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Spatio-temporal climate change risk assessment: Mangaung Metropolitan Municipality, South Africa

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ABSTRACT

Scientists have warned about global warming, resulting in climate change risks such as droughts. In 2015, the Free State provincial government declared a state of drought risk disaster which was extended into 2016. The current study aimed to (i) assess the climate change risk on annual and seasonal temporal scales over all areas of the Mangaung Metropolitan Municipality, (ii) determine most-at-risk areas and (iii) advise government authorities /risk disaster management stakeholders about disaster risk reduction projects aimed at resilience and capacity building against adverse effects of climate risk disasters. Ten climate change vulnerability variables were collected from Stats SA, census, 2011. The study applied principal component analysis to determine the key variables that give rise to the existing vulnerability conditions in the study area. A 43 year long time series data set (1973- 2016) was also collected from an online source for RDI computation. The results show that some of the main underlying variables behind high vulnerability in this municipality are; number of people with no income, the young (0-14) and the elderly (65+), as identified by principal component analysis. The main towns seem to be less vulnerable compared to the rest of the other areas under study. The most vulnerable areas are in the outskirts of Thaba Nchu. Furthermore, climatic hazard analysis using RDI showed constant hazard severity and probability over a 43 year long time series data set on annual basis. To further assess climate change, RDI was computed on seasonal time scales which also showed no significant differences in both severity and probability. Due to the fact that the study used only one station over Mangaung Metropolitan Municipality to assess climate change conditions, the risk assessment analysis differences were influenced by differences in the vulnerability levels. High risk levels are therefore in the rural areas. The study recommends that the government and all relevant stakeholders set up income generating projects through which young people will not necessarily seek jobs in urban areas and help afford higher education costs.

Key words: *Climate change risk, Disaster, Reconnaissance drought index, Temporospatial, Vulnerability*

Introduction

Scientists and government agencies assert that global climate will continue to change thereby having adverse effects on planning and day to day operations of businesses and increasing drought extremes which adversely affect food security(Abu *et al*. 2017: Carling *et al*. 2017) These manifestations will include increased temperatures, altered precipitation patterns and more severe and frequent climate extreme eventssuch as floods and droughts (Department of the Environment and Heritage, 2006: Beven,

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2006:Franz *et al,* 2009: Ho Ming and Yusof, 2012: Štìpánek *et al*, 2013). Climate change therefore results in high rainfall variability at both seasonal, inter-annual and multi decadal time scales therefore having ripple negative effects on; food production, food access and livelihoods (Mdao, n.d: Seyhan, 1966). African continent in particular is faced with potential direct liability in excess of 150 USD billion to repair and maintain existing road infrastructure damaged by temperature and precipitation changes directly linked with high climate change variability (Verhaeghe *et al*. 2016: Cheng, and Bear, 2010). South Africa is not an exception in climate change risks, in 2015 this fast economy growing country faced a drought disaster risk where five of her provinces were greatly affected. After a year into this disaster phenomenon, weather reports indicate no signs of La Niña event forming (City Press, 2016). South Africa is therefore faced with the worst drought disaster since 1982 with now eight provinces affected where 2.7 million households are facing water shortages across the country (AllAfrica, 2016). Free State is one of the nine provinces hard hit by drought event, where farmers are battling to keep their livestock and crops alive and water restriction implemented. The department of Agriculture also mentioned that only 1% of the farmers were fit to grow crops(eNCA, 2015). Given the current drought situation in this province, which is said to be the bread-basket of the entire country, it is therefore necessary to assess the climate changes risks to aid government and all other relevant stakeholder in planning and mitigation strategies against negative knock off effects of climate change extreme events.

Reconnaissance drought index (RDI) is a new index developed by Tsakiris and others in Greece, which is based on cumulative values of both precipitation and potential evapotranspiration. This index exists in three expressions; initial, normalised and standardised. The standardised is directly compared to Standardised Precipitation Index (SPI) (Tsakiris and Vangelis, 2005: Allaby, 2003). These authors assert that potential evapotranspiration incorporation makes RDI more representative of deficient water balance conditions than any index based on only precipitation data. This index is mostly applied in areas where impacts on agriculture and water are of concern. Apart from this being a good representative of water balance, it provides a good indication of drought severity conditions (WMO and GWP, 2016: Tigkas *et al*. 2013). The following are temperature-based methods for computing Potential Evapotranspiration used in DrinC software.

PET, Hargreaves equations

Evaporation is a main water transfer process in the hydrological circle, where water is transformed from liquid to vapour state (Karlsson and Pomade, 2016). The following are temperature methods used in Drought Calculator software (DrinC); Thornthwaite, Hargreaves and Blaney-Criddle formulae.

