



## 1 **Linking drought indices to impacts to support drought risk** 2 **assessment in Liaoning province, China**

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10 **Abstract.** Drought is a ubiquitous and reoccurring hazard that has wide ranging impacts on society, agriculture and the  
11 environment. Drought indices are vital for characterizing the nature and severity of drought hazards, and there have been  
12 extensive efforts to identify the most suitable drought indices for drought monitoring and risk assessments. However, to date,  
13 little effort has been made to explore which index(s) best represents drought impacts for various sectors in China. This is a  
14 critical knowledge gap, as impacts provide important ‘ground truth’ information. They can be used to demonstrate whether  
15 drought indices (used for monitoring or risk assessment) are relevant for identifying impacts, thus highlighting if an area is  
16 vulnerable to drought of a given severity. The aim of this study is to explore the link between drought indices and drought  
17 impacts, using Liaoning province (northeast China) as a case study due to its history of drought occurrence. To achieve this  
18 we use independent, but complementary, methods (correlation and random forest analysis). Using multiple drought indices –  
19 Standardized Precipitation Index (SPI), Standardized Precipitation Evapotranspiration Index (SPEI), Soil Moisture (SoilM)  
20 and the Normalized Difference Vegetation Index (NDVI) – and drought impact data (on crop yield, livestock, rural people and  
21 the economy) correlation and random forest analysis were used to identify which indices link best to the recorded drought  
22 impacts for cities in Liaoning. The results show that the relationship varies between different categories of drought impacts  
23 and between cities. SPEI with a 6-month accumulation (SPEI6) had a strong correlation with all categories of drought impacts,  
24 while SPI12 had a weak correlation with drought impacts. Of the impact datasets, ‘drought suffering area’ and ‘drought impact  
25 area’ had a slightly strong relationship with all drought indices in Liaoning province, while ‘population and number of livestock  
26 with difficulty in accessing drinking water’ had weak correlations with the indices. Based on the linkage, drought vulnerability  
27 was analyzed using various vulnerability factors. Crop cultivated area was positively correlated to the drought vulnerability  
28 for five out of the eight categories of drought impacts, while the total population had a strong negative relationship with drought  
29 vulnerability for half the drought impact categories. This study can support drought planning efforts in the region, and  
30 provides a methodology for application for other regions of China (and other countries) in the future, as well as providing  
31 context for the indices used in drought monitoring applications, so enabling improved preparedness for drought impacts.



## 32 **1 Introduction**

33 Drought is one of the most pervasive natural hazards with some of the greatest societal impacts (Belal et al., 2014), but is  
34 challenging to understand, quantify and manage. These challenges arise from the typically wide spatial extent of droughts,  
35 their frequent occurrence and the non-structural, diffuse and delayed nature of drought impacts (Biswas et al., 2013; Mishra  
36 and Singh, 2010). China has experienced numerous droughts, which have caused great economic losses since the 1950s,  
37 especially in Liaoning province in the dry northeast of the country (Zhang, 2004). From spring 2000 to autumn 2001, Liaoning  
38 province experienced a severe drought, which captured a large amount of attention from stakeholders and caused serious  
39 impacts on many sectors because of the successive years of drought (Chen et al., 2016).

40 The costly nature of droughts means it is essential to plan and prepare for droughts proactively. Drought risk assessment is an  
41 essential prerequisite of this proactive approach (Wilhite and Buchanan-Smith, 2005; Wilhite et al., 2000), providing methods  
42 to predict the potential drought risk to society and the environment. There are numerous approaches to drought risk assessment,  
43 and these can be grouped into two broad classes: one based on the definition of drought risk, which combines the frequency  
44 of drought and the possible drought impacts. The other is an assessment method for establishing indices to measure the hazard,  
45 vulnerability and exposure of drought (Jin et al., 2016). The majority of risk assessment efforts focus primarily on  
46 meteorological indices of drought, e.g. assessing the risk of a given severity of meteorological drought using historical  
47 precipitation data. However, to adequately define risk it is also necessary to characterize the consequences of drought  
48 occurrence, i.e. the impacts of drought on society, the economy and the environment.

49 A wealth of drought indices have been used in the literature (Lloyd-Hughes, 2014), although predominantly for drought  
50 monitoring and early warning (e.g. the review of Bachmair et al. 2016b) rather than risk assessment. The range of drought  
51 indices reflects the different types of drought which can be monitored, e.g., meteorological, hydrological and agricultural; the  
52 selected index should reflect the type of drought one wishes to monitor and manage. Many indices, such as the Standardized  
53 Precipitation Index (SPI), can be calculated over different time scales. This enables deficits to be assessed over different periods,  
54 and can help monitor different types of drought. For example, shorter time scales, such as the SPI for three or six months are  
55 used for agricultural drought monitoring while SPI values for 12 or 24 months are normally applied to hydrological drought  
56 monitoring (Hong et al., 2001; Seiler et al., 2002). The relationship between drought indices and drought impacts, established  
57 by a correlation or some other similar analysis (e.g. Bachmair et al. 2016a), can thus be used for drought risk assessment and  
58 appraisal of vulnerability. Vulnerability is by its nature difficult to define and measure, but in effect, drought impacts provide  
59 a proxy for vulnerability by demonstrating adverse consequences of a given drought severity (Stahl et al., 2016).

60 There are many different types of drought impact affecting many aspects of society and the environment, but drought impacts  
61 are rarely systematically recorded (Bachmair et al., 2016b). Some countries and regions have established drought impact  
62 recording systems to analyze historical drought impacts. A leading example of this is the US Drought Impacts Reporter



63 (Svoboda and Hayes, 2011) which was launched as a web-based system in July 2005. More recently, the European Drought  
64 Impact report Inventory (EDII) has been established (Stahl et al., 2016). Such databases are an important step forward, but the  
65 information in them is necessarily partial and biased, being effectively crowd-sourced text-based information based on  
66 'reported' impacts a range of sources (the media, grey literature, etc.). In contrast to many other countries, China has a relatively  
67 complete and systematically assembled, quantitative drought impact information collection system. Data are collected and  
68 checked at the county level by the Drought Resistance Department via a formalized network of reporters, who collect drought  
69 impacts statistics in every village. These data then are fed up to the national government and held by the State Flood Control  
70 and Drought Relief Headquarters (SFDH). This consistent collection of impact reporting provides a rich resource for drought  
71 risk assessment. However, impacts by themselves are not fully informative; to help inform risk assessment there is a need to  
72 understand their relationship with quantitative drought indices.

73 Understanding the relationship between drought indices and drought impacts, and drought vulnerability, is a vital step to  
74 improve drought risk management (Hong and Wilhite, 2004). However, whilst there have been many studies developing,  
75 applying and validating drought indices, relatively few studies have assessed the link between indices and observed impacts.  
76 Bachmair et al. (2016a) noted that this literature tended to be dominated by studies focused on agricultural drought, linking  
77 generally indices like the SPI/SPEI and crop yield. Examples appraising multi-sectoral impacts are much sparser – recent  
78 studies tend to be in Europe, utilizing the EDII. Bachmair et al. (2014) and Bachmair (2016b) used drought impacts from the  
79 EDII, and various time scales of SPI, SPEI and streamflow percentiles. They found that the relationships between indices and  
80 impacts varied significantly by region, season, impact types, etc. Whilst Blauhut et al. (2015) developed a quantitative  
81 relationship between drought impact occurrence and SPEI using logistic regression in four European regions. They assumed  
82 drought impacts were only measured by the drought impact occurrence, meaning that all drought impacts have equal weight  
83 without considering the duration, intensity or spatial extent of the impacts; a similar logistic regression approach was also used  
84 by Stagge (Stagge et al., 2014). Karavitis et al. (2014) described drought impacts transformed into monetary losses to measure  
85 drought impacts in Greece. However, it is challenging to transform all drought impacts into monetary units – especially the  
86 indirect impacts of droughts.

