adopts the average of maximum temperature over mean temperature to construct the vulnerability index. Even though mean temperature indicates a significant trend, the application is restrictive. The daily mean temperature is the average of the maximum and minimum temperatures; this transformation does not capture the daily higher threshold temperature (Welch *et al.* 2010; D'Agostino & Schlenker 2016).

To construct the exposure sub-index, variability in rainfall and temperature was estimated. Maximum temperature: four seasonal classifications have been carried out based on the cropping pattern: kharif season temperature, rabi season temperature, post-rabi season temperature and summer season temperature. For each district, daily maximum temperature was averaged individually for four seasonal classifications. Season-wise variability for 21 years was estimated using standard deviation. For rainfall, we considered two major rainfall seasons (kharif and rabi). For each district, daily average rainfall was summed for kharif and rabi seasons, respectively. The CV was estimated for 21 years to identify the variability in rainfall for each district.

4.2. Sensitivity

To construct the sensitivity sub-index, we include the population involved in cultivation and the area under cultivation, which are highly sensitive to climate change. The data on the cultivators and agricultural labourers for each district were collected from the census report of India for three periods, i.e. 1991, 2001 and 2011. The proportion of the cultivators to the total working population and agricultural labourers to the working population was estimated for each district. The weighted average method was used to estimate the average population involved in agriculture for each district (1991, 2001 and 2011). The data regarding the net sown area and the rain-fed area were extracted from the Directorate of Economics and Statistics (DES, Karnataka), Karnataka and the Directorate of Economics and Statistics (DES, India), Ministry of Agriculture, Government of India. The growth in the average net sown area and the rain-fed area for each district was estimated for the period 1998–2012.

4.3. Adaptive capacity

To measure a particular region's resilience to climate shocks, six indicators have been considered to construct the adaptive capacity indicator. The literacy rate for each district was estimated as the proportion of the total literate population in the rural area to the total population in the rural area. The literacy rate was collected from the census report of India for three periods, i.e. 1991, 2001 and 2011. The weighted average method was used to estimate the final literate population for each district. Agriculture GDP to total GDP expressed in constant prices was used in the study. Canal irrigation and bore-well irrigation are the two major irrigation sources in Karnataka state. The total area under each source of irrigation in the year 2012 was used in the study. The extent of crop diversification followed in a district has been calculated using the following formula:

$$CD = 1 - \sum \left(\frac{a_j}{A} \right)^2 \quad (1)$$

where a_j is the area under the j th crop and A is the gross cropped area. As the study focused on addressing the limitation of cross-sectional analysis, time-series growth of indicators has been estimated. The growth rate in gross cropped area, irrigated area, cropping intensity, crop diversification and GDP for the time period 1998–2012 was estimated using the following

method:

$$Y_j = \frac{x_{ij} - X_{ij}}{X_{ij}} \quad (2)$$

where Y is the growth rate and x_{ij} is the actual value of i th indicator for j th district in the present year. X_{ij} is the average value of i th indicator for j th district over the distribution.

5. NORMALIZATION AND WEIGHTING

The indicators considered for the study are measured in different units. It is necessary to standardize the indicators in a comparable range. Among the studies related to vulnerability assessment, normalization is used to represent the indicators in one single functional form (Vincent 2004). The normalization has been calculated using the following equation:

$$Y_{ij} = \frac{x_{ij} - \text{Min}(x_{ij})}{\text{Max}(x_{ij}) - \text{Min}(x_{ij})} \quad (3)$$

On the contrary, if the variable is with a negative relationship in the value of the indicator, then the normalization has been achieved using the following equation:

$$Y_{ij} = \frac{\text{Max}(x_{ij}) - x_{ij}}{\text{Max}(x_{ij}) - \text{Min}(x_{ij})} \quad (4)$$

where Y_{ij} is the normalized score for the i th indicator related to j th district. x_{ij} is the actual value of i th indicator for j th district. $\text{Max}(x_{ij})$ & $\text{Min}(x_{ij})$ are the maximum and minimum values of i th indicator among all the districts. The final vulnerability index is derived from three components. 'Unweighted Index' (without weights) and 'Weighted Index' (with weights) were the two methods followed to integrate the components of vulnerability index.

5.1. Unweighted index

The unweighted index includes all the indicators with equal importance and treated with equal weights.

5.2. Weighted index

The indicators may not be equally important while arriving at the vulnerability index, as different weights are assigned due to the disproportionate influence of indicators on the vulnerability index. The weights assigned based on the expert judgment are subjective in nature. Therefore, to overcome the bias, the present study assigns weights based on the factor analysis. Factor analysis is a multivariate analysis that is used to extract key factors from a larger pool of variables. Factor analysis was estimated for each of the components (exposure, sensitivity and adaptive capacity). The orthogonal basis varimax rotation was used to rotate the matrix. Based on the variance, the loadings from the first principal component corresponding to indicators were used as their weights for constructing the three components of the vulnerability index. The construction of each sub-index (exposure, sensitivity and adaptive capacity) after assigning weights to each indicator is given by:

$$Z_j = \frac{\sum_i^k Y_{ij} * w_i}{\sum_i^k w_i} \quad (5)$$

Z_j is the index score for the j th district; w_i is the weight corresponding to the i th variable; k is the total number of indicators and $\sum_i^k w_i$ is the summation of weights.