Thornthwaite formular;

This formula is based mainly on temperature with an adjustment being made for the number of daylight hours. An estimate of the potential evapotranspiration, calculated on a monthly basis, is given by:

$$PE_m = 16 N_m \left(\frac{10 \bar{T}_m}{I} \right)^a \text{ mm} \qquad .. (1)$$

where m is the months 1, 2, 3…12, Nm is the monthly adjustment factor related to hours of daylight, Tm is the monthly mean temperature (C), I is the heat index for the year, given by:

$$I = \sum i_m = \sum \left(\frac{\bar{T}_m}{5} \right)^{1.5} \quad \text{for m = 1…12} \qquad .. (2)$$

Blaney-Criddle formular;

This formula, based on another empirical model, requires only mean daily temperatures T (C) over each month. Then:

$$PE = p.(0.46.T + 8) \text{ mm/day} \qquad .. (3)$$

where p is the mean daily percentage (for the month) of total annual daytime hours (Lecture notes).

Hargreaves formular;

The Samani and Hargreaves method is a temperature-based empirical approach. Currently this Hargreaves and Samani method is generally described as:

$$ET_0 = 0.0023 Ra(T\ mean + 17.8)*(T\ D)^{0.5} \qquad .. (4)$$

Where

ET_o = reference evapotranspiration [mm day^{-1}], T_{mean} = mean daily air temperature at 2 m height

[°C],

T_{max} = daily maximum temperature at 2 m height [°C],

T_{min} = daily minimum temperature at 2 m height [°C],

Ra = extraterrestrial radiation [MJ m^{-2} day^{-1}].

TD =T_{max}-T_{min}

Ra=(24*60/3.14)* 0.82*dr* (ws*sin(lati. (rad)*sin (del) + cos (lati.(rad)*cos (lati.(rad)*sin(ws))

Disaster risk is defined as a potential loss of live, health status, livelihoods, assets and services which can occur in a particular community in a specified future time (International Strategy for Disaster Reduction, 2009: Apollov *et al.*, 1964). This is therefore a function of hazard and vulnerability. A disaster occurs on when a hazard impact on vulnerable communities (International Federation of Red Cross and Crescent Society, 2014). Hazard is then defined as a dangerous phenomenon or a condition that can cause harm or injury to life, damage to property, economic disruptions and damage to environment (International Strategy for Disaster Reduction, 2009). Another important factor that contributes significantly to disaster risk is vulnerability which has various definitions by various scholars across disciplines. However, Cardona *et al.* (2012) define vulnerability as a condition of people or communities that makes them exposed to hazards. The abovementioned terms can be brought together by a risk assessment model equation which has been used as the conceptual framework to this current study. The Severity, Exposure and Probability (SEP) Risk Assessment Modeltherefore states; Disaster Risk = Severity x Exposure x Probability (5).

Methods and Materials

Data control

A 43 year long time series was collected from an online source (Tutiempo-climate-Africa) on precipitation, maximum and minimum average temperature. This data set had gaps only in 2016 September, October, November and December 2016. The missing values for the four months were estimated from Expectation Maximum (EM) algorithm using IBM SPSS v.24. Expectation Maximum is defined as an iterative method which attempts to estimate the maximum likelihood estimator of parameter theta of parametric probability distribution (Gupta and Chen, 2011). Vulnerability variable indicators were collected from Census, 2011 (Stats SA). The study selected only ten variables linked with climate change. A Principal Component Analysis (PCA)was applied to further reduce the number of variables leaving those with highest variance for further analysis. Prior to any analysis, in the PCA, Bartle's test of sphericity (0.000< p = 0.05) and Kaiser-Meyer-Olkin Measure of Sampling Adequacy (0.577 H" 0.6) were applied. Both tests were significant as shown in the table below.

Methods

In order to accomplish the objectives of this study, both vulnerability and hazard analysis must be performed, therefore for vulnerability, all the selected proxy variables were normalised according to the functional relationships they have with vulnerability. Vulnerability indicators bear various units, and for this reason all indicators' values must be normalised according to the functional relationship each indicator has with vulnerability.

For increasing and decreasing functional relationship with vulnerability, normalisation was done using the formulae respectively;

$$Xij = \frac{Xij - Min\{Xij\}}{Max\{Xij\} - Min\{Xij\}} \quad .. (3)$$

and $$Xij = \frac{Max\{Xij\} - Xij}{Max\{Xij\} - Min\{Xij\}} \quad .. (3)$$

Where Xij is the value of the indicator j, corresponding to region i.

