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Agricultural drought risk assessment of Northern New South Wales, Australia using geospatial techniques

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Response to Reviewers:	The detailed response note has been uploaded as a separate word file.

Highlights

- Evaluated agricultural drought risk for Northern New South Wales, Australia.
- The model considered all risk components and 16 relevant criteria.
- Geospatial techniques were used to prepare the drought risk model.
- Risk model identified the spatial extents and levels of agricultural drought risk.

Agricultural drought risk assessment of Northern New South Wales, Australia using geospatial techniques

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Abstract

Droughts are recurring events in Australia and cause a severe effect on agricultural and water resources. However, the studies about agricultural drought risk mapping are very limited in Australia. Therefore, a comprehensive agricultural drought risk assessment approach that incorporates all the risk components with their influencing criteria is essential to generate detailed drought risk information for operational drought management. A comprehensive agricultural drought risk assessment approach was prepared in this work incorporating all components of risk (hazard, vulnerability, exposure, and mitigation capacity) with their relevant criteria using geospatial techniques. The prepared approach is then applied to identify the spatial pattern of agricultural drought risk for Northern New South Wales region of Australia. A total of 16 relevant criteria under each risk component were considered, and fuzzy logic aided geospatial techniques were used to prepare vulnerability, exposure, hazard, and mitigation capacity indices. These indices were then incorporated to quantify agricultural drought risk comprehensively in the study area. The outputs depicted that about 19.2% and 41.7% areas are under very-high and moderate to high risk to agricultural droughts, respectively. The efficiency of the results is successfully evaluated using a drought inventory map. The generated spatial drought risk information produced by this study can assist relevant authorities in formulating proactive agricultural drought mitigation strategies.

Keywords: Agricultural drought; Risk assessment; Remote sensing; GIS; Fuzzy logic, Australia.

1. Introduction

Droughts are recurrent natural disasters that affect most climatic zones in the world (Kim et al. 2015; Deng et al. 2018; Meza et al. 2020). The most common characteristics of droughts are gradual development, affecting larger areas, longer duration, and severity (Hao et al. 2012). Economic activities, agricultural production, environmental components, and socio-economic aspects are adversely affected by drought events (Rahman and Lateh 2016; Pei et al. 2018; Dikshit et al. 2020c). In the long run, droughts cause higher economic losses (Ekrami et al. 2016; Dahal et al. 2016) Few recent studies show that the projected economic losses triggered by droughts worldwide is about US 6–8 billion dollars every year (Zhang et al. 2015; Zeng et al. 2019). In recent decades, drought frequencies and intensities are higher in many parts of the world (Wang et al. 2019; Li et al. 2019; Mohsenipour et al. 2018), such as Australia. This increasing trend of droughts with its severe consequences will continue in the future due to the adverse impact of climate change and rising of water demand (Jiao et al. 2019; Rahman and Lateh 2016; Pei et al. 2019).

Droughts are very common events in Australia due to its hydroclimatic variability and geographical location (Kirono et al. 2011; Baik et al. 2019). In Australia, several major droughts are well reported in the past decades, for example, Federation drought (1895–1903), World War II drought (1937– 1945), and Millennium drought (2001-2010) (Baik et al. 2019; Rahmat et al. 2015). NSW state is considered one of the severely drought-affected states in Australia (Dikshit et al. 2020c; Tian et al. 2020; Verdon and Franks 2007). This state has experienced every major drought event that had occurred in Australia. Recently this state is suffering from a drought event that has started in 2017 (Dikshit et al. 2020c; Baik et al. 2019). These droughts badly affected crop production, livestock farming, river flows, water-dependent ecosystems, rural and urban communities (Rahmat et al. 2015; Verdon and Franks 2007). These negative impacts caused by drought in NSW is causing a severe socio-ecological and economic imbalance.

Formulating effective adaptation and mitigation policies and their appropriate implementation can reduce drought impacts (Wijitkosum and Sriburi 2019; Ekrami et al. 2016). The causes, influencing variables, and spatial patterns of hazard, vulnerability, mitigation capacity, and drought risks are necessary information for formulating effective drought mitigation and adaptation policies (Wijitkosum and Sriburi 2019; Belal et al. 2014; Hoque et al. 2020). Here drought risk mapping can be a useful tool for managing drought. Drought risk mapping provides this supporting spatial information analyzing the causes and variable of droughts and integrating all the spatial variables in the mapping of hazard, vulnerability, mitigation capacity and risk for identifying their spatial pattern of droughts (Hao et al. 2012; Pei et al. 2019; Zhang et al. 2020; Dikshit et al. 2020a). Generally, the risk is the result of the interaction between hazard, vulnerability and exposure as well as mitigation capacity (Hoque et al. 2018; Shahid and Behrawan 2008; Gu et al. 2017). The term hazard describes an event that creates adverse impacts on community and environment, where vulnerability explains the level of impacts on a particular community and environment by a specific hazard event (Zeng et al. 2019; Rashid 2013). Exposure represents the population, and properties are located within the hazard-prone areas (Hoque et al. 2018). Mitigation capacity refers to existing mitigation measures that are taken to reduce the drought impacts (Khan 2008). The risk maps can assist decision making departments to formulate effective drought mitigation strategies to minimize the adverse impacts of droughts (Pei et al. 2019; Belal et al. 2014; Wijitkosum and Sriburi 2019).

Drought risk assessment requires a large spatial and non-spatial dataset (Hoque et al. 2020; Hao et al. 2012; Zhang et al. 2011a). Spatial analysis coupled with remote sensing are potentially useful techniques to support all of these procedures (Palchaudhuri and Biswas 2016; Zeng et al. 2019). Several drought risk mapping approaches are documented in the published literature (Zeng et al. 2019; Hao et al. 2012; Wijitkosum and Sriburi 2019; Pei et al. 2019; Guo et al. 2016). Since drought is a complex phenomenon and several criteria influence different types of drought events, multi-criteria based mapping approaches are considered highly useful to generate detailed drought risk information (Ajaz et al. 2019). Some multi-criteria assessment approaches, for example, multiple criteria decision analysis (MCDM) (AHP, FAHP, Fuzzy Logic, etc.) (Hoque et al. 2020; Hategekimana et al. 2018; Jun et al. 2013), statistical models (SM) (Arabameri et al. 2019; Bui et al. 2011), and machine learning (ML) (Mojaddadi et al. 2017; Dayal et al. 2017a) are applied for mapping various natural hazards. In risk mapping, physical factors, along with socio-economic criteria, are also considered. Therefore, to assess the risk of a particular hazard, MCDM techniques such as AHP, FAHP, Fuzzy Logic, and other models have proven best among all other hazard assessment models (Dayal et al. 2018). However, fuzzy logic is considered most appropriate as it reduces the imprecision and subjectivity in the multi-criteria decision-making process (Jun et al. 2013; Al-Abadi et al. 2017; Wu et al. 2013; Zhang et al. 2011b). It is quite acceptable that an advanced machine learning approach may provide better results in mapping susceptibility of a hazard.

Four types of droughts are found in the literature: meteorological, agricultural, hydrological, and socio-economic (Sharafati et al. 2019; Nabaei et al. 2019; Deng et al. 2018). Australia is frequently affected by agricultural drought events (Rahmati et al. 2019; Dikshit et al. 2020b). Numerous studies have been carried out in Australia in the field of drought mapping, monitoring and management (Rahmati et al. 2019; Dayal et al. 2018; Dayal et al. 2017a; Mpelasoka et al. 2008; Chiew et al. 2011; Verdon and Franks 2007; Feng et al. 2019; Deo et al. 2017; Deo and Şahin 2015; Barua et al. 2011; Dikshit et al. 2020c). However, studies about agricultural drought risk mapping are very limited (Feng et al. 2019; Rahmati et al. 2019). Recently, Feng et al. (2019) assessed the agricultural drought risk in some parts of NSW directly using some limited variables through machine learning approaches without considering required risk components (vulnerability, exposure, hazard, and mitigation capacity). In contrast, Rahmati et al. (2019) mapped agricultural drought hazard (a component of risk) in Southeast Queensland utilizing some relevant variables applying machine learning approaches. The selection of appropriate risk components and their relevant criteria are pre-condition for mapping accurate and detailed agriculture drought risk information (Belal et al. 2014; Rashid 2013). In addition, existing mitigation capacity criteria that are in place to reduce the agricultural drought impacts should be integrated into the appropriate drought risk assessment procedure to get the actual drought risk information (Belal et al. 2014; Hoque et al. 2018). Therefore, a comprehensive agricultural drought risk assessment approach that incorporates all the risk components with their influencing criteria are essential to derive detailed drought risk information for operational drought management. Although the Northern NSW region has been exposed to severe and long drought events in Australia, no study has been conducted to assess detailed agricultural drought risk incorporating all risk components with their relevant variables using the fuzzy logic approach.