Quartile analysis has been carried out to classify the districts based on vulnerability. The study used the STATA 13 software for analysis. The estimated score of three sub-indices with weights and without weights was combined to derive overall vulnerability using the following equation:

$$\text{Vulnerability Index } (V_{ij}) = \text{Exposure } (E_{ij}) + \text{Sensitivity } (S_{ij}) - \text{Adaptive Capacity } (AC_{ij})$$

where V_{ij} is the vulnerability index for j th district, E_{ij} is the composite exposure index for j th district, S_{ij} is the sensitivity index for j th district and AC_{ij} is the adaptive capacity index for j th district.

6. RESULTS

The following section will include the results of the exposure, sensitivity and adaptive capacity and overall vulnerability index to climate change in Karnataka.

6.1. Exposure

The most important driving forces in a natural environment that impact the agriculture are rainfall and temperature. The rank of the districts varied in different seasons of rainfall and temperature. The district-wise mapping of a region's exposure to climatic changes without weight and with weight are presented in Figures 1 and 2. The districts under exposure index were mapped into four categories, i.e. extremely vulnerable, highly vulnerable, moderately vulnerable and low vulnerability. An average score of exposure index with equal weight was 0.381, and wide variations in exposure to climate variability are evident from the range of scores from 0.11 (minimum for Kodagu district) to 0.86 (highest for Bidar district). The district-wise scores for exposure index of each district are presented in Appendix 1 (Tables 1.2 and 1.3). The results remained similar after adding weights to the indicator. The estimated exposure index with equal weights puts forth the results wherein the Bidar district featured as extremely vulnerable to climate variability, followed by Gulbarga, Raichur, Bijapur and Dharwad. Furthermore, in the second quartile, Kolar, Chitradurga, Bellary, Shimoga and Bangalore Urban districts were categorized as highly vulnerable regions. Excluding Bellary, the districts in the highly vulnerable category are in southern Karnataka. These districts can be referred to as the second-order districts that are vulnerable to climatic variation. There was no significant difference found after providing weights in the order of districts. From the analysis, it was noted that the majority of northern districts of Karnataka are extremely vulnerable to climate variability. Though the order of the districts altered with and without weights, five of the seven districts from the northern region remained extremely vulnerable on the exposure index. The top five districts with high variation in temperature in the rabi season are from the northern region of the state. Overall, the variation in maximum temperature is found to be highest among the districts in the northern region. The north interior region of Karnataka is highly exposed to significant variation in the climate, followed by the southern region and the coastal region.

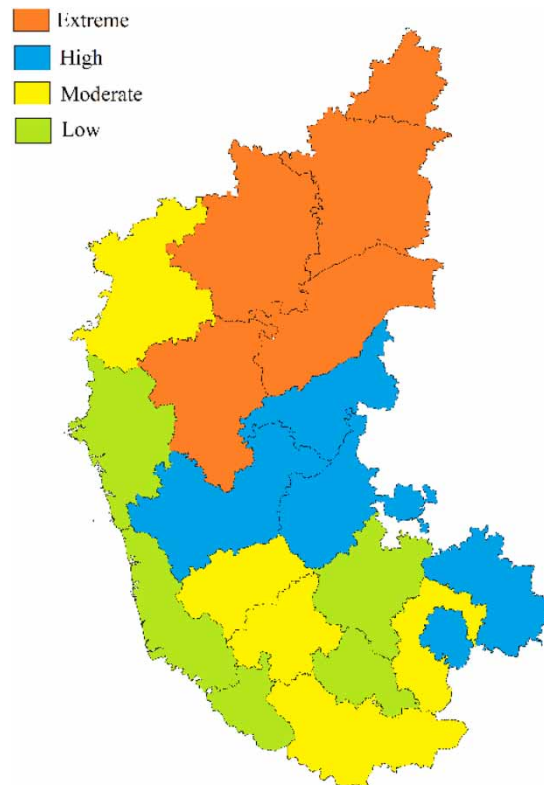


Figure 1 | Classification of districts based on the exposure component (without weights). Please refer to the online version of this paper to see this figure in colour: <http://dx.doi.org/10.2166/wcc.2021.197>.

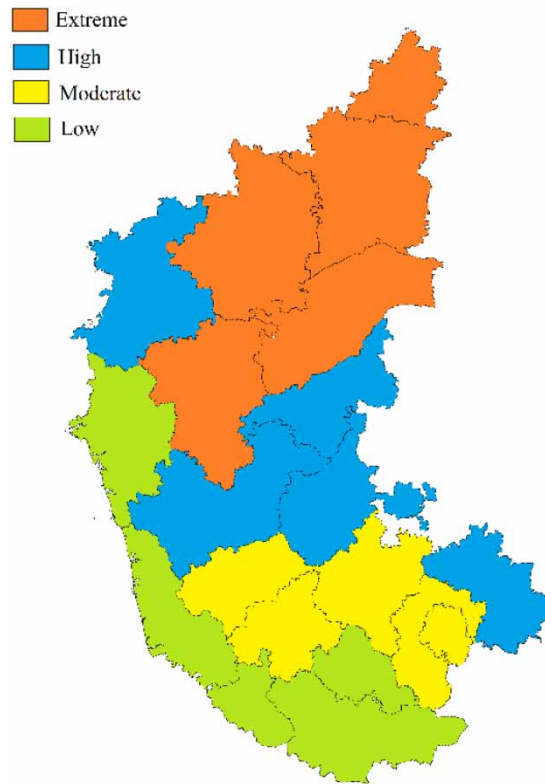


Figure 2 | Classification of districts based on the exposure component (with weights). Please refer to the online version of this paper to see this figure in colour: <http://dx.doi.org/10.2166/wcc.2021.197>.