Normalisation is a procedure that transforms data values from their original units to no units state, which leaves all values ranging from 0 to 1 (Hlalele and Belle, 2015). After normalisation process, all the ten variables were subjected to a data reduction algorithm (PCA) which used verimax rotation for final variable detection with the highest variance. The study used scree plot to determine the number of factors as shown in Figure 1 below. The

Table 1. Kaiser-Meyer-Olkin and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.577
Bartlett's Test of Sphericity	Approx. Chi-Square	662.167
	df	45
	Sig.	.000

scree plot revealed four factors using 'eigenvalue greater than 1' rule.

After the varimax rotation, factors with the highest loadings are shown in Table 2 below. Variables V1, V2, V3, V4, V5 and V7 bore the highest loading after rotation. Therefore the study considered them for further analysis.

For hazard analysis, the study used one climatic index known as Reconnaissance Drought Index (RDI) developed by Tsakiris and Tigkas in 2005 in Greece. One of the merits of this index is that it used both precipitation and temperature as input vari-

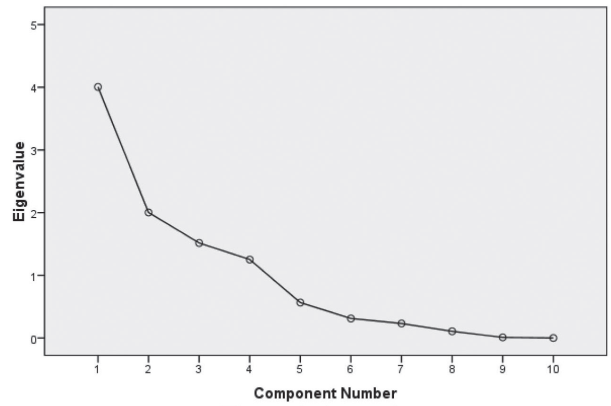

Fig. 1. Scree plot

Table 2. Selected variable indicators

	Selected indicators	Description	Dimension	Functional relationship with vulnerability	Source
1	No income %	the number of people with no income increases failure to cope with adverse climatic events	Economic	Increasing	Belle and Hlalele, 2015: IFAD, 2009: Cutter, 2013
2	Young (0-14)	Young people and children are most vulnerable groups to any disaster events	Social	Increasing	UNICEF, 2011: Cutter, 2013
3	Working Age (15-64)	The greater the number of people working the better they are able to cope with any form of disasters	Socio-economic	Decreasing	Cutter, 2013
4	Elderly (65+)	The elderly groups have difficulties in coping climatic change impacts	Social	Increasing	Cutter, 2013
5	Dependency ratio	If the families have large number of dependents, they face difficulties in coping with disasters	Social 2015	Increasing	Belle and Hlalele,
6	No schooling aged 20+	Non-schooling increases vulnerability during	Social	Increasing	Belle and Hlalele, 2015
7	Higher education aged20+	This indicator ensures resilience through knowledge in combating disasters.	Social	Decreasing	
8	Matric aged 20+	A community with more people possessing matric or more, members are employable and can face disasters with ease	Social	Decreasing	Adger *et al.* 2004
9	Average household size	During droughts, poor families with many members have difficulties in feeding their members.	Social	Increasing	Adger *et al.* 2004
10	Flush toilet connected to sewerage	Flush toilets put high pressure on members during disasters (drought)	Environmental	Increasing	Adger *et al.* 2004

Source: Stats SA, Census, 2011: Belle and Hlalele, 2015 ables. It is a water balance index suitable for tracking climate change variability. First, average maximum and minimum temperature data sets were loaded onto Drought Index Calculator (DrinC) for Potential Evapotranspiration (PET). Hagreaves method was chosen as it requires both maximum and minimum temperature values. In order to compute RDI, both precipitation and PET are required, therefore, only standardised values were determined on only seasonal and annual basis. To calculate the risk levels, a simple modified Severity, Exposure & Probability (SEP) Risk Assessment Model was deployed.

Risk = Severity x Exposure x Probability .. (3)

Where Severity (Se) is defined by the absolute value of all values equal or less than -1, as determined by the RDI threshold values. Table 4 shows the RDI threshold values.

$$S_e = \left| \sum_{j=1}^{m} Index_j \right|_e \quad ..(4)$$

Exposure is in this study referred to as vulnerability, therefore the value to represent exposure is the vulnerability index copmputed per area in Mangaung Municipality. Probability of an event is defined asthe number of ways event A can occur divided by the total number of possible outcomes (Weiers, 2010; Psycharis and Kynigos, 2009; Williams, 2014). In this study five scales (four seasons and annual basis) were used to compute and rank areas in terms of their risk levels. To verify the ranking, a Kendall's coefficient of concordance was applied.