This study aimed to prepare a comprehensive agricultural drought risk assessment approach incorporating all components of risk with their relevant criteria using geospatial techniques and apply the prepared approach for the Northern NSW region of Australia. The objectives of this study are to: (1) develop a comprehensive drought risk assessment approach incorporating all components of risk with their relevant criteria and weighting the criteria using a fuzzy logic; (2) apply the developed approach for assessing spatial pattern of agricultural drought risk of the Northern NSW region of Australia; and (3) evaluate the generated agricultural drought risk assessment results. The rest of the paper is organized as follows. A brief discussion of the study area is followed by an explanation of material and methods. The results are presented in the next section, followed by discussion of results compared with relevant literature. Finally, summary of the findings is provided in the conclusion section.

2. Material and methods

The present study focused on a comprehensive agricultural drought risk mapping approach through fuzzy logic-based MCDM technique by incorporating all the risk components such as vulnerability, exposure, hazard as well as the mitigation capacity. The MCDM technique of fuzzy logic is quite efficient in analysing susceptibility, vulnerability, and the risk of a certain hazard (Dayal et al. 2018; Mullick et al. 2019; Pradhan 2011; Sahana and Patel 2019). Each criterion of the risk components was prepared on a similar pixel size of 90 m, and then all the criteria were ranked respectively based on the capability of influencing agricultural drought. Subsequently, the fuzzy membership function was assigned in the reference of possible significance for applying the fuzzy overlay operation (Fig. 1).

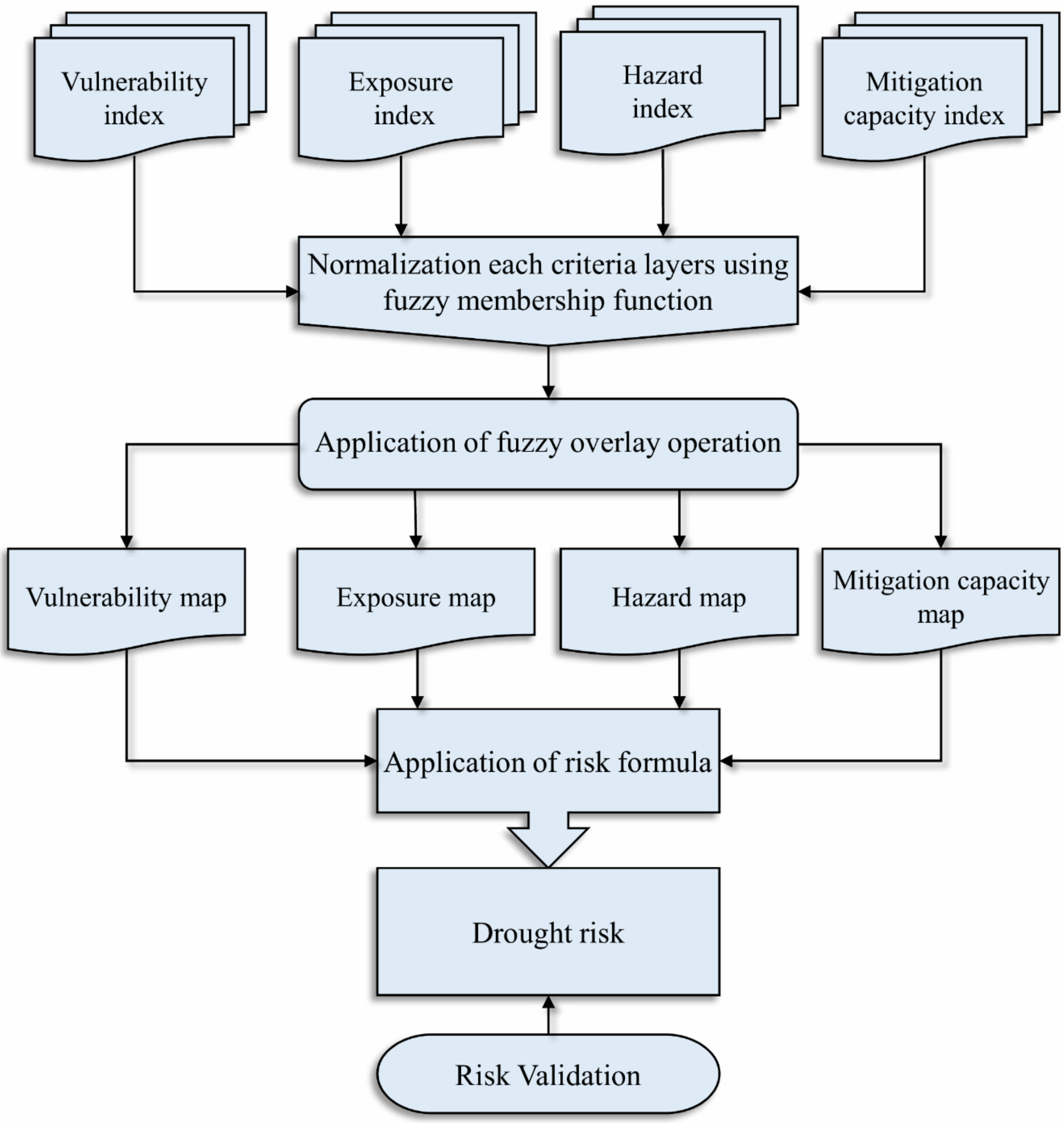

Fig. 1 Processing flowchart used for assessing agricultural drought risk in this study

2.1 Study area

The study area is located in the Northern NSW region of Australia. This region includes the northwest and northern tablelands of NSW (Fig. 2), and it covers an area of 122198.47 sq. km. The study region is geographically extended between 28°54´–31°15´ S latitude and 149°00´–151°21´ E longitude. About 156256 people are living in this region, and the number of population is increasing rapidly due to ongoing migration from other states and overseas to this region (Buckle and Drozdzewski 2018). Agriculture is the predominant industry of this region, and considered being the backbone of the local economy. The area is famous for dryland cropping, irrigation, horticulture, cattle grazing, livestock production, cotton farming, and orchard growing (Feng et al. 2019; Dikshit et al. 2020b). Agricultural activities of this region are challenged by climate change, water availability, and economic burdens (Dikshit et al. 2020c). Droughts are very common events in this region and adversely impact all kinds of agricultural and socio-economic activities (Verdon and Franks 2007). Further, the frequency and severity of droughts are increasing due to altering rainfall patterns by climate change (Dikshit et al. 2020c). A humid sub-tropical climate dominates northern NSW. The average daily maximum temperature ranges during summer between 34.2 and 35.2°C, whereas it varies averaging between 20 and 21.6°C overnight. In contrast, the average daily maximum temperature ranges during winter between 18.7 and 20.7°C, whereas it varies averaging between 4.8 and 6.2°C overnight. The average temperature of this region is steadily increasing since 1960s and years between 2008-2019 were the hottest on record. The considerable variation is found in the rainfall pattern of this region. The region experiences 780.82 mm annual average rainfall, which varies in the range of 800-1200 mm.

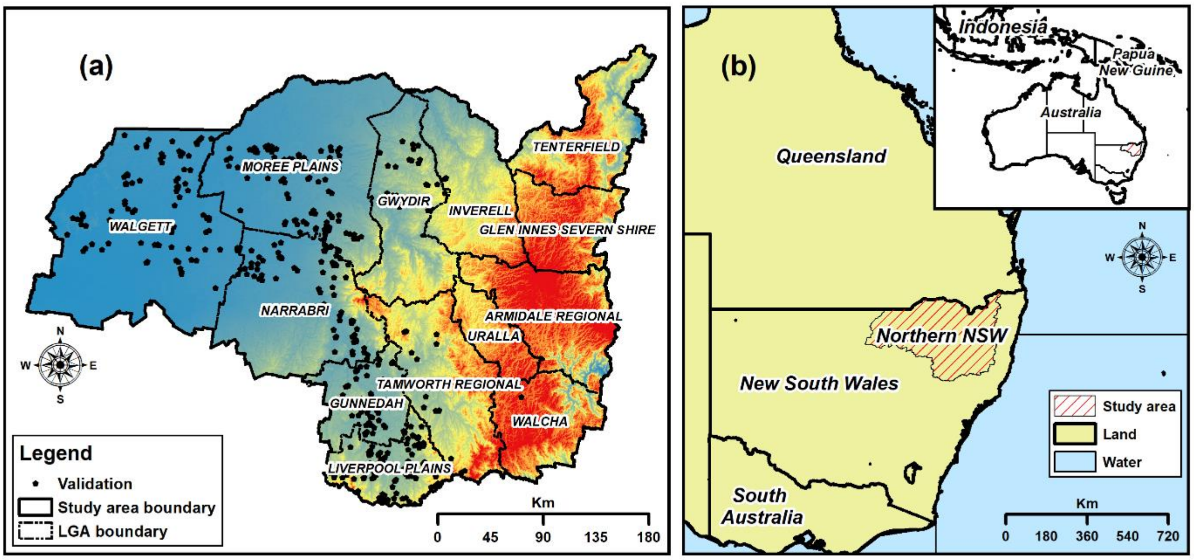

Fig. 2 (a) Study area with local government areas LGA boundary and location of validation points, and (b) Location of the study area in the context of the entire NSW States and Australia.

