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ORIGINAL PAPER

Spatio-temporal drought risk mapping approach and its application in the drought-prone region of south-east Queensland, Australia

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Abstract Strategic management of water resources in drought-vulnerable regions can be greatly hampered by frequent, severe and long-lasting droughts. To enable better drought relief policy and amicable solutions and proactive actions for preparedness and mitigation of drought impacts, this study adopts a spatio-temporal methodology for the assessment of drought risk of drought-prone areas in south-east Queensland, Australia. In this study, the spatially representative depiction of the drought risk in a drought-prone region with multiple vulnerability, exposure and drought hazard indicators is considered in order to develop a geographic information systems-based drought risk mapping tool. Spatial indicators of drought are categorised into various subclasses, and the conditional joint probability of each indicator is the determined in accordance with the Bayes theorem. The fuzzy logic approach is then embraced as a new approach in this study to standardise the different drought factors on a range of 0–1 followed by an aggregation of drought vulnerability, exposure and hazard indices using the fuzzy GAMMA overlay operation in ArcGIS 10.5 to produce the optimal drought risk map for the case study region. The analysis of drought's different phases shows varying vulnerability levels in different austral seasons (summer, autumn and spring of 2007) and annually (2007, 2009 and 2013) that is well represented by drought hazard index, i.e. rainfall departure. The application of the fuzzy set to incorporate and classify drought factors reveals its useful implications for handling of spatial drought-related data and the development of the drought risk index. The validation of the method performed with upper and lower layer soil moisture data reveals significant correlation with the drought risk index. The study has implications for drought risk mapping, particularly in utilising the ability of the fuzzy logic-based analytical technique integrated with GIS-based mapping tools for spatio-temporal drought risk

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studies. The approach in this paper can be considered as a practical mapping tool for drought studies, to better enable drought management, drought mitigation and relief-planning actions that need to be implemented by different decision-makers in water resources, agriculture and other socio-economic areas.

Keywords Drought risk · Hazard/exposure/vulnerability index · Fuzzy logic · Geographic information system (GIS)

1 Introduction

Drought is a socio-environmental phenomenon where climatic, hydrological, environmental, socio-economic and cultural forces act concomitantly (Kallis 2008) to have an effect on the severity. The need for interdisciplinary analysis of drought events and collective assessments with the participation of stakeholders, scientists, policy makers and public is crucial to provide effective, useful and new information for understanding and managing drought events. A proactive risk management attempts for more concerted efforts towards planning for drought events, which are no doubt dependent on drought vulnerability assessments (Ekrami et al. 2016; Jain et al. 2015; Pandey et al. 2010; Thomas et al. 2016; Wilhelmi and Wilhite 2002).

While a number of studies have focussed on modelling and characterisation of drought in terms of severity, intensity and duration (Dayal et al. 2016, 2017a, b; Deo et al. 2016, 2017; Deo and Şahin 2015), the temporal and spatial assessment in terms of mapping drought risk has remained very limited. A recent study by Zarafshani et al. (2016) described a number of ways to map vulnerability with multiple hazards via a conceptual framework, targeted at farmers' level of perception for before, during and after the drought onset. Their study suggests that the drought risk must be mapped on both temporal and spatial scales (and consider the interacting factors) for any given region.

Drought risk is a product of the exposure to the hazard and the vulnerability to the hazardous conditions (Wilhite 2000). An area is expected to have greater risk if it has a high exposure and a low coping capability for the impact of drought. The vulnerability, however, is likely to elevate over time with an increased demand for water resources. The climatic events or other static or semi-static factors such as technology, population behaviour, practices and policies may also vary albeit over longer-term scales, making the drought vulnerability assessment a highly challenging task. Hence, the continuous assessment of a drought's spatial vulnerability is as important as its temporal vulnerability. The dual characteristics of drought events have been addressed in a number of literature sources (e.g. Downing and Bakker 2000; Hewitt 2014; Jain et al. 2015; Pandey et al. 2010; Tánago et al. 2016; Wilhelmi and Wilhite 2002). For the case of the Australian continent that is highly stressed due to drought events, there is a dire need for an improved and easily implemented spatio-temporal approach for drought vulnerability and risk assessments.

Drought risk management involves three primary activities: (1) identification of the risk and the assessment of its significance, (2) development of new methods and utilisation of available resources to minimise or mitigate the drought risk and (3) development of new strategies to manage the drought risk. The difficulty, however, in enforcing any of these perspectives is the subjectivity in the measurement of regional drought vulnerability that is usually quantified as a relative measure (Downing and Bakker 2000). The challenges with vulnerability mapping and assessment are an ongoing issue because vulnerability levels are dynamic, and they are moderated due to changes in land use, population density, technology, farming practices and climate variability. Therefore, mitigating the regional drought impacts could involve some level of subjectivity in the assessment as there are no standard criteria on mapping drought vulnerability, hence to quantify drought risk. However, to minimise the subjectivity in the vulnerability assessment, the application of fuzzy logic theory in geospatial information system (GIS) for natural hazard mapping is instrumental in the design of efficient tools for spatial decision-making (Aksoy and Ercanoglu 2012; Al-Abadi et al. 2017; Espada Jr et al. 2012; Jun et al. 2013; Karabegovic et al. 2006; Liu and Lai 2009; Tangestani 2003; Wu et al. 2013).

Introduced by Zadeh (1965), the fuzzy set theory embraces the membership function to operate on a range of numbers (0, 1), reflecting the degree of certainty of membership (Pradhan 2011) instead of using the crisp sets that only allow values of either 0 or 1 as levels of truth (Jun et al. 2013). It is an alternative logical foundation that comes from artificial intelligence technology with several useful implications for geospatial modelling. The idea of using fuzzy logic in natural hazard mapping is to consider spatial objects on a map as members of a set wherein the unconstrained (subjective judgement) fuzzy membership values must lie on (0, 1) range rather than being measured over discrete intervals. For complex problems such as drought risk assessment, fuzzy logic tool is attractive because it is easy to understand and implement, allows flexibility of combining several map layers, can be readily implemented in GIS (Pradhan 2011) and manipulates spatial objects of different measurement units into standardised values between 0 and 1 (Espada Jr et al. 2012). Fuzzy logic has been used for landslide and flood risk mapping, assessing water-harvesting zones, multi-hazard impact assessment flood disaster validation and decision support for environmental impact assessment, among the others (Aksoy and Ercanoglu 2012; Al-Abadi et al. 2017; Araya-Muñoz et al. 2017; Espada Jr et al. 2012, 2013; Jun et al. 2013; Karabegovic et al. 2006; Tangestani 2003). Therefore, the application in other environmental sectors of hazard and risk assessment is a motivation to apply fuzzy logic tool for drought risk assessment, considering south-east Queensland, Australia as a study region.

Developing a comprehensive set of metrics for drought assessment is challenging due to the dynamic nature of environmental and socio-economic factors (Hinkel 2011). In many previous drought vulnerability assessment studies, the indicating variables were mainly aggregated with deductive approach (e.g. expert judgement) or by normative approach (e.g. equal weighting). Consequently, the delivery of robust results is an issue due to subjective judgements in the former approach and the multi-dimensionality of variables to different stakeholders in the latter approach (Hinkel 2011). Assigning equal weights to factors or through expert judgement based on experience leaves room for errors. To circumvent the issue of multi-dimensionality in the normative argument of equal weights, the Bayesian joint conditional probability of each indicating variable for the weighted overlay operations is recommended.

Since vulnerability assessment is a relative measure due to its region-specific nature, drought analysts must define the critical levels (Downing and Bakker 2000). There are numerous factors that influence drought vulnerability (Price et al. 2011) and their inclusion may depend on available data. Undeniably, drought vulnerability has a close correlation with man-made infrastructure and socio-economic conditions (Wilhelmi and Wilhite 2002). According to the literature, studies performed outside of Australia has included various climatic and physiographic factors to produce integrated maps of vulnerability, e.g. (Ekrami et al. 2016; Jain et al. 2015; Pandey et al. 2010; Safavi et al. 2014; Thomas et al. 2016; Wilhelmi and Wilhite 2002). Therefore, region-specific integrated physiographic, climatic and social factors are essential for the assessment of drought vulnerability. This approach is yet to be applied in Australia, except for one study that used only two factors (i.e. plant available water capacity and soil moisture level) to analyse drought vulnerability and risk in rain-fed agriculture across Australia (Stone and Potgieter 2008).