Table 4. RDI threshold values

Level	Drought category	RDI value
0	No drought	0<index 1
1	Mild drought	–1.0 < Index < 0
2	Moderate	–1.5 < Index ≤ –1.0
3	Severe drought	–2.0 < Index ≤ –1.5
4	Extreme drought	Index ≤ -2.0

Source: Tan *et al*. 2015

Results and Discussion

Vulnerability/Exposure analysis

The five variables obtained from the rotated matrix were then averaged for each area under Mnagaung Local Municipality (Now Mangaung Metropolitan Municipality). The table below depicts areas under Mangaung Local Municipality with their composite vulnerability indices. The higher the value(Index) the more vulnerable such an area is to climate change impacts. According to Census (2011), there is total population of 747 432 in Mangaung, therefore using the table below, there are 32 vulnerable areas with a vulnerability index of at least 60% or more. This leaves about 10 663 people exposed to climate change risks. The results reveal most of these areas in the outskirts of Thaba Nchu Area (known as trusts).

Hazard analysis

Hazard analysis forms an essential part of the risk analysis, therefore without hazard, no matter how vulnerable the system is, no disaster can occur (Hlalele and Belle, 2015).Table 6 shows the results of RDI-3 and annual as computed from DrinC.

Applying the risk equation; Risk = Severity x

Table 3. Rotated Component Matrix

No.		Variable			
		1	2	3	4
1	No income % (V1)	.018	.213	.879	-.011
2	Young (0-14)(V2)	.953	.210	.091	-.113
3	Working Age (15-64)(V3)	.922	.188	.126	.266
4	Elderly (65+)(V4)	.051	-.028	.106	.947
5	Dependency ratio(V5)	.879	.262	.058	.348
6	No schooling aged 20+(V6)	.264	.148	.656	.324
7	Higher education aged 20+(V7)	.141	.927	.167	-.111
8	Matric aged 20+(V8)	.030	.520	-.582	.469
9	Average household size(V9)	.872	-.230	.041	-.175
10	Flush toilet connected to sewerage(V10)	-.099	-.930	-.142	-.122

Table 5. Final vunerability indices per Mangaung area

Area	V1	V2	V3	V4	V5	V7	Final Vul index
Balaclava	0.29	0.99	0.89	0.45	0.81	0.96	0.73
Bloemfontein	0.17	0.58	0.47	0.31	0.31	0.44	0.38
Bofulo	0.44	0.63	0.68	0.72	0.52	0.93	0.66
Botshabelo	0.23	0.79	0.64	0.27	0.48	0.90	0.55
Eureka	0.00	0.00	0.00	0.46	0.00	1.00	0.24
Feloane Trust	0.59	0.78	0.64	0.28	0.47	0.96	0.62
Gladstone	0.24	0.88	0.86	0.60	0.76	0.91	0.71
Grootdam	0.16	0.73	0.72	0.62	0.58	0.97	0.63
Groothoek	0.00	0.11	0.01	0.24	0.00	1.00	0.23
Houtnek	0.10	0.75	0.85	0.88	0.74	0.88	0.70
Kgalala	0.29	0.78	0.78	0.64	0.65	0.87	0.67
Klipfontein	0.27	0.91	1.00	0.88	1.00	0.98	0.84
Kommissiedrif	0.31	0.78	0.74	0.54	0.59	0.99	0.66
Longridge	1.00	0.30	0.40	0.79	0.26	0.93	0.61
Mangaung	0.22	0.67	0.52	0.26	0.36	0.78	0.47
Mangaung NU	0.11	0.57	0.44	0.26	0.29	0.73	0.40
Maraisdal	0.26	0.68	0.65	0.54	0.49	0.97	0.60
Merino	0.49	0.77	0.66	0.36	0.50	0.94	0.62
Middeldeel	0.33	0.72	0.73	0.65	0.59	0.89	0.65
Modutung	0.35	0.71	0.78	0.79	0.65	0.91	0.70
Morago	0.47	0.69	0.63	0.48	0.47	0.93	0.61
Moroto	0.41	0.79	0.75	0.54	0.61	0.95	0.67
Motlala	0.30	0.86	0.78	0.47	0.65	0.92	0.66
Nogas Post	0.81	0.78	0.71	0.46	0.55	0.96	0.71
Paradys	0.23	0.70	0.62	0.43	0.46	0.99	0.57
Post	0.37	0.13	0.29	0.87	0.17	0.84	0.45
Potsane	0.24	0.68	0.65	0.55	0.50	0.86	0.58
Rakhoi	0.45	0.86	0.87	0.66	0.77	1.00	0.77
Ratabane	0.31	0.66	0.65	0.59	0.50	0.95	0.61
Rietfontein	0.53	0.81	0.87	0.79	0.78	0.96	0.79
Rooibult	0.12	0.81	0.75	0.50	0.61	0.84	0.61
Rooifontein	0.38	0.79	0.70	0.42	0.55	0.95	0.63
Rustfontein	0.00	0.23	0.43	1.00	0.28	0.00	0.32
Sediba A	0.39	0.79	0.75	0.54	0.60	0.95	0.67
Sediba B	0.37	0.83	0.78	0.51	0.64	0.98	0.69
Soetdoring Nature Reserve	0.28	0.74	0.48	0.00	0.33	0.71	0.42
Spitsko	0.11	0.68	0.64	0.51	0.48	0.99	0.57
Springfontein	0.11	0.94	0.98	0.77	0.96	1.00	0.79
Tabane	0.26	0.92	0.87	0.55	0.77	0.98	0.72
Talla	0.34	0.73	0.71	0.57	0.56	0.95	0.64
Thabanchu	0.24	0.71	0.59	0.32	0.43	0.77	0.51
Thubisi	0.17	0.67	0.69	0.65	0.54	0.92	0.61
Tiger River	0.34	0.71	0.72	0.64	0.57	0.98	0.66
Tweefontein	0.37	0.80	0.84	0.74	0.73	0.91	0.73
Woodbridge	0.31	1.00	0.94	0.54	0.89	0.99	0.78
Yorksford	0.31	0.86	0.77	0.44	0.64	0.93	0.66