87 In China, previous studies have also focused on agricultural drought. Zhao et al. (2011) established the relationship between  
88 drought frequency and simulated crop yield data in Henan Plain. Jia et al. (2011) used the water stress coefficient and duration  
89 to establish a drought index. Li et al. (2009) analyzed the links between historical crop yield and meteorological drought and  
90 established a meteorological drought risk index by combining the drought frequency, intensity, yield loss and extent of  
91 irrigation. The drought index was found to explain 60-75% of the major crop yield reduction.

92 In summary, previous studies have focused on linking impacts to only one characteristic of drought (such as intensity, duration  
93 of occurrence) with most focusing on meteorological drought and agricultural impacts. But with the exception of Blauhut et



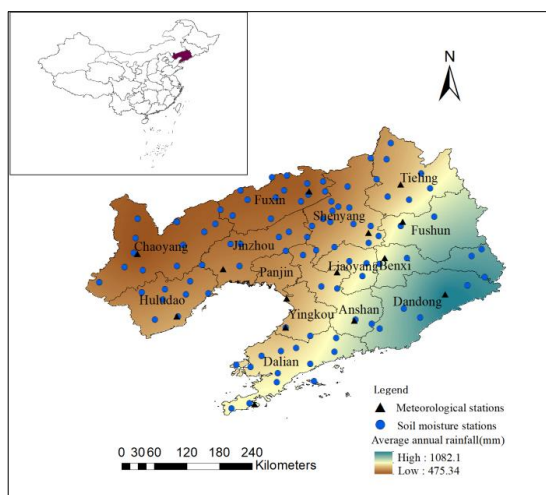
94 al. (2015), there is little application of the results to drought vulnerability assessments. Here we link drought indices to drought  
95 impacts in 14 cities in Liaoning province, northeast China, showcasing the use of the Chinese drought impact data from the  
96 SFDH. Using the drought impact-index linkage, we evaluate the drought vulnerability in Liaoning province and assess what  
97 factors affect drought vulnerability. A drought vulnerability evaluation method that can be extended to other areas is then  
98 developed. The objectives of this paper are:

- 99 1. To identify when and where the most severe droughts occurred between 1990 and 2013 in Liaoning province;
- 100 2. To identify which drought indices best link to drought impacts in Liaoning province;
- 101 3. To determine which city or area has higher drought vulnerability, based on the correlation analysis from objective 2,  
102 in Liaoning province; and,
- 103 4. To ascertain which vulnerability factor or set of vulnerability factors have a higher contribution to drought  
104 vulnerability, as quantified in objective 3.

## 105 2 Materials

### 106 2.1 Study area

107 Located in the northeastern of China, Liaoning province, comprised of 14 cities, has a temperate continental monsoon climate  
108 with an annual average precipitation of 686.4mm, which is unevenly distributed both temporally and spatially (Cai et al., 2015).  
109 Figure 1 shows the annual average rainfall across Liaoning, the south-east receiving on average more than 1000mm a year,  
110 whilst the north-west receives less than 500mm per year.



111  
112 **Figure 1: Map showing the 14 cities, the distribution of meteorological and soil moisture stations and the average annual**  
113 **precipitation in Liaoning province.**

114 The annual average volume of water resources is 34.179 billion m<sup>3</sup>, and the annual average per capita water resources is 769



115 m<sup>3</sup> – about one-third of the per capita water resources for the whole China. Thus, Liaoning is one of the severe water-shortage  
116 provinces in northern China. Liaoning province is also a highly productive area for agriculture. Spring maize is the dominant  
117 crop in agriculture production which makes it an important high-quality maize production area (Liu et al., 2013; Ren and Zhou,  
118 2009). Due to these characteristics, when drought occurs, as has frequently been the case in Liaoning province, it causes a  
119 significant reduction in agricultural production (Yan et al., 2012). According to the SFDH, between 2000 and 2016 the average  
120 annual yield loss due to drought was 1.89 million tons in Liaoning province, with an average annual direct agricultural  
121 economic loss of 1.87 billion yuan.

## 122 2.2 Data

### 123 1) Meteorological data

124 Daily precipitation and temperature data for each city in Liaoning province for the period 1990-2013 were obtained from the  
125 China Meteorological Administration (<http://data.cma.cn/>), including daily precipitation and temperature. Although there are  
126 52 meteorological stations in Liaoning province, due to the quality and length of the records, and location of the stations, one  
127 representative meteorological site in each city was selected to represent the meteorological condition for the whole city in  
128 order to derive drought indices.

### 129 2) Soil moisture data

130 Daily soil moisture data for 96 soil moisture stations in Liaoning province from 1990 to 2006 were obtained from Liaoning  
131 Provincial Department of Water Resources. Daily soil moisture was measured at three different depths: 10cm, 20cm and 30cm  
132 using frequency domain reflection soil moisture sensors, which are based on the principle of electromagnetic pulse. Soil  
133 moisture data were not available between November and February at most stations due to freezing conditions.

### 134 3) Normalised Difference Vegetation Index (NDVI) data

135 Monthly MODIS NDVI data from 2000 to 2013 was collected in Liaoning province from the Geospatial Data Cloud  
136 (<http://www.gscloud.cn/>); the daily maximum data were used to derive the monthly average NDVI.

### 137 4) Impact data

138 In contrast to many other countries, China has a systematic, centralized drought impact information collection system. Drought  
139 statistics include drought impacts, drought mitigation actions and benefits of action to agriculture, hydrology and civil affairs.  
140 During a drought event, impact statistics are collected from every day to every three weeks, according to the drought warning  
141 level (Wang, 2014). When a drought warning is not triggered, drought impact data are collected after an event has ended which  
142 could be several months afterwards; and no data are collected when there is no drought event. Statistics for eight drought  
143 impact types were collected from the SFDH between 1990 and 2016, and aggregated to annual totals, the impact types used  
144 are listed in Table 1.



145 **Table 1: The eight drought impacts used in this study collected by the SFDH for Liaoning province.**

Impact	Abbreviation	Description	Unit
Drought suffering area	DSA	The area that was officially declared in drought.	kha
Drought impacted area	DIA	The area that suffered crop yield loss by 10% or more	kha
Disaster area	DA	The area that suffered crop yield loss by 30% or more.	kha
Recessed area	RA	The area that suffered crop yield loss by 80% or more.	kha
Population with difficulty in accessing drinking water	PHD	Rural populations that cannot access normally to drinking water.	10k
Number of livestock with difficulty in accessing drinking water	NLH	Number of livestock that cannot access normally to drinking water.	10k
Yield loss due to drought	YLD	The amount of yield losses due to drought.	10k ton
Direct economic loss in agriculture	DELA	Direct losses of agricultural economy caused by drought.	0.1b yuan

146 5) Vulnerability factors

147 Vulnerability factors were collected from the 2017 Liaoning province Statistical Yearbook to explain the drought vulnerability  
 148 (Liaoning Province Bureau of Statistical, 2017). The drought impacts described above are mainly focused on agriculture, rural  
 149 populations, agricultural productivity and the agricultural economy; therefore, factors relevant to these sectors were selected.  
 150 The selected vulnerability factors and data from the 2017 Liaoning Statistical Yearbook are shown in Table 2.