Considering the need for a spatially relevant drought risk mapping for the drought-prone SEQ region, the purpose of this study is to apply fuzzy logic tool to generate drought hazard, exposure and vulnerability indices using multiple physiographic and climatic factors where the indices are then overlayed to generate a risk map. The aim is to develop a model for assessing drought risk that is expected to improve rationality and accuracy of results. The drought risk map can be used as a framework for a timely implementation of mitigation measures and effective monitoring system. The specific objectives are to: (1) identify available spatial and temporal physiographic and climatic factors relevant for the region; (2) estimate probable weights of each factor conditional on rainfall departure using Bayesian theorem; (3) standardise factors using fuzzy membership functions and generate vulnerability, exposure and hazard indices maps; and (4) produce integrated drought risk map using fuzzy overlay operation available in ArcGIS 10.5.

2 Theoretical overviews

2.1 Concept of vulnerability, exposure and risk

The risk is a product (or sum) of hazard, vulnerability and/or exposure. According to Downing and Bakker (2000), the risk can be expressed mathematically as:

$$\text{Risk} = \text{Hazard} \times \text{Vulnerability} \times \text{Exposure} \tag{1}$$

$$\text{Risk} = \text{Hazard} + \text{Vulnerability} \tag{2}$$

IPCC (2012) defines hazard as “the potential occurrence of a natural or human-induced physical event that may cause loss of life, injury, or other health impacts, as well as damage and loss to property, infrastructure, livelihoods, service provision, and environmental resources”. The risk is defined as “the likelihood over a specified time period of severe alterations in normal functioning of a community or a society due to hazardous physical events interacting with vulnerable social conditions, leading to widespread adverse human, material, economic, or environmental effects that require immediate emergency response to satisfy critical human needs and that may require external support for recovery” (IPCC 2012). The term vulnerability has numerous definitions. Since vulnerability usually bounds by context, a specific definition is difficult to justify. In response to hazard-centric perception of disasters in 1970s, the term vulnerability was introduced to describe the extent to which people suffer from calamities and socio-economic circumstances to cope with (Schneiderbauer and Ehrlich 2004). Geoscience Australia (2010a) conceptualised vulnerability as the impact a hazard has on the people, infrastructure and the economy. Lastly, *exposure* is defined in terms of the assets such as “people, property, systems or other elements present in hazard zones that are thereby subject to potential losses” (ISDR 2009).

2.2 Fuzzy logic approach

The fuzzy logic is an approach that computes the "degree of truth" instead of absolute terms "true or false" (i.e. 1 or 0) Boolean logic (Zadeh 1968, 1975). Fuzzy theory embraces the membership function (or the true and false) to operate over a range of numbers between 0 and 1, reflecting the degree of certainty of the membership (Pradhan 2011). It includes 0 and 1 as the extreme cases of truth but also various states in between, i.e. fuzzy logic permits partial membership mathematically given as:

$$\mu_A(x) : X \rightarrow [0, 1] \tag{3}$$

In Eq. (3), $\mu_A(x)$ refers to the grade of membership for element x in a fuzzy set A, and the X is the universal set defined in specific problem.

To build a fuzzy logic-based model, a careful selection must be made for the appropriate membership function. In context of the present study, the fuzzy membership functions transform the input raster onto a 0–1 scale based on a specified fuzzification algorithm. A value of 1 indicates full membership in a fuzzy set, while membership decreasing to a value of 0 indicates it is not a member of the fuzzy set. In this study, three membership algorithms, LINEAR, LARGE and SMALL, are used.

In the LARGE fuzzy membership, the larger inputs have membership values closer to 1 and the function is defined by a user-specified midpoint value that is assigned a membership value of 0.5. The mathematical expression of LARGE fuzzy membership function is given as (Tsoukalas and Uhrig 1996):

$$\mu(x) = \frac{1}{1 + \left(\frac{x}{f2}\right)^{-f1}} \tag{4}$$

In Eq. (4), $f1$ is the spread and $f2$ is the midpoint. The fuzzy LARGE function is useful when large input values have higher membership where the input values can be either an integer or floating point positive values.

The fuzzy SMALL defines membership function with smaller input values having a membership value closer to 1. Mathematical expression for fuzzy SMALL function is given as:

$$\mu(x) = \frac{1}{1 + \left(\frac{x}{f2}\right)^{f1}} \tag{5}$$

The fuzzy SMALL function is useful when small input values have higher membership.

The fuzzy LINEAR membership function applies a linear function between the user-specified minimum and maximum values. Anything below the minimum will be assigned a 0 (definitely not a member) and anything above the maximum a 1 (definitely a member).

After input variable standardisation, the fuzzy overlay operation is performed. There are five different fuzzy overlay types: AND, OR, PRODUCT, SUM and GAMMA in ArcGIS 10.5, where the user can choose the overlay type to suit the purpose of their study. This study used GAMMA overlay that uses the algebraic product of the "increasive" fuzzy SUM and "decreasive" fuzzy PRODUCT effects, both raised to the power of gamma. The fuzzy GAMMA overlay operation is chosen to avoid bias on which risk equation (Eqs. 1–2) to be used in the assessment (Espada Jr et al. 2012, 2013) where the mathematical expression of fuzzy GAMMA is (Tangestani 2003):

$$\mu_{\text{gamma}} = (\mu_{\text{sum}})^{\gamma} \times \left(\mu_{\text{product}}\right)^{1-\gamma} \tag{6}$$

where μ_{gamma} is the calculated fuzzy membership function, γ is a parameter chosen between 0 and 1; μ_{sum} is the fuzzy algebraic SUM and μ_{product} is the fuzzy algebraic PRODUCT that is mathematically expressed as:

$$\mu_{\text{sum}} = 1 - \prod_{i=1}^{n} (1 - \mu_i) \text{ and } \mu_{\text{product}} = 1 - \prod_{i=1}^{n} (\mu_i) \tag{7}$$

where μ_i is the fuzzy membership for the ith map, and i = 1, 2, …, n maps to be combined. In the fuzzy GAMMA operation, $\gamma = 0$ is equivalent to the fuzzy algebraic PRODUCT and $\gamma = 1$ is equivalent to fuzzy algebraic SUM. The judicious choice of the gamma value depends on the user in order to ensure a flexible compromise between the "decreasive" and "increasive" tendencies of fuzzy PRODUCT and fuzzy SUM, respectively. This study uses the default gamma value of 0.9, consistent with Espada Jr et al. (2013) that also used fuzzy GAMMA overlay for developing flood risk maps for Brisbane city area.

3 Materials and method

To produce an integrated drought risk map for the SEQ study region, various layers representing spatial maps of different factors are prepared using ArcGIS software. Spatial maps representing vulnerability, exposure and hazard per unit area are prepared on a grid system of 100 × 100 m. Spatial information on the above maps is categorised in sub-classes in respect of their degree of significance in vulnerability to drought to obtain probable weight of a factor conditional on the hazard.

3.1 Study area

The study area is located in the south-east Queensland (SEQ) region, Australia. It covers an area of 123,897.53 square kilometres. Rural areas make up about 85% of SEQ, much of which is managed by farmers. Grazing takes up major portion of the land use ($\approx$51%). Other intensive agricultural activities include horticulture and animal production. For sustainable agriculture, key challenges in SEQ region include climate change, water supply, population growth and economic pressures. The projected impact of climate change directly affecting agriculture includes more frequent and severe droughts (Pearce et al. 2007). As such, the agricultural production will require more water efficient practices due to increasing demand for water when supply becomes less reliable under drought conditions. The study area covers six catchments: Condamine–Balonne, Moonie, Border Rivers, Logan, Gold Coast and Moreton. The topography of the study area varies between 14.74 m below sea level to 1360.24 m high. The higher elevations exist on the Great Dividing Range that is Australia's most substantial mountain range and the third longest land-based range in the world. The high elevated terrains have high slopes as well. The climatic conditions vary on either side of the Great Dividing Range (Chiew and McMahon 2002).

3.2 Identification and significance of factors

Drought is driven by precipitation deficiency in space and time, while the severity of drought depends on numerous factors. Drought risk to agriculture can be viewed as a product of exposure to the climatic hazard and vulnerability to cropping practices to drought conditions (Wilhelmi and Wilhite 2002). To assess regions with high risk of droughts from integrated drought risk map, drought vulnerability, exposure and hazard factors need to be identified. While there are various, yet no certain fixed factors, previous investigations elsewhere have shown a number of static and semi-static physiographic and dynamic climatic factors that are closely associated with drought conditions. The most common yet immediate associations with droughts are slope, soil type, elevation, plant available water capacity (PAWC), soil depth, land use and population density. The rainfall deficiency is considered as the drought hazard.