Table 6. Mangaung hazard analysis

Time scale	Severity level	Probability value
Annual	I-8.63I = 8.63	5/43=0.12
Oct –Dec	I-9.58I=9.58	6/43=0.14
Jan-Mar	I-10.85I=10.85	8/43=0.19
April-June	I-8.22I=8.22	6/43=0.14
July -Sep	I-11.41I=11.41	9/43=0.21

Vulnerability x Probability, the results are shown in the Table below.

From Table 7, Bloemfontein areas experiences the lowest risk level over all other areas in the Municipality, this is probably because this area is the capital of the Free State and most urban. However the majority of the areas that are constantly bearing

Table 7. Mangaung Areas risk levels

Area	Severity x Probability	Final Vul index	Risk value	Severity × Probability	Risk value-	Severity × Probability	Risk value	Severity × Probability	Risk value	Severity × Probability	Risk value
	Annual			Oct-Dec		Jan-Mar		Apr-June		July-Sep	
Balaclava	1.04	0.73	0.76	1.34	0.98	2.06	1.51	1.15	0.84	2.40	1.75
Bloemfontein	1.04	0.38	0.40	1.34	0.51	2.06	0.79	1.15	0.44	2.40	0.92
Bofulo	1.04	0.66	0.68	1.34	0.88	2.06	1.35	1.15	0.75	2.40	1.57
Botshabelo	1.04	0.55	0.57	1.34	0.74	2.06	1.13	1.15	0.63	2.40	1.32
Eureka	1.04	0.24	0.25	1.34	0.33	2.06	0.50	1.15	0.28	2.40	0.58
Feloane Trust	1.04	0.62	0.65	1.34	0.83	2.06	1.28	1.15	0.71	2.40	1.49
Gladstone	1.04	0.71	0.74	1.34	0.95	2.06	1.46	1.15	0.82	2.40	1.70
Grootdam	1.04	0.63	0.65	1.34	0.84	2.06	1.29	1.15	0.72	2.40	1.51
Groothoek	1.04	0.23	0.24	1.34	0.30	2.06	0.47	1.15	0.26	2.40	0.54
Houtnek	1.04	0.70	0.73	1.34	0.94	2.06	1.44	1.15	0.80	2.40	1.68
Kgalala	1.04	0.67	0.69	1.34	0.89	2.06	1.38	1.15	0.77	2.40	1.60
Klipfontein	1.04	0.84	0.87	1.34	1.13	2.06	1.73	1.15	0.97	2.40	2.01
Kommissiedrif	1.04	0.66	0.68	1.34	0.88	2.06	1.35	1.15	0.76	2.40	1.58
Longridge	1.04	0.61	0.64	1.34	0.82	2.06	1.26	1.15	0.71	2.40	1.47
Mangaung	1.04	0.47	0.49	1.34	0.63	2.06	0.97	1.15	0.54	2.40	1.13
Mangaung NU	1.04	0.40	0.41	1.34	0.53	2.06	0.82	1.15	0.46	2.40	0.96
Maraisdal	1.04	0.60	0.62	1.34	0.80	2.06	1.23	1.15	0.69	2.40	1.43
Merino	1.04	0.62	0.65	1.34	0.83	2.06	1.28	1.15	0.71	2.40	1.49
Middeldeel	1.04	0.65	0.68	1.34	0.88	2.06	1.35	1.15	0.75	2.40	1.57
Modutung	1.04	0.70	0.73	1.34	0.94	2.06	1.44	1.15	0.80	2.40	1.68
Morago	1.04	0.61	0.64	1.34	0.82	2.06	1.26	1.15	0.70	2.40	1.47