2.2 Data set and sources

The intensity of agricultural drought considers various factors, including physiographic, climatic as well as socio-economic variables. Therefore, all the related and available factors that influence drought intensity were utilized to calculate vulnerability, hazard, exposure, and mitigation capacity to generate agricultural drought risk maps. Each risk components consist of four separate criteria. In total, 16 dynamic criteria (Dayal et al. 2018; Baik et al. 2019; Hao et al. 2012; Kim et al. 2015; Pei et al. 2018; Zeng et al. 2019) were used in this study. All the data were aggregated from multiple sources comprised of both local and international organizations. Information about the data sources and their necessary characteristics is outlined briefly in Table 1.

Table 1. Data type and sources used for drought risk assessment.

Criteria	Types	Source	Period
LULC	Shapefile	Department of Planning, Industry and Environment. (https://data.nsw.gov.au/)	2017
Elevation	3-second DEM data (90m resolution)	Queensland Spatial Catalogue–QSpatial	2000
Slope	In percentages	TERN - Terrestrial Ecosystem Research Network	2000
Population density	Population number	Australian Bureau of Statistics (https://quickstats.censusdata.abs.gov.au/)	2011
Plant available water capacity (PAWC)	90m resolution	National Agricultural Monitoring System (NAMS; http://www.nams.gov.au)	2014
Soil depth, Sand percentage	90m resolution	TERN - Terrestrial Ecosystem Research Network	2014
Soil Moisture	NetCDF format	Australian Government, Bureau of Meteorology (http://www.bom.gov.au)	2005 - 2019
Distance to river, river density, lithology, and distance to road	Shapefile	Geoscience Australia (https://www.ga.gov.au/)	2016
Mean annual rainfall, mean annual maximum temperature, mean annual evaporation and mean annual humidity	90m resolution	Australian Government, Bureau of Meteorology (http://www.bom.gov.au)	1970-2018

2.3 Risk evaluation criteria, alternatives and mapping

All the selection criteria were selected based on a literature review, data availability, and its relevance to the agricultural drought risk(Dayal et al. 2018; Baik et al. 2019; Hao et al. 2012; Kim et al. 2015; Pei et al. 2018; Zeng et al. 2019). Thematic layers of risk components for each criterion were prepared using different software such as ArcGIS, ENVI, and Erdas Imagine. The mapping techniques and causes of their selection, justification, argument, and characteristics of each risk component are explained in detail in the following sections.

2.3.1 Criteria for vulnerability mapping

Four criteria, such as soil depth, sand percent, soil moisture, and lithology are generally associated with agricultural drought. Hence, these criteria were used for vulnerability mapping (Baik et al. 2019; Dayal et al. 2018). Soil depth and sand percent play great importance in assessing the vulnerability of agricultural drought. For instance, soil depth has a great influence on providing the necessary nutrients and water, which has a significant role in crop growth (Jain et al. 2015). Therefore, the areas containing a richer soil depth have a better ability of water holding capacity and provide sufficient moisture for the crops to minimize the drought vulnerability (Dayal et al. 2018). Likewise, the sand percent also has the capability of controlling the water holding capacity, although sand percent works inversely and has the opposite rule over drought vulnerability (Pandey et al. 2012). Following that, the soil depth and sand percent data were used from TERN in 90 m spatial resolution, and the further procession of these criteria was followed by Dayal et al. (2018) (Fig.3a-d).

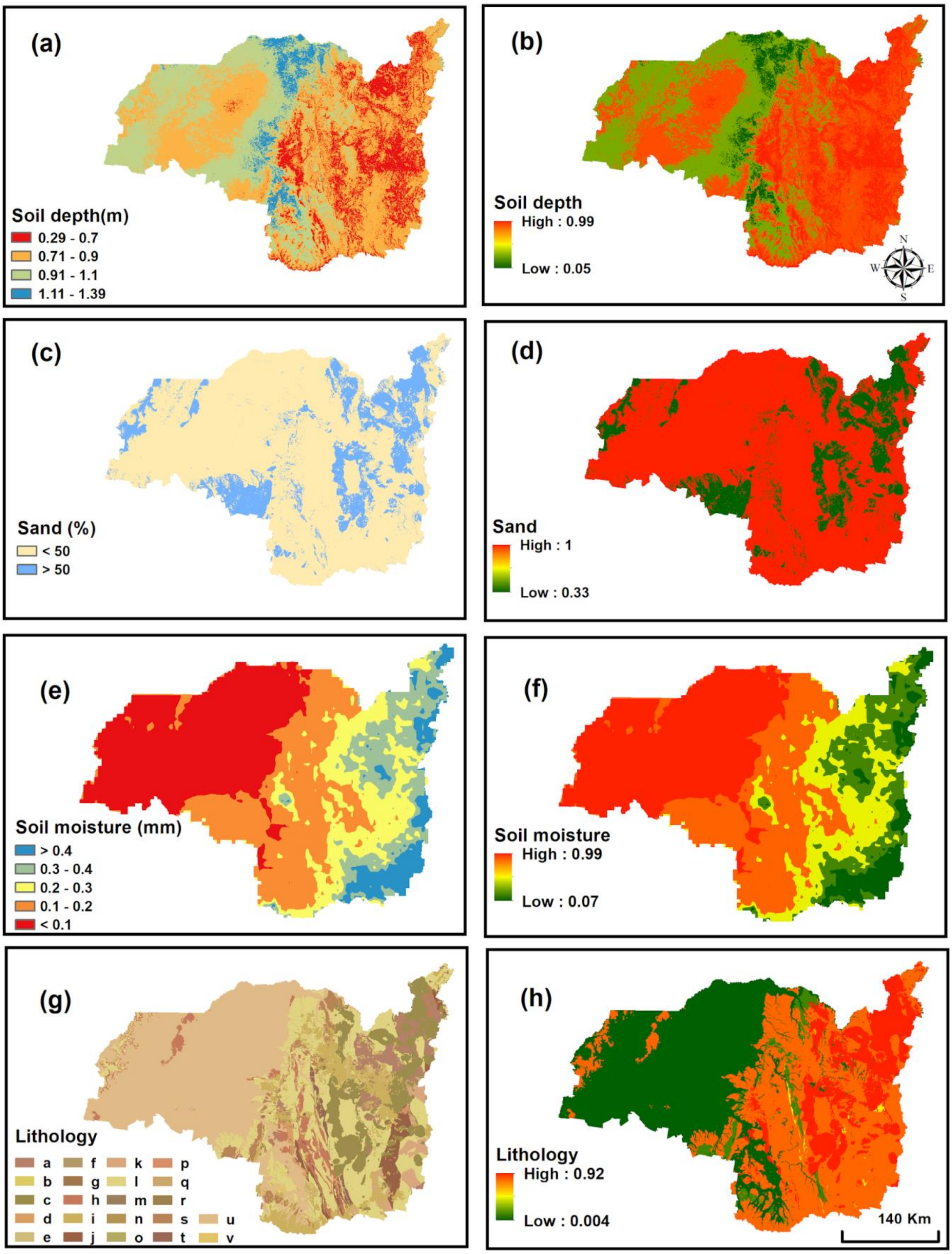

Fig. 3 The original drought vulnerability factors in absolute units (left): (a) soil depth, (c) sand, (e) soil moisture, (g) lithology and the corresponding standardized drought vulnerability factors (right) using the fuzzy membership.

Soil moisture also an important criterion which has a big influence on determining agricultural drought vulnerability; as higher the soil moisture lesser the drought vulnerability (Hoque et al. 2020). The soil moisture data was collected from the Bureau of Meteorology, Australia, in NetCDF format from 2005 to 2019. The procedure was maintained following few steps such as the conversion of NetCDF format to raster. The average of all year values was aggregated in a single raster layer using the raster calculator of ArcGIS (Fig. 3e,f). Similarly, lithology data was collected from Geoscience Australia for 2016 in shapefile format and categorized on the basis of relativity to agricultural drought vulnerability (Fig. 3g, h).

2.3.2 Criteria for exposure mapping

The economic condition of the people, infrastructure, and other environmental resources situated in a hazard affected area is known as exposure. The high elevation and slope area's agricultural resources are more exposed to drought hazards because of low water holding capacity (Dayal et al. 2018; Wu et al. 2017; Zeng et al. 2019). Hence, land use and population density along with elevation and slope were selected as exposure, 3-second DEM data (90m resolution) were used from (qld.auscover.org.au) to generate elevation raster (Fig. 4a,b) while slope was obtained from TERN in percentage (Fig.4c,d).