Rainfall The best and most common single measure of water availability in Australia is the rainfall (ABS 2012). The rainfall deficiency is the primary factor responsible for occurrence of drought as it is the cause of subsequent soil moisture shortage for crops (Jain et al. 2015). In this study, the rainfall departure (RD) from normal (i.e. normal $\cong$ base period from 1971 to 2000) is considered as the hazard index. The year 2007 was one of the driest years, and the spring season (September–October–November; SON) was the driest season in 2007 during the Millennium Drought. The formula for calculating RD is given as:

$$\mathrm{RD}\,(\%) = \frac{x_i - \bar{x}_i}{\bar{x}_i} \times 100 \tag{8}$$

where x_i = rainfall for the given month, season or year and $\bar{x}_i$ = average rainfall for the month, season or year over the base period 1971–2010 (Deo et al. 2009).

In SON 2007 season, $\sim$ 12.70% of the study region had RD $\leq -75\%$, $\sim$ 12.41% of the study region had $-75\% < \mathrm{RD} < -50\%$, $\sim$ 13.08% of the study region had $-50\% < \mathrm{RD} < -25\%$, and $\sim$ 11.12% of the study region had $-25\% < \mathrm{RD} < 0\%$. In other words, a total of $\sim$ 49.31% of the study region was under rainfall deficient state in the spring season of year 2007. We based the numerical weighting of RD subclasses according to Jain et al. (2015) and Safavi et al. (2014). Similarly, rainfall departure for autumn (March–April–May; MAM) and summer (December–January–February; DJF) seasons of 2007 and annual, i.e. 2007, 2009 and 2013 drought years, is estimated, and Table 1 enumerates the extreme values in the study region.

Figure 1 shows an example of annual (1960–2013) and seasonal (2000–2013) per cent rainfall departure for a point location in the study region, i.e. for Brisbane (153.03°E,

Table 1 The maximum and minimum values of rainfall departure from the base period during the drought years in the present study region. (*DJF* December–January–February, *MAM* March–April–May, *SON* September–October–November, *JJA* June–July–August)

Rainfall departure	Drought season (2007)			Drought year		
	DJF (%)	MAM (%)	SON (%)	2007 (%)	2009 (%)	2013 (%)
Maximum	225.26	466.34	378.56	19.50	27.74	41.08
Minimum	− 73.18	− 100.00	− 100.00	− 41.71	− 49.47	− 62.51

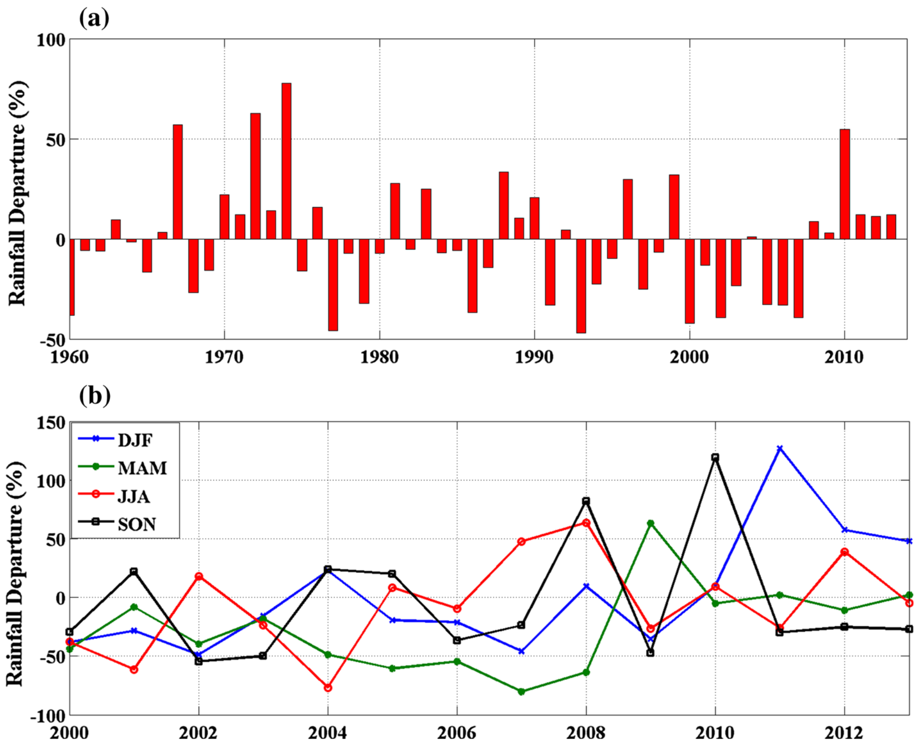

Fig. 1 Climatological conditions for the study region (Brisbane, 153.03°E, 27.47°S). **a** Annual rainfall departure (expressed as a percentage) over 1960–2013. **b** Seasonal rainfall departure (expressed as a percentage) over Millennium Drought

27.47°S). The seasonal rainfall departure has been mostly negatives as well during this Millennium Drought period.

Soil In seasonally dry and semi-arid tropics and subtropics, the low and erratic rainfall puts a major constraint on rain-fed agriculture. In these areas, soil moisture is crucially important for fullest expression of the production potential of plants over time. It is important, however, to note that irregular and an insufficient amount of rainfall is not the only cause of lack of moisture in the soil. For instance, the water-holding capacity of the soil depends on the soil porosity, which in turn depends on the soil texture. The soil texture is important because it influences the amount of water soil can hold, the rate of water movement through the soil and how workable the soil is for growing plants (FAO 2005). In SEQ region, soil texture varies from clay, loam, silt and sand. The clay soil generally holds more water while the sandy soil is well aerated but does not hold much water, i.e. it has high water infiltration rate. Therefore, sandy soils are most vulnerable to drought due to its least moisture holding capacity.

This study utilised the sandy soil data for the year 2014, sourced from the Terrestrial Ecosystem Research Network (TERN) (TERN 2009). Sand data are estimated in percentages by taking 20 µm-2 mm mass fraction of the < 2 mm soil material determined using the pipette method. The sand digital maps are available at six defined depth intervals: 0–5 cm, 5–15 cm, 15–30 cm, 30–60 cm, 60–100 cm and 100–200 cm. In this study, the values for all depth levels were averaged to obtain a single layer map of sand. Figure 3 shows the spatial distribution of the sand percentages. Much of the low sand percentage is found at the higher elevation area.

Soil depth Soil depth refers to the thickness of the soil materials that provide structural support, nutrients and water for plants (Scherer et al. 2013). The greater the depth of the soil, the higher the soils capacity to store and supply moisture to plants for growth. Therefore, greater soil depths are considered less vulnerable to droughts. Shallow depths mean less water storage by the soil; hence, it is more vulnerable to droughts. The soil depth data were obtained from TERN for the year 2014. The depth of soil on a geospatial map is shown in Fig. 3.

Slope The slope that measures the inclination of the land surface from the horizontal is another important drought vulnerability factor. The water runoff is considerably higher on steeper terrain compared to the near ground surface. Therefore, the terrain areas with lesser slopes are relatively less vulnerable to droughts compared to hilly plains (Jain et al. 2015). The slope data (in percentages) were obtained from TERN for the year 2000. The spatial distribution of the slope percentage is shown in Fig. 3.

Plant available water capacity (PAWC) The PAWC refers to the difference in water content between field capacity and permanent wilting point of plants. Stone and Potgieter (2008), following the work of Wilhelmi et al. (2002), provided a compelling argument on the importance of PAWC for the Australian droughts. In their study, Stone and Potgieter (2008) developed initial indications of PAWC based on the knowledge of local specialists, agronomists and rural extension officers working "in the field". It was found that many parts of eastern Australia had relatively low levels of PAWC (e.g. 75–100 mm) that, potentially, increased the vulnerability to drought risk. To be consistent with the scales used in their study, we used the similar effective index-scale of PAWC shown in Table 2. The PAWC data were obtained from the National Agricultural Monitoring system (NAMS; http://www.nams.gov.au). The PAWC spatial distribution is shown in Fig. 3.

Elevation Water availability also greatly depends on the elevation of the plain. The digital elevation model (DEM) describes landforms and ground surface topography is crucial for addressing issues relating to the impacts of climate change, disaster management, water security and environmental management. The 3-second DEM data for the year 2000 were obtained from Queensland Spatial Catalogue–QSpatial. The elevation corresponds well with the per cent slope where higher elevation has higher slopes and vice versa. For instance, the elevation less than 500 m has slope less than 5%. In Fig. 3, the high elevations are where the Great Diving Range is, while the area closer to the coast is mostly low-elevated zone.