6.2. Sensitivity

The mapping of district-wise sensitivity of the region with and without weights is presented in Figures 3 and 4, respectively. The district-wise scores for the sensitivity index of each district are presented in Appendix 1 (Tables 1.4 and 1.5). The sensitivity indicator is broadly classified into three indicators: the population that is dependent on agriculture for their livelihood, the net sown area and the rain-fed area. Among the smallholders' community, even the cultivators themselves work as labourers for their livelihood. The large number of cultivators are found mostly in the southern region of Karnataka, namely Hassan, Mandya, Tumkur, Bangalore Rural, Chitradurga and Kolar. The agricultural labourers are highly concentrated in the northern districts of Karnataka: Gulbarga, Bellary, Raichur, Dharwad, Chitradurga and Bijapur districts have the highest number of agricultural labourers. The large concentration of agricultural labourers among the northern districts indicates a less-diversified economic activity, and the higher cultivators in the southern region indicate the fragmented agricultural land among small-scale farmers.

The net sown area represents agricultural land cultivated in the district, which is sensitive to climate variation. The districts with the high net sown area are Bijapur, Gulbarga, Dharwad, Raichur, Belgaum and Shimoga districts. These districts represent almost 50% of the cultivated area in the state of Karnataka; this includes five districts from the northern region and one from the south interior region. Furthermore, the total rain-fed cultivable area has been considered as another indicator for sensitivity; Kodagu, Chikmagalur, Bidar, Gulbarga, Dharwad and Chitradurga are the districts that constitute the majority of the land under rain-fed cultivation. Rain-fed cultivation assumes a lot of significance in estimating sensitivity: a higher area under rain-fed cultivation indicates the region's sensitivity to the exposure at the maximum level. Among the six districts with the large area under rain-fed cultivation, Kodagu and Chikmagalur have a mean rainfall of 2,806 and 1,845 mm, respectively, as the two districts receive an adequate amount of rainfall for cultivation (Bhende 2013). Hence, the requirement of irrigation among these districts is the least. However, Bidar, Gulbarga, Dharwad and Chitradurga districts have the mean rainfall of <400 mm, which suggests that these districts are highly sensitive. Any small variation in the rainfall among these regions can cause drought, which leads to crop failure and an acute shortage of drinking water.

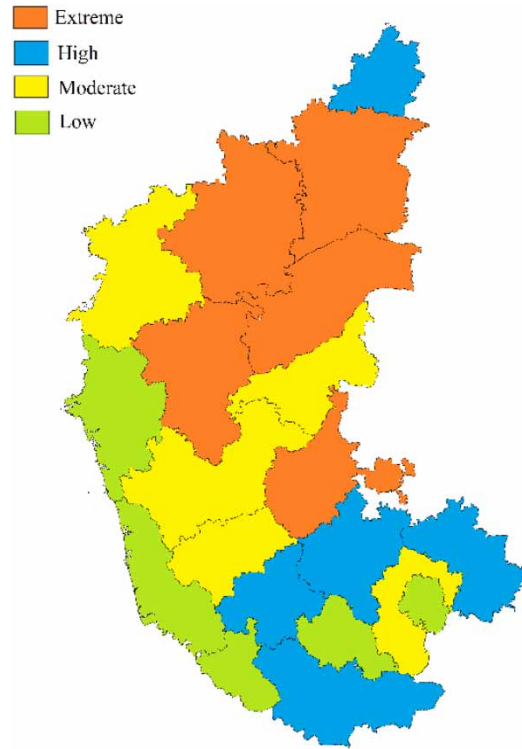


Figure 3 | Classification of districts based on the sensitivity component (without weights). Please refer to the online version of this paper to see this figure in colour: <http://dx.doi.org/10.2166/wcc.2021.197>.