LULC data in shapefile format was acquired from the Department of Planning, Industry, and Environment, NSW for 2017. LULC data revealed that the study area is dominated by agricultural land and grassland (Fig. 4e,f). In the context of the agricultural drought, agricultural land class was ranked the highest, while water bodies class was ranked the lowest (Table 2). Population data were collected from the Australian Bureau of Statistics (ABS 2012) following the 2011 census, considering the fact of higher population density means higher exposure to agricultural drought (Fig.4g,h). The high population density areas will be more exposed to food scarcity and famine situations because of drought conditions.

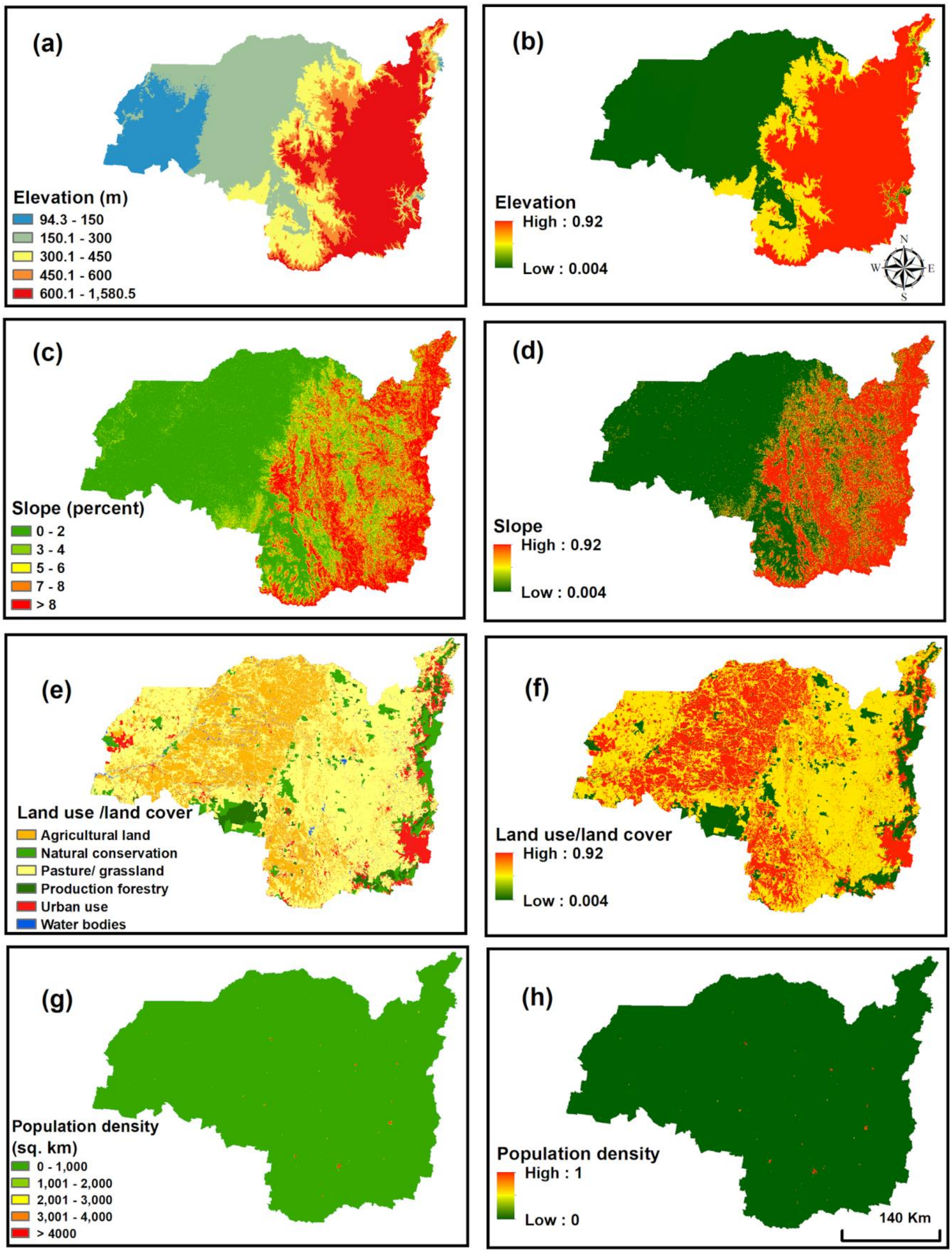

Fig. 4 The original drought exposure factors in absolute units (left): (a) elevation, (c) slope, (e) LULC, (g) population density and the corresponding standardized drought exposure factors (right) using the fuzzy membership functions

Table 2. Land use and land cover classes details.

Land use/land cover classes	Description
Production forestry	Production native forests, Plantation forests, Irrigated plantation forests
Water bodies	Lake, reservoir, dam, river, channel aqueduct, wetlands
Urban use	Manufacturing and industrial, residential and farm infrastructure, Services, utilities, Transportation system
Pasture/ grassland	Grazing native vegetation, grazing modified pastures, grazing irrigated modified pastures
Natural conservation	Nature conservation and protected area
Agricultural land	Cropping, perennial horticulture, seasonal horticulture, irrigated cropping.

2.3.3 Criteria for hazard mapping

The possibility of occurrence of potentially hazardous incidents in a certain area and for a specific period of time is known as a hazard (Hoque et al. 2019). Four climatic variables such as mean rainfall, maximum temperature, mean humidity, and evaporation were considered hazard criteria because the agricultural drought is highly influenced by these climatic variables (Dikshit et al. 2020a; Dahal et al. 2016; Eklund and Seaquist 2015). The deficiency of rainfall and humidity intensify the drought condition, thereby, regions with low rainfall and humidity are very much prone to drought (Esfahanian et al. 2017). In contrast, areas with low temperatures and evaporation are likely to be less susceptible to drought conditions (Karamouz et al. 2015). All the data for preparing the criteria of hazard components were collected from the Bureau of Meteorology, Australia, for 48 years (1970 – 2018). The climatic data were obtained from 55 weather stations situated either inside or adjacent to the study area. 90 m spatial resolution was considered to generate the raster layers by applying a globally accepted Kriging interpolation technique in ArcGIS(Nasrollahi et al. 2018) (Fig.5).

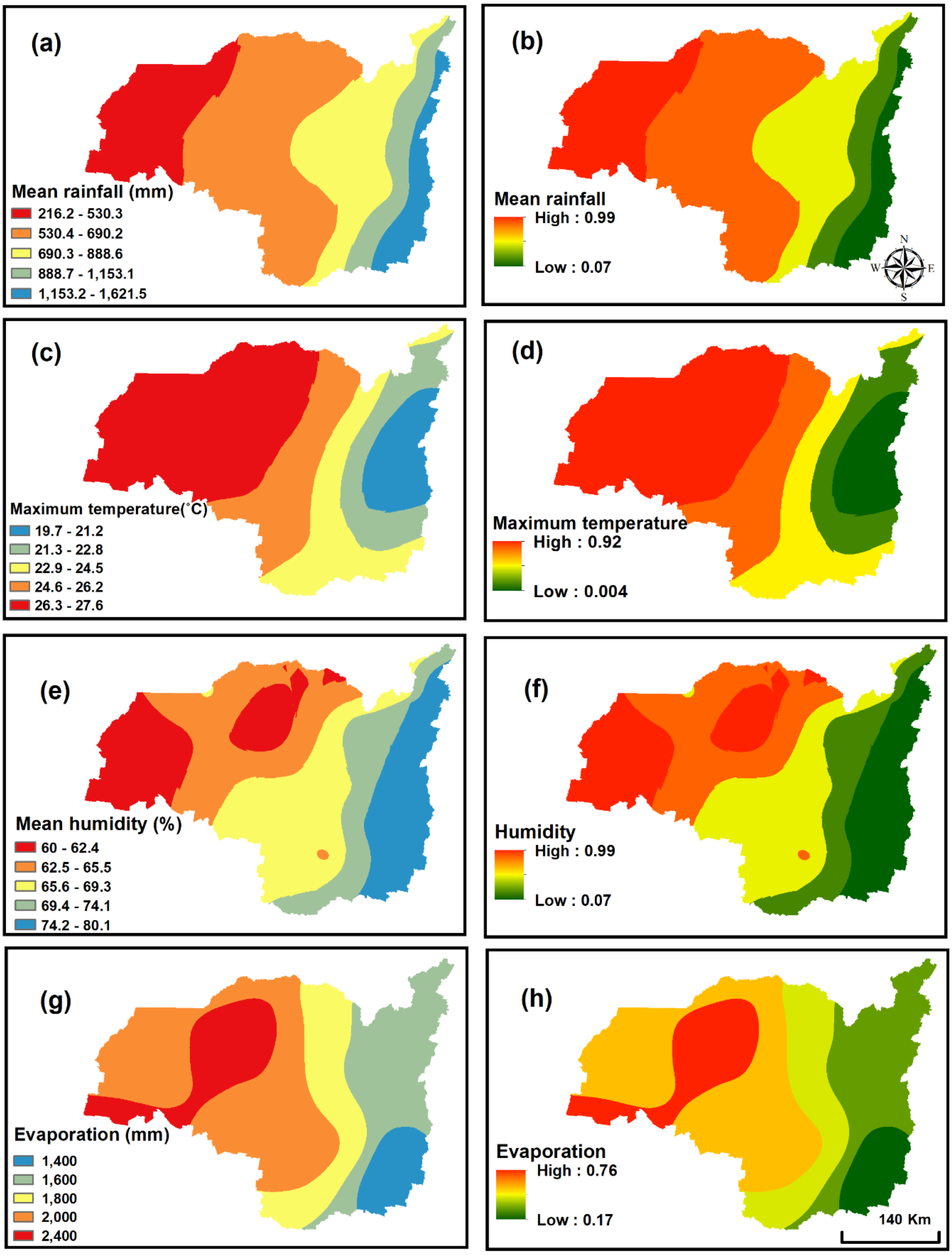

Fig. 5 The original drought hazard factors in absolute units (left): (a) mean rainfall, (c) mean maximum temperature, (e) mean humidity, (g) evaporation and the corresponding standardized drought hazard factors (right) using the fuzzy membership functions.