Land use The drought vulnerability can be regarded in a dynamic sense as a result of land use and management, including government farm practices and societal factors (Nelson et al. 2005). Land use is one of the most important factors influencing vulnerability to drought. In this study, it is considered as an exposure factor because of its dynamic nature. The land use data was obtained from the Queensland Land use Mapping Program (QLUMP) for the year 2016, available at QSpatial data portal. Land use in the study region is dominated by pasture/grassland (about 63.8%) followed by agriculture (20.3%), production forestry (7.4%), nature conservation (4.3%), urban use (3.1%) and water body (1.1%), as shown in Fig. 3. Among the six listed land use types, it is implicit that agriculture (urban use) becomes the first (second) sufferer due to water deficiency and drought compared to other land uses because of their dependency on water for survival. Therefore, agriculture subclass is given the highest numerical weight value because it was considered as relatively more vulnerable to drought. In contrast, the nature conservation encompasses rare socio-economic activities and is therefore assigned less weight as it is considered less

Table 2 Numerical weights assigned to the subclasses of drought vulnerability, drought exposure and drought hazard factors

Factors	Assumption	Classification of drought vulnerability factors	Weights assigned
Land use	The classified land use after numerical weight assignment is directly related to the degree of vulnerability. The subclass with higher numerical weight is more vulnerable to drought, and vice versa Fuzzy LARGE	Water body Nature conservation Production forestry Pasture/grassland Urban use Agriculture	− 100 (*masking*) 2 4 6 8 10
Soil texture–sand	Sand: directly related to the degree of vulnerability. The higher the percentage of sand means higher degree of vulnerability Fuzzy LARGE	$< 50\%$ $> 50\%$	5 10
Slope (%)	Directly related to the degree of vulnerability. The higher the percentage of slope means higher degree of vulnerability Fuzzy LARGE	0–2 2–5 5–8 8–12 > 12	2 4 6 8 10
Population density (per km^2)	Directly related to the degree of vulnerability. The higher the number of people living in a square kilometre grid, the higher the degree of vulnerability Fuzzy LINEAR	0–1000 1000–2000 2000–3000 3000–4000 ≥ 4000	2 4 6 8 10
Soil depth (m)	Inversely related to the degree of vulnerability. The greater the depth of soil, the less the degree of vulnerability Fuzzy SMALL	≥ 1 < 1 to ≥ 0.8 < 0.8 to ≥ 0.6 < 0.6	1 3 6 9
Plant available water capacity (*PAWC*; mm)	Inversely related to the degree of vulnerability. The less amount of PAWC, the higher the degree of vulnerability Fuzzy SMALL	≥ 175 150–175 100–150 75–100 ≤ 75	− 100 (masking) 2 4 8 10
Elevation (m)	Directly related to the degree of vulnerability. The higher the elevation, the higher the degree of vulnerability Fuzzy LARGE	> 500 250–500 0–250 ≤ 0	10 6 3 − 100 (*masking*)
Rainfall departure (%)	Inversely related to the degree of vulnerability. The smaller the rainfall departure index, the higher the degree of vulnerability Fuzzy LINEAR › fuzzy SMALL	> -10 (near normal + surplus) -10 to -15 (dry spell) -15 to -25 (mild drought) -25 to -35 (moderate drought) -35 to -50 (severe drought) < -50 (extreme drought)	0 5 10 15 20 25

sensitive to water shortages. The water bodies such as lakes, dams and reservoir are assigned a negative value of -100 for masking as these areas are considered non-vulnerable to drought.

Population The water demand is also affected by the population density. In the areas where population density is high, the water usage and demand are also high. Therefore, areas with larger population density are considered relatively more vulnerable to drought than areas with smaller population density. In this study, population density is categorised as an exposure factor because as the population grows, the demand for water mounts and pressure on finite water resources intensifies. The continuous growth of population density will impact water availability in any given area; hence, the exposure to drought will subsequently increase. The population density data were obtained from the Australian Bureau of Statistics (ABS 2012) for the year 2011. Much of the study area has less than 1000 people to none per square grid; therefore, the exposure to drought is less in these areas, as shown in Fig. 3. Conversely, the population density is relatively high in the south-east study region that covers the populous Brisbane city and Gold Coast. This indicates that high population density and high population growth rates in the SEQ region have high chances to face water scarcity or water stress situations.

3.3 Proposed weighting scheme

To produce vulnerability, exposure and hazard indices map, a differential weighting scheme based on relative importance of the factors is proposed. The weight assignment is based on the assumption of relative degree of influence of a factor on overall vulnerability to droughts. In the proposed scheme, the rainfall deficiency in terms of rainfall departure is considered most influential factor and is therefore assigned highest weights ranging from 0 to 25 (Table 2). The weight value of 25 represents very extreme dryness that poses highest risk to droughts. Comparatively, other factors are considered moderately influential to drought vulnerability and are thus given weight assignment between 0 and 10, where a value of 10 corresponds to the factor subclass being highly vulnerable to drought. For instance, the water demand and availability tend to vary considerably with land use types and since agriculture and urban use are the primary focus in this study, they are assigned higher weights. Similarly, elevation, soil depth, sand soil type, plant available water capacity and slope are divided in subclasses and assigned weights based on their relative importance to drought vulnerability. The differential weights are then used to determine the joint conditional probability based on Bayes theorem discussed next. It is important to note that the weight assignment to the factor subclasses was only done to estimate the joint conditional probability that showed the relevance of each factor conditional on the hazard.

3.4 Bayesian joint conditional probability

Normative argument is often used for assigning equal weights to indicating variables. In the normative argument, the indicating variables are aggregated such that each dimension is given equal importance in characterising the state of development. However, vulnerability assessment is not a simple, straightforward exercise because multiple stakeholders value the dimensions differently (Hinkel 2011). In the spatial dimension context, the development of risk maps from indicating variables varies spatially. To address the multi-dimensionality issue in the normative argument of equal weights, the Bayesian probability is used in this study. The Bayesian joint conditional probable weights are calculated as:

$$P(\mathrm{DR}_i|V_i) = \frac{P_{\max}(\mathrm{DR}_i \cap V_i)}{\sum nP_{\max}(DR_i \cap V_i)} \text{ and } P(\mathrm{DR}_i|E_i) = \frac{P_{\max}(\mathrm{DR}_i \cap E_i)}{\sum nP_{\max}(\mathrm{DR}_i \cap E_i)} \tag{9}$$

where DR is the drought risk represented by drought hazard as a priori event, V and E are vulnerability and exposure indicating variables, respectively, i is the level of perceived drought risk (vulnerability/exposure subclasses), $P_{\max}$ is the maximum probability of an indicating variable, and n is the number of indicating variables

The weight values are used in aggregating the vulnerability and exposure indicating variables. Table 3 lists the probable importance of each factor to the rainfall departure hazard index. It is important to note that no matter what month, season or year is considered for the analysis, these probability values do not change and it has been confirmed from the computational analysis of all the seasons and years analysed.

Subsequently, the fuzzy-standardised vulnerability and exposure factors (fw_j) are first multiplied by 100 to obtain integer values, and then weighted overlay operation is performed where weights are the per cent conditional probability values (P_j). The output is then divided by 100 to obtain the eventual vulnerability and exposure index maps (V_i *or* E_i) on 0 to 1 scale, as per Eq. 10.

$$V_i \text{ or } E_i = \left(\sum_{j=1}^{n} P_j \times \left(100 \times fw_j\right) \right) / 100 \tag{10}$$

3.5 Framework for derivation of drought risk map

A diagram of the input–process–output model that presents the flowchart of the study is shown in Fig. 2. Under the input component, drought hazard (rainfall departure), vulnerability (soil type, soil depth, elevation, PAWC and slope) and exposure (population and land use) were assessed with corresponding details and assumptions, enumerated in Table 2. All inputs were continuous data except for land use that needed to be reclassified and assigned weights based on the significance and influence on droughts. Under process component, the inputs were standardised from original values into 0–1 scale, analysed and processed using applicable GIS operations with emphasis on fuzzy logic operations on ArcGIS 10.5. The standardised vulnerability and exposure factors were then evaluated using Eq. 10. The procedure in turn produced initial outputs representing drought risk component indices maps (i.e. hazard, vulnerability and exposure indices). The analytical and processing operations using fuzzy GAMMA overlay led to generation of drought risk map as the ultimate output. Figure 3 shows the original values of the vulnerability and exposure factors in the left column, while the right column shows the corresponding standardised factors based on respective fuzzy operations.