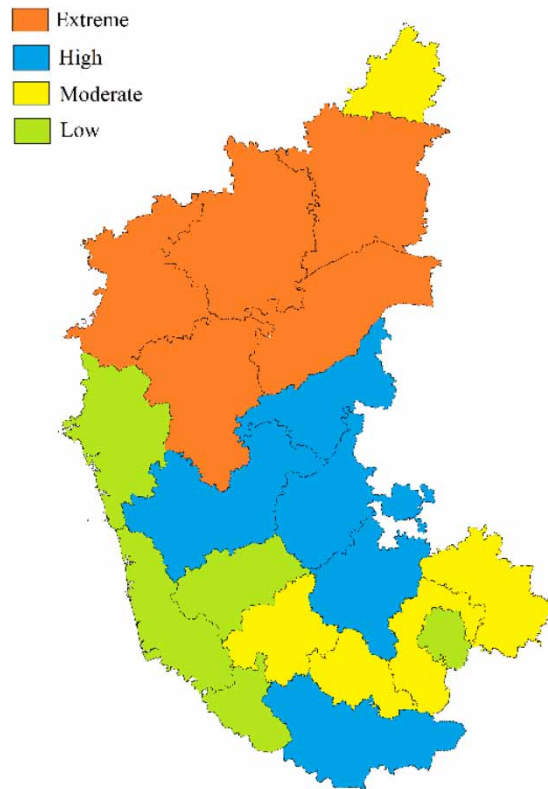


Figure 4 | Classification of districts based on the sensitivity component (with weights). Please refer to the online version of this paper to see this figure in colour: <http://dx.doi.org/10.2166/wcc.2021.197>.

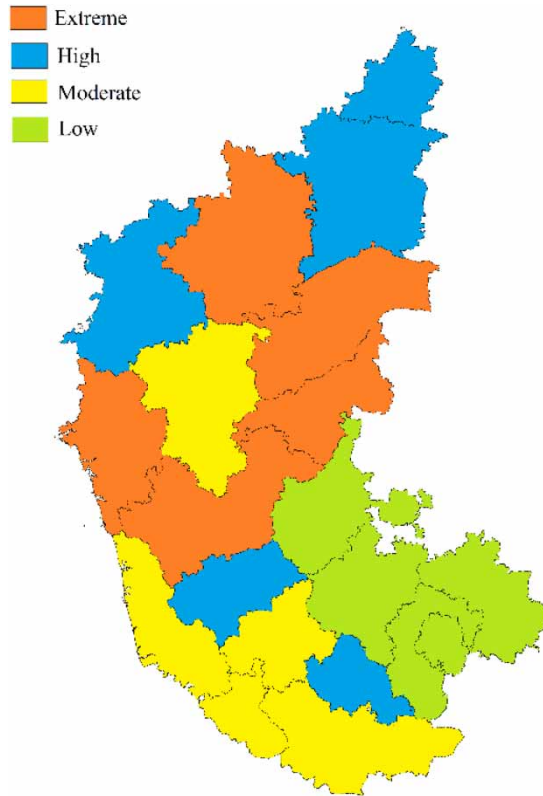


Figure 5 | Classification of districts based on the adaptive capacity component (without weights). Please refer to the online version of this paper to see this figure in colour: <http://dx.doi.org/10.2166/wcc.2021.197>.

The overall sensitivity index indicated that Gulbarga, Dharwad, Bijapur, Raichur and Chitradurga are extremely sensitive districts of the state. Among them, Gulbarga was found to be having the highly sensitive environment to climate variation due to two specific indicators, namely the highest percentage of area under agriculture and the largest population being dependent on agriculture for their livelihood. The districts in the second quartile are Tumkur, Hassan, Mysore, Bidar and Kolar, although the risk associated with the climate change in highly sensitive districts may be less when compared with the extremely sensitive districts. However, necessary policy has to be formulated for these second-order districts, as the long-term effect of climate change may significantly hamper the agricultural production. Moderately sensitive and low-sensitive regions are those districts that are less dependent on agriculture. The districts under moderately sensitive regions are Belgaum, Bangalore Rural, Bellary, Chikmagalur and Shimoga. The districts with a low-sensitive score are Mandya, Uttara Kannada, Kodagu, Bangalore Urban and Dakshin Kannada. With inclusion of weights to the indicators, no significant difference is found in the degree of sensitivity among the districts compared with the earlier results without weights. A small shift in the order of sensitivity rank among the districts can be noticed. For example, the Kolar district has moved from highly sensitive to moderately sensitive category, whereas the Belgaum district has moved from moderately sensitive to extremely sensitive environment.

6.3. Adaptive capacity

The mapping of district-wise adaptive capacity of the region with and without weights is presented in Figures 5 and 6, respectively. The district-wise scores for the adaptive capacity index of each district are presented in Appendix 1 (Tables 1.6 and 1.7). Education remains key in knowledge transfer to enhance the livelihoods of inhabitants. The literacy among rural livelihood helps them to adapt in response to climate change. The literacy rate is used as a proxy for the education. Dakshin Kannada, Kodagu, Uttara Kannada, Bangalore Urban, Chikmagalur and Hassan districts had high literacy rates. The bottom three districts were from the northern region that had low literacy rates, which reflects the low transfer of knowledge and learning process among the northern districts. The low level of literacy rate is also combined with high poverty incidence and less economic diversification, which can be found among the northern districts. Bidar, Raichur, Kodagu, Uttara Kannada and