2.3.4 Criteria for mitigation capacity mapping

Four criteria such as distance to the river, river density, plant available water capacity, and distance to road were considered for assessing the study area's agricultural drought mitigation capacity. The areas close to the river channels are less susceptible to agricultural droughts and can easily mitigate the drought condition as the river and reservoirs provide the necessary water for irrigation activities (Lakshmi 2016; Thomas et al. 2016). Likewise, river density also has an undeniable impact on checking the drought condition, and the high river density regions have more potential to reduce drought impact than the regions with low river density (Pandey et al. 2012). Furthermore, the availability of major roads plays a crucial role during drought conditions, particularly the provision of necessary aid, relief, and conducting the rescue operation to save the farmers and their agricultural lands. Therefore, the river channel and road network data were acquired from “Geoscience Australia” for 2016 in shapefile format. For the preparation of the raster layers, distance to river and distance to road, the Euclidean distance tool was used, while line density was used to generate river density criteria (Fig 6a-f).

Similarly, plant available water capacity (PAWC) has a significant influence on agriculture-related drought mitigation capacity. The variation in the water content difference within field capacity and the permanent wilting point is known as PAWC (Dayal et al. 2018). Therefore, when the degree of PAWC increases, drought vulnerability of agriculture decreases, which means the mitigation capacity of that particular area against agricultural drought also enhances (Stone and Potgieter 2008). Hence, a PAWC spatial layer was produced using the Australian National Agricultural Monitoring System (NAMS) for the 2014 (Fig. 6g-h).

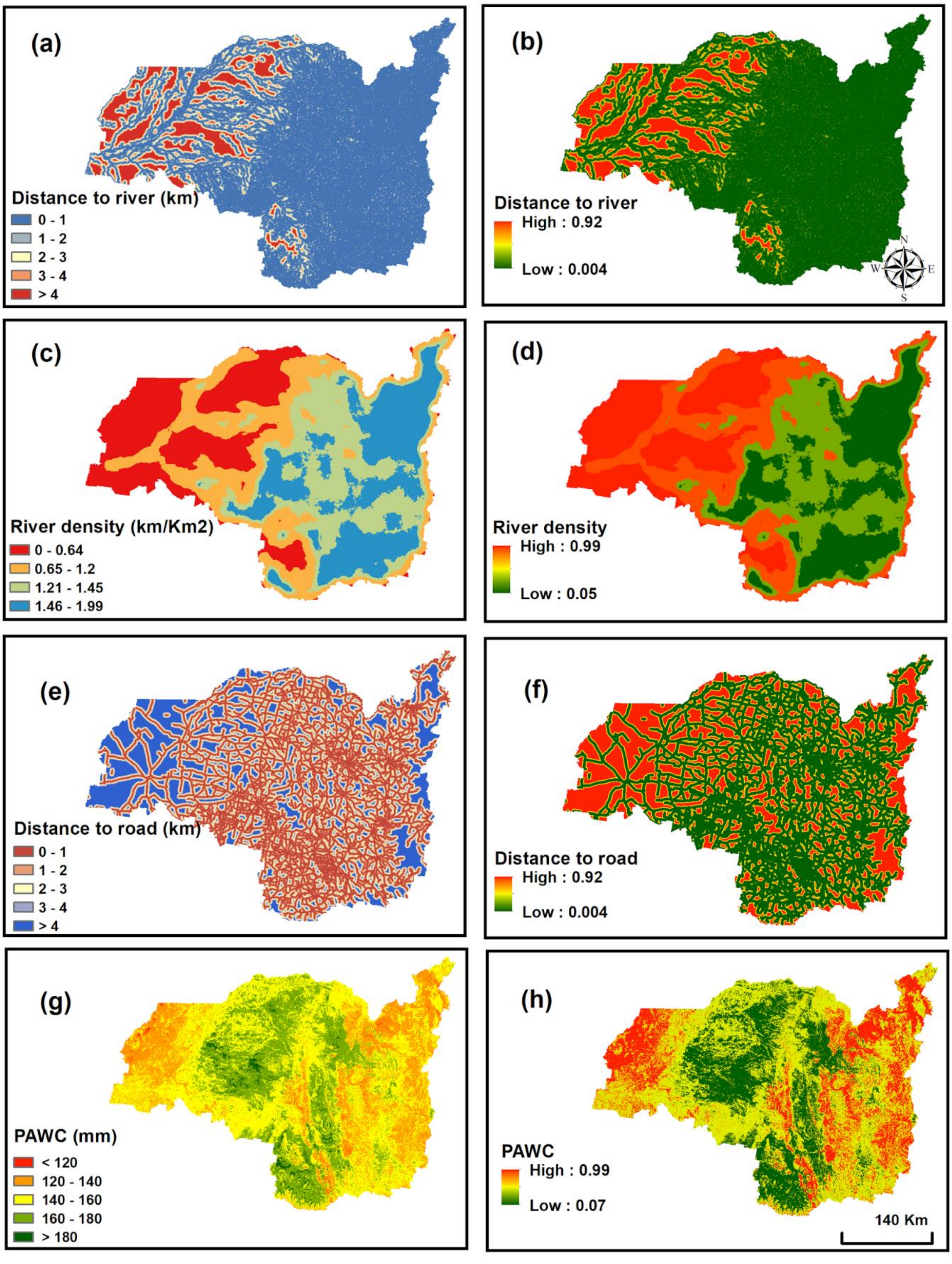

Fig. 6. The original drought mitigation capacity factors in absolute units (left): (a) distance to river, (c) river density, (e) distance to road, (g) PAWC and the corresponding standardized drought mitigation capacity factors (right) using the fuzzy membership functions.

2.4 Assigning weight using fuzzy membership function

Boolean logic usually computes the value of a function in the absolute value of true or false, while fuzzy logic has the ability to calculate the degree of truth. For instance, fuzzy logic has advanced the weighting methods by converting the value 0 or 1 (Boolean logic) to 0 and 1 (Fuzzy logic) utilizing different fuzzy membership functions. However, the initial step was to classify the criteria into different classes, applying natural break, equal interval, and manual classification. In the next steps, fuzzy membership function and fuzzy-small for the criteria were assigned which are inversely related to soil depth, soil moisture, mean rainfall, mean humidity, river density, and PAWC (Table 3). Conversely, the factors related directly; fuzzy-large membership function, i.e., sand percent, lithology, elevation, slope, LULC, mean maximum temperature, evaporation, distance to the river, and road were assigned (Table 3). Besides, fuzzy linear was used for only population density criteria (Table 3). The formula for fuzzy large and fuzzy small resembles equations 1 and 2, respectively, and the characteristics and logic behind using those functions have described in detail by Mullick et al. (2019).

$$\mu(x) = \frac{1}{1 + \left(\frac{x}{f2}\right)^{-f1}} \quad (1)$$

$$\mu(x) = \frac{1}{1 + (\frac{x}{f2})^{f1}} \quad (2)$$

Table 3. Subclasses of drought vulnerability, exposure, hazard factors, and mitigation capacity factors and their numerical weights.