The *hazard index* consisted of the rainfall departure (%). Relative to the base period (1971–2000), the seasonal and annual rainfall departure are used as the sole hazard indices. To obtain the hazard index, the fuzzy LINEAR followed by fuzzy SMALL membership function are applied to the rainfall departure. The fuzzy SMALL transformation function is used when the smaller input values are more likely to be a member of the set, as in this study the negative rainfall departure percentages corresponded to the drought condition, hence the hazard in consideration. The midpoint of the rainfall departure identified the crossover point (assigned a membership of 0.5) with values greater than the midpoint having a lower possibility of being a member of the fuzzy set and vice versa. Accordingly, the values closer to 1 in the standardised rainfall departure corresponded to high drought

Table 3 Probable weights applied for the vulnerability and exposure factors conditional on rainfall departures based on the Bayes theorem

	P_{max}	Bayes conditional probability
Exposure factors		
Land use	0.3590	0.3941
Population	0.5519	0.6059
Total P_{max}	0.9109	1.0000
Vulnerability factors		
DEM	0.3124	0.1634
PAWC	0.2525	0.1321
Sand	0.5158	0.2698
Slope	0.3392	0.1775
Soil depth	0.4916	0.2572
Total P_{max}	1.9115	1.0000

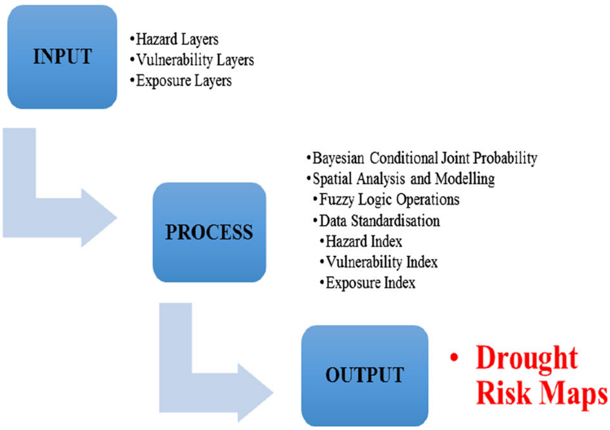

Fig. 2 Conceptual flowchart of a three-layer input–process–output schematic model for drought risk mapping adopted in the present study

risk member. Seasonal and annual drought hazard indices are prepared, and the results for seasonal (2007) and annual (2007, 2009 and 2013) are presented. These years are recent drought years in the SEQ region. The 2007 and 2009 are part of the catastrophic Millennium Drought, while the 2013 drought occurred after the wet La Niña season (2010–2011). Figure 4 shows the hazard indices maps for drought years 2009 and 2011. The red colours correspond to high risk areas, i.e. rainfall departure below normal.

The *vulnerability index* consisted of integrated layer of soil depth, sand, PAWC, elevation and slope. Guided by the assumptions in Table 2, the fuzzy LARGE or fuzzy SMALL membership functions are applied to the indicators. With fuzzy SMALL membership function, the smaller original pixel values are assigned with higher fuzzy membership values (closer to 1) in the function to indicate higher vulnerability. Conversely, the fuzzy LARGE membership function was applied whereby the larger original pixel values were assigned with higher fuzzy membership values (closer to 1) in the function to indicate higher vulnerability. Equation (10) was applied following the standardisation process. The resulting map was the vulnerability index, as shown in Fig. 5.

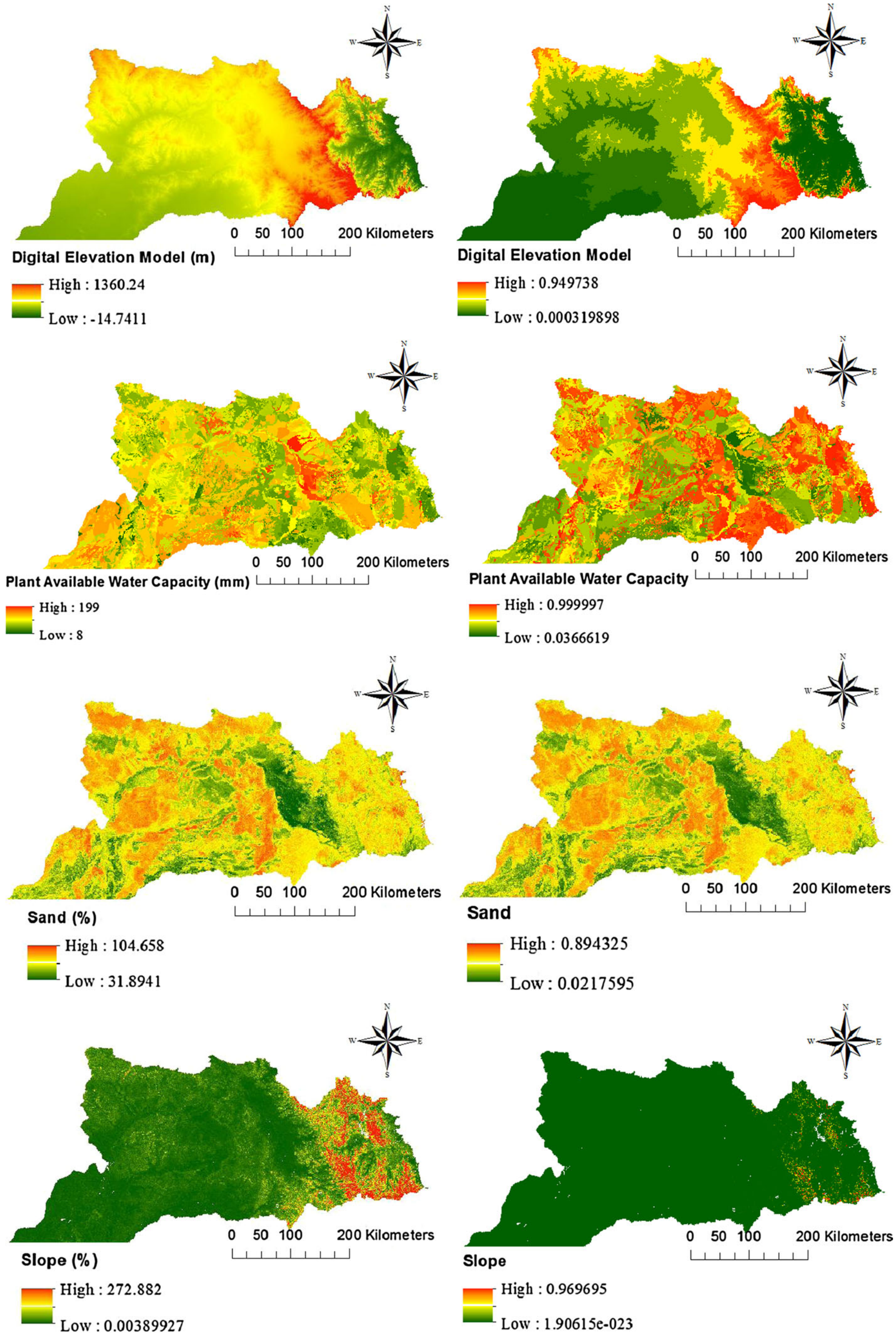

Fig. 3 The original drought vulnerability factors in absolute units (left) and the corresponding standardised drought vulnerability factors (right) using the fuzzy membership functions bounded by [0, 1] utilised for the construction of spatial drought vulnerability map