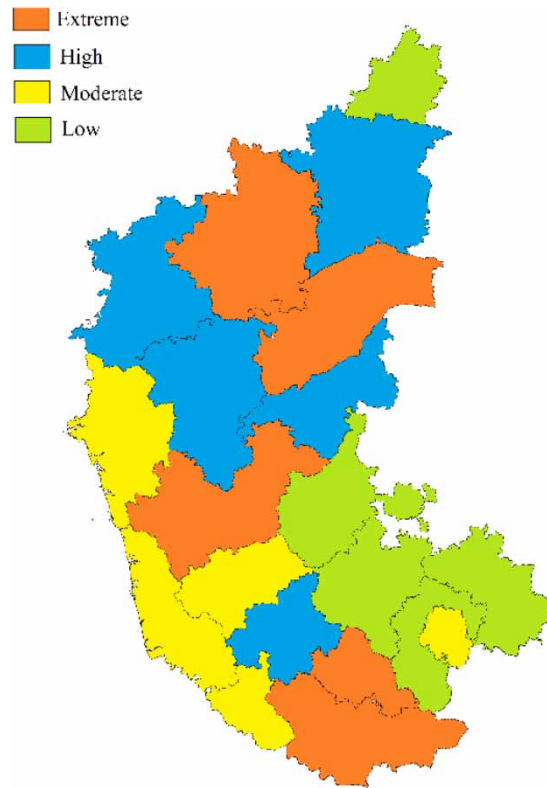


Figure 6 | Classification of districts based on the adaptive capacity component (with weights). Please refer to the online version of this paper to see this figure in colour: <http://dx.doi.org/10.2166/wcc.2021.197>.

Bellary were the top five districts where a significant growth can be noticed in agriculture GDP. The result was surprising as the growth in the agriculture GDP was noted among three northern districts. Cropping intensity is the utilization of the land in more than one season in a particular year, and the indicator indicates the intensity of utilization of agricultural land. Kolar, Belgaum, Kodagu, Bangalore Urban and Bellary were the districts with high cropping intensity. Similarly, the high level of crop diversification was found in Uttara Kannada, Chitradurga, Bijapura, Gulbarga and Kodagu districts. The common approach of adaptation is additional water source from various sources of irrigation; however, canal irrigation and ground water are the most common irrigated sources. Raichur, Bijapura, Mysore, Gulbarga, Shimoga and Mandya had the highest canal and bore-well irrigation within the state. High growth in the net irrigated land has been experienced in Chikmagalur, Belgaum, Uttara Kannada, Dharwad, Gulbarga and Bijapura districts in Karnataka.

The integration of the drivers and determinants of adaptation to one common indicator represents the adaptive capacity of the region. The top five districts in terms of adaptive capacity sub-index were Raichur, Bijapura, Shimoga, Uttara Kannada and Bellary. The high-ranked districts, Raichur and Bijapura, were found to be more resilient due to effective irrigation and well-diversified cropping pattern. The districts with high adaptive capacity were Mandya, Gulbarga, Chikmagalur, Belgaum and Bidar. The moderately and less adaptive districts are those with less irrigation and agriculture-related adaptation was found to be low. The districts that were moderate resilient are Mysore, Hassan, Dakshin Kannada, Dharwad and Kodagu. The districts with low adaptive capacity were found in Chitradurga, Kolar, Bangalore Urban, Tumkur and Bangalore Rural. After necessary weights were added, a variation in the order of the districts can be noted. Raichur, Bijapura and Shimoga retained the same position after the weights were assigned. However, Mandya and Mysore districts, which were categorized under high and moderately adaptive, jumped to extremely adaptive. This shift after adding weights in the adaptive capacity index is due to the influence of literacy, agricultural GDP and irrigation source.

6.4. Vulnerability index

The relative strength and interaction of sensitivity, exposure and adaptive capacity component determines the score of vulnerability index and thereby the level of vulnerability of a particular district. Figure 7 presents the district-wise analysis of

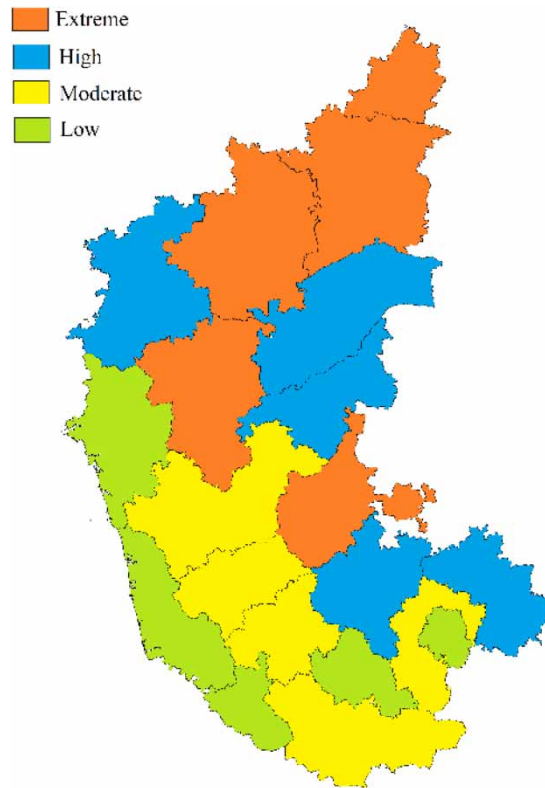


Figure 7 | Classification of districts based on the vulnerability index (without weights). Please refer to the online version of this paper to see this figure in colour: <http://dx.doi.org/10.2166/wcc.2021.197>.