Moroto	1.04	0.67	0.70	1.34	0.90	2.06	1.39	1.15	0.78	2.40	1.62
Motlala	1.04	0.66	0.69	1.34	0.89	2.06	1.37	1.15	0.76	2.40	1.59
Nogas Post	1.04	0.71	0.74	1.34	0.95	2.06	1.47	1.15	0.82	2.40	1.71
Paradys	1.04	0.57	0.59	1.34	0.76	2.06	1.18	1.15	0.66	2.40	1.37
Post	1.04	0.45	0.46	1.34	0.60	2.06	0.92	1.15	0.51	2.40	1.07
Potsane	1.04	0.58	0.60	1.34	0.78	2.06	1.20	1.15	0.67	2.40	1.39
Rakhoi	1.04	0.77	0.80	1.34	1.03	2.06	1.58	1.15	0.88	2.40	1.85
Ratabane	1.04	0.61	0.64	1.34	0.82	2.06	1.26	1.15	0.70	2.40	1.47
Rietfontein	1.04	0.79	0.82	1.34	1.06	2.06	1.63	1.15	0.91	2.40	1.90
Rooibult	1.04	0.61	0.63	1.34	0.81	2.06	1.25	1.15	0.70	2.40	1.46
Rooifontein	1.04	0.63	0.66	1.34	0.84	2.06	1.30	1.15	0.72	2.40	1.51
Rustfontein	1.04	0.32	0.34	1.34	0.43	2.06	0.67	1.15	0.37	2.40	0.77
Sediba A	1.04	0.67	0.70	1.34	0.90	2.06	1.38	1.15	0.77	2.40	1.61
Sediba B	1.04	0.69	0.71	1.34	0.92	2.06	1.41	1.15	0.79	2.40	1.65

Table 7. *Continued..*

Area	Severity × Probability	Final Vul index	Risk value	Severity × Probability	Risk value-	Severity × Probability	Risk value	Severity × Probability	Risk value	Severity × Probability	Risk value
		Annual		Oct-Dec		Jan-Mar		Apr-June		July-Sep	
Soetdoring Nature Reserve	1.04	0.42	0.44	1.34	0.57	2.06	0.87	1.15	0.49	2.40	1.02
Spitsko	1.04	0.57	0.59	1.34	0.76	2.06	1.16	1.15	0.65	2.40	1.36
Springfontein	1.04	0.79	0.82	1.34	1.06	2.06	1.63	1.15	0.91	2.40	1.90
Tabane	1.04	0.72	0.75	1.34	0.97	2.06	1.49	1.15	0.83	2.40	1.74
Talla	1.04	0.64	0.67	1.34	0.86	2.06	1.33	1.15	0.74	2.40	1.54
Thabanchu	1.04	0.51	0.53	1.34	0.68	2.06	1.05	1.15	0.59	2.40	1.22
Thubisi	1.04	0.61	0.63	1.34	0.81	2.06	1.25	1.15	0.70	2.40	1.46
Tiger River	1.04	0.66	0.69	1.34	0.88	2.06	1.36	1.15	0.76	2.40	1.58
Tweefontein	1.04	0.73	0.76	1.34	0.98	2.06	1.50	1.15	0.84	2.40	1.75
Woodbridge	1.04	0.78	0.81	1.34	1.04	2.06	1.60	1.15	0.89	2.40	1.87
Yorksford	1.04	0.66	0.69	1.34	0.88	2.06	1.36	1.15	0.76	2.40	1.58

higher risk levels are the rural outskirts of the three main towns of this municipality (Thaba Nchu, Botshabelo and Bloemfontein) mostly those in Thaba Nchu area. The severity levels and probability values over all the three time scales are almost the same, implying that this municipality is experiencing constant to increasing climate change impacts.