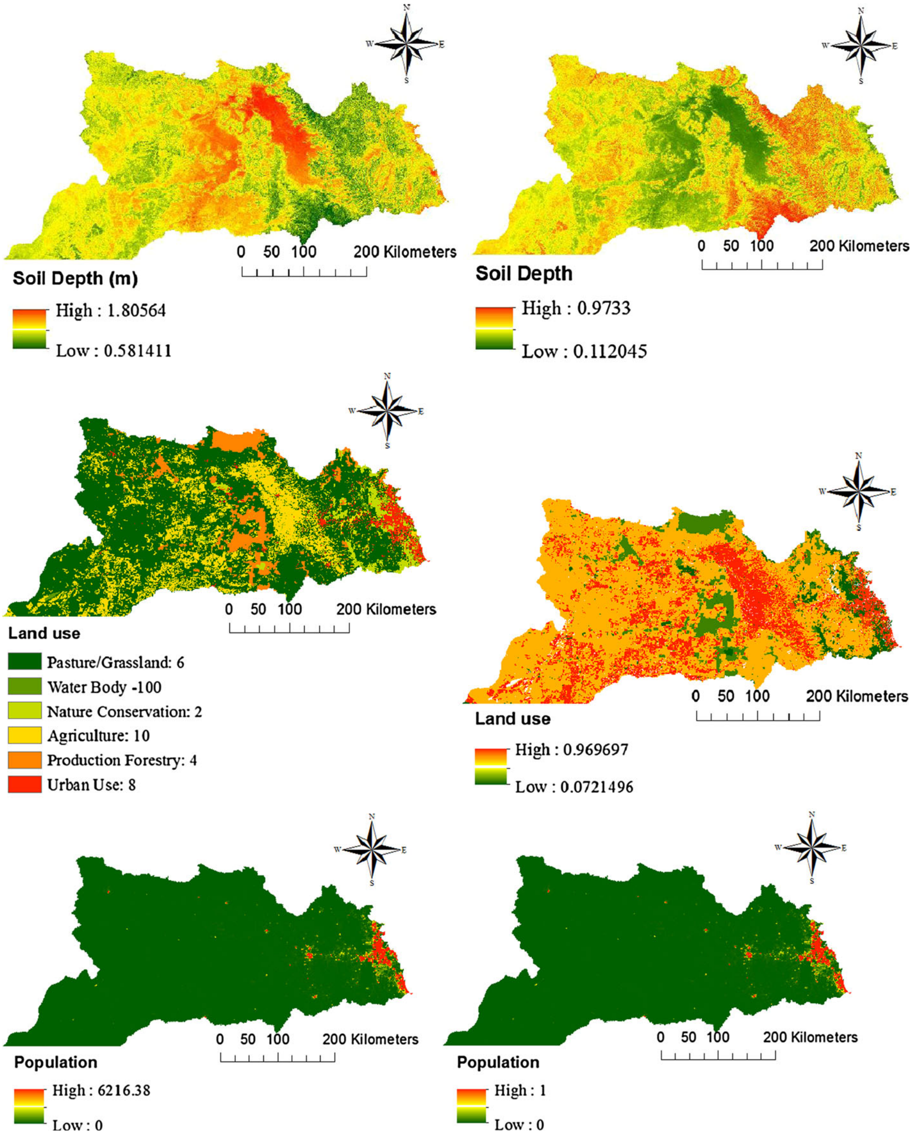

Fig. 3 continued

The *exposure index* consisted of integrated layer of land use and population. The fuzzy LARGE and fuzzy LINEAR membership functions are applied to land use and population, respectively. The fuzzy LINEAR membership function is more appropriate to standardise population density since the availability and demand for water resources vary with change in population density over time; hence, there is a direct proportionality between water demand and population density. The resulting exposure index is shown in Fig. 5.

Usually analyst has the choice of whether to defuzzify the output of the fuzzy system to generate the crisp output or leave the output without modification, which is also

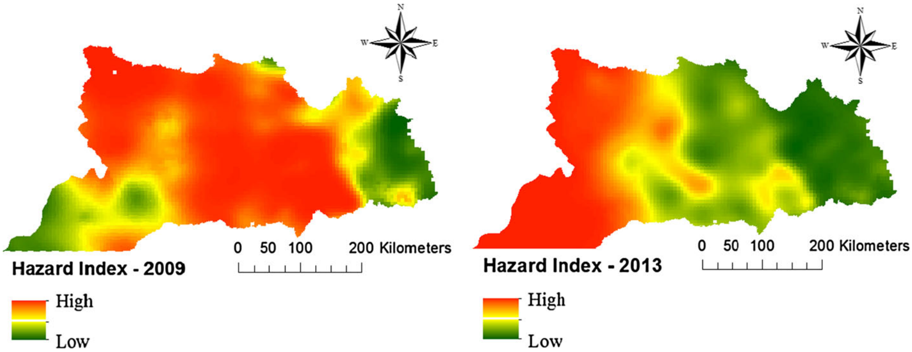

Fig. 4 The drought hazard index for the two selected study years (i.e. 2009 and 2013) defined by the standardised rainfall departure from the normal period using the fuzzy LINEAR and fuzzy SMALL membership functions

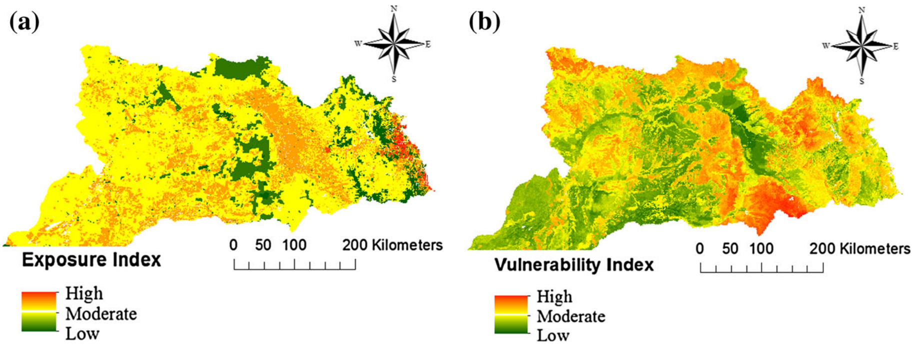

Fig. 5 **a** The drought exposure index comprised of factors defined by the land use and population density. **b** The drought vulnerability index comprised of the sand, soil depth, slope, plant available water capacity and digital elevation model

appropriate. In this study the final output was defuzzified into five discrete intervals according to the perceived level of drought risk: none, low, moderate, high and very high. Defuzzification is a process in fuzzy synthetic evaluation that calculates the crisp value (i.e. grade interval) of a fuzzy set (Sadiq et al. 2004). The grade intervals for this study were obtained through geometric interval classification of the raster data fuzzy set. As a compromise method between equal interval and quantile (ESRI 2017), geometric intervals were used to delineate classes based on natural groupings of fuzzy membership values. This option tries to find a balance between highlighting the changes in the middle and the extreme values.

Drought risk assessment methods are generally designed to characterise and understand the system's degree of risk to drought (e.g. low, moderate, high and very high). In GIS, this is known as descriptive modelling that refers to characterisation of direct interactions of system components to gain insight and understand the system processes (Berry 1996). This study attempts to contribute a new knowledge by developing spatial analytical technique in generating descriptive drought risk maps. Hence, it is suggested that this type of approach can provide useful strategic information for decision-makers involved in drought risk monitoring.

3.6 Validation of the drought risk index

In order to validate the drought risk output maps, the ideal measure would be a field study that can literally verify the areas subjected to certain level of risk. Since a field study was beyond the scope of this paper, this study has undertaken the spatial correlation approach using the band collection (Erdey-Heydorn 2008; Gergely et al. 2016), a spatial analyst tool that provides statistics for the multi-variate analysis of a set of raster bands. The correlation is given as:

$$\mathrm{Corr}_{i,j} = \frac{\mathrm{Cov}_{i,j}}{\sigma_i \sigma_j} \tag{11}$$

Seasonal and annual drought risk maps were correlated with rainfall departures to estimate the dependency between them. Since rainfall departure was a core hazard variable in generating the drought risk maps, and to avoid such bias, the upper (0–0.2 m) and lower (0.2–1.5 m) layers of soil moisture were used alternatively. It is noteworthy that the soil moisture for our study region is obtained from Australian Water Availability Project historical runs constructed from the *WaterDyn* hydrological model (Raupach et al. 2009, 2012). These data have been used for drought studies in the present region (Dayal et al. 2017a, b). Validation of drought risk maps with soil moisture is appropriate since moisture content is an important indicator of agricultural droughts and its memory contributes to spatial and temporal variation of regional drought (Mpelasoka et al. 2008). Subsequently, seasonal drought risk maps were correlated with the 3-month running mean of soil moisture leading up to the following season.

4 Results and discussion

The resulting seasonal and annual maps of drought risk are obtained by application of fuzzy GAMMA overlay operation in ArcGIS. Figures 6 and 7 show the seasonal and annual drought risk maps, respectively, while Table 4 enumerates the percentage area of the five risk classes: no risk, low risk, moderate risk, high risk and very high risk. The maps show that the majority of the study area is at moderate to very high risk to drought. The very high risk regions in the SON 2007 seasonal drought risk maps carry much higher percentages compared to the annual drought risk maps. This could be due to the JJA season rainfall offsetting the total accumulated rainfall in other seasons of the year 2007. In the JJA season (map not presented here), the rainfall departure index is in the positives (i.e. minimum of 34.69% and maximum of 1508.78% in the study region). This is why the 2007 annual drought risk map (Fig. 6d) has smaller percentage of high and very high risk regions compared to separate DJF, MAM and SON seasons.