adaptive capacity without weights, and **Figure 8** presents the district-wise analysis of adaptive capacity with weights. The district-wise scores for the vulnerability index of each district are presented in Appendix 1 (Tables 1.8 and 1.9). The mapping of climate change vulnerability to agriculture in the state of Karnataka indicated the Gulbarga district as extremely vulnerable, followed by Bidar, Dharwad, Bijapura and Chitradurga districts. Excluding the Chitradurga and Bidar districts, the extremely vulnerable districts were mapped in exposure and sensitivity sub-index. Raichur was mapped as the highly vulnerable district in the second quartile followed by Kolar, Bangalore Rural, Tumkur and Hassan. The assessment from first and second quartiles broadly indicates the majority of districts from the northern region followed by the southern region. Mysore, Shimoga, Chikmagalur, Belgaum and Bellary districts were grouped under moderately vulnerable (third quartile). Bangalore Urban, followed by Mandya, Uttara Kannada, Kodagu and Dakshin Kannada districts, was grouped as the low vulnerable district in the state of Karnataka.

The overall vulnerability index varied with the weights, and the Bidar district was characterized as the ‘extremely vulnerable’ district followed by Gulbarga, Dharwad, Bijapura and Chitradurga districts. The shift in the order of districts was evident in the highly vulnerable regions after using weights. This shift resulted due to high variability in rainfall and agriculture sensitivity. Kolar, Raichur, Bellary and Tumkur districts were classified as highly vulnerable regions. However, no significant shift was found among the moderately and low vulnerable districts. The overall vulnerability index indicated seven districts of the north interior region under extremely and highly vulnerable regions, of which five of them were categorized under the extremely vulnerable region. Among 11 districts of the south interior region, three were categorized in the extremely and highly vulnerable regions, five districts in the moderately vulnerable region and three districts in the low vulnerable categories. However, both the districts from the coastal region were categorized in low vulnerable regions.

7. DISCUSSION AND CONCLUSION

The present study assesses the climate change vulnerability of intra-state regions in Karnataka using a combination of social, agriculture, economic and climate data. The three regions of Karnataka, namely coastal, north interior and south interior are

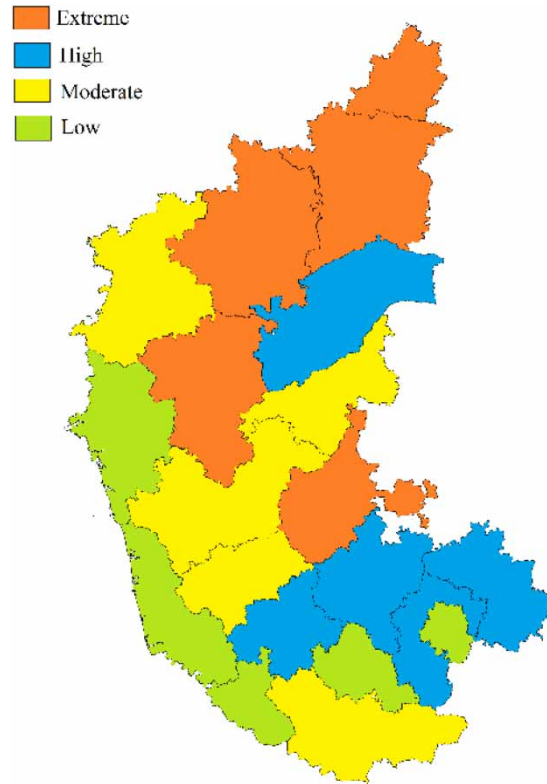


Figure 8 | Classification of districts based on the vulnerability index (with weights). Please refer to the online version of this paper to see this figure in colour: <http://dx.doi.org/10.2166/wcc.2021.197>.

in focus. The study advances the methodology of climate vulnerability analysis by employing the longitudinal data for climate and non-climate indicators. The most common exposure indicators, rainfall and temperature, were employed in the innovative approach. For example, rainfall is based on the cropping season (kharif and rabi) rather than considering annual; maximum temperature was employed with focus on the cropping season. The study avoids the bias of broad indicator approach and the repeatability of indicators. For example, variation in climate data was given importance rather than employing average. While in adaptive capacity, agricultural adaptation by farmers was captured. Diversification and cropping intensity are well-versed indicators that reflect farmers' adaptation, which have received less attention in past studies. Past studies have limited the usage of longitudinal data analysis to climate indicators (Sridevi *et al.* 2014; Kumar *et al.* 2016a, 2016b; Raju *et al.* 2017). The present study employs longitudinal data with historical dataset rather than focusing on 1-year cross-sectional dataset. Furthermore, to overcome the inconsistency of equal weightage to the indicators, we construct the index with and without the weights. We focus on measuring the indicators relatively and describing the scope in the context of vulnerability assessment. Findings show that the north interior region is highly agriculture-vulnerable to climate change in the state. The topography of the north interior Karnataka is arid, constituting a higher proportion of black soil. Although the crops that are cultivated in black soil can sustain high temperature, the variation in rainfall may cause significant loss in the crop production. The northern region experiences frequent droughts that are often due to extremely uneven rainfall causing flood or drought. The southern region shows a significant variability in temperature limiting the agricultural productivity. Similarly, the coastal region is vulnerable to soil salinity arising from wide variation in climate and can cause significant threats to livelihoods.