151 **Table 2: Vulnerability factors for Liaoning province collected from the 2017 Liaoning Statistical Yearbook(Liaoning Province**  
 152 **Bureau of Statistical, 2017)**

City	Per capita gross domestic product(k yuan)	Population (10k)	Crop cultivated area(kha)	Annual per capita water supply( m <sup>3</sup> )	Per unit area of Fertilizer application(kg/ha)	Effective irrigation rate (%)	Number of electromechanical wells(k)	Reservoir total storage capacity(m <sup>3</sup> )	Per unit area of major agricultural products(kg/ha)	Livestock production (10k ton)
Shenyang	755.8	733.9	656.0	91.5	1000.4	40.0	27.6	686.6	7090.5	64.5
Dalian	1143.4	595.6	327.0	73.4	1437.2	22.8	19.0	2523.0	4914.3	70.8
Anshan	422.9	345.7	247.7	42.3	1031.8	30.1	4.1	91.9	6641.6	36.7
Fushun	402.7	214.8	116.1	94.7	776.9	37.4	1.8	2575.5	6342.9	10.4
Benxi	511.1	150.0	58.0	167.9	756.3	29.9	0.4	6078.8	6606.3	9.3
Dandong	315.8	237.9	190.4	28.0	1049.7	41.7	1.4	16202.8	6056.9	20.2
Jinzhou	341.8	302.2	457.2	46.6	915.4	41.3	18.7	977.9	6825.7	64.0
Yingkou	496.7	232.8	109.4	42.4	1564.6	67.7	12.3	269.6	7325.0	13.5
Fuxin	215.9	188.9	479.4	39.7	881.9	30.1	26.6	545.0	5243.6	49.6
Liaoyang	373.4	178.6	162.8	42.4	1002.6	44.8	4.0	1418.8	7202.2	11.0
Panjin	778.3	130.1	143.0	70.2	937.0	68.7	1.0	141.5	8918.3	23.8



Tieling	196.5	299.9	548.5	12.2	960.2	32.0	18.1	2174.5	8397.1	46.0
Chaoyang	210.1	341.1	464.5	15.8	874.7	42.0	17.4	2085.6	6292.0	63.6
Huludao	230.8	280.5	249.7	18.7	976.8	28.9	14.0	892.7	4852.3	35.4

153 **2.3 Methods**

154 1) Drought indices

155 Two meteorological indices were selected, Standardized Precipitation Index (SPI; McKee et al., 1993) and Standardized  
 156 Precipitation Evapotranspiration Index (SPEI; Vicente-Serrano et al., 2010). These standardized indices are widely used in  
 157 drought monitoring applications, and the World Meteorological Organization recommend the use of the SPI to monitor  
 158 meteorological drought (Hayes et al., 2011). This is due to the relatively simple calculation, flexibility of calculation at different  
 159 time scales, and the fact it can be compared across time and space.

160 The SPI, in its default formulation, assumes that precipitation obeys the Gamma ( $\Gamma$ ) skewed distribution, which is used to  
 161 transform the precipitation time series into a normal distribution. After normalization, classes of drought can be defined with  
 162 the cumulative precipitation frequency distribution (Botterill and Hayes, 2012; Hayes et al., 1999). The SPEI is a very similar  
 163 concept, using the climatic water balance (that is, precipitation minus potential evapotranspiration, PE). Here, PE is calculated  
 164 by the Thornthwaite method (Thornthwaite, 1948), using observed temperature and sunlight hours (estimated from latitude)  
 165 as inputs. SPEI are calculated by normalizing the climatic water balance using a log-logistic probability distribution (Yu et al.,  
 166 2014).

167 SPI and SPEI are easily calculated and can fit a wide range of time scales (e.g. 1, 3, 12, 24, 72 months) of interest (Edwards,  
 168 1997). SPEI has the added advantages of characterizing the effects of temperature and evapotranspiration on drought. In this  
 169 study, SPI and SPEI were calculated for five accumulation periods (6, 12, 15, 18 and 24-months) from 1990 to 2013 for 14  
 170 meteorological stations (i.e. one in each city). In Liaoning province, precipitation is concentrated between April and September;  
 171 this is also when the growth stage of spring maize occurs. Considering the climatology and crop growth period, SPI6 and  
 172 SPEI6 ending in September were selected, i.e. calculated using precipitation during April to September. The 12, 15, 18 and 24  
 173 months SPI and SPEI in ending December were analyzed with the annual drought impacts.

174 Using the daily soil moisture of 10 cm, 20 cm and 30 cm depths, the daily average soil moisture for each station was calculated  
 175 using Eq. (1) and Eq. (2) (Lin et al., 2016).

176 
$$\theta_1 = \theta_{10} \quad \theta_2 = \frac{\theta_{10} + \theta_{20}}{2} \quad \theta_3 = \frac{\theta_{20} + \theta_{30}}{2} \quad (1)$$

177 
$$\bar{\theta} = \frac{\sum_{i=1}^3 (\theta_i \times h_i)}{H} \quad (2)$$

178 Where  $\theta_i$  is the soil moisture of the  $i$ -th layer ( $i=1, 2, 3$ ).  $\theta_{10}$ ,  $\theta_{20}$  and  $\theta_{30}$  are the measured value at different depths  
 179 (10cm, 20cm and 30cm).  $\bar{\theta}$  is the average soil moisture.  $h_i$  is the thickness of the  $i$ -th layer of soil, and  $H$  is the total



180 thickness of the measured soil.  
181 Some of the daily soil moisture data were missing, however, this was limited to 17% of total soil moisture data. In some cases  
182 there were missing data for one depth of soil moisture measurement. In these cases, the average soil moisture of the other two  
183 layers was calculated, and where there was only one layer of soil moisture available it was used to represent the average soil  
184 moisture. The annual average soil moisture was calculated based on the available daily soil moisture (March to October) and  
185 was analyzed with the annual drought impact data. As each city has more than one station, the annual soil moisture of each  
186 station was calculated and then averaged into one value for each city.

187 The area-averaged NDVI at city unit was calculated based on the monthly NDVI. The critical stages of the spring maize growth  
188 in Liaoning is in July, so the area-averaged NDVI in July was selected for the analysis with the annual drought impacts.

### 189 2) Correlation analysis

190 The Pearson correlation method was used to characterize the correlation between indices and various drought impacts (Özger  
191 et al., 2009). Due to the limited availability of soil moisture data, correlation analysis of soil moisture and drought impact data  
192 was only carried out in 9 cities. The linkage between drought indices and impacts was used to assess the drought vulnerability  
193 in Liaoning province. It can be inferred that the greater impact caused by the same severity of drought (as measured by the  
194 relevant index e.g. SPI/SPEI), the higher drought vulnerability of the city.