It is apparent that the regions' drought risk levels coincide well with the corresponding hazard indices where regions with high hazard index are also critically vulnerable to drought. This is possibly due to hazard index values being assigned an entire probability value of 1 in the GAMMA overlay operation, while the vulnerability and exposure factors were multiplied by their probability values conditional on the hazard index. Overall, the results indicate that regions receiving much less rainfall relative to the base period consequently have greater drought-related negative impacts. Considering the temporally and spatially varying factors, the simple yet effective methodology developed in this study will help to identify regions vulnerable to droughts and can be greatly useful in better decision-

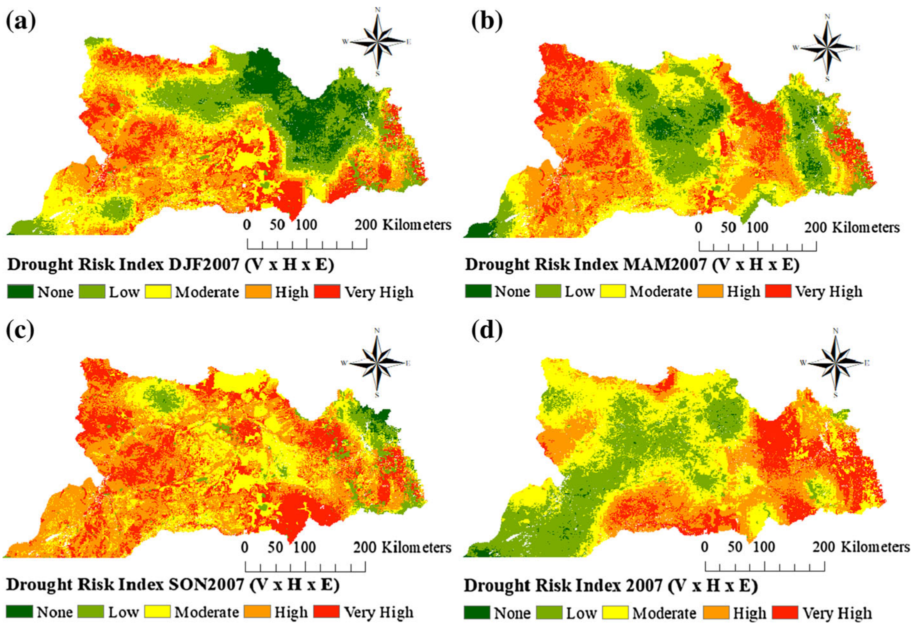

Fig. 6 Spatial drought risk map and its classification thresholds for the serious drought year (2007) generated with vulnerability, hazard and exposure indices overlay by the fuzzy Gamma function. **a** December–January–February (DJF) summer period. **b** March–April–May (MAM) autumn period. **c** September–October–November (SON) spring period. **d** Annual map. *Note*: Drought year was selected according to Fig. 1

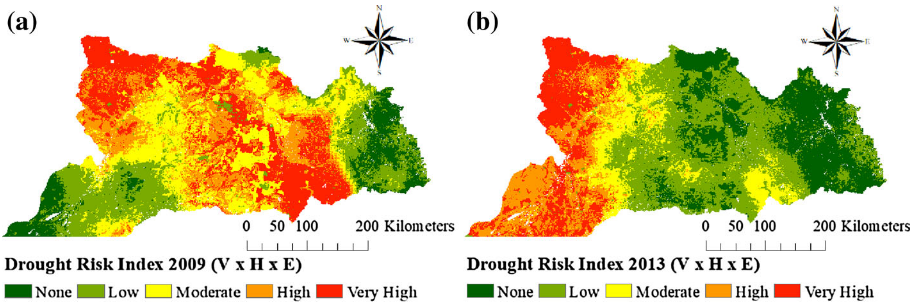

Fig. 7 Spatial drought risk map and its classification thresholds for moderate drought year (2009) and non-drought year (2013) generated with vulnerability, hazard and exposure indices overlay by the fuzzy gamma function. *Note*: Drought year was selected according to Fig. 1

making processes for drought mitigation and management. The descriptive vulnerability and drought risk map are also intended for farmers who can make judicious decisions as to which crop to plant based on the water availability.

The anthropogenic activities influence the level of risk associated with droughts. To demonstrate this, another set of drought risk maps excluding exposure factors (land use and population) are generated and presented in Fig. 8. The difference between Figs. 8 and 6 and 7 manifests the importance of exposure factors drought risk assessments. The

Table 4 Per cent area falling under various vulnerability classes

Vulnerability class Seasonal	Discrete interval DJF 2007	Area (%)	Discrete interval MAM 2007	Area (%)	Discrete interval SON 2007	Area (%)
None	0.14–0.51	0.10	0.14–0.49	0.04	0.12–0.50	0.01
Low	0.51–0.69	0.22	0.49–0.68	0.23	0.50–0.69	0.07
Moderate	0.69–0.78	0.26	0.68–0.77	0.24	0.69–0.78	0.26
High	0.78–0.82	0.27	0.77–0.83	0.32	0.78–0.83	0.41
Very high	0.82–0.91	0.15	0.83–0.93	0.17	0.83–0.92	0.25
Annual	2007		2009		2013	
None	0.11–0.35	0.01	0.13–0.50	0.10	0.11–0.50	0.24
Low	0.35–0.54	0.28	0.50–0.68	0.21	0.50–0.68	0.34
Moderate	0.54–0.68	0.34	0.68–0.77	0.26	0.68–0.76	0.13
High	0.68–0.79	0.23	0.77–0.81	0.20	0.76–0.80	0.14
Very high	0.79–0.93	0.14	0.81–0.90	0.24	0.80–0.89	0.15

difference is more apparent in the low to no risk regions where inclusion of exposure factors has increased the level of risk to moderate. This result shows that assessment of drought risk must account for human factors to benefit from appropriate decision-making and mitigation procedures.

For verification of the drought risk maps, Table 5 shows the correlation matrix of drought risk with rainfall departure and soil moisture. There is a high correlation of drought risk with rainfall departure due to the latter being used as a hazard index in producing the former. To avoid the bias, the upper (0–0.2 m depth) and lower (0.2–1.5 m depth) layer soil moistures were also correlated with drought risk index. The upper layer soil moisture is well correlated with both seasonal and annual droughts, while the lower layer soil moisture tends to show higher correlation in JJA and SON seasons of 2007, as well as for 2009 and 2013 annual drought periods. For the case of seasonal droughts (Table 5a), the correlation remains high for 3-month running mean soil moisture values leading up to the next season. Therefore, despite the field study verification of the drought risk maps, the correlations with soil moisture reveal the effectiveness of the drought risk output maps, which therefore validates the drought risk index to be adopted for drought management purposes.

Assessment of drought risk and vulnerability in this study has largely reinforced the initial concept of Wilhite (2000), and several other studies on vulnerability assessment elsewhere (e.g. (Jain et al. 2015; Pandey et al. 2010; Thomas et al. 2016; Wilhelmi and Wilhite 2002)) but it does extend the only study performed in Australia (Stone and Potgieter 2008). Our study shows that drought risk must be viewed as a product (and sum) of exposure to climatic hazard and the underlying vulnerability of economic, demographic and agricultural practices including physiographic features. Droughts occur in virtually all climatic regimes, i.e. in both high and low-precipitation areas where aridity is considered a normal feature (Wilhite 2009). This makes droughts to be considered as a relative phenomenon, and therefore, the risk to drought must be addressed as a relative measure (Downing and Bakker 2000). In consequence, it is difficult to reach standard criteria for drought risk assessment. The overlay of several factors based on regional conditions

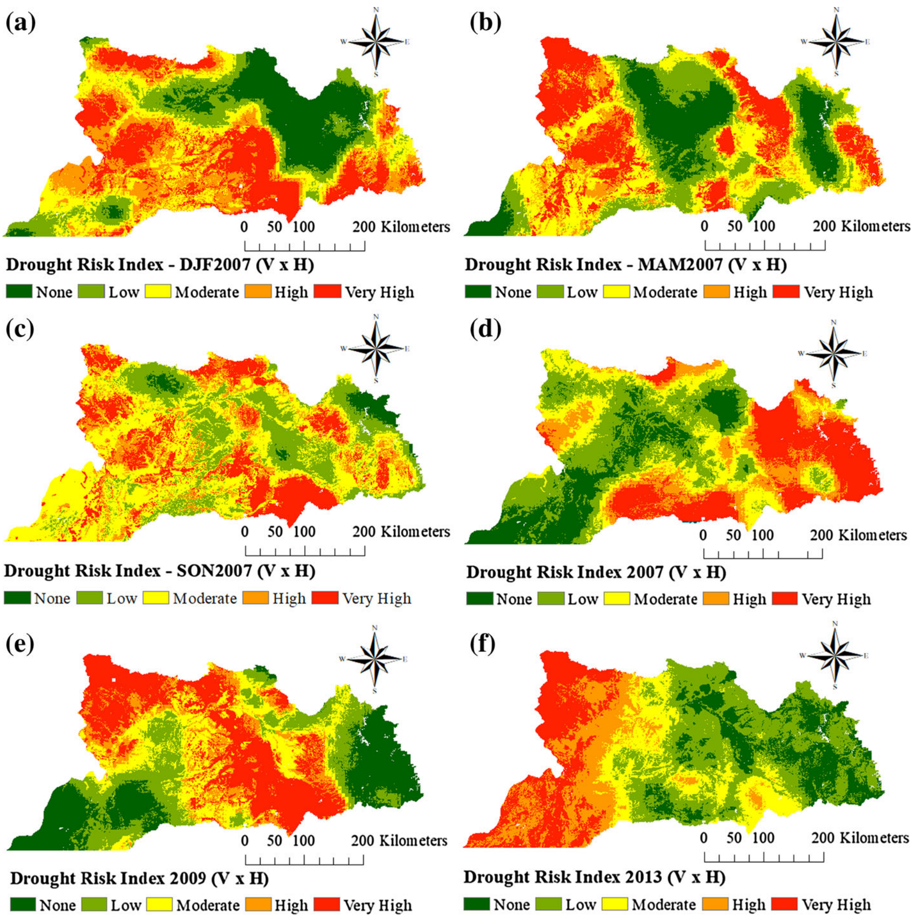

Fig. 8 Spatial drought risk map and its classification thresholds for seasonal (2007) and annual (2007, 2009 and 2013) generated with only vulnerability and hazard indices overlay by the Fuzzy Gamma function

therefore establishes a relative criterion that makes the drought risk assessment feasible. A further refinement on the subclassification of factors may also be required given the nature of the regional climate. This study has attempted to present a methodology that can be used to assess drought vulnerability and risk in any given area.