Criteria	Break value	Rating	Weights assigned	Fuzzy membership function	Assumption
Soil depth (m)	< 0.7	1	Very high	Fuzzy-Small	Inversely related
	0.7 – 0.9	3	High		
	0.9 – 1.1	6	Low		
	> 1.1	9	Very low		
Sand (%)	< 50	5	Low	Fuzzy-Large	Directly related
	> 50	10	High		
Soil moisture (mm)	> 0.4	10	Very low	Fuzzy-Small	Inversely related
	0.3 – 0.4	8	Low		
	0.2 – 0.3	6	Moderate		
	0.1 – 0.2	4	High		
	< 0.1	2	Very high		
Lithology	a-Igneous felsic volcanic b-Igneous mafic intrusive c-Igneous felsic intrusive d-Igneous felsic-intermediate volcanic	10	Very high	Fuzzy-Large	Directly related

	e-Igneous intermediate volcanic				
	f-High grade metamorphic rock				
	g-Igneous intermediate intrusive				
	h-Argillaceous detrital sediment	8	High		
	i-Igneous mafic volcanic				
	J- Feldspar- or lithic-rich arenite to rudite				
	k-Metasedimentary siliciclastic				
	l-Sedimentary siliciclastic				
	m-Igneous; sedimentary				
	n-Sedimentary carbonate	6	Moderate		
	o-Meta-igneous ultramafic				
	p-Igneous felsic-intermediate intrusive				
	q-Meta-igneous mafic				
	r-Meta-igneous mafic volcanic				
	s-Quartz-rich arenite to rudite	4	Low		
	t-Sedimentary non-carbonate chemical or biochemical				
	u-Regolith	2	Very low		
	v-Others				
Elevation (m)	94.2 – 150	2	Very low	Fuzzy-Large	Directly related
	150 – 300	4	Low		
	300 – 450	6	Moderate		
	450 – 600	8	High		
	> 600	10	Very high		
Slope (percent)	0 – 2	2	Very low	Fuzzy-Large	Directly related
	2 – 4	4	Low		
	4 – 6	6	Moderate		
	6 – 8	8	High		
	> 8	10	Very high		
LULC	Water body	-100	No member	Fuzzy-Large	Directly related
	Natural conservation	2	Very low		
	Production forestry	4	Low		
	Pasture/ grassland	6	Moderate		
	Urban use	8	High		
	Agricultural lands	10	Very high		
Population density (sq. km)	0 – 1000	2	Very low	Fuzzy-Linear	Directly related
	1000 – 2000	4	Low		
	2000 – 3000	6	Moderate		
	3000 - 4000	8	High		
	> 4000	10	Very high		

Mean rainfall (mm)	216.2 – 530.3	2	Very high	Fuzzy-Small	Inversely related
	530.4 – 690.2	4	High		
	690.3 – 888.6	6	Moderate		
	888.7 – 1153.1	8	Low		
	1153.2 – 1621.5	10	Very low		
Mean maximum temperature (˚C)	19.7 – 21.2	2	Very low	Fuzzy-Large	Directly related
	21.3 – 22.8	4	Low		
	22.9 – 24.5	6	Moderate		
	24.6 – 26.2	8	High		
	26.3 – 27.6	10	Very high		
Mean humidity (%)	74.2 – 80.1	10	Very low	Fuzzy-Small	Inversely related
	69.4 – 74.1	8	Low		
	65.6 – 69.3	6	Moderate		
	62.5 – 65.5	4	High		
	60 – 62.4	2	Very high		
Evaporation (mm)	1200 – 1400	2	Very low	Fuzzy-Large	Directly related
	1400 – 1600	4	Low		
	1600 – 1800	6	Moderate		
	1800 – 2000	8	High		
	> 2000	10	Very high		
Distance to river (km)	< 1	2	Very low	Fuzzy-Large	Directly related
	1 – 2	4	Low		
	2 – 3	6	Moderate		
	3 – 4	8	High		
	>4	10	Very high		
River density (km/km2)	>1.46	9	Very High	Fuzzy-Small	Inversely related
	1.21 – 1.45	6	High		
	0.65 – 1.2	3	Low		
	< 0.64	1	Very low		
Distance to road (Km)	0 – 1	2	Very high	Fuzzy-Large	Directly related
	1 – 2	4	High		
	2 – 3	6	Moderate		
	3 – 4	8	Low		
	>4	10	Very low		
PAWC (mm)	>180	10	Very high	Fuzzy-Small	Inversely related
	160 – 180	8	High		
	140 – 160	6	Moderate		
	120 – 140	4	Low		
	<120	2	Very low		

2.5 Risk assessment

After normalization of ratings, a fuzzy overlay operation was performed for each risk component incorporating their assigned weight following Table 3. In the ArcGIS toolbox, there are five types of fuzzy overlay operations available, i.e., AND, OR, PRODUCT, SUM, and GAMMA. However, in this research, the GAMMA overlay was applied for calculating each component. The argument of choosing the GAMMA overlay has been described in detail by Dayal et al. (2018). Once all the risk components were prepared, the following formula was applied in the raster calculator of ArcGIS to produce the final risk map (Equation 3). The risk map and its every component were classified into five classes following the severity of drought using the statistical method of natural break classification.

$$\text{Risk} = \text{vulnerability} \times \text{exposure} \times \text{hazard} / \text{mitigation capacity} \quad (3)$$

2.6 Efficiency test of drought risk mapping

The receiver operating characteristics curve (ROC) and the area under the curve (AUC) were used to test the produced agricultural drought risk map's efficiency. This method is widely used to test the accuracy of the susceptibility and risk model, which is an appropriate technique for assessing deterministic and probabilistic justification (Hoque et al. 2020).

In this study, only the prediction rate curve was prepared with reference to soil moisture data. Validation of agricultural drought risk map using soil moisture data is suitable as the moisture content is an essential indicator of agricultural droughts (Mpelasoka et al. 2008). The procedure has been conducted following a few steps. First, the soil moisture data was collected from the Australian Government, Bureau of Meteorology, from 2005 to 2019. In the next step, following Rahmati et al. (2019) methods, the relative departure of soil moisture (RDSM) was calculated and created an integrated drought inventory map following equation 4.

$$RDMS = \frac{S_i - \underline{S}_i}{\underline{S}_j} \times 100 \quad (4)$$

Where, S_i is mean annual soil moisture for 2019 (One of the driest year in the history of NSW) and $\underline{S}_j$ is mean annual soil moisture between 2005 and 2019.

In the next step, RDSM was standardized from their original values into a 0–1 scale using a fuzzy logic operation process, and a threshold of 0.5 was then used for the RDSM (i.e., RDSM > 0.5) to identify drought locations in the study area. Then randomly, 447 drought locations were selected to validate a produced drought risk map where validation datasets resemble 100% of the drought points (Fig. 1).

3. Results

3.1 Vulnerability mapping

Fig. 7a depicts different vulnerability levels to droughts according to the influence of some relevant criteria in the study area. Approximately 26.7% (32648.2 km^2) and 30.8% (37561.5 km^2) of the study area fall under very-high and high drought vulnerability categories, respectively (Fig. 7a). In total, this area covers 57.5% of the total study area. These high to very-high drought vulnerable areas are observed in eastern, northeastern and southeastern parts of the study area, especially, Tenterfield, Walcha, Uralla, Armidale regional, Inverell, Glen Inn Seven Shire, Tamworth regional and Liverpool plain. Areas at moderately vulnerable to droughts are found in some parts of Moree plains and Walgett, which cover 13.1% (16051.6 km^2) of the total study area. On the contrary, low and very-low vulnerable to droughts comprise 29.4% (35,882.3 km^2) of the study area. These areas are observed in the western part of Walgett, northern part of Moree plains, and some portion of Narrabri. .

3.2 Exposure mapping

The spatial extents of exposed people, infrastructure, and other environmental resources to droughts in the study area are illustrated in Fig. 7b. About 30.9% (37698.3 km^2) of the study area is moderately exposed to droughts, which is dominating compared to other categories of exposure. These areas are dispersed in the northern, central, southern, and some parts of the eastern region of the study area. In contrast, areas at highly to very highly exposed to drought are located in parts of the Tenterfield, Walcha, Uralla, Armidale regional, Inverell, Glen Inn Seven Shire, and Tamworth regional. These areas constitute 21.8% (26618.5 km^2) and 16.4% (20055.6 km^2) of the total study area, respectively. The areas are classified as less exposed to drought are situated in Walgett and some southern portion of Narrabri covering 20.2% (24652.0 km^2) and 10.7% (13119.3 km^2) of the study area.