The vulnerability assessment done in our study serves as a link to frame suitable adaptation policies in the state of Karnataka. There are several forms of adaptation to climate change in the context of agriculture. The coping mechanism to overcome the climate variability with reference to Karnataka could be framing institutional reform to actively support adaptation strategies; training and capacity building to farmers on tailor-made adaptation based on the region; financial incentives to modernize the agriculture to sustain climate change impacts; crop insurance policy to safeguard the farmers from adverse

events. Karnataka state is a semi-arid region, where water resources are scarce and effective utilization of water resources in the state is crucial. Irrigation is one of the transformative adaptations, where higher usage of water resources (ground water) led to a decrease in the ground water depletion causing an imbalance in the natural environment. Therefore, expansion of rainwater harvesting, water storage and conservation techniques and efficient usage need to be adopted by the farmers. Meanwhile, policymakers should focus on deliberating the policies focusing on the efficient usage of water and enabling the knowledge on over-exploitation of water resources. Furthermore, we make a few recommendations based on the regions of Karnataka. The north interior region of the state being highly susceptible to climate change requires special attention in terms of climate adaptive measures. In addition to this, we suggest timely provision of heat-tolerant seeds at subsidized price and make the crop advisory information available on the basis of crop suitability in that particular region. The study also suggests focusing on institutional support to educate the farmers to reduce the climate shocks. Though the south interior and coastal regions receive higher average rainfall and possess well-established infrastructure, there is still a need to modernize the irrigation facilities. For effective utilization of irrigation facilities, farmers need to shift from high water-demanding crops to heat-resistant crops such as millet to meet the needs of a growing population in the climate change scenario.

DATA AVAILABILITY STATEMENT

All relevant data are included in the paper or its Supplementary Information.

REFERENCES

- Adger, W. N. 2006 *Vulnerability*. *Global Environmental Change* **16** (3), 268–281.
- Anandhi, A. 2010 *Assessing impact of climate change on season length in Karnataka for IPCC SRES scenarios*. *Journal of Earth System Science* **119** (4), 447–460.
- Bhende, M. J. 2013 *Agricultural Profile of Karnataka State*. Agricultural Development and Rural Transformation Centre Institute for Social and Economic Change, Bangalore.
- Biradar, N. & Sridhar, K. 2009 *Consequences of 2003 drought in Karnataka with particular reference to livestock and fodder*. *Journal of Human Ecology* **26** (2), 123–130.
- Bohle, H. G., Downing, T. E. & Watts, M. J. 1994 *Climate change and social vulnerability: toward a sociology and geography of food insecurity*. *Global Environmental Change* **4** (1), 37–48.
- Cutter, S. L., Boruff, B. J. & Shirley, W. L. 2012 *Social vulnerability to environmental hazards*. *Social science quarterly* **84** (2), 242–261.
- D'Agostino, A. L. & Schlenker, W. 2016 *Recent weather fluctuations and agricultural yields: implications for climate change*. *Agricultural Economics* **47** (S1), 159–171.
- Dimitrov, R. S. 2016 *The Paris agreement on climate change: behind closed doors*. *Global Environmental Politics* **16** (3), 1–11.
- Downing, T. E. 1991 *Vulnerability to hunger in Africa: a climate change perspective*. *Global Environmental Change* **1** (5), 365–380.
- Fekete, A., Hufschmidt, G. & Kruse, S. 2014 *Benefits and challenges of resilience and vulnerability for disaster risk management*. *International Journal of Disaster Risk Science* **5** (1), 3–20.
- Ford, J. D., Pearce, T., McDowell, G., Berrang-Ford, L., Sayles, J. S. & Belfer, E. 2018 *Vulnerability and its discontents: the past, present, and future of climate change vulnerability research*. *Climatic Change* **151** (2), 189–203.
- Fu, R. 2015 *Global warming-accelerated drying in the tropics*. *Proceedings of the National Academy of Sciences* **112** (12), 3593–3594.
- Guhathakurta, P., Rajeevan, M., Sikka, D. R. & Tyagi, A. 2015 *Observed changes in southwest monsoon rainfall over India during 1901–2011*. *International Journal of Climatology* **35** (8), 1881–1898.
- Hong, H., Li, F. W. & Xu, J. 2019 *Climate risks and market efficiency*. *Journal of Econometrics* **208** (1), 265–281.
- IPCC, C. C 2007 *The Physical Science Basis*.
- IPCC, C. C 2014 *Mitigation of climate change*. In: *Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*.
- IPCC 2018 *Summary for Policymakers*. In: *Global Warming of 1.5 °C. An IPCC Special Report on the impacts of global warming of 1.5 °C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change, sustainable development, and efforts to eradicate poverty*.
- Kalli, R. & Jena, P. R. 2020 *Impact of climate change on crop yields: evidence from irrigated and dry land cultivation in semi-arid region of India*. *Journal of Environmental Accounting and Management* **8** (1), 19–30.
- Kumar, S., Raizada, A. & Biswas, H. 2014 *Prioritising development planning in the Indian semi-arid Deccan using sustainable livelihood security index approach*. *International Journal of Sustainable Development & World Ecology* **21** (4), 332–345.
- Kumar, S., Raizada, A., Biswas, H., Srinivas, S. & Mondal, B. 2016a *Assessment of vulnerability to climate change: a case study of Karnataka*. *Indian Journal of Soil Conservation* **44** (3), 314–320.
- Kumar, S., Raizada, A., Biswas, H., Srinivas, S. & Mondal, B. 2016b *Application of indicators for identifying climate change vulnerable areas in semi-arid regions of India*. *Ecological Indicators* **70**, 507–517.