The selection of vulnerability, exposure and hazard factors can be arbitrarily executed (Araya-Muñoz et al. 2017; Hinkel 2011; Luers et al. 2003). In this study, we selected drought associated physiographic and climatic factors based on current knowledge of the drought hazard as well as on the availability of reliable and most recent data. We assumed that this would explain the regions with high risk to drought; however, the results could change as knowledge on the subject expands and more data become available. There are, however, several other factors that could be considered in the drought risk analysis. For instance, Thomas et al. (2016) used soil moisture availability, Pandey et al. (2010) used ground and surface water availability, Ekrami et al. (2016) used evaporation, and Jain et al. (2015) used soil moisture deficit index for their study regions. These factors were a limitation to our entire study region and their inclusion could be possible if the analysis is

Table 5 Validation of drought risk index in terms of the correlation matrix of seasonal (a) and annual (b) drought risk index with rainfall departure (RD) and the upper and lower layer soil moisture (SM) within the drought study region and different periods

Soil moisture	DJF 2007 Correlation matrix		MAM 2007 Correlation matrix		JJA 2007 Correlation matrix		SON 2007 Correlation matrix	
	Drought risk	Drought risk 1.0000	Drought risk	Drought risk 1.0000	Drought risk	Drought risk 1.0000	Drought risk	Drought risk 1.0000
(a)								
	RD (%)	− 0.8555	RD (%)	− 0.8623	RD (%)	− 0.8665	RD (%)	− 0.5543
Upper SM	DJF	− 0.3808	MAM	− 0.4486	JJA	− 0.6800	SON	− 0.2748
Lower SM	DJF	0.0450	MAM	0.1348	JJA	− 0.2266	SON	− 0.2987
Upper SM	JFM	− 0.1064	AMJ	− 0.3312	JAS	− 0.5499	OND	− 0.0092
Lower SM	JFM	0.0402	AMJ	0.0901	JAS	− 0.2880	OND	− 0.2211
Upper SM	FMA	− 0.0937	MJJ	− 0.3546	ASO	− 0.4437	NDJ	− 0.1957
Lower SM	FMA	0.0486	MJJ	0.0071	ASO	− 0.2910	NDJ	− 0.1903
Upper SM	MAM	− 0.0538	JJA	− 0.3515	SON	− 0.2394	DJF	− 0.3530
Lower SM	MAM	0.0576	JJA	− 0.0627	SON	− 0.2559	DJF	− 0.1915

Layer	Layer statistics				Correlation matrix
	MIN	MAX	MEAN	STD	Drought risk
(b)					
2007					
Drought risk	0.1108	0.9273	0.6265	0.1328	1.0000
RD (%)	− 41.7092	19.5005	− 11.9427	10.9399	− 0.8738
Upper layer SM	0.1346	0.4339	0.2177	0.0338	0.1039
Lower layer SM	0.0250	0.6432	0.1762	0.0847	0.0991
2009					
Drought risk	0.1254	0.9031	0.7121	0.1310	1.0000
RD (%)	− 49.4654	27.7423	− 21.3567	13.6609	− 0.8865
Upper layer SM	0.1059	0.5883	0.1976	0.0565	− 0.5520
Lower layer SM	0.0341	0.9024	0.3090	0.1534	− 0.4452
2013					
Drought risk	0.1146	0.8870	0.6282	0.1511	1.0000
RD (%)	− 62.5084	41.0766	− 12.4865	23.3613	− 0.8949
Upper layer SM	0.0864	0.5684	0.2092	0.0675	− 0.7302
Lower layer SM	0.1137	0.8815	0.3773	0.1429	− 0.5785

carried out for the basins where these datasets are readily available. Future analyses could also incorporate social factors such as diversity of local economies, people's sources of income, per cent of farms acquiring insurance. Data acquisition of the biophysical and socio-economic factors was beyond the scope of this study, and authors recognise this limitation. The spatial resolution of the indicators is also very important for mapping high-resolution details. The hazard indicator, i.e. rainfall departure, was initially at a coarser 5 km × 5 km spatial resolution compared to other factors used in the analysis. The resolution of the hazard index used in this study is considered as a limitation because after reducing the cell size to 100 m × 100 m, the several neighbouring pixels consequently had similar rainfall value.

Application of fuzzy logic tool to develop the drought risk index is a novel contribution of this study. Although the fuzzy logic theory (Zadeh 1965) has been out there for long enough, its application on geospatial analysis has just made a breakthrough in recent years. Fuzzy logic is an alternative logical foundation coming from artificial intelligence (AI) technology with several useful implications for spatial data handling, where it accommodates the imprecision in information, human cognition, perception and thought (Karabegovic et al. 2006). Accordingly, fuzzy logic is more suitable for dealing with real world problems, because most human reasoning is imprecise. Major advantage of this fuzzy logic theory is that it avoids the bias through subjective judgements and allows the natural description, in linguistic terms, of problems that should be solved rather than in terms of relationships between precise numerical values. With this advantage, fuzzy logic theory is a widely applied in technique to deal with the complex systems in simple way. Therefore, fuzzy logic appears to be instrumental in the design of efficient tools for spatial decision-making, and its application for drought risk assessment in this study has shown it to be excellent for designing efficient tools to support the spatial decision-making processes.

In spite of the significant merits and foresights provided by the spatio-temporal drought risk mapping approach, the scope of this study has been limited to the computational analysis only. To further validate the drought risk output maps, the actual field study is thus required that creates an opportunity for future and more extensive independent work. It is hoped that this study will seed better insights into the assessment of relative vulnerability and exposure to droughts in SEQ region and is likely to assist decision-makers in better planning, management and mitigation strategies. Fuzzy logic method has provided a good estimate of agricultural drought risk due to its high correspondence with soil moisture on spatial and temporal domain and therefore could be useful for the demarcation of areas vulnerable to drought to facilitate proactive planning for coping with future drought events.

5 Conclusions

A descriptive drought vulnerability and drought risk assessment index has been accomplished by a new methodology that incorporates vulnerability, exposure and hazard factors by integrating with fuzzy logic analytical tool in ArcGIS. Fuzzy logic approach was found to be advantageous as it aimed to minimise the subjectivity in the drought risk assessment. By choosing fuzzy GAMMA overlay, the different fuzzy overlay operations available in ArcGIS allowed great flexibility in quantifying drought risk expressed in truth values that range in degrees between 0 and 1. Given the significance of the approach and its ability for spatio-temporal risk assessment, the results are likely to advance the application of ArcGIS for disaster risk reduction and in solving complex drought issues through adaptation strategies.

The methodology developed in this study can be applied to support the existing drought (or any disaster) risk reduction plans and policies prepared by any authorities, organisations, enterprises or any sectors involved in coordinating their development plans, resource allocation and the implementation of their respective programme of activities. Given that this study presented a new methodology for drought risk assessment, the coverage for the entire nature and extent for drought risk is limited as there could be many more hydro-meteorological, physiographic, environmental and social factors incorporated in the analysis, provided the availability and reliability of the data. Therefore, some recommended future work includes the following: inclusion of other factors in analysing drought hazard (e.g. meteorological, hydrological and agricultural drought indices); review of the technical characteristics of climate change and how it could affect drought risk assessment process; and identification and field validation of the vulnerability, exposure, hazard and drought risk indices including the quantity and quality of the data to be used as inputs in the model. Such studies can employ our approach to yield useful pathways for water resource management in a drought-prone region.

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