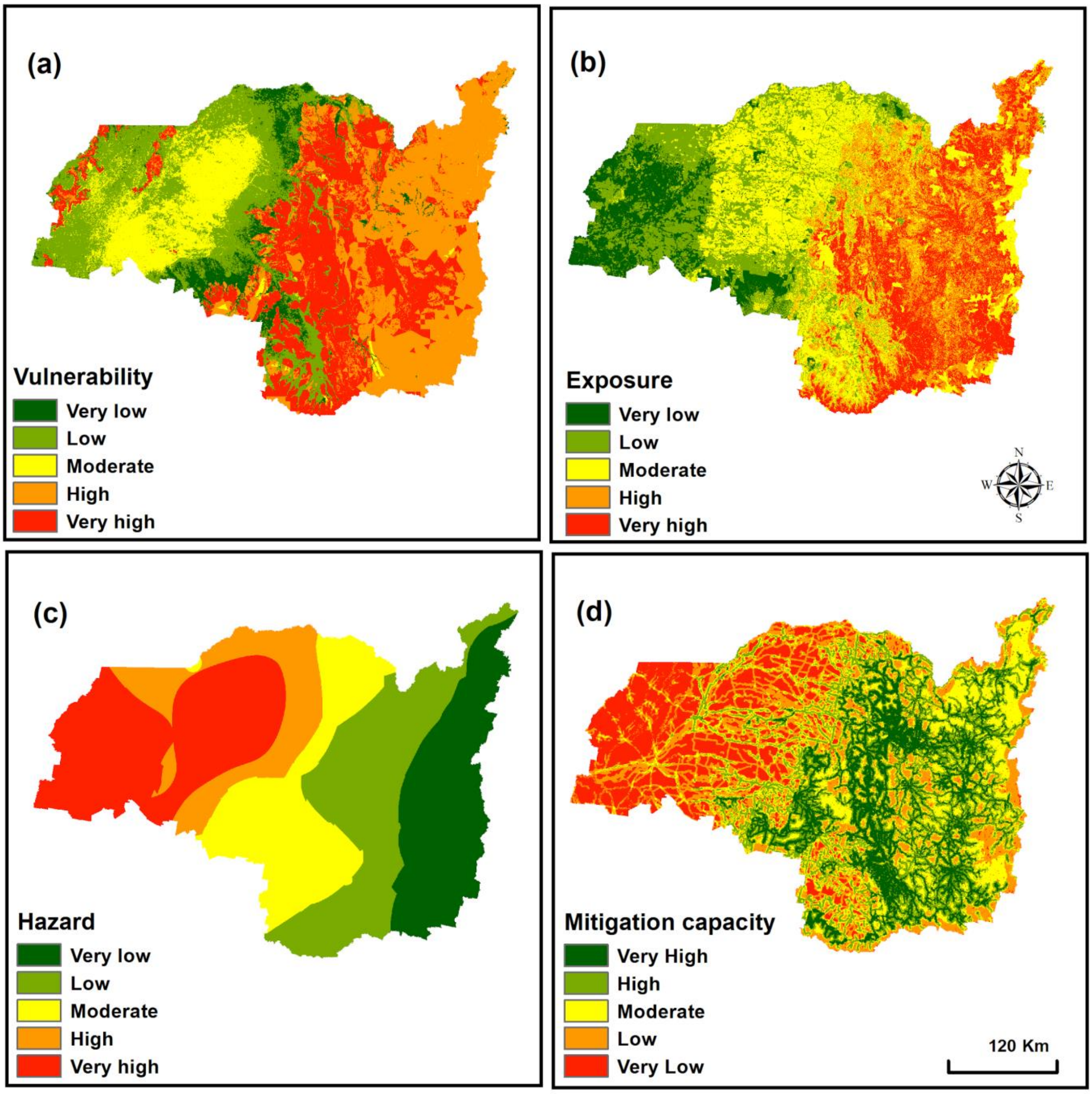

Fig. 7. Maps of risk assessment components: (a) Vulnerability, (b) Exposure, (c) Hazard, and (d) Mitigation capacity.

3.3 Hazard mapping

Fig. 7c presents the spatial distribution and levels of drought hazard in the study area. Approximately 23.1% (43,601.1 km^2) of the study area were classified as a very-high hazard to droughts. These very high to high hazard areas are located covering the entire part of

Walgett, some western parts of Morre Plains and Narrabri. Furthermore, areas at moderate drought hazard are mainly concentrated in the central part of the study area, covering the partial parts of southern Narrabri and Gunnedah and the northern part of Gwidir. These areas constitute 27390.8 km^2 of the entire study area. In contrast, 41.9% of the study area falls under low to very-low hazard zones covering an area of 27838.0 km^2 and 23313.9 km^2, respectively, and located in eastern, northeastern and southeastern parts of the study area.

3.4 Mitigation capacity mapping

The spatial distribution and degree of mitigation capacity to study area to droughts are shown in Fig. 7d. Very high and high mitigation capacity to droughts are observed sporadically in the eastern, southeastern and northeastern and some central portion of the study area, particularly, Walcha, Uralla, Armidale regional, Inverell, Tenterfield and Glen Inn Seven Shire. These areas occupy about 38.5% (47072.7 km^2) study area Figure 7d also shows that 21.4% (26134.6.4 km^2) area has a moderate mitigation capacity to address the drought events and is located scattered all over the study area. In contrast, the areas that have low to very-low mitigation capacity comprise approximately 20.1% (25331.4 km^2) and 19.3% (23604.9 km^2) of the study area. These areas are mainly located in the western, northwestern and southwestern portions, exclusively, Walgett, Moree plains, and Narrabri.

3.5 Risk mapping

Fig. 8 outlines the spatial extent and levels of risk to droughts in the study area. Approximately 4.54 (23430.0 km^2) and 33.2% (40503 km^2) of the study areas are identified as very-high to high-risk to droughts, respectively. These very-high to high-risk zones are distributed sporadically in the northern, northwestern, southwestern, central, and southern parts, especially the majority of Moree Plain, Walegatt, Gawdir, Liverpool Plains, Inverell and some areas of Tenterfield, Uralla, Gunnedah, Tamworth regional. The areas under a moderate risk of droughts cover a considerable amount of the study area, with an area of 35202.9 km^2 (28.8%). These moderate drought-prone areas are common throughout the study area, more specifically in the western, northern, northeastern, and central parts of the study area. In contrast, 10.06% and 23.4% of the study area areas were identified under low and very-low risk to droughts. These areas are located in some southern portion of Narrabri and Gunnedah as well as the majority of the Wacha, Armidale regional, and Glen Innes Seven Shire. Almost the entire area, except some areas of eastern and southern parts, could be marked as drought-prone.

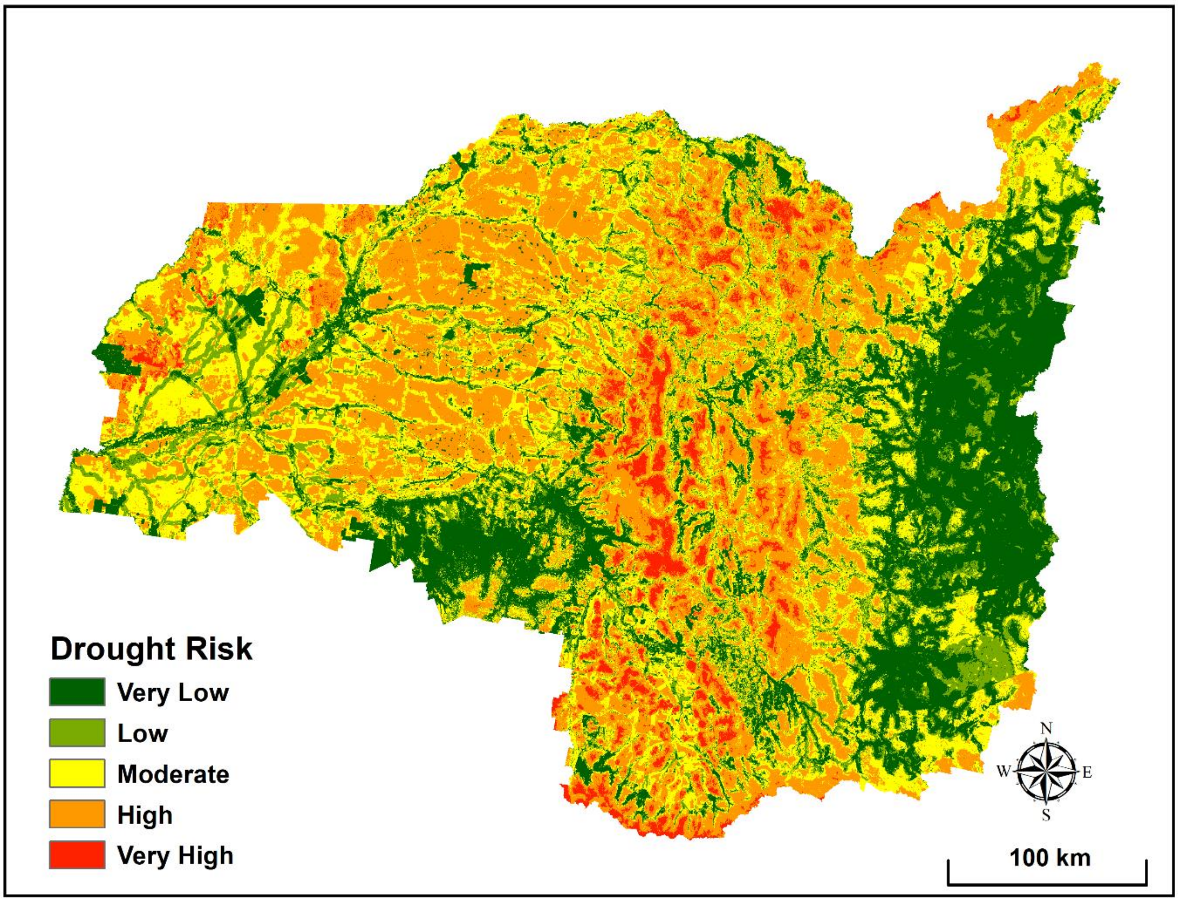

Fig. 8. Agricultural drought risk map of the study area

3.6 Outcome of the efficiency test

The prediction rate curves are illustrated in Fig. 9, showing model efficiency applied in this study. The AUC of the risk model's prediction rate was 0.827, which indicates 82.7% prediction accuracy for the applied model. In general, an AUC value near 1 indicates a higher accuracy of the model (Chen et al., 2018).Therefore, AUC values of prediction rate (82.7%) of this analysis presenting a successful outcome of the developed drought risk assessment approach.