Conclusion

In conclusion, a vast difference is detected in the vulnerabilities of the areas under Mangaung Metropolitan Municipality. The results show that some of the top underlying variables behind high vulnerability in this municipality are; number of people with no income, the young (0-14) and the elderly(65+) groups as detected by the principal component analysis. The main towns seem to remain less vulnerable compared to the rest of the other areas under study. These most vulnerable areas lay in the outskirts of Thaba Nchu mainly. Furthermore, climatic hazard analysis using RDI results showed constant hazard severity and probability over a 43 year long time series data set on annual basis. To further employ climate changes, RDI was computed on seasonal time scales which also showed no significant differences in both severity and probability. Due to the fact that the study used only one station over Mangaung Metropolitan Municipality to assess climate change conditions, the risk assessment analysis differences were influenced by differences in the vulnerability levels. High risk levels are therefore in the rural areas. The study therefore recommends that the government and all relevant stakeholders to set up income generating projects through which young people will not necessarily seek jobs in urban areas and hep afford higher education costs.

References

Abu R. Md., Islam, T., Shen, S., Hu, Z. and Atiqur Rahman, M. 2017. Drought Hazard Evaluation in Boro Paddy Cultivated Areas of Western Bangladesh at Current and Future Climate Change Conditions. *Advances in Meteorology*. Article ID 3514381, 12 pages, 2017. doi:10.1155/2017/3514381

Adger W.N., Brooks, N., Bentham, G., Agnew, M. and Eriksen, S. 2004. New indicators of vulnerability and adaptive capacity. Norwich, University of East Anglia.

Anon, 2016 Severity, Exposure & Probability (SEP) Risk Assessment Model https://www.wilderness.net/toolboxes/documents/safety/Severity,%20Exposure%20&%20Pr obability%20(SEP)%20Risk%20Assessment%20Model.pdf Date of access: 21 Sep. 2016.

Allaby, M. 2003. Droughts. New York, NY: Facts on file, Inc. AllAfrica, 2016. Africa: South Africa in Midst of 'Epic Drought.

http://allafrica.com/stories/201511041432.html Date of access: 02 Oct. 2016.

Anon, 2016. Quantitative assessment of Vulnerability to Climate Change: Computation of Vulnerability Indices http://danida.vnu.edu.vn/cpis/files/Papers_on_CC/Vulnerability/Quantitative%20assessment%20of%20 Vulnerability% 20to%20Climate%20Change.pdf Date of access: 10 Sep. 2016.

Apollov, B.A., Kalinin, G.P. and Komarov, V.D. 1964. Hydrological forecasting. Washington, D.C: The national science foundation.

Australia. Department of the Environment and Heritage, 2006. Climate Change Impacts & Risk Management: A Guide for Business and Government. Australian Government Greenhouse office.

Belle J.A. and Hlalele, B.M. 2015. Vulnerability Assessment of Agricultural Drought Hazard: A Case of Koti-Se-Phola Community Council, Thabana Morena, Mafeteng District in Lesotho. *Journal of Geography & Natural Disasters*. 5(2): 1-6.

Bhattacharjee, D. and Wang, J. 2010. Assessment of Facility Deprivation in the Households of the North Eastern States of India. http://www.csub.edu/~jwang/poster_IASP_A3.pdf Date of access: 10 Sep. 2016.

Beven, K.J. 2006. Rainfall-Runoff modelling. Chichester, NY: John Wiley & Sons, Ltd.

Cardona, O.D., M.K. van Aalst, J. Birkmann, M. Fordham, G. McGregor, R. Perez, R.S. Pulwarty, E.L.F. Schipper, and B.T. Sinh, 2012: Determinants of risk: exposure and vulnerability: Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation. Cambridge University Press, Cambridge, UK, and New York, NY, USA, pp. 65-108.

Carling, C., Hay, Harriet, C. P., Lau, Natalya G., Jacqueline, A., Evelyn, Powell, J.X. Mitrovica, Konstantin, L. and Douglas, A. W. 2017. Sea Level Fingerprints in a Region of Complex Earth Structure: The Case of WAIS. *Journal of Climate.* 30(6): 1881–1892.

Cheng, A.H.D. and Bear, J. 2010. Modelling groundwater flow and contaminant transport. London, NY: Springer.

City Press, 2016. SA prays for rain after drought losses. http://city- press.news24.com/Business/sa-prays-for-rain-after-drought-losses-20160826 Date of access: 02 Oct. 2016.

Cutter, S. 2013. Social Vulnerability Analysis: Background to Concept and Measurement. https://c.ymcdn.com/sites/www.nibs.org/resource/resmgr/Conference/MMC_SCutter.pdf Date of access: 03 Sep. 2016.

eNCA, 2016. Free State declared disaster area as drought continues. https://www.enca.com/south-africa/free-state-declared-disaster-area-drought-continues. Date of access: 02 Oct. 2016.

Franz G. K., Andrea T., Elena X., Della-Marta, P.M., Jürg L. and Heinz, W. 2009. Homogenization of daily maximum temperature series in the Mediterranean. *Journal of Geophysical Research.* 114(15): 225-355.

Gupta, M.R. and Chen, Y. 2011. Theory and Use of the EM Algorithm. *Foundations and Trends in Signal Processing,* 4(3): 223–296.

Ho Ming, K. and Yusof, F. 2012. Homogeneity Tests on Daily Rainfall Series in Peninsular Malaysia. Int. *Journal of Contemporary Mathematics and Sciences*. 7 (1): 9–22.

IFAD, 2009. Drought, coping mechanisms and poverty: Insights from rain-fed rice farming in Asia. https://www.ifad.org/documents/10180/a8c7fb9f-f3da-4749-ab06-35ff2fc455c6 Date of access: 03 Sep. 2016.

International Federation of Red Cross and Crescent Society, 2014. What is a disaster? http://www.ifrc.org/en/what-we-do/development/ Date of access: 10 Oct. 2016.

International Strategy for Disaster Reduction, 2009. 2009 UNISDR terminology on disaster risk reduction. United Nations, Switzerland, Geneva.

Karlsson, E. and Pomade, L. 2016. Methods of estimating potential and actual evaporation. http://civil.utah.edu/~mizukami/coursework/cveen7920/ETMeasurement.pdf Date of access: 03 Oct. 2016.

Kumar, N. S., Solmon, P.K. and Vishnu-Sankar, R.D. 2014. Assess the vulnerability of climate change in Krishna river basin of Andhra Pradesh. *International Journal of Development Research*. 4(5): 1059-1061.

Mdao, n.d. Climate risk and food security in Senegal: Analysis of climate impacts on food security and livelihoods. National Agency for Civil Aviation and Meteorology, Senegal.

Psycharis, G. and Kynigos, C. 2009. Normalising geometrical figures: Dynamic manipulation and construction of meanings for ratio and proportion. *Research in Mathematics Education*. 11(2) : 149-166.

Seyhan, E. 1966. Introduction to multivariate statistical analysis in hydrology. Amsterdam, Netherlands: Institute of Earth Science.

Štìpánek, P., Zahradníèek, P. and Farda, A. 2013. Experiences with data quality control and homogenization of daily records of various meteorological elements in the Czech Republic in the period 1961. v 2010. *Quarterly Journal of the Hungarian Meteorologi-*

cal Service. 117(1): 123–141.
Stat, S.A. 2011. Census 2011. http://www.statssa.gov.za/?page_id=964 Date of access: 10 Sep. 2016.
Tigkas, D., Tsakiris, G. and Vangelis, H. 2013. The RDI as a composite climate index. *European Water.* 41: 17-22.
Tsakiris, G. and Vangelis, H. 2005. Estab;ishing a drought index incorporating evapotranspiration. *European Water.* 9(10) : 3-11.
UNICEF, 2011. Climate change: Children's challenge. United Kingdom, UNICEF.
Tan, C., Yang, J. and Li, M. 2015. Temporal-Spatial Variation of Drought Indicated by SPI and SPEI in Ningxia Hui Autonomous Region, China. *Atmosphere*. 6 : 1399-142.
Verhaeghe, B., Paige-Green, P., Engelbrecht, F., Head, M., le Roux, A., Makhanya, S. and Van Huyssteen, E. 2016. Climate Adaptation: Risk Management and Resilience Optimisation for Vulnerable Road Access in Africa: Inception Report. Africa Community Access Partnership (AfCAP)
Weiers, R.M. 2010. Introduction to business statistics. 7th Ed. Canada, USA: Cengage learning.
Williams, M. 2014. Climate change in deserts. United States, USA: Cambridge University Press.
World Meteorological Organnisation (WMO) and Global Water Partnership (GWP), 2016. Handbook of drought indicators and indices. Integrated Drought Management Tools and Guidelines series 2. Geneva.