- Monterroso, A., Conde, C., Gay, C., Gómez, D. & López, J. 2014 Two methods to assess vulnerability to climate change in the Mexican agricultural sector. *Mitigation and Adaptation Strategies for Global Change* **19** (4), 445–461.
- Moore, W. R. 2010 The impact of climate change on Caribbean tourism demand. *Current Issues in Tourism* **13** (5), 495–505.
- Neset, T. S., Wiréhna, L., Opachb, T., Glaasa, E. & Linnéra, B. O. 2019 Evaluation of indicators for agricultural vulnerability to climate change: the case of Swedish agriculture. *Ecological Indicators* **105**, 571–580.
- O'Brien, K., Eriksen, S., Nygaard, L. P. & Schjolden, A. N. E. 2007 Why different interpretations of vulnerability matter in climate change discourses. *Climate Policy* **7** (1), 73–88.
- Pai, D. S., Sridhar, L., Badwaik, M. R. & Rajeevan, M. 2015 Analysis of the daily rainfall events over India using a new long period (1901–2010) high resolution (0.25 × 0.25) gridded rainfall data set. *Climate Dynamics* **45** (3–4), 755–776.
- Raju, K. V., Deshpande, R. S. & Bedamatta, S. 2017 Vulnerability to climate change: a sub-regional analysis of socio-economic and agriculture sectors in Karnataka, India. *Journal of Development Policy and Practice* **2** (1), 24–55.
- Shukla, J. L., Sachdev, K. & Joshi, P. K. 2018 Demystifying vulnerability assessment of agriculture communities in the Himalayas: a systematic review. *Natural Hazards* **91**, 409–429. <https://doi.org/10.1007/s11069-017-3120-z>.
- Singh, C., Deshpande, T. & Basu, R. 2017 How do we assess vulnerability to climate change in India? A systematic review of literature. *Regional Environmental Change* **17** (2), 527–538.
- Smit, B. & Pilifosova, O. 2003 Adaptation to climate change in the context of sustainable development and equity. *Sustainable Development* **8** (9), 9.
- Sridevi, D., Jyotishi, A., Mahapatra, S., Jagadeesh, G. & Bedamatta, S. 2014 *Climate Change Vulnerability in Agriculture Sector: Indexing and Mapping of Four Southern Indian States*.
- Srivastava, A. K., Rajeevan, M. & Kshirsagar, S. R. 2009 Development of a high resolution daily gridded temperature data set (1969–2005) for the Indian region. *Atmospheric Science Letters* **10** (4), 249–254.
- Steiner, J. L., Briske, D. D., Brown, D. P. & Rottler, C. M. 2018 Vulnerability of Southern Plains agriculture to climate change. *Climatic Change* **146**, 201–218. doi:10.1007/s10584-017-1965-5.
- Varadan, R. J. & Kumar, P. 2015 Mapping agricultural vulnerability of Tamil Nadu, India to climate change: a dynamic approach to take forward the vulnerability assessment methodology. *Climatic change* **129** (1), 159–181.
- Vincent, K. 2004 Creating an index of social vulnerability to climate change for Africa. *Tyndall Center for Climate Change Research, Working Paper* **56** (41), 1–50.
- Wan, K. K. W., Li, D. H. W. & Lam, J. C. 2011 Assessment of climate change impact on building energy use and mitigation measures in subtropical climates. *Energy* **36** (3), 1404–1414.
- Wani, S. P., Sreedevi, T. K., Rockström, J. & Ramakrishna, Y. S. 2009 Rainfed agriculture—past trends and future prospects. *Rainfed Agriculture: Unlocking the Potential* **7**, 1–33.
- Welch, J. R., Vincent, J. R., Auffhammer, M., Moya, P. F., Dobermann, A. & Dawe, D. 2010 Rice yields in tropical/subtropical Asia exhibit large but opposing sensitivities to minimum and maximum temperatures. *Proceedings of the National Academy of Sciences* **107** (33), 14562–14567.
- Wiréhna, L. 2018 Nordic agriculture under climate change: a systematic review of challenges, opportunities and adaptation strategies for crop production. *Land Use Policy* **77**, 63–74. <http://dx.doi.org/10.1016/j.landusepol.2018.04.059>.
- Wood, S. A., Jina, A. S., Jain, M., Kristjanson, P. & DeFries, R. S. 2014 Smallholder farmer cropping decisions related to climate variability across multiple regions. *Global Environmental Change* **25**, 163–172.
- Yohe, G. & Tol, R. S. 2002 Indicators for social and economic coping capacity – moving toward a working definition of adaptive capacity. *Global Environmental Change* **12** (1), 25–40.

First received 13 May 2021; accepted in revised form 5 November 2021. Available online 24 November 2021