### 195 3) Random forest modeling

196 Random forest (RF) is an algorithm that consists of a series of independent decision trees. RFs can be used for classification  
197 and regression (Sethi et al., 2012). Classification RFs aggregate votes from individual trees to estimate the outcome class. In  
198 this analysis random forests were built for regression. The results of the leaf nodes at different trees are aggregated for  
199 regression (Liaw and Wiener, 2002). The advantages of RF include: its fast training speed, good accuracy and relative  
200 efficiency (Mutanga et al., 2012). Additionally, once RF models are established, the values of the predictor that correspond to  
201 the first split in the decision tree can be extracted as thresholds corresponding to impact occurrence (Bachmair et al., 2016a).  
202 The R package ‘randomForest’ was employed to identify the relationship of drought indices to drought impacts in this research  
203 (Kursa, 2017; Liaw and Wiener, 2002). There are 5000 decision trees for each RF model. The variance explained was used to  
204 determine the goodness of fit of random forest model (Fukuda et al., 2013). The mean squared error (MSE), Eq. (1), was used  
205 to evaluate the importance of each index:

$$206 \quad MSE = \frac{1}{n} \sum_{i=1}^{i=n} (y_i - \hat{y}_i)^2 \quad (3)$$

207 Where  $y_i$  and  $\hat{y}_i$  are the each drought impacts and estimated drought impacts of each city,  $i$ , respectively.  $n$  is the length of  
208 time series.





209 The percent change of MSE (MSE%) is based on how much the accuracy decreases when the effect of the variable is excluded,  
 210 as the values are randomly shuffled, the higher the value, the higher the index importance (Carolin et al., 2009). The first  
 211 splitting values of each decision tree was also extracted. Soil moisture and NDVI were not analyzed using random forest due  
 212 to missing data and short time series.

#### 213 4) Standardization of drought impacts and vulnerability factors

214 To ensure comparability and to facilitate the visualization of the drought impacts and vulnerability factors, they were  
 215 standardized to a value from 0 to 1 using Eq. (3) and Eq. (4) (Below et al., 2007).

$$216 \quad SDI_i = \frac{DI_i - \min DI}{\max DI - \min DI} \quad (4)$$

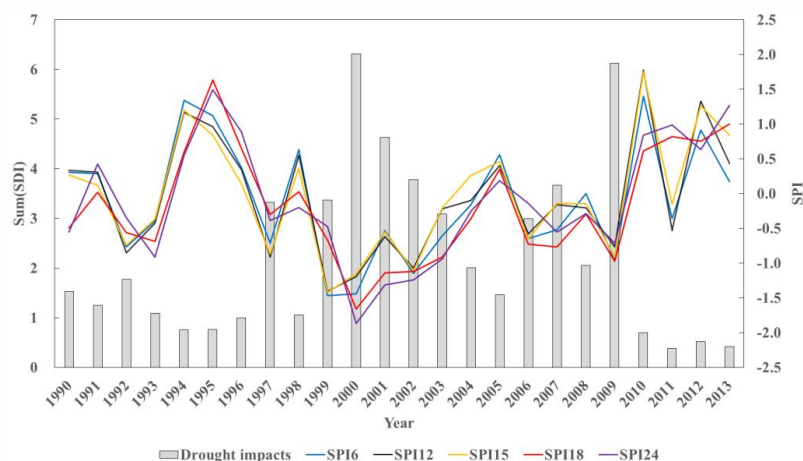
$$217 \quad SVF_j = \frac{VF_j - \min VF}{\max VF - \min VF} \quad (5)$$

218 Where  $SDI_i$  and  $DI_i$  are the Standardized Drought Impacts and drought impacts of year  $i$  in Liaoning province, respectively.  
 219  $\max DI$  and  $\min DI$  is the maximum and minimum values of drought impacts in all year for the given impact type.  $SVF_j$  and  
 220  $VF_j$  is the Standard Vulnerability Factors and vulnerability factors of city  $j$  in Liaoning province, and  $\max VF$  and  $\min VF$  are  
 221 the maximum and minimum values of each category of vulnerability factors in all cities.

### 222 3. Results

#### 223 3.1 Drought monitoring and drought impacts

224 Figure 2 shows high consistency between the drought monitoring indices (in this case the SPI) and the drought impact data.

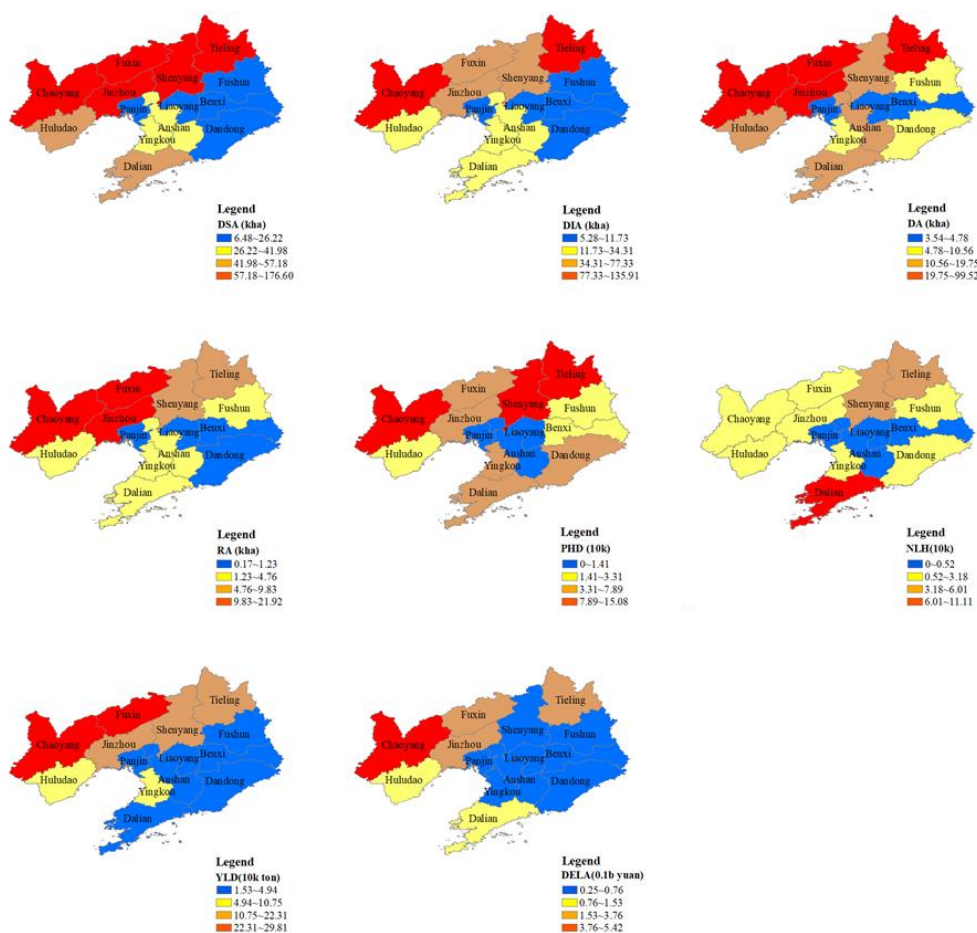


225  
 226 **Figure 2: Standardized Precipitation Index (SPI) for 6-, 12-, 15-, 18- and 24-month accumulation periods and the sum of the**  
 227 **Standardised Drought Impacts (SDI) for each impact type listed in Table 1 for Liaoning province from 1990 to 2013.**

228 The most severe droughts occurred in 2000, 2001, and 2009, whilst in 1994, 1995, 2012 and 2013 there was above normal



229 precipitation. The largest impacts are generally associated with the lowest index values. This suggests that there is a  
 230 relationship between the drought indices and drought impacts, and this will be explored quantitatively in the next sections.  
 231 Figure 3 shows the spatial distribution of the annual average of each drought impact type collected between 1990 and 2016. It  
 232 shows that for all categories of drought impacts, more drought impacts were recorded in the drier northwestern part of Liaoning  
 233 province than in eastern parts of the province. The NLH was highest in Dalian, whilst Shenyang had the biggest PHD.



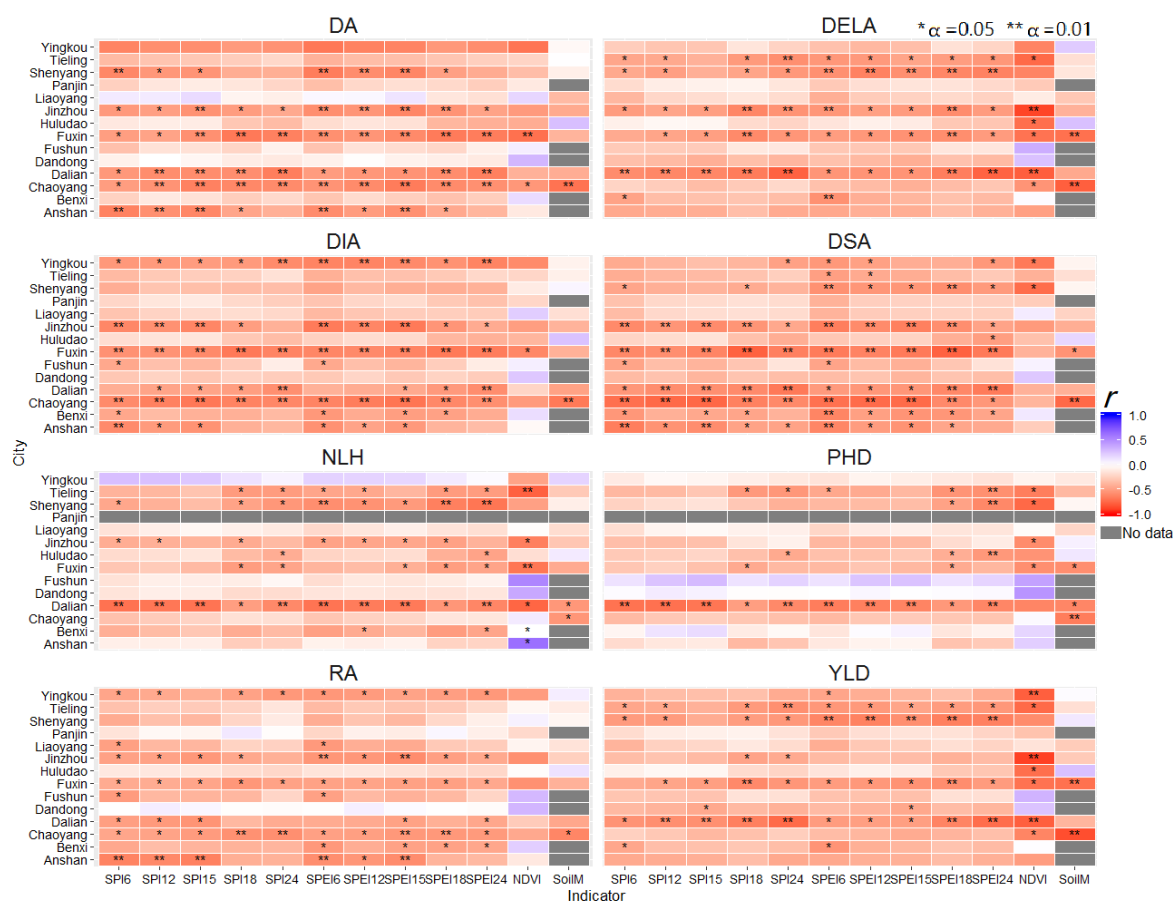
234  
 235 **Figure 3: Distribution of average drought impacts (for each impact type, identified by the codes in Table 1) for the period 1990-2013**  
 236 **in Liaoning province.**

237 **3.3 Correlation of indices with impacts**

238 The Pearson correlation coefficient ( $r$ ) for each city and drought impacts is shown in Figure 4. In most cases the drought index  
 239 is negatively correlated with the drought impacts, suggesting that the lower the drought index, the greater drought impact.  
 240 However, correlation strength, and direction, varied between the cities and impact types, ranging between -0.890 to 0.621. In



241 most cities of Liaoning province, NDVI and SoilM have a weak correlation with most of types of drought impacts. In Dalian,  
 242 Chaoyang and Fuxin, all drought indices had a strong correlation with DA, whilst there was a significant correlation for drought  
 243 impacts area in Jinzhou, Fuxin and Dalian, where most of the correlations were significant ( $p < 0.01$ ). The strongest correlation  
 244 was found between indices and PHD in Dalian, while it was weakest in Dandong. There is a positive correlation between PHD  
 245 and NDVI in Fushun, whilst NLH has a positive correlation with NDVI in Anshan. Generally, SPEI6 had the strongest  
 246 correlation with all types of drought impacts, whilst SPI12 had the weakest correlation. SPEI typically exhibited stronger  
 247 correlations with drought impacts than SPI with the same accumulation period.



248 **Figure 4: Correlation coefficient ( $r$ ) between drought indices (SPI, SPEI, NDVI and SoilM) and drought impacts for different impact**  
 249 **types (identified by the codes in Table 1) in Liaoning province. The significance level of the correlation is indicated using asterisks.**  
 250

251 DSA and DIA had a strong correlation with all drought indices in Liaoning province, while PHD and NLH had a weak  
 252 correlation. The average correlation coefficient across all drought indices and DSA in Liaoning was -0.43, while the average  
 253 correlation coefficient with PHD and NLH was -0.22 and -0.27, respectively. Drought indices showed a moderate correlation  
 254 with RA and YLD with average correlation coefficients of -0.32 and -0.37, respectively.

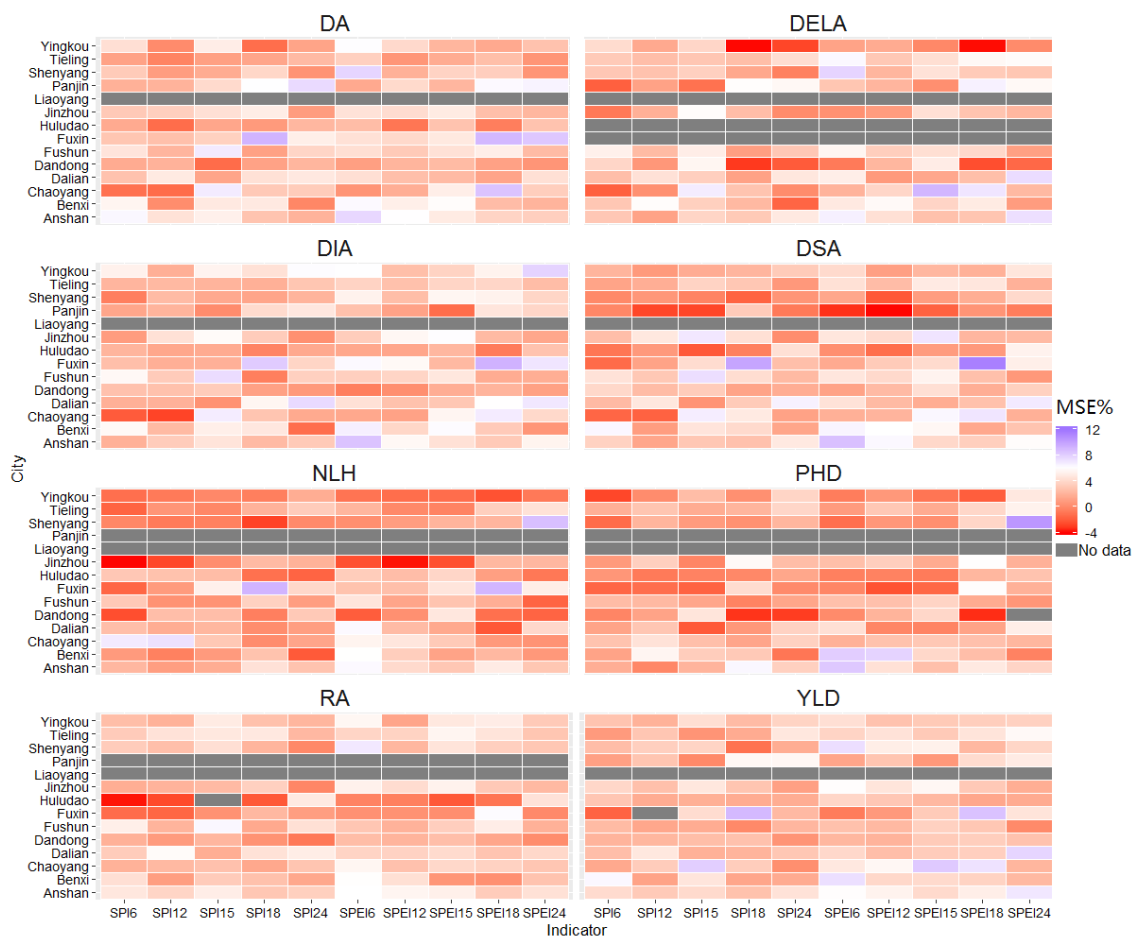
255 The performance of soil moisture varied significantly between cities and impact types (Figure 4); it had a strong correlation



256 with the impacts in Chaoyang, and a weak correlation in Huludao. In Chaoyang, the correlation between soil moisture and  
 257 drought impacts was significant ( $\alpha=0.01$ ), whilst other cities were not significantly correlated.

### 258 3.4 Index importance in random forest models

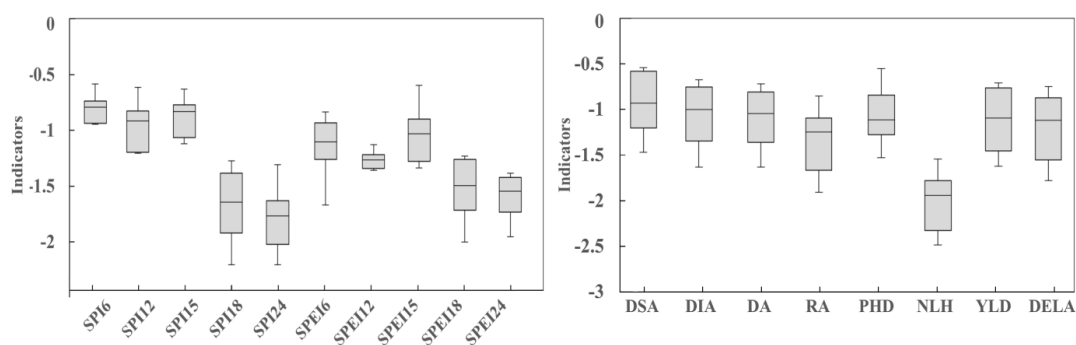
259 Each drought impact type was selected as the response variable in the random forest. On average the random forests explained  
 260 41% of the variance observed within the drought impacts. The MSE% for each city and impact type is shown in Figure 5. The  
 261 MSE% can be seen to vary between different impact types. DIA and YLD have higher MSE% than other impact types, with  
 262 average MSE% is 3.02 and 3.01, respectively. The PHD and NLH had lower MSE%, with average of MSE% of 1.58 and 1.39,  
 263 respectively. DSA and RA had a moderate relationship with drought indices. SPEI performed better than SPI with same  
 264 durations; SPEI6 had the highest importance with drought impacts. SPI12 was the least important index to drought impacts.  
 265 Indices had a higher importance with impacts in Anshan and Dalian and lower importance in Yingkou and Dandong.



266  
 267 **Figure 5: The MSE% of drought indices (SPI and SPEI) with drought impacts (identified by the codes in Table 1) in Liaoning**  
 268 **province using random forest.**



269 The variables identified MSE% from the random forest analysis generally match those with strong negative correlations. This  
270 supports the statement that indices are negatively related to impacts. The threshold of impact occurrence based on the indices  
271 were also identified in the RF analysis using the first splitting value. Figure 6 shows the distribution of first splitting values of  
272 each decision tree within the RF. The average first splitting values for SPI18 and SPI24 were higher than those of SPI6, SPI12  
273 and SPI15 (i.e. a more negative index value and more severe meteorological drought state) for all categories of drought impacts.  
274 For SPEI, the results were similar (i.e. long-term deficits must be more severe to result in equivalent impacts compared to short-  
275 term deficits) but there was more variability between accumulations. When viewed in terms of impact types, DSA had a low  
276 threshold, indicating that DSA impacts occur more readily than DA or RA, as may be expected. The impact occurrence of  
277 index values increase for DSA, DIS, DA and RA; and YLD and DELA tended to occur for more severe water deficits, with  
278 the highest severity threshold being for NLH, indicating that only very severe drought conditions triggered impacts on livestock.



279  
280 **Figure 6: Box plots showing the splitting value (i.e. the thresholds of impacts) in random forest construction across all impact types**  
281 **for each index (left), and across all indices for each impact type (right) in Liaoning province.**

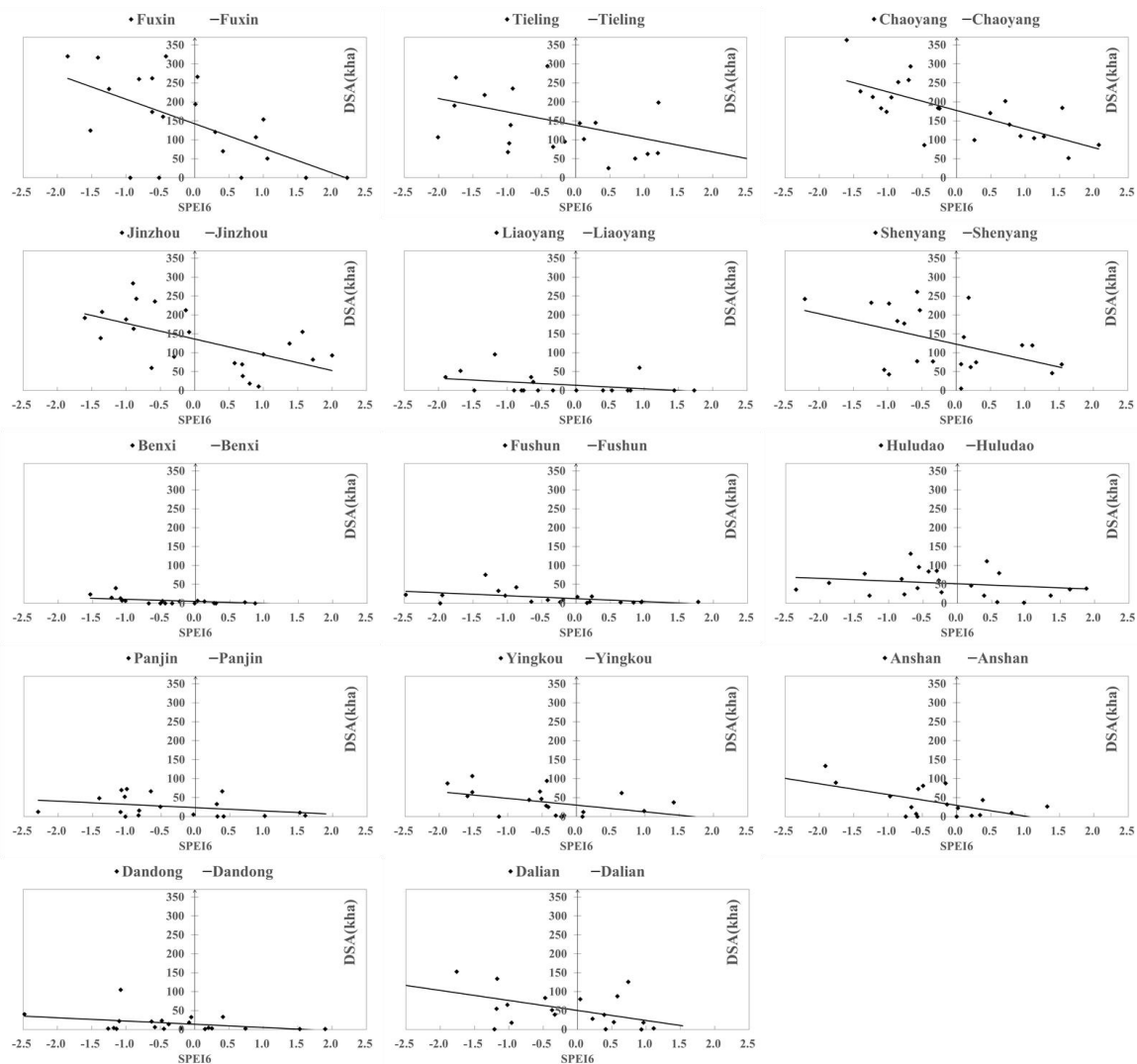
### 282 3.5 Drought vulnerability evaluation

283 The results of correlation analysis and random forest show that in most parts of Liaoning province, SPEI at 6-month  
284 accumulation period had the strongest correlation with drought impacts. SPEI6 was therefore selected to assess the drought  
285 vulnerability of the 14 cities. Regression analysis was performed on the SPEI6 for each category of drought impact, and an  
286 example is given in Figure 7 which shows the linear regression of DSA with SPEI6 in the 14 cities. It can be surmised, for  
287 practical purposes, that the worse the drought impacts associated with a given drought severity (defined by SPEI6), the higher  
288 drought vulnerability of the city to the given impact. Fuxin, Tieling, Chaoyang, Jinzhou and Shenyang have a higher  
289 vulnerability to DSA compared to the other cities.

290 Similar analyses were conducted for all impact types, and Figure 8 summarises which drought impacts each city was the  
291 most vulnerable to. It can be seen from Figure 8 that there is little difference between cities in terms of sensitivity to various  
292 categories of drought impacts. Considering the various impacts, Chaoyang, Jinzhou, Tieling, Fuxin and Shenyang had the

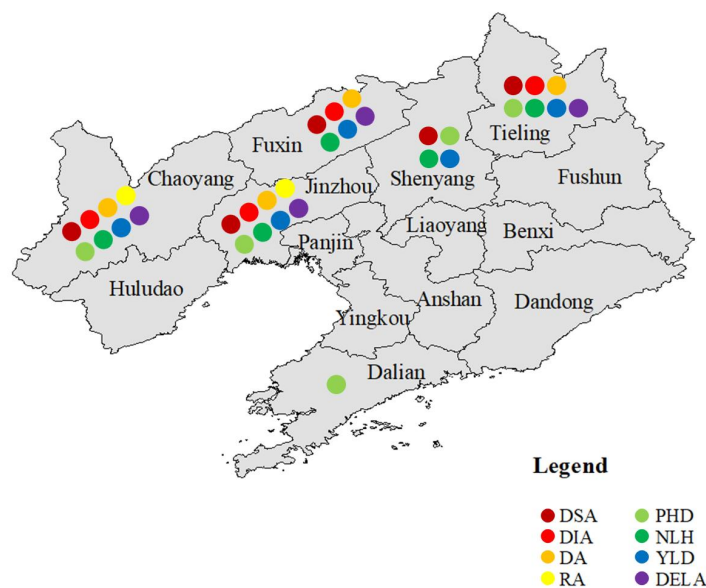


293 highest drought vulnerability, which are all located in the northwest part of Liaoning province. Dalian was most vulnerable to  
 294 NLH.



295

296 **Figure 7: Linear regression results of DSA with SPEI6 in each of the 14 cities in Liaoning Province.**



297

298 **Figure 8: Map showing which drought impacts each city in Liaoning province is most vulnerable to based on the results of the linear**  
 299 **regression.**

### 300 3.6 Vulnerability analysis

301 A further stepwise regression model was built to explain the variation in each type of Standardised Drought Impact where  
 302 SPEI6 is equal to -1.5, using vulnerability factors (listed in Table 2) as predictors. Table 3 shows the results of stepwise  
 303 regression model, demonstrating the contribution of vulnerability factors to each category of drought impact. The results varied  
 304 for each impact type.

305 **Table 3: The vulnerability factors selected for the stepwise regression model and the R<sup>2</sup> of the resulting model for each impact type**  
 306 **(identified by the codes in Table 1).**

Drought impact	Predictors (vulnerability factors)	R <sup>2</sup>
DSA	Crop cultivated area/Population/Livestock production	0.894
DIA	Crop cultivated area/Population	0.743
DA	Livestock production /Per capita gross domestic product	0.731
RA	Number of electromechanical wells/Per capita gross domestic product	0.541
PHD	Crop cultivated area/Reservoir total storage/Per unit area of Fertilizer application	0.805
NLH	Population	0.474
YLD	Crop cultivated area	0.606
DELA	Crop cultivated area/Population/Livestock production	0.786

307 Crop cultivated area had a significant relationship with drought vulnerability for DSA, DIA, PHD, YLD and DELA impact  
 308 types; and population had a significant relationship with DSA, DIA, NLH and DELA. Population was the only significant



309 predictor identified for DELA, with an  $R^2$  of 0.474. Crop cultivated area increases drought vulnerability significantly for 5 out  
310 of 8 drought impacts types, while population reduces the drought vulnerability significantly for four drought impact types.  
311 With the exception of PHD and NLH, crop cultivated area is directly related to the other drought impact types. Crop cultivated  
312 area was the only significant predictor for YLD.

#### 313 **4 Discussion**

314 The methodology in this research has the following characteristics. Firstly, it combines multiple sources of data such as remote  
315 sensing data (NDVI data), soil moisture and meteorological data, and takes many drought impacts, across a range of sectors,  
316 into consideration. Secondly, the extensive drought impact data was systematically collected from the county level, which is a  
317 consistent and reliable data source enabling regional comparisons. The drought impact data used here included impact variables  
318 that are rarely available in other studies such as PHD, NLH, YLD and DELA. Thirdly, we not only considered the occurrence  
319 of drought events, but also the severity of drought and its spatial extent. Finally, the drought indices-impacts linkage was  
320 applied to assess drought vulnerability in Liaoning province.

321 The biggest challenge of this study was the spatial and temporal matching between the drought impacts and indices. The  
322 regularity with which impact data are collected is determined by the drought warning level and as such they are not evenly  
323 spaced in time; as a result of this, the data were aggregated to annual totals. It was important to match the accumulation period  
324 and timing of the selected drought indices to the timescales critical for the drought impacts; SPEI6 in September covers the  
325 critical maize growth period and when the majority of precipitation falls. Soil moisture data are collected at a daily resolution,  
326 in order to match up soil moisture and impact data, the March to October average was used in the correlation analysis. However,  
327 short term soil moisture deficits can have serious impacts on crops which are sometimes unrecoverable. The average soil  
328 moisture may not have captured these short-term deficits, particularly if soil moisture was, in general, sufficient the rest of the  
329 year. For this reason, soil moisture data can be used for real-time drought monitoring applications, but may not appropriate to  
330 present drought impacts on an annual scale for risk assessment, as applied here. In some cities, the lack of soil moisture data  
331 means that the annual average soil moisture does not reflect the occurrence of typical agricultural drought during the year.

332 NDVI data for the critical growth period of spring maize was used in the analysis with annual drought impacts, but again this  
333 does not take all drought events during crop growth period into account. The correlation coefficients characterizing the  
334 relationship between NDVI and drought impacts are both positive and negative. This is likely due to the complexity of NDVI  
335 drivers (e.g. diversity of land cover).

336 The results from the correlation analysis were consistent with the results from the RF analysis. DSA and DIA had strong  
337 correlations with all drought indices in Liaoning province, while PHD and NLH have a weak correlation with indices. This  
338 was because DSA and DIA are direct impacts of agricultural drought, whilst PHD and NLH are related to many factors, such





339 as drinking water source location and the amount of water resources available.

340 The random forest algorithms presented in this paper explained an average of 41% of the variance observed within the drought  
341 impact data. This is relatively modest, because of the limitation of the impacts data. Collinearity of the drought indices (e.g.  
342 SPI6 is correlated with SPEI6) is also a potential cause of the low MSE%. The correlation coefficients calculated for drought  
343 indices and NLH in Yingkou, and PHD in Fushun were positive. This result is unexpected given the interpretation of these  
344 indices as estimations of the drought severity, and the majority of reported correlation coefficients being negative. Therefore,  
345 it seems likely this result is not representative of the true relationships between these indices and impacts, and instead an  
346 artifact of imperfect data. To explore this the correlation coefficients were estimated with the largest impact years removed.  
347 This resulted in a negative correlation coefficient, providing further evidence for the positive correlation coefficients not being  
348 representative of the true relationships. The availability of more data would enable a better approximation of the true  
349 relationships between indices and impacts.

350 For all the drought impacts, Dalian and Fuxin had the highest correlation coefficient for all drought impact types and indices.  
351 The most vulnerable cities were Fuxin, Tieling, Chaoyang, Jinzhou and Shenyang, which are all located in the northwestern  
352 part of Liaoning province indicating there is a high drought vulnerability and drought risk in northwestern Liaoning. This is  
353 consistent with existing research by (Yan et al., 2012; Zhang et al., 2012), which established a drought risk assessment index  
354 system to assess drought risk in northwestern Liaoning. The number of electromechanical wells is associated with low drought  
355 vulnerability – this is the critical water source for irrigation and human drinking.

356 The first splitting value tended to decrease as the accumulation periods increase, suggesting that higher water deficits are  
357 required for the same amount of impact at longer accumulation periods. There is a more severe water deficits of RA occurrence  
358 since it caused yield loss by 80% or more, compared to 10% and 30% for DIA and DA, respectively. Livestock drinking water  
359 requires lower water quality compare to human and lot of water source available for livestock. For this reason, NLH showed  
360 least sensitivity to water deficits.

361 The relationships analysed in this research support the development of a drought impacts predictor. The drought vulnerability  
362 map can be used to support drought risk planning, helping decision makers to inform drought mitigation activities (e.g. sinking  
363 more wells to enhance resilience to drought). The impact thresholds identified can also support improved drought warning and  
364 planning. The methods used here can be applied in other areas to better understand drought impacts and drought vulnerability.  
365 While systematic, statistical archives of drought impact are comparatively rare, globally, there are numerous other potential  
366 sources of impact data that could be used (e.g. see Bachmair et al. 2016).

## 367 **5 Conclusion**

368 This study used correlation analysis and random forest methods to explore the linkage between drought indices and drought



369 impacts. It assessed drought risk in Liaoning province, and proposes a drought vulnerability assessment method which is  
370 applied to study the contribution of various socioeconomic factors to drought vulnerability. Here, we return to the original  
371 objectives of the study to summarise the key findings.

372 1: When and where the most severity drought and impact occurred in study area?

373 Based on the drought monitoring results of SPI, severe drought occurred in 2000, 2001, and 2009. In 2000-2001, drought  
374 resulted in many impacts in Liaoning province, particularly in the northwestern part of Liaoning province. The drought  
375 monitoring data showed good consistency with the recorded drought impacts.

376 2: Whether there is an obvious link between drought impact data and drought indices. Which index or set of indices  
377 performance best in study area?

378 The results showed that the indices varied in their capacity to identify the different type of drought and impacts. The strongest  
379 correlation was found for SPEI at 6 months, whilst SPI12 had a weak correlation with drought impacts. SPEI was found to  
380 better link to drought impacts than SPI of the same accumulation period. NDVI and soil moisture showed some links with  
381 impacts in some cities, but the results were generally weaker and less consistent than for either SPI/SPEI – primarily reflecting  
382 the limitations in the soil moisture and NDVI datasets

383 3. Which city or areas have a high drought vulnerability in Liaoning province?

384 Chaoyang, Jinzhou, Fuxin, Shenyang and Tieling had higher drought vulnerability, all of which are located in the northwestern  
385 part of Liaoning province, indicating that drought vulnerability is higher in these regions than in other parts, which is consistent  
386 with previous research. However, in contrast with past work, the present research provides a much more comprehensive  
387 assessment based on the occurrence of observed impacts data.

388 4: Which vulnerability factor or set of vulnerability factors contribute most to drought vulnerability?

389 Population had a strong negative relationship with drought vulnerability, whilst crop cultivated area was positively correlated  
390 with drought vulnerability.

391 The results shown here give a clearer understanding about drought conditions in Liaoning province. The linkage developed  
392 can be used to assess drought risk and to map vulnerability. It can also be used to help develop early warning systems and  
393 predict drought impacts, which are vital tools for drought management. The results of the vulnerability analysis can guide  
394 management measures to mitigate drought impacts – an important step to shift from post-disaster recovery to proactive pre-  
395 disaster prevention.

#### 396 **Author Contributions**

397 Yaxu Wang, Juan Lv, Jamie Hannaford, Yicheng Wang and Lucy Barker discussed and developed the aims of the paper. Yaxu  
398 Wang was responsible for the data analysis, visualization and prepared the original manuscript, with contributions from



399 Hongquan Sun, Lucy Barker, Jamie Hannaford, Miaomiao Ma, Zhicheng Su and Michael Eastman.

#### 400 **Competing interests**

401 The authors declare they have no conflict of interest.

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