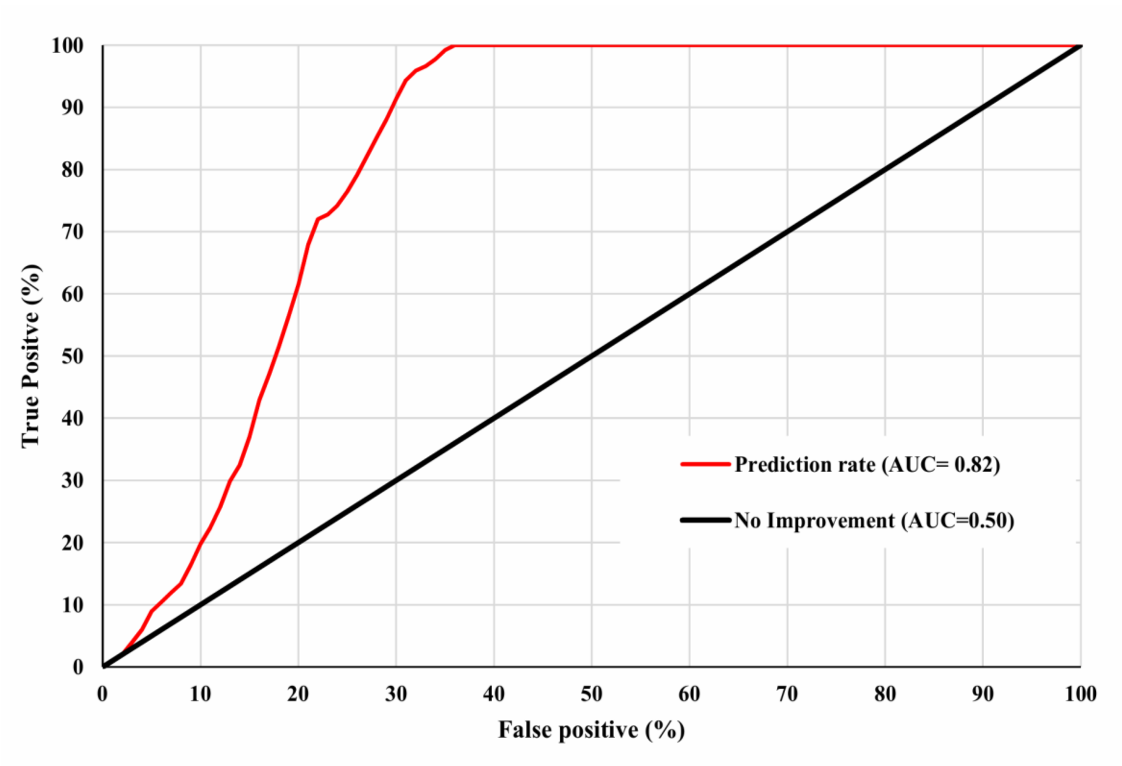

Fig. 9 Area under curve (AUC) for prediction rate.

4. Discussion

In the recent past, the intensity and degree of drought events in Australia have increased dramatically and affecting crop production, livestock farming, the river flows, water-dependent ecosystems, rural and urban communities significantly (Verdon and Franks 2007; Rahmat et al. 2015). Several relevant studies predicted that such events will be more severe and frequent under the future climate change scenario (Burke et al. 2006; Rezaei et al. 2015; Wanders and Wada 2015; Zeng et al. 2019). Therefore, a detailed drought risk mapping technique incorporating all the risk components is highly efficient in order to minimize the challenge of yield losses, ecology, and overall economic impact.

Worldwide, numerous methods have been performed to assess the agricultural drought risk using geospatial techniques. Most of the studies were conducted considering limited risk components, either index-based or performed without taking into account mitigation capacity (Zeng et al. 2019; Meza et al. 2020; Palchaudhuri and Biswas 2016; Dayal et al. 2017b; Gopinath et al. 2015). Therefore, the motivation of the research was to propose an agricultural drought assessment technique, which is more robust in the sense that it covered a total of 16 criteria under all (four) risk components. Moreover, this study provided more detailed information regarding the mitigation capacity of agricultural drought, which can be used by the policymaker and the administrator.

The findings demonstrated that approximately 4.54% and 33.2% of the study areas are identified as very-high to high-risk to droughts and mostly distributed sporadically in the northern, northwestern, southwestern, central, and southern parts of northern NSW. Regarding vulnerability and exposure components, the very-high and high vulnerable class combined accounted for around 57% and 38%, respectively, while about 23% of the study area fell into high to very-high susceptible class. On the contrary, around 38% of the study area consists of high to ver- high mitigation capacity to cope up with the extreme drought condition. Consistency was found among vulnerability and exposure components, which revealing the eastern parts of the study area mostly fell to high to very-high vulnerable class. Such findings are consistent with the outcome of the developed drought map by the NSW government (https://edis.dpi.nsw.gov.au/) using CDI (Combined Drought Indicator). Those regions are mainly comprised of vulnerable factors of both vulnerability and exposure that intensify the drought condition for instance high sand percentage, less soil depth, vulnerable land-use class, high elevation, steep slope, and susceptible lithology class. Regarding the hazard components, all the factors indicating the western portion of the study area fell to a very-high susceptible class which revealing the consistency among all the climatic variables. Apart from these, the integration of mitigation capacity in the final risk formula strengthened the drought risk assessment technique previously followed by other similar research of Zeng et al. (2019); Palchaudhuri and Biswas (2016); Dayal et al. (2017b) and Gopinath et al. (2015) where mitigation capacity was not included for assessing drought risk. Evidently, the integration of mitigation capacity has strengthened the agricultural drought risk assessment approach by showing efficiency of around 83%. This suggests the significance of mitigation capacity as well as all the risk components in terms of predicting the drought risk for agriculture accurately. Thus, the proposed integrated risk model can be applied by planners and engineers to restrict future agriculture drought consequences and maintain sustainable development.

This study has some drawbacks too. As many criteria were required, it was not easy to collect high-quality datasets. For example, a 90 m resolution DEM was used for preparing the slope and elevation spatial layers. However, higher resolution datasets can provide more accurate results. It would be good to incorporate a few more criteria, for instance, NDVI, irrigation, crop yield, etc.; however, it was not possible to include those due to data constraints, time frame, and funding. The validation of prepared approach outputs was conducted using soil moisture datasets only, but specific field based datasets would enhance validation processes. Future research can consider addressing the above issues. Nevertheless, the prepared approach can still provide satisfactory outputs for agricultural drought mapping in formulating drought mitigation measures. Accordingly, this validated approach may be extended to any drought-prone region with modifying criteria and datasets to derive detailed spatial patterns and extent of droughts.

5. Conclusion

This study was carried out to prepare and apply a comprehensive agricultural drought risk assessment approach incorporating all components of risk using fuzzy logic and geospatial techniques in the Northern NSW region of Australia to identify the spatial pattern of agricultural drought risk. For the first time, the relevant criteria of each risk component, including hazard, vulnerability, exposure, and mitigation capacity, are combined to map the spatial pattern of agricultural drought risk in the study region. ROC and AUC techniques were applied using a drought inventory map to evaluate the efficiency of the results. The results demonstrated that geospatial techniques integrated with fuzzy logic were promising for successfully mapping agricultural drought risk. Further, the outputs suggested that risk results were considerably influenced by the incorporation of mitigation capacity measures. The risk map presents very-high to high drought risk for most parts of Moree Plains, Walgett, Gawdir, Liverpool Plains, Inverell, and some areas of Tenterfield, Uralla, Gunnedah, Tamworth regional. These higher-risk areas cover around 40% of the study area. About 28.8% moderate drought-prone areas are common throughout the study area, more specifically in the western, northern, northeastern, and central parts of the study area. The prediction efficiency of the produced drought risk map was 82.7%. The produced spatial distribution maps of agricultural drought risk can assist policymakers in preparing effective drought mitigation measures to resist drought impacts reasonably.

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CRediT authorship contribution statement

Muhammad Al-Amin Hoque: Conceptualization, Methodology, Modelling, Writing original draft, Validation.

Biswajeet Pradhan: Visualization, Review & Editing, Supervision, Funding.

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Declaration of interests

☒ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☐The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: