**Manuscript nhess-2019-310 "Linking drought indices to impacts to support drought risk assessment in Liaoning province, China" – Response to Reviewer 1**

The authors have addressed my previous comments, and the scientific quality of the paper has improved.

However, English language is still poor, the paper is not easy to read, and many sentences are not clear enough to the reader. Just to mention a few examples:

**We thank the referee for the feedback to our manuscript, we will improve the English in the revised manuscript, paying particular attention to the examples given below.**

Lines 27-29: The term drought is defined as meteorological, agricultural, hydrological, social and ecological drought. Meteorological drought is defined as a deficit of rainfall for a period in respect to the long term mean (Le Houérou, 1996). Then other types of drought can follow this definition.

**We will improve the English and clarity of this sentence in the revised paper.**

Lines 46-47: In China, many indices were used for types of drought monitoring, such as Palmer Drought Severity Index (PDSI), SPEI, SPI, China Z index, relative soil moisture and remote sensing indices.

**We will improve the English and clarity of this sentence in the revised paper.**

Lines 93-94: In Hao et al. (2011), drought impact s only measured by affected crop area in a 10 day time step in 93 county level.

**We will improve the English and clarity of this sentence in the revised paper.**

Lines 301-303: Considering the various impacts, Chaoyang, Jinzhou, Tieling, Fuxin and Shenyang had the highest drought vulnerability, which are all located in the northwest part of Liaoning province.

**We will improve the English and clarity of this sentence in the revised paper.**

Lines 373-374: The above results are also in general agreement with Hao et al. (2011), their study used 10 day affected crop area data as the drought impacts to assess drought risk in China in county unit.

**We will improve the English and clarity of this sentence in the revised paper.**

**Manuscript nhess-2019-310 "Linking drought indices to impacts to support drought risk assessment in Liaoning province, China" – Response to reviewer 2 (Veit Blauhut)**

The authors did a very good job in revising their manuscript. I added few suggestions and marked some words / lines to be rephrased.

**Thank you for your comments on the manuscript – we have responded to each of your comments below in bold text.**

Line 20 'slightly'

**Answer: We will revise this sentence.**

Line 29 'Then other types of drought can follow this definition. '

**Answer: We will revise this sentence.**

Line 34 'means'

**Answer: We will revise this sentence.**

Line 35 'this'

**Answer: We will revise this sentence.**

Line 36 'Some'

**Answer: We will revise this sentence.**

Line 39 you might ref to un-isdr 2009 or Hagenlocher et al.2019 here.

**Answer: we will added the suggested reference.**

Line 52 'Drought indices are focus..'

**Answer: we replaced 'Drought indices are' with 'Drought monitoring '**

Line 55 'some other similar analysis'

**Answer: we have replaced 'some other similar analysis' with 'random forest modeling '**

Line 57 Good reference for the wealth of impacts, not so good for vulnerbility.

**Answer: we have replaced the reference.**

Line 63 'necessarily'

**Answer: We will revise this sentence.**

Line 67 please add the information pooled---agriculture, water supply…?

**Answer: we have replaced 'drought impacts statistics in every village' with 'drought impacts on agriculture, industrial economy, and water supply in every village. '**

Line 94 Again please explan what city leve means in China I guess it is prefectural level?

**Answer: yes, the cities are prefectural, we will make this clearer in the revised paper.**

L98-99 Please rephrase, there are more including vulnerability... you might check on hagenlocher et al. 2019; of casue you can use this as an example, thank you

**Answer: We will rephrase this sentence and add the suggested reference to the revised paper.**

Line 178 'The 12, 15, 178 18 and 24 months SPI and SPEI in ending December were analyzed with the annual drought impacts during 1990 to 2013. '

**Answer: We will revise this sentence**

Figure 7 bad resolution, you might consider to put them all in one an colorscheme them.

**Answer: We will improve the resolution and clarity of the figure – we initially had all the cities on one plot, but this was hard to see – particualy due to the high number of colours required.**

Line 311 But this shows you the quality of linkage between losses and index, but not the vulnerabiluty itself! Please rephrase.

**Answer: we have rephrased the sentence ' Since drought impacts are symptoms of vulnerability, it can be used to estimate vulnerability (Blauhut et al., 2015a). For a specific severity of drought…'**

Line 321 'more or less population'

**Answer: we have added the 'more'.**

Line 323 sorry I kind of was expecting a final vulnerability map here.

**Answer:Thanks for your suggestion, it would be more readable to show the linkage between the vulnerability factors and drought impacts. Therefor we have added the stepwise regression Standardized Coefficients of each model in Table 3.**

Line 325-329 first and second are same

**Answer: we have rephrased the sentence.**

Line 331 of what?

**Answer: we have rephase the sentence with '.to assess drought vulnerability of eight drought impacts in Liaoning province.' to make it clearer.**

Line 332-L333 how, why, and how did you include them yet?

**Answer: We have revised this paragraph to provide more exaplanation for how the impact data were used given their**

Line 337 what did others find out on that?

**Answer: The results may change if we used multi-year drought impacts, as longer index accumulation periods may have a stronger correlation with multi-year drought impacts than single year drought impacts. Other research has noted the importance of multi-year droughts in very long instrumental and archive records for Liaoning (Tang et al. 2019), suggesting this could be an avenue for further research (e.g. Tang et al. 2019)**

Line 341 thoughts and findings of other studies are missing here.

**Answer: In Nam et al. (2012) study, effective drought management can be achieved using drought monitoring**

**if the current conditions can be assessed and be updated on the latest drought situation. Then, the annual soil moisture does not reflect current drought conditions at a specific time.**

Line 346-348 But why? I suggets irrigation is a major driver? Please explicityl dicuss this here at your exampes.

**Answer: We will expand this discussion in the revised paper.**

Line 356 I'm not fully sure, but this could also be an issue of "freedom" in the model, nummber of trees, overfitting?, number of max. layers!

**Answer: We replaced this sentence to be more inclusive of the range of limitations that may have determined the RF performance.**

Line 402 some

**Anwer: We will revise this sentence**

Line 411 you might inlcude a "Hit list" of most important vulneravility factors-----some thing readers really like. Not forgetting the vulnerabilty map

**Answer: Thanks for your suggestion, The "Hit list" of most important vulnerability factors are displayed in Table 3. We have also clarified which the most 'important' vulnerability factors are in the conclusion.**

**List of all relevant changes made in the manuscript**

Line 10 ‘recurring’ →‘recurring’

Line 11 ‘characterizing’→ ‘characterising’

Line 14 we insert the sentence :‘for indices used in monitoring activities. ’

Line 18-22 ‘To achieve this we use independent, but complementary, methods (correlation and random forest analysis) to identify which indices link best to drought impacts for prefectural-level cities in Liaoning province, using a comprehensive database of reported drought impacts whereby impacts are classified into a range of categories. The results show that Standardised Precipitation Evapotranspiration Index with a 6-month accumulation (SPEI6) had a strong correlation with all categories of drought impacts, while Standardised Precipitation Index with a 12-month accumulation (SPI12) had a weak correlation with drought impacts.’ → ‘To achieve this we use independent, but complementary, methods (correlation and random forest analysis) to identify which indices link best to drought impacts for prefectural-level cities in Liaoning province, using a comprehensive database of reported drought impacts whereby impacts are classified into a range of categories. The results show that Standardised Precipitation Evapotranspiration Index with a 6-month accumulation (SPEI6) had a strong correlation with all categories of drought impacts, while Standardised Precipitation Index with a 12-month accumulation (SPI12) had a weak correlation with drought impacts.’

Line 22 we deleted the ‘sightly’

Line 23 ‘the study.’ → ‘The results of this study’

Line 24 we added ‘and’

Line 25 we added ‘The study also demonstrates the potential benefits of routine collection of drought impact information on a local scale.’

Line 28 ‘ hazards, and can cause numerous and severe societal impacts.’ → ‘ hazards, and can cause numerous and severe societal impacts.’

Line 29 ‘ and delayed with respect to the event; ’ → ‘are often have a delayed onset in relation to the start of the drought event;’

Line 30 ‘The term drought is defined as ’ → ‘ There are a number of ‘types’ of drought (Wilhite and Glantz, 1985), such as’

Line 31 ‘Meteorological drought is defined as a deficit of rainfall for a period in respect to the long term mean (Houérou, 1996). (Maracchi, 2000)Then other types of drought can follow this definition.’→ ‘As these rainfall deficits propagate through the hydrological cycle, the other drought types occur as deficits occur in river flows, soil moisture and groundwater. Eventually impacts become manifest on the environment and society. '

Line 31 'From spring 2000 to autumn 2001, Liaoning province experienced a severe drought, which captured a large amount of attention from stakeholders and caused serious impacts on many sectors because of the consecutive years of drought.'→ 'Liaoning province experienced a severe drought from spring 2000 to autumn 2001 which captured a large amount of attention from stakeholders and caused serious impacts as a result of the consecutive years of drought '

Line 38 'providing'→' and provides the'

Line 39 'Some'→' Some of'

Line 39 'on'→' on the'

Line 41 'characterize '→ 'characterise '

Line 44 'A wealth of drought indices have been used in the literature'→' There are a wealth of drought indices in the literature'

Line 45 'although predominantly for drought monitoring and early warning (e.g. the review of Bachmair et al. 2016b) rather than risk assessment. '→' however they have predominantly used for drought monitoring and early warning (e.g. Bachmair et al. 2016b) rather than drought risk assessment applications.'

Line 47 'Standardized'→ 'Standardised '

Line 49-50 'SPI for three or six months are used for agricultural drought monitoring while SPI values for 12 or 24 months are normally applied to hydrological drought monitoring'→' SPI accumulations for 12 or 24 months are often applied to monitor hydrological droughts '

Line 51 'many indices were used for types of drought monitoring'→' many indices are used for drought monitoring'

Line Line 54 we delete 'the'.

Line 55 emphasizs → emphasis

Line 56 Drought indices are focus on meteorological and agricultural drought monitoring in China. → Drought monitoring efforts in China tend to focus on meteorological and agricultural drought monitoring;

Line 57 . Based on previous drought studies, SPI, SPEI, soil moisture → based on this and previous drought studies, the SPI

Line 59 established by a correlation or some other similar analysis (e.g. Bachmair et al. 2016a), can thus be used → established by statistical methods (e.g. Bachmair et al. (2016a)), can be used

Line 55 drought impacts provide a proxy for vulnerability by demonstrating adverse consequences of a given drought severity (Blauhut et al., 2015a). → drought impacts are 'symptoms' of drought vulnerability and provide a proxy for vulnerability appraisal by demonstrating adverse consequences of a given drought severity (Blauhut et al., 2015a).

Line 65 analyze → analyse

Line 68 we insert the ' as a result of '

Line 71 formalized →formalised

Line 55 who collect drought impacts statistics in every village. → who collect information on drought impacts on agriculture, industrial economy, and water supply in every village.

Line 80 linking generally→ generally linking

Line 81 – recent studies tend to be in Europe, utilizing the EDII. → there are several recent studies in Europe, utilising impact reports from the EDII

Line 85 However, they → However, all four studies

Line 86-87, meaning that all drought impacts had an equal weight without considering the duration, intensity or spatial extent of the impacts. → the number of impacts or a combination of both. This means that all drought impacts had an equal weight without considering the duration, intensity or spatial extent of the individual impacts.

Line 87-88, In contrast, Karavitis et al. (2014) analysed drought impacts transformed into monetary losses to measure drought impacts in Greece; however, it is → Karavitis et al. (2014) described drought impacts transformed into monetary losses to measure drought impacts in Greece. However, it

Line 92 we added 'and'

Line 93 analyzed → analysed

Line 96-101 Xiao-jun et al. (2012) collected annual drought affected area, damaged area, and annual losses in food yield in nation level from China Water Resources Bulletins to explore the water management strategies during droughts. In Hao et al. (2011), drought impacts were only measured by the affected crop area at the 10-day time step at the county level. In our research, eight types of drought impacts are collected to measure drought impacts in at the city unit (i.e. prefectural) level in Liaoning province, including the drought affected area, damaged area and yield loss, but also drought impacts on humans, livestock and the agricultural economy. →Xiao-jun et al. (2012) collected annual drought affected area and damaged area, annual losses in food yield in nation level from China water resources bulletins, which is the secondary data, to explore the water management strategies. In Hao et al. (2011), drought impacts is only measured by affected crop area in county level. In our research, eight types of drought impacts are collected to measure drought impacts in prefectural level in Liaoning province, which include not only drought affected area, damaged area and yield loss, but also drought impact on human, livestock and agricultural economy.

Line 102-104 In summary, previous studies have been focused on linking impacts to only one characteristic of drought (such as intensity, duration of occurrence) with most focusing on meteorological drought and agricultural impacts. But with the exception of Blauhut et al. (2015a) and Blauhut et al. (2016), there is little application of the results to drought vulnerability assessments. → In summary, previous studies have focused on linking impacts to only one characteristic of drought (such as intensity or duration of occurrence) with most focusing on meteorological drought and agricultural impacts with little application of the results to drought vulnerability assessments, with the exception of Blauhut et al. (2015a), Blauhut et al. (2016) and Hagenlocher et al. (2019), for example.

Line111 we delete ‘, based on the correlation analysis from objective 2,’

Line 117, 122 ‘cities’→ ‘prefectural ’

Line 124 we insert ‘in Liaoning province ’

Line 128. Spring maize → ‘; spring maize’

Line 137 we deleted the sentence ‘ representative ’

Line 142-143 frequency domain reflection soil moisture sensors, which are based on the principle of electromagnetic pulse. Soil moisture data were not available between November and February at most stations due to freezing conditions. → frequency domain reflectometry soil moisture sensors Soil moisture data were not available at most stations between November and February due to freezing conditions.

Line 145 Monthly MODIS NDVI data → Monthly MODIS Normalised Difference Vegetation Index (NDVI) data

Line148 ‘centralized’→ ‘centralised

’

**Line 155** **Table 1: The eight drought impact categories for Liaoning province used in this study collected by the SFDH.→Table 1: The eight drought impacts used in this study collected by the SFDH for Liaoning province.**

Line159 ‘Liaoning province ’→ ‘Liaoning Province

Line160 ‘, shown in Table 2’→ .‘and are shown in Table 2 for each city unit.

Line161 ‘Vulnerability factors for each city in Liaoning province ’→ ‘Vulnerability factors for Liaoning province

Line165 and in the whole manuscript ‘Standardized→ ‘Standardised

Line167 ‘Organization’→ ‘Organisation

Line171 ‘normalization’→ ‘normalisation

Line 174 Here→ In this study

Line 175 ‘The SPEI are calculated by normalizing’→ ‘ The SPEI is calculated by normalising the climatic

Line174 ‘ of time scales (e.g. 1, 3, 12, 24, 72 months) of interest (Edwards, 1997).’→ ‘ of accumulation periods of interest (e.g. 1, 3, 12, 24, 72 months) (Edwards, 1997)

Line180 we added the ‘ one in each city – as shown in Figure 1

Line181 ‘; this ’→ ‘ which

Line195-199 ‘As each city has more than one station, the annual soil moisture of each station was calculated and then averaged into one value for each city.

The area-averaged NDVI at city unit was calculated based on the monthly NDVI. The critical stages of the spring maize growth in Liaoning is in July, so the area-averaged NDVI in July was selected for the analysis with the annual drought impacts during 2000 to 2013.’→ As each city has more than one soil moisture station, the annual soil moisture of each station was calculated and then averaged to one value for each city.

The area-averaged NDVI at the city unit was calculated using the monthly NDVI. The critical stags of the spring maize growth in Liaoning is in July, so the area-averaged NDVI in July was selected for the analysis with the annual drought impacts from 2000 to 2013.

Line201 ‘ various’→ ‘the selected

Line207-223 ‘Random forest (RF) is an algorithm that consists of a series of independent decision trees.

RFs can be used for classification and regression (Sethi et al., 2012). Classification RFs aggregate votes from individual trees to estimate the outcome class. In this analysis random forests were built for regression. The results of the leaf nodes at different trees are aggregated for regression (Liaw and Wiener, 2002). The advantages of RF include: its fast training speed, good accuracy and relative efficiency (Mutanga et al., 2012). Additionally, once RF models are established, the values of the predictor that correspond to the first split in the decision tree can be extracted as thresholds corresponding to impact occurrence (Bachmair et al., 2016a).

The R package 'randomForest' was employed to identify the relationship of drought indices to drought impacts in this research (Kursa, 2017;Liaw and Wiener, 2002). There are 5000 decision trees for each RF model. The variance explained was used to determine the goodness of fit of random forest model (Fukuda et al., 2013). The mean squared error (MSE), Eq. (3), was used to evaluate the importance of each index:

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

(3)

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

The percent change of MSE (MSE%) is based on how much the accuracy decreases when the effect of the variable is excluded (i.e. if the SPEI6 is excluded from the model, the MSE% of the model may increase), as the values are randomly shuffled, the higher of MSE%, the higher the index importance (Carolin et al., 2009). The first splitting values of each decision tree was also extracted. Soil moisture and NDVI were not analyzed using random forest due to missing data and short time series.

'→ Decision trees are regularly implemented for machine learning tasks. They resemble flowcharts, consisting of a series of branches, internal nodes, and leaf nodes. Internal nodes typically represent binary conditions of the explanatory variables. These nodes are connected to other internal nodes by branches, which represent the outcome of the previous internal node. Leaf nodes represent the outcome classes. Internal nodes are eventually connected to leaf nodes, which represent the outcome classes of the classification task. Whilst quick to train and interpretable, decision trees are limited by overfitting to the training set. Random forests (RFs) reduce overfitting by fitting an ensemble of uncorrelated decision trees. This is achieved using bootstrap aggregation with replacement (bagging) and only considering a random subset of features for splitting at each internal node (Breiman and Leo, 2001). As well as the reduction in overfitting compared to decision trees, the advantages of RF include: its fast training speed, good accuracy and relative efficiency (Mutanga et al., 2012). Additionally, once RF models are established, the values of the predictor that correspond to the first split in the decision tree can be extracted as thresholds corresponding to impact occurrence (Bachmair et al., 2016a).

In this analysis random forests were built for regression. This is achieved by assigning categorical outcomes at each leaf node, and using the mean prediction as the outcome. The R package 'randomForest' was employed to identify the relationship of drought indices to drought impacts (Kursa, 2017;Liaw and Wiener, 2002) using 5000 decision trees for each RF model. The variance explained was used to determine the goodness of fit of random forest model (Fukuda et al., 2013). The mean squared error (MSE), Eq. (3), was used to evaluate the importance of each index:

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

(3)

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

The percent change of MSE (MSE%) is the difference in accuracy when the effect of the variable is excluded (i.e. if the SPEI6 is excluded from the model, the MSE% of the model may increase). Higher MSE% represents higher the index importance . The first splitting values of each decision tree was also extracted.

Soil moisture and NDVI were not analysed using the random forest approach due to their short time series and prevalence of missing data.

Line225 'visualization'→ 'visualisation

Line229 we insert 'the'

Line 229-232 '.'→ ';

Line235-236 'Figure 2 shows the drought monitoring indices (in this case the SPEI) and the drought impact data. *Sum of SDI* means the sum of all types of Standardized Drought Impacts in 14 cities for each year.'→ 'Figure 2 shows the SPEI and the drought impact data for Liaoning province from 1990 to 2013; the *Sum of SDI* is the sum of all types of Standardised Drought Impacts in the 14 cities for each year.

Line 240 ‘The most severe droughts ’→ ‘Figure 2 shows that the most severe droughts

Line242 ‘s, and this will be explored quantitatively in the next sections.

’→ ‘s. This relationship is explored quantitatively in the next sections.

Line 244 we delete the ‘annual’

Line245 ‘serious→ ‘severe’

Line 255 we insert ‘(and more severe)’

Line 273 ‘3.4 Drought index’→ ‘3.4 Index

Line 279 ‘ SPI12 was the least important index to drought impacts. ’→ SPI12 was the least important index in terms of drought impacts.

Figure 5 we revise the figure 5

Line286 ‘were’→ ‘was

Figure 6 we revise the figure 6

Line297-298 ‘The results of correlation analysis and random forest show that in most parts of Liaoning province, SPEI at 6-month accumulation period had the strongest correlation with drought impacts. ’→ ‘The results of correlation analysis and random forest suggest that in most parts of Liaoning province, SPEI at 6-month accumulation period has the strongest relationship with drought impacts.

Line304 ‘8 displays which drought’→ ‘ displays the drought impacts ea

Line306 vulnerability which are all’→ ‘vulnerability - these cities are all

Figure 7 we increase the resolution of figure 7

Line319 ‘Map showing which drought ’→ ‘Map showing which the drought

Line322-328 ‘A further stepwise regression model was built to explain the variation in each type of Standardised Drought Impact using vulnerability factors (listed in Table 2) as predictors. Since drought impacts are symptoms of vulnerability, it can be used to estimate vulnerability (Blauhut et al., 2015a). For a specific severity of drought, basically, the more serious the impact caused, the more vulnerable the region is. Thus, the regressed Standardized Drought Impacts at a moderate drought severity with SPEI6 equals -1.5 were applied to measure the drought vulnerability. Table 3 shows the results of stepwise regression model, demonstrating the contribution of vulnerability factors to each category of drought impact. The results varied for each impact type.

’→ ‘A stepwise regression model was built to explain the variation in each type of Standardised Drought

Impact using vulnerability factors (listed in Table 2) as predictors. Drought impacts are symptoms of vulnerability and so can be used to estimate vulnerability to drought (Blauhut et al., 2015a). The vulnerability to drought can be assessed by maintaining a constant severity of drought (i.e. particular drought index values), and comparing the resultant impacts. More serious impacts correspond to higher vulnerability. Thus, the Standardised Drought Impacts corresponding toat a moderatesevere meteorological  drought severity (, SPEI6 equal to -1.5), were regressed on the standardiszed drought vulnerability factors for 2017 to assess drought vulnerability for each drought impact type. Table 3 shows the results of stepwise regression model, demonstrating the contribution of vulnerability factors to each category of drought impact; the results varied for each impact type.

The relatively high R2 values demonstrate the ability of the vulnerability factors to explain the variability exhibited by each drought impact. This is particularly the case for DSA, drought suffering area, and PHD, population with difficulty in accessing drinking water, which had associated R2 values of 0.894 and 0.805, respectively. Population, crop cultivated area, and livestock production explained 89.4% of the variation in DSA. Population, in combination with per unit area of fertilizser application, and reservoir total storage capacity, also contributed to the DA model, explaining 80.5% of DA variation.

Population, crop cultivated area, and livestock production were identified as significant predictors in four, five, and three models, respectively, more than other vulnerability factors. Crop cultivated area, the most frequently significant predictor of drought impacts, also exhibited relatively high regression coefficients, demonstrating the strong relationship between the areas cultivated for crops, and the vulnerability to drought impacts. These results are paralleled in a composite drought vulnerability tool, which assigns relatively high weighting to area of land irrigated (Quinn, et al. 2014).

Population exhibited negative regression coefficients for three of four drought impacts, suggesting that as the population increased, the vulnerability to drought impacts decreased. However, population exhibits correlation with crop cultivated area, and livestock production. This, paired with potential unaccounted interactions between population and other predictors, may have resulted in inaccurate population coefficient estimation. This is supported by a positive population coefficient for predicting NLH. Population was used exclusively to predict NLH, thus correlation with other predictors, and interaction effects were unable to influence the coefficient. Furthermore, Figure 9_____ demonstrates that as population increases, DSA, DIA, and DELA increase. The composite drought vulnerability tool of Quinn et al. (2014) does not explicitly account for population, making a direct comparison not possible.

However, it does assign a positive relationship between the ratio of rural population and drought vulnerability, which may explain the unexpected negative coefficients presented here.

The number of electromechanical wells also exhibited a positive coefficient, suggesting that as the number of wells increases, drought impacts increase. However, it's possible that electromechanical wells are more prevalent in more drought prone areas,, thus, the positive coefficient may simply demonstrate an association between electromechnicalelectrometrical wells and RA.

Whilst drought vulnerability factors were able to explain 47.4-89.4% of the variability in drought impacts, annual per capita water supply, effective irrigation rate, and per unit area of major agricultural products were not identified as significant predictors of any drought impact type. It is important to consider, however, that correlation between these vulnerability factors and other vulnerability factors could result in these vulnerability factorsthem not being identified as not significant, as the information is already contained within other vulnerability factors. This is supported by drought impact correlations with per capita water supply, and effective irrigation rate. However, minimal correlations between drought impacts and unit area of major agricultural products were observed, suggesting that the absence of a detected relationship between unit area of major agricultural products and drought impacts may be a true reflection.

Table 3 we insert the 'Standardised Coefficients'

We added the Scatterplots as figure 9.

We made a majoy revision of the discussion.

The methodology in this research has a number of distinctive characteristics in relation to previous drought impact and vulnerability assessments. The method takes many drought impacts, across a range of sectors, into consideration. The extensive drought impact data were systematically collected at county level, which is a consistent and reliable data source enabling regional comparisons. The drought impact data used here included impact variables that are rarely available in other settings: e.g. population with difficulty in accessing drinking water, number of livestock with difficulty in accessing drinking water, yield loss due to drought and direct economic losses in agriculture. In addition, we not only considered the occurrence of drought impacts, but also the severity of impacts and their spatial variation between regions. Finally, the relationship between drought indices and drought impacts was explored using different statistical approaches, and this linkage was used to assess drought vulnerability in Liaoning province using a range of vulnerability factors.

TThe study has some important limitations which must be considered in interpreting the outcomes. The biggest challenge was the spatial and temporal matching between the drought impacts and indices. The regularity with which impact data are collected is determined by the drought warning level and as such they are not evenly spaced in time; as a result of this, the data were aggregated to annual totals. It was important to match the accumulation period and timing of the selected drought indices to the timescales critical for the drought impacts; for example SPEI6 in September covers the critical maize growth period and is when the majority of precipitation falls. However, the results may change if we used multi-year drought impacts, as longer index accumulation periods may have a stronger correlation with multi-year drought impacts than single year drought impacts. Soil moisture data were collected at a daily resolution, in order to match up soil moisture and impact data, the March to October average soil moisture was used in the correlation analysis. However, short term soil moisture deficits can have serious impacts on crops which are sometimes unrecoverable. The average soil moisture may not have captured these short-term deficits, particularly if soil moisture was, in general, sufficient the rest of the year. Also in some cities, the lack of soil moisture data means that the annual average soil moisture does not reflect the occurrence of typical agricultural drought during the year. For this reason, soil moisture data can be used for real-time drought monitoring applications, but may not appropriate to present drought impacts on an annual scale for risk assessment, as applied here. NDVI data for the critical growth period of spring maize was used in the analysis with annual drought impacts (i.e. July-month), but again this does not take all drought events during crop growing period into account. The correlation coefficients characterising the relationship between NDVI and drought impacts are both positive and negative; this is likely due to the complexity of NDVI drivers (e.g. diversity of land cover, crop types and growth stages etc.). For this reason, some studies have used the NDVI to identify the impact of drought on vegetation (Miao et al., 2018;Rajpoot and Kumar, 2018;Trigo et al., 2015;Wang et al., 2015).

The results from the correlation analysis were consistent with the results from the RF analysis. Drought suffering area (DSA) and drought impact area (DIA) had strong correlations with all drought indices in Liaoning province, while PHD and NLH have a weak correlation with indices. This was because DSA and DIA are direct impacts of agricultural drought, whilst PHD and NLH are related to many additional factors, such as drinking water source location and the quality of water resources; for example, livestock can drink water from the river directly, but the quality of the river water means it is not suitable for humans – for this reason, NLH showed least sensitivity to water deficits.

The random forest algorithms presented in this paper explained an average of 41% of the variance observed within the drought impact data. This is relatively modest, and may be partially due to limitation associated with the impacts data. The collinearity of the drought indices (e.g. SPI6 is correlated with SPEI6) is also a potential cause of the low MSE%. The correlation coefficients calculated for drought indices and NLH in Yingkou, and PHD in Fushun were positive. This was unexpected given the interpretation of these indices as estimations of the drought severity, and the majority of reported correlation coefficients being negative. Therefore, it seems likely this result is not representative of the true relationships between these indices and impacts, and instead is an artifact of imperfect impact data. To explore this, years with the highest numbers of impacts were removed before the correlation coefficients were estimated. This resulted in a negative correlation coefficient, providing further evidence for the positive correlation coefficients not being representative of the true relationships in these cities. The availability of more data would enable a better approximation of the true relationships between indices and impacts.

For all the drought impacts, Dalian and Fuxin showed the highest correlation coefficients among drought impacts and drought indices in all cases. The most vulnerable cities were Fuxin, Tieling, Chaoyang, Jinzhou and Shenyang, which are all located in the northwestern part of Liaoning province indicating there is a high drought vulnerability and drought risk in northwestern Liaoning. This is consistent with existing research by Yan et al. (2012) and Zhang et al. (2012), which established a drought risk assessment index system to assess drought risk in northwestern Liaoning. Zhang et al. (2012) used indicators such as precipitation, water resources, crop area, irrigation capacity and drought resistance cost to measure drought risk and found that Fuxin, Chaoyang and Shenyang had a high drought risk.

The above results are also in general agreement with Hao et al. (2011), who used 10-day affected crop area data as the drought impacts to assess drought risk in China at the county unit. Their result showed that the West Liaohe Plain had a high risk. The results presented in our paper identify Chaoyang and Fuxin as having the highest drought vulnerability – the majority of these two cities are located on the West Liaohe Plain.

s the accumulation period increased, the first splitting value extracted from the random forest model tended to decrease, suggesting that at longer accumulation periods, larger water deficits are required for equivalent impacts to occur. There is asevere water deficits of RA occurrence since it caused more yield loss compared to DIA and DA. Drinking water for livestock requires lower water quality compared to that for humans, for example, livestock can drink water from the river directly, but the water quality of the river cannot meet the human drinking needs. For this reason, NLH showed least sensitivity to water deficits.

The relationships analysed in this research support the use of drought indices as a predictor of drought impacts and the impact thresholds identified can also support improved drought warning and planning. The drought vulnerability map (Figure 8) can be used to support drought risk planning, helping decision-makers to implement appropriate drought mitigation activities through an improved understanding of the drivers of drought vulnerability – for example, by sinking more wells to enhance resilience to drought (noting of course, that this measure has potential longer-term implications, for example, on groundwater exploitation e.g. Changming et al. (2001)).

)The methods used here can be applied in other areas to better understand drought impacts and drought vulnerability, where similar data (e.g. drought impacts, meteorological data) are collected. While systematic, statistical archives of drought impact are comparatively rare, globally, there are numerous other potential sources of impact data that could be used (e.g. see Bachmair et al. 2016b).

Line 408 ‘linkage’→’relationship’

Line 412 we change the style of 1: ,2: to 1.,2. and so on.

‘linkage’→’relationship’

Line 415 ‘ good consistency’→’corresponded well’

Line 427-429 4: Which vulnerability factor or set of vulnerability factors have a higher contribution to drought vulnerability? Population had a strong negative relationship with drought vulnerability, whilst crop cultivated area was positively correlated with drought vulnerability. → Which vulnerability factor or set of vulnerability factors have a higher contribution to drought vulnerability? Population and crop cultivated area were strongly associated with drought vulnerability, suggesting these factors are good indicators of drought vulnerability. However, the complexities of these relationships with drought vulnerability require further investigation.

Line 435 ‘Some data, used during the study are proprietary or confidential in nature and may only be provided with restrictions (e.g. drought impacts data and daily meteorological data).’→’Some data, used during the study are proprietary or confidential in nature and may only be provided with restrictions (e.g. drought impacts data, soil moisture) Daily meteorological data can be explored at http://data.cma.cn/ but access to data is restricted. NDVI data can be obtained from the Geospatial Data Cloud (http://www.gscloud.cn/). Vulnerability data were from the Liaoning Statistical Yearbook which can be obtained from Liaoning Province Bureau of Statistics (http://www.ln.stats.gov.cn/).

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

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**Abstract.** Drought is a ubiquitous and rec~~occ~~urring hazard that has wide ranging impacts on society, agriculture and the environment. Drought indices are vital for characteri~~z~~sing the nature and severity of drought hazards, and there have been extensive efforts to identify the most suitable drought indices for drought monitoring and risk assessment. However, to date, little effort has been made to explore which index(s) best represents drought impacts for various sectors in China. This is a critical knowledge gap, as impacts provide important 'ground truth' information for indices used in monitoring activities. The aim of this study is to explore the link between drought indices and drought impacts, using Liaoning province (northeast China) as a case study due to its history of drought occurrence. To achieve this we use independent, but complementary, methods (correlation and random forest analysis) to identify which indices link best to ~~the recorded~~ drought impacts for prefectural-level cities in Liaoning province~~.~~, using a comprehensive database of reported drought impacts whereby impacts are classified into a range of categories. ~~–~~The results show that Standardi~~z~~sed Precipitation Evapotranspiration Index with a 6-month accumulation (SPEI6) had a strong correlation with all categories of drought impacts, while Standardi~~z~~sed Precipitation Index with a 12-month accumulation (SPI12) had a weak correlation with drought impacts. Of the impact datasets, 'drought suffering area' and 'drought impact area' had a ~~slightly~~ strong relationship with all drought indices in Liaoning province, while 'population and number of livestock with difficulty in accessing drinking water' had weak correlations with the indices. The results of this~~is~~ study can support drought planning efforts in the region and provide context for the indices used in drought monitoring applications, and so enabling improved preparedness for drought impacts. The study also demonstrates the potential benefits of routine collection of drought impact information on a local scale.~~–~~

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## 1 Introduction

Drought is one of the most pervasive natural hazards~~ which~~, and can cause ~~huge~~ numerous and ~~large~~severe societal impacts. Drought impacts are mainly non-structural, widespread over large areas, and are often have a delayed onset ~~with respect~~in relation to the start of the drought event; therefore, it is challenging to properly define, quantify and manage drought (Mishra

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and Singh, 2010). There are a number of ‘types’ of drought (Wilhite and Glantz, 1985)~~(e.g. Wilhite & Glantz, 1985)~~, such as ~~The term drought is defined as~~ meteorological, agricultural, hydrological, social and ecological drought. Meteorological drought is defined as a deficit of rainfall for a period in respect to the long term mean (Houérou, 1996). As these rainfall deficits propagate through the hydrological cycle, the other drought types occur as deficits occur in river flows, soil moisture and groundwater. Eventually impacts ~~occur in~~ become manifest on the environment and society~~. Then other types of drought can follow this definition~~. China has experienced numerous droughts, which have caused great impact in many sectors since the 1950s, especially in Liaoning province in the dry northeast of the country (Zhang, 2004). Liaoning province experienced a severe drought ~~F~~from spring 2000 to autumn 2001~~, Liaoning province experienced a severe drought,~~ which captured a large amount of attention from stakeholders and caused serious impacts ~~on many sectors~~ ~~because~~ as a result of the consecutive years of drought (Chen et al., 2016).

The costly nature of droughts means it is essential to plan and prepare for droughts proactively. Drought risk assessment is an essential prerequisite of this proactive approach (Wilhite, 2000;Wilhite and Buchanan, 2005), and provides~~ing~~ the methods to predict the potential drought risk to society and the environment. Some~~ of~~ risk assessment efforts focus primarily on the meteorological indices of drought, e.g. assessing the risk of a given severity of meteorological drought using historical precipitation data (Potopová et al., 2015). However, to adequately assess drought risk it is also necessary to characteri~~z~~se the consequences of drought occurrence, i.e. the impacts of drought on society, the economy and the environment (United Nations International Strategy for Disaster Reduction (UNISDR), 2009).

There are~~A~~ a wealth of drought indices ~~have been used~~ in the literature (Lloyd-Hughes, 2014), ~~although~~ however they have predominantly used for drought monitoring and early warning (e.g. ~~the review of~~ Bachmair et al. 2016b) rather than drought risk assessment applications. The range of drought indices reflects the different types of drought which can be monitored, e.g., meteorological, hydrological and agricultural (Erhardt and Czado, 2017). Many indices, such as the Standardi~~z~~sed Precipitation Index (SPI), can be calculated over different time scales. This enables deficits to be assessed over different periods, and can help monitor different types of drought. For example, shorter time scales, such as the SPI for three or six months are used for agricultural drought monitoring while SPI ~~values~~ accumulations for 12 or 24 months are ~~normally~~ often applied to monitor hydrological droughts ~~monitoring~~ (Hong et al., 2001;Seiler et al., 2002). In China, many indices ~~were~~ are used for ~~types of~~ drought monitoring, such as Palmer Drought Severity Index (PDSI), SPEI, SPI, China-Z index, relative soil moisture and remote sensing indices (Hong et al., 2001;Wang and Chen, 2014;Wu et al., 2012;Yanping et al., 2018). Li et al. (2015) found that serious drought events occurred in 1999, 2000, 2001, 2007 and 2009 in China using SPEI. Zhao et al. (2015) compared ~~the~~ drought monitoring results between self-calibrating PDSI and SPEI in China with emphasi~~z~~se on difference of timescales. Wu et al. (2013) developed an Integrated Surface Drought Index for agricultural drought monitoring in mid-eastern China. Drought ~~indices~~ monitoring efforts in China tend to ~~are~~ focus on meteorological and agricultural drought monitoring~~,~~. ~~in~~



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~~China. B~~B~~b~~ased on this and previous drought studies, the SPI, SPEI, soil moisture and NDVI were selected in this research ~~for~~ to characteriz~~s~~e meteorological and agricultural drought. The relationship between drought indices and drought impacts, established by statistical methods ~~a correlation or random forest modelingsome other similar analysis~~ (e.g. Bachmair et al. (2016a)~~Bachmair et al. 2016a~~), can ~~thus~~ be used for drought risk assessment and appraisal of vulnerability. Vulnerability is by its nature difficult to define and measure, but in effect, drought impacts are 'symptoms' of drought vulnerability and provide a proxy for vulnerability appraisal by demonstrating adverse consequences of a given drought severity (Blauhut et al., 2015a) ~~(Stahl et al., 2016)~~.

There are many different types of drought impacts affecting many aspects of society and the environment, but drought impacts are rarely systematically recorded (Bachmair et al., 2016b). Some countries and regions have established drought impact recording systems to analy~~z~~se historical drought impacts. A leading example of this is the US Drought Impacts Reporter (Svoboda and Hayes, 2011) which was launched as a web-based system in July 2005. More recently, the European Drought Impact report Inventory (EDII) has been established (Stahl et al., 2016). Such databases are an important step forward, but the information in them is necessarily partial and biased, as a result of being effectively crowd-sourced text-based information based on 'reported' impacts from a range of sources (the media, grey literature, etc.). In contrast to many other countries, China has a relatively complete and systematically assembled, quantitative drought impact information collection system. Data are collected and checked at the county level by the Drought Resistance Department via a formali~~z~~sed network of reporters, who collect information on drought impacts ~~statistics~~ on agriculture, industrial economy, and water supply in every village. These data then are fed up to the national government and held by the State Flood Control and Drought Relief Headquarters (SFDH). This consistent collection of impact reporting provides a rich resource for drought risk assessment. However, impacts by themselves are not fully instructive and to help inform risk assessment there is a need to understand their relationship with quantitative drought indices.

Understanding the relationship between drought indices and drought impacts, and drought vulnerability, is a vital step to improve drought risk management (Hong and Wilhite, 2004). However, whilst there have been many studies developing, applying and validating drought indices, relatively few studies have assessed the link between indices and observed impacts. Bachmair et al. (2016b) noted that this literature tended to be dominated by studies focused on agricultural drought, generally linking ~~generally~~ indices like the SPI/SPEI and crop yield. Examples appraising multi-sectoral impacts are much sparser – there are several recent studies ~~tend to be~~ in Europe, utili~~z~~sing impact reports from the EDII. Stagge et al. (2014) and Bachmair (2016b) used drought impacts from the EDII, and various time scales of SPI, SPEI and streamflow percentiles. They found that the relationships between indices and impacts varied significantly by region, season, impact types, etc. whilst Blauhut et al. (2015a) and Blauhut et al. (2015b) developed a quantitative relationship between drought impact occurrence and SPEI using logistic regression in four European regions. However, ~~they~~ all four studies assumed drought impacts were only measured

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by the drought impact occurrence (i.e. whether there was, or was not, an impact in a given month), the number of impacts or ~~some~~a combination of both. This means ~~meaning~~ that all drought impacts had an equal weight without considering the duration, intensity or spatial extent of the individual impacts. In contrast, Karavitis et al. (2014) ~~described~~ analysed drought impacts transformed into monetary losses to measure drought impacts in Greece; ~~. H~~however, it is challenging to transform all drought impacts into monetary units – especially the indirect impacts of droughts.

In China, previous studies have also focused on agricultural drought risk assessment. Hao et al. (2011) applied the information diffusion theory to develop a drought risk analysis model which used affected crop area to measure the drought disaster. Zhao et al. (2011) established the relationship between drought frequency and simulated crop yield data in Henan Plain, and~~.~~ Jia et al. (2011) used the water stress coefficient and duration to establish a drought index. Li et al. (2009) analy~~z~~sed the links between historical crop yield and meteorological drought and established a meteorological drought risk index by combining the drought frequency, intensity, yield loss and extent of irrigation. The drought index was found to explain 60-75% of the major crop yield reduction. In drought impacts studies, Xiao-jun et al. (2012) collected annual drought affected area, ~~and~~ damaged area, and annual losses in food yield in nation level from China W~~w~~ater R~~r~~esources B~~b~~ulletins~~, which is the secondary data,~~ to explore the water management strategies during droughts. In Hao et al. (2011), drought impacts were only measured by the affected crop area ~~in~~ at the~~a~~ 10-day time step ~~in~~ at the county level. In our research, eight types of drought impacts are collected to measure drought impacts in ~~city level~~ at the city unit (i.e. prefectural) level ~~prefectural level~~ in Liaoning province, ~~which~~ including~~e~~ ~~not only~~the drought affected area, damaged area and yield loss, but also drought impacts on humans, livestock and the agricultural economy.

In summary, previous studies have ~~been~~ focused on linking impacts to only one characteristic of drought (such as intensity or~~,~~ duration of occurrence) with most focusing on meteorological drought and agricultural impacts with little application of the results to drought vulnerability assessments, with the exception of ~~. But with the exception of~~ Blauhut et al. (2015a), ~~and~~ Blauhut et al. (2016) and Hagenlocher et al. (2019), for example~~, there is little application of the results to drought vulnerability assessments~~. Here we link drought indices to drought impacts in 14 cities in Liaoning province, northeast China, showcasing the use of the Chinese drought impact data from the SFDH. Using the drought impact-index linkage, we evaluate ~~the~~ drought vulnerability in Liaoning province and assess what factors affect drought vulnerability. A drought vulnerability evaluation method that can be extended to other areas is then developed. The objectives of this paper are:

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

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vulnerability, as quantified in objective 3.

## 2 Materials

### 2.1 Study area

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

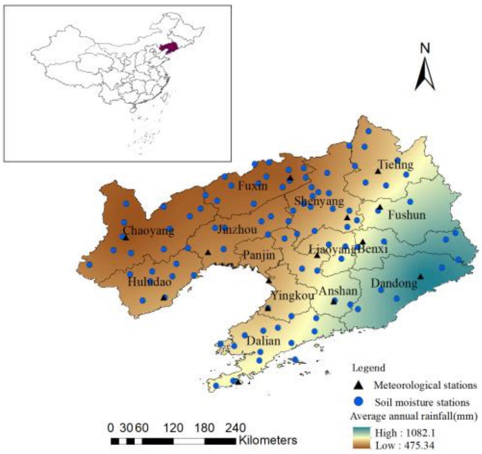


**Figure 1: Map showing the 14 prefectural cities, the distribution of meteorological and soil moisture stations and the average annual precipitation in Liaoning province.**

The annual average volume of freshwater resources in Liaoning province is 34.179 billion $m^3$, and the annual average per capita water resources is 769 $m^3$ – about one-third of the per capita water resources for the whole of China. Freshwater resources are unevenly distributed within Liaoning province, with more freshwater resources in the south-east than the north-west (Liu and Guo, 2009;Cao et al., 2012). Thus, Liaoning province is one of the provinces with severe water-shortages in northern China. Liaoning province is also a highly productive area for agriculture~~; –~~ ~~S~~spring maize is the dominant crop in agriculture production which makes it an important high-quality maize production area (Liu et al., 2013;Ren and Zhou, 2009). Due to these characteristics, when drought occurs, as has frequently been the case in Liaoning province, it causes a significant reduction in agricultural production (Yan et al., 2012). According to the SFDH, between 2000 and 2016 the average annual yield loss due to drought was 1.89 million tons in Liaoning province, with an average annual direct agricultural economic loss of 1.87 billion yuan.

**2.2 Data**

2.2.1 Meteorological data

Daily precipitation and temperature data for each city in Liaoning province for the period 1990-2013 were obtained from the China Meteorological Administration (http://data.cma.cn/). Although there are 52 meteorological stations in Liaoning province, due to the quality and length of the records, and location of the stations, one ~~representative~~ meteorological site in each city (shown in Figure 1) was selected to represent the meteorological condition for the whole city in order to derive drought indices.

2.2.2 Soil moisture data

Daily soil moisture data for 96 soil moisture stations in Liaoning province (shown in Figure 1) from 1990 to 2006 were obtained from Liaoning Provincial Department of Water Resources. Daily soil moisture was measured at three different depths: 10cm, 20cm and 30cm using frequency domain reflectometry ~~ion~~ soil moisture sensors~~, which are based on~~use ~~the principle of electromagnetic pulses~~. Soil moisture data were not available at most stations between November and February ~~at most stations~~ due to freezing conditions.

2.2.3 Normalised Difference Vegetation Index (NDVI) data

Monthly MODIS Normalised Difference Vegetation Index (NDVI) ~~NDVI~~ data from 2000 to 2013 was collected in Liaoning province from the Geospatial Data Cloud (http://www.gscloud.cn/); the daily maximum data were used to derive the monthly average NDVI.

2.2.4 Impact data

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

**Table 1: The eight drought impact categories~~s~~ for Liaoning province 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 |

5) Vulnerability factors

The drought impacts described in Section 2.2.4 are mainly focused on agriculture sector. As a result of this, the availability of data and the findings of Junling et al. (2015) and Kang et al. (2014), vulnerability factors relevant to these impacts were selected. Vulnerability factors were collected from the 2017 Liaoning ~~province~~ Province Statistical Yearbook to assess their contribution to the drought vulnerability (Liaoning Province Bureau of Statistics, 2017), and are shown in Table 2 for each city unit.

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**Table 2: Vulnerability factors for each city in Liaoning province collected from the 2017 Liaoning Statistical Yearbook (Liaoning Province Bureau of Statistics, 2017)**

| City | Per capita gross domestic product (k yuan) | Population (10k) | Crop cultivated area (kha) | Annual per capita water supply ( m$^3$) | Per unit area of Fertili~~z~~ser application (kg/ha) | Effective irrigation rate (%) | Number of electromechanical wells (k) | Reservoir total storage capacity (m m$^3$) | 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 |

## 2.3 Methods

### 2.3.1 Drought indices

Two meteorological indices were selected, the Standardi~~z~~sed Precipitation Index (SPI; McKee et al., 1993) and the Standardi~~z~~sed Precipitation Evapotranspiration Index (SPEI;Vicente-Serrano et al., 2010). These standardi~~z~~sed indices are widely used in drought monitoring applications around the world, and the SPI is recommended by World Meteorological Organi~~z~~sation to monitor meteorological drought (Hayes et al., 2011). This is due to the flexibility of being able to derive SPI over different time scales~~,~~ and that it can be compared across time and space.

The SPI, in its default formulation, assumes that precipitation obeys the Gamma (Γ) skewed distribution, which is used to transform the precipitation time series into a normal distribution. After normali~~z~~sation, classes of drought can be defined with the cumulative precipitation frequency distribution (Botterill and Hayes, 2012;Hayes et al., 1999). The SPEI uses the same standardi~~z~~sation concept using the climatic water balance (that is, precipitation minus potential evapotranspiration; PET) instead of precipitation. ~~Here~~In this study~~,~~ PET is calculated by the Thornthwaite method (Thornthwaite, 1948), using observed temperature and sunlight hours (estimated from latitude) as inputs. The SPEI ~~are~~ is calculated by normali~~z~~sing the climatic water balance using a log-logistic probability distribution (Vicente-Serrano et al., 2010).

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

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

$$\theta_1=\theta_{10} \qquad \theta_2=\frac{\theta_{10}+\theta_{20}}{2} \qquad \theta_3=\frac{\theta_{20}+\theta_{30}}{2} \tag{1}$$

$$\bar{\theta}=\frac{\sum_{i=1}^{3}(\theta_2\times h_i)}{H} \tag{2}$$

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 (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 thickness of the measured soil.

Some of the daily soil moisture data were missing, however~~,~~ this was limited to 17% of the total soil moisture data. In some cases there were missing data for one depth of soil moisture measurement. In these cases, the average soil moisture of the other two layers was calculated, and where there was only one layer of soil moisture available it was used to represent the average soil moisture. The annual average soil moisture was calculated based on the available daily soil moisture (March to October) and was analy~~z~~sed with the annual drought impact data during 1990 to 2006. As each city has more than one soil moisture station, the annual soil moisture of each station was calculated and then averaged to ~~into~~ one value for each city.

The area-averaged NDVI at the city unit was calculated ~~based~~ using~~on~~ the monthly NDVI. The critical stages of the spring maize growth in Liaoning is in July, so the area-averaged NDVI in July was selected for the analysis with the annual drought impacts ~~during~~ from 2000 to 2013.

2.3.2 Correlation analysis

The Pearson correlation method was used to characteri~~z~~se the correlation between indices and ~~various~~ the selected drought impacts (Özger et al., 2009). Due to the limited availability of soil moisture data, correlation analysis of soil moisture and drought impact data was only carried out in 9 cities~~ (list the 9 cities here)~~. The linkage between drought indices and impacts was used to assess the drought vulnerability in Liaoning province. It can be inferred that the greater the impact caused by droughts at a specific severity (measured according to SPI/SPEI), the higher the drought vulnerability of the city.

2.3.3 Random forest modeling

Decision trees are regularly implemented for machine learning tasks. They resemble flowcharts, consisting of a series of branches, internal nodes, and leaf nodes. Internal nodes typically represent binary conditions of the explanatory variables. These nodes are connected to other internal nodes by branches, which represent the outcome of the previous internal node. Leaf nodes represent the outcome classes. Internal nodes are eventually connected to leaf nodes, which represent the outcome classes of the classification task. Whilst quick to train and interpretable, decision trees are limited by overfitting to the training set. Random forests (RFs) reduce overfitting by fitting an ensemble of uncorrelated decision trees. This is achieved using bootstrap aggregation with replacement (bagging) and only considering a random subset of features for splitting at each internal node (Breiman and Leo, 2001)~~(Breiman, 2001)~~. As well as the reduction in overfitting compared to decision trees, the advantages of RF include: its fast training speed, good accuracy and relative efficiency (Mutanga et al., 2012). Additionally, once RF models are established, the values of the predictor that correspond to the first split in the decision tree can be extracted as thresholds corresponding to impact occurrence (Bachmair et al., 2016a).

In this analysis random forests were built for regression. This is achieved by assigning categorical outcomes at each leaf node, and using the mean prediction as the outcome~~ (Sethi et al., 2012).~~ ~~Random forest (RF) is an ensemble learning method for classification and regression (Sethi et al., 2012). The algorithm operates by constructing a multitude of independent at training time and outputting the class that is the of the classes (classification) or mean prediction (regression) of the individual trees. algorithm that consists of a series of independent decision trees. RFs can be used for classification and regression (Sethi et al., 2012). Classification RFs aggregate votes from individual trees to estimate the outcome class. In this analysis random forests~~

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~~were built for regression. The results of the leaf nodes at different trees are aggregated for regression (Liaw and Wiener, 2002). The advantages of RF include: its fast training speed, good accuracy and relative efficiency (Mutanga et al., 2012). Additionally, once RF models are established, the values of the predictor that correspond to the first split in the decision tree can be extracted as thresholds corresponding to impact occurrence (Bachmair et al., 2016a).~~

The R package 'randomForest' was employed to identify the relationship of drought indices to drought impacts ~~in this research~~ (Kursa, 2017;Liaw and Wiener, 2002) using~~. There are~~ 5000 decision trees for each RF model. The variance explained was used to determine the goodness of fit of random forest model (Fukuda et al., 2013). The mean squared error (MSE), Eq. (3), was used to evaluate the importance of each index:

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

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

The percent change of MSE (MSE%) is ~~based on how much~~ the difference in accuracy ~~decreases~~ when the effect of the variable is excluded (i.e. if the SPEI6 is excluded from the model, the MSE% of the model may increase)~~, as the values are randomly shuffled, .~~ ~~the h~~Higher ~~of~~ MSE% represents~~, the~~ higher the index importance ~~(Carolin et al., 2009)~~. The first splitting values of each decision tree was also extracted.

Soil moisture and NDVI were not analy~~z~~sed using the random forest approach due to ~~missing data and~~ their short time series and prevalence of missing data.

2.3.4 Standardi~~z~~sation of drought impacts and vulnerability factors

To ensure comparability and to facilitate the visuali~~z~~sation of the drought impacts and vulnerability factors~~,~~ they were standardi~~z~~sed to a value from 0 to 1 using Eq. (4) and Eq. (5) (Below et al., 2007).

$$SDI_i = \frac{DI_i - \min DI}{\max DI - \min DI} \tag{4}$$

$$SVF_j = \frac{VF_j - \min VF}{\max VF - \min VF} \tag{5}$$

Where $SDI_i$ and $DI_i$ are the Standardi~~z~~sed Drought Impacts and the drought impacts of year *i* in Liaoning province, respectively;~~.~~ max *DI* and min *DI* are the maximum and minimum values of drought impacts in all year for the given impact type~~,~~;~~.~~ $SVF_j$ and $VF_j$ is the Standard Vulnerability Factors and vulnerability factors of city *j* in Liaoning province~~,~~; and max *VF* and min *VF* are the maximum and minimum values of each category of vulnerability factors in all cities.

## 3. Results

### 3.1 Drought monitoring and drought impacts

Figure 2 shows the SPEI ~~drought monitoring indices (in this case the SPEI)~~ and the drought impact data for Liaoning province from 1990 to 2013; the~~.~~ *Sum of SDI* ~~means~~ is the sum of all types of Standardi~~z~~sed Drought Impacts in the 14 cities for each year.

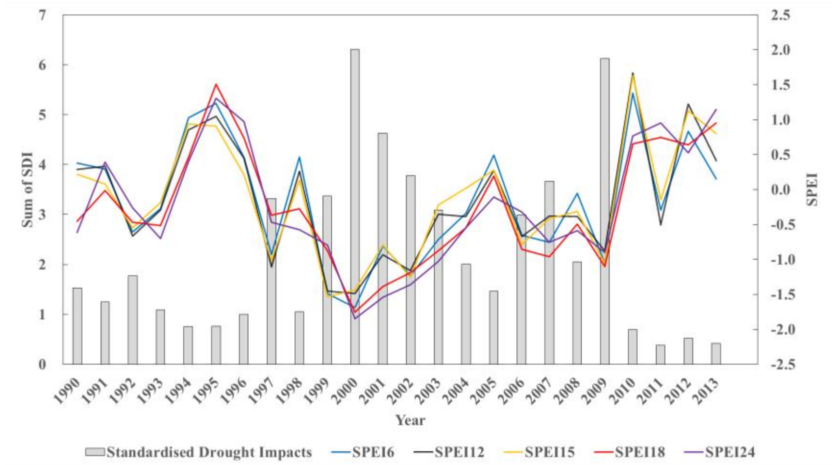


**Figure 2: Standardi~~z~~sed Precipitation Evapotranspiration Index (SPEI) for 6-, 12-, 15-, 18- and 24-month accumulation periods and the sum of the Standardised Drought Impacts (SDI) for each impact type listed in Table 1 for Liaoning province from 1990 to 2013.**

Figure 2 shows that t~~T~~he most severe droughts occurred in 2000, 2001, and 2009, whilst in 1994, 1995, 2012 and 2013 there was above normal precipitation. From a visual inspection, the largest impacts are generally associated with the lowest index values. This suggests that there is a relationship between the drought indices and drought impacts. ~~, and t~~This relationship is ~~will be~~ explored quantitatively in the next sections.

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Figure 3 shows the spatial distribution of the ~~annual~~ average of each drought impact type collected between 1990 and 2016. It shows that more ~~serious~~ severe drought impacts were recorded in the drier northwestern part of Liaoning province than in eastern parts of the province; the NLH was highest in Dalian, whilst Shenyang had the biggest PHD.

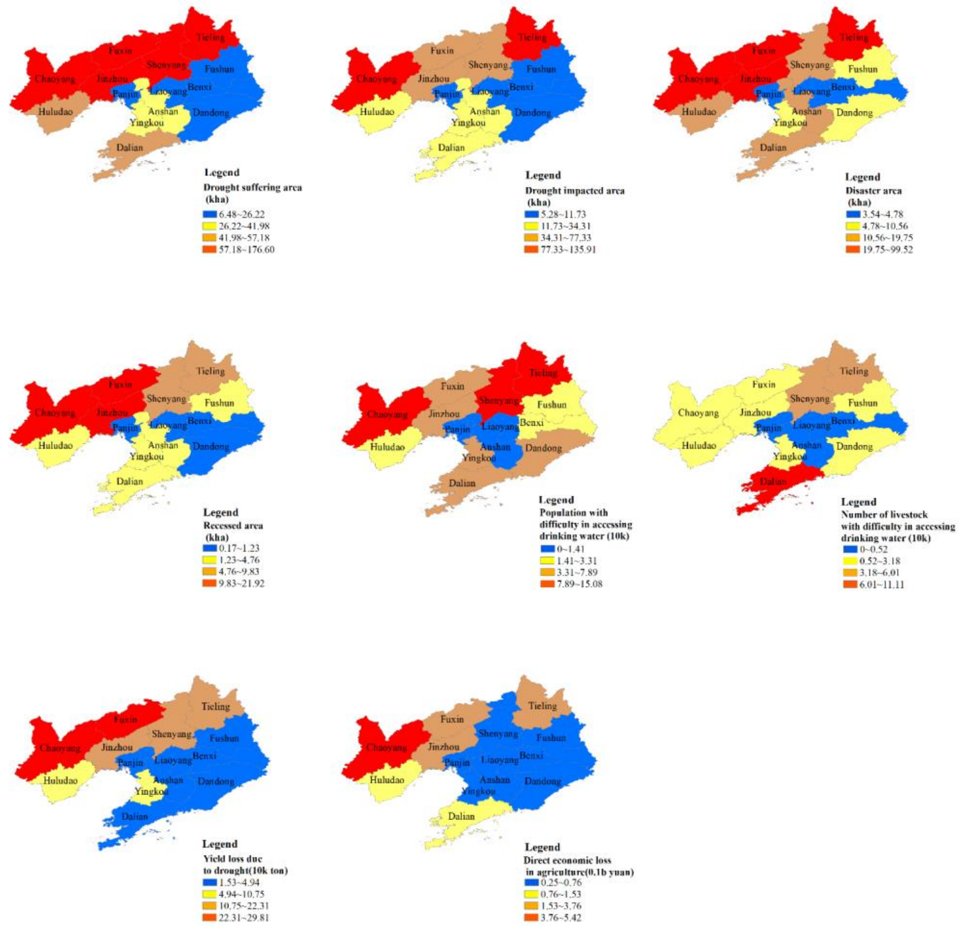



**Figure 3: Distribution of average drought impacts (for each impact type, identified by the codes in Table 1) for the period 1990-2016 in Liaoning province.**

### 3.3 Correlation of indices with impacts

The Pearson correlation coefficient ($r$) for each city and drought impacts is shown in Figure 4. In most cases the drought index is negatively correlated with the drought impacts, suggesting that the lower (and more severe) the drought index, the greater drought impact. However, correlation strength, and direction, varied between the cities and impact types, ranging between -0.890 to 0.621. In most cities of Liaoning province, NDVI and SoilM have a weak correlation with most of types of drought impacts. In Dalian, Chaoyang and Fuxin, all drought indices had a strong correlation with DA, whilst there was a significant correlation for drought impacts area in Jinzhou, Fuxin and Dalian, where most of the correlations were significant ($p < 0.01$).

The strongest correlation was found between indices and PHD in Dalian, while it was the weakest in Dandong. There is a positive correlation between PHD and NDVI in Fushun, whist NLH has a positive correlation with NDVI in Anshan. Generally, SPEI6 had the strongest correlation with all types of drought impacts, whilst SPI12 had the weakest correlation. SPEI typically exhibited stronger correlations with drought impacts than SPI with the same accumulation period.

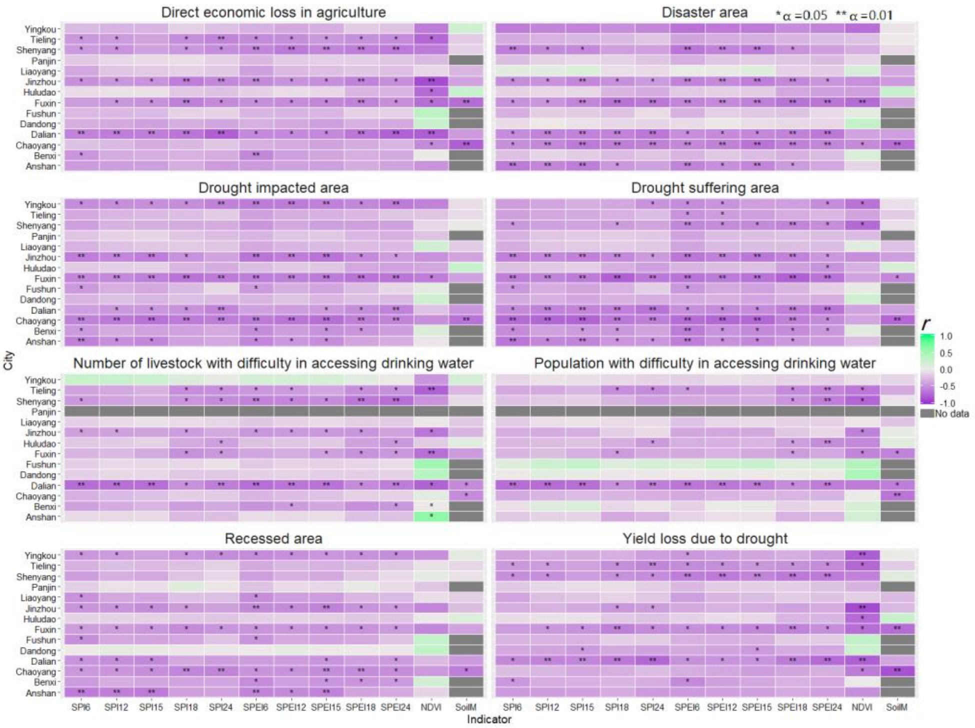


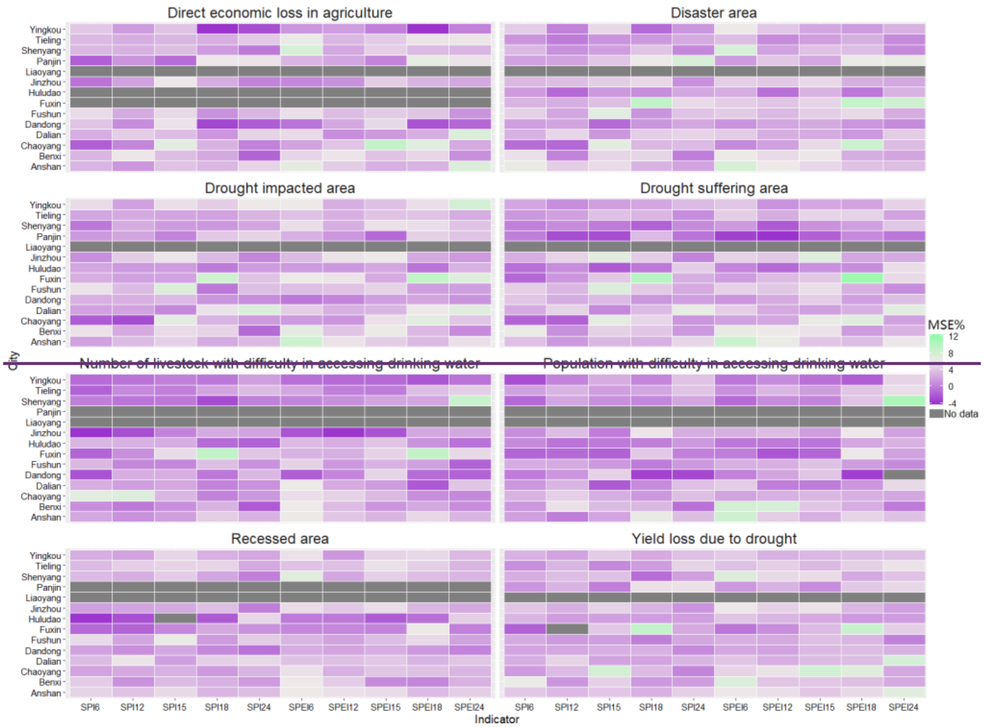

**Figure 4: Correlation coefficient (*r*) between drought indices (SPI, SPEI, NDVI and SoilM) and drought impacts for different impact types (identified by the codes in Table 1) in Liaoning province. The significance level of the correlation is indicated using asterisks.**

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

The performance of soil moisture varied significantly between cities and impact types (Figure 4); it had a strong correlation with the impacts in Chaoyang, and a weak correlation in Huludao. In Chaoyang, the correlation between soil moisture and drought impacts was significant ($\alpha$=0.01), whilst other cities were not significantly correlated.

**3.4 Drought ~~i~~Index importance in random forest models**

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



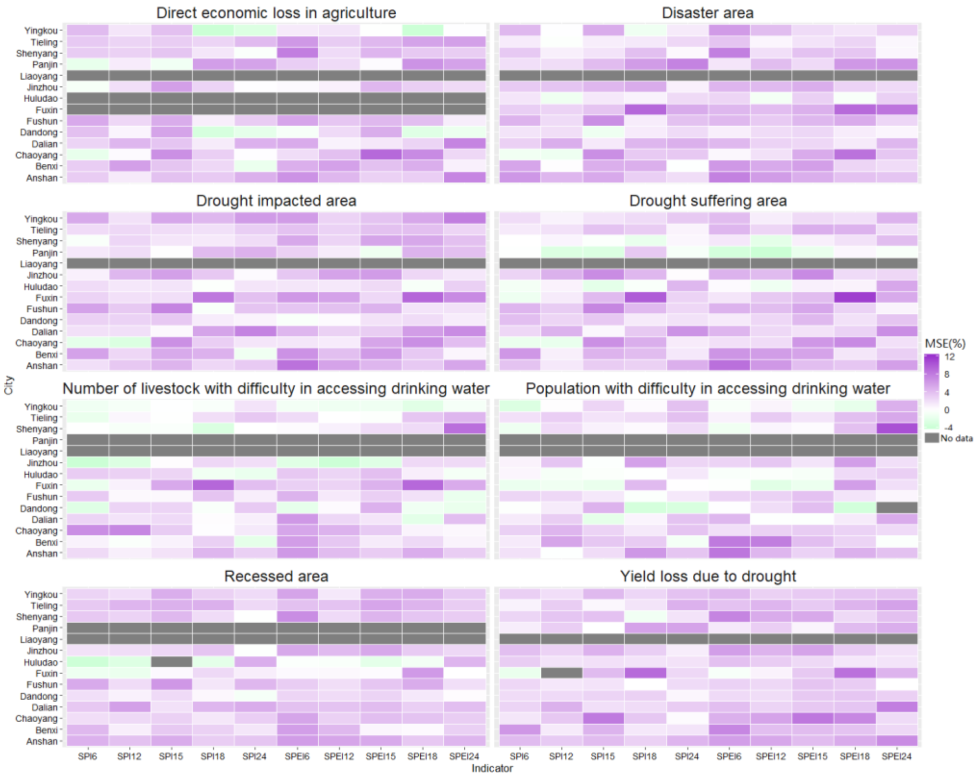



**Figure 5: The MSE% of drought indices (SPI and SPEI) with drought impacts (identified by the codes in Table 1) in Liaoning province using random forest.**

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

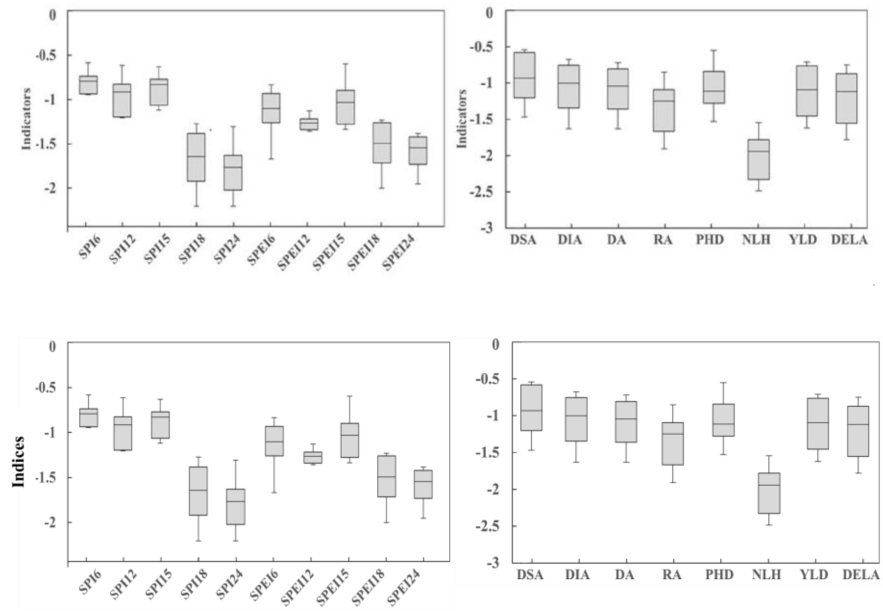
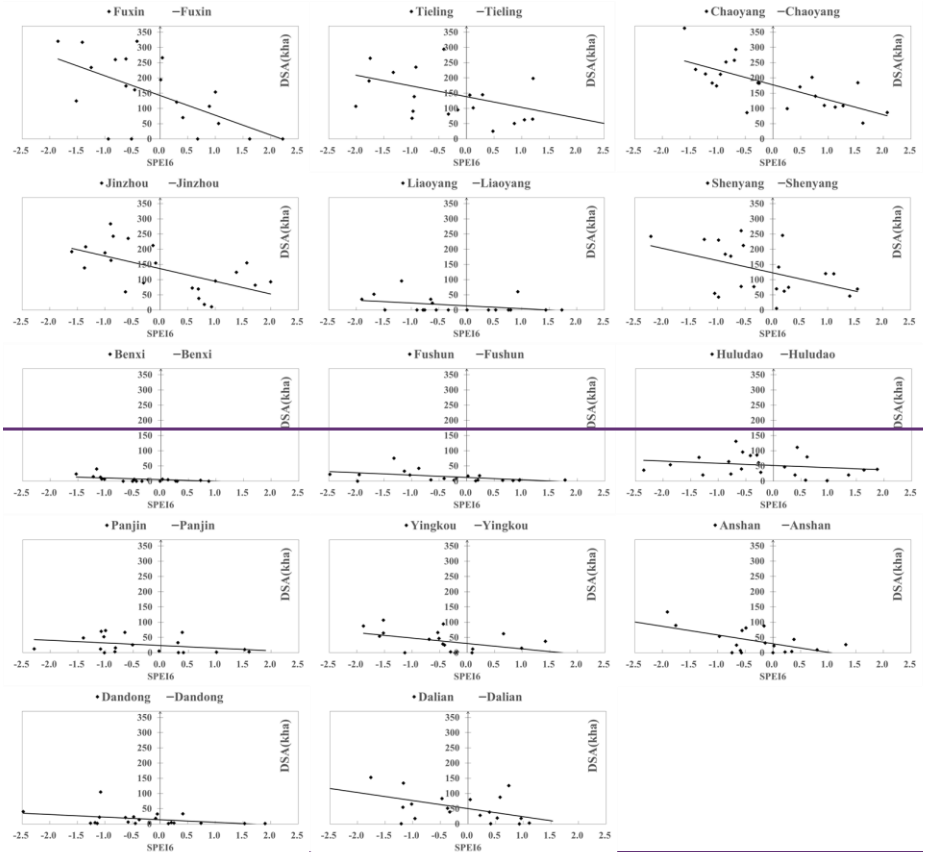


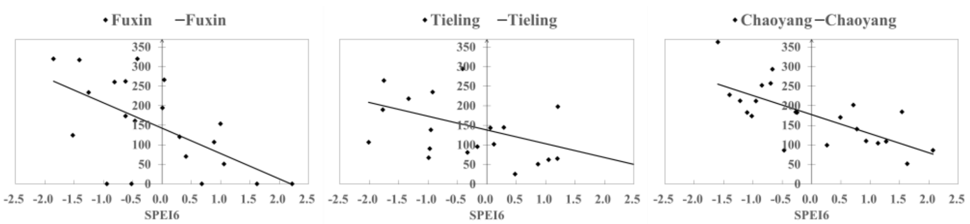

**Figure 6: Box plots showing the splitting value (i.e. the thresholds of impacts) in the random forest construction across all impact types for each index (left), and across all indices for each impact type (right) in Liaoning province.**

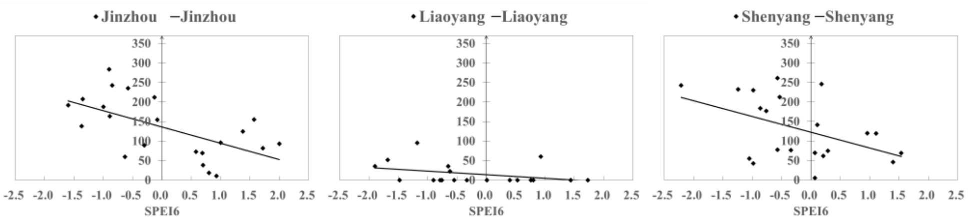
### 3.5 Drought vulnerability evaluation

The results of correlation analysis and random forest ~~show~~ suggest that in most parts of Liaoning province, SPEI at 6-month accumulation period has~~d~~ the strongest ~~correlation~~ relationship with drought impacts. SPEI6 was therefore selected to assess the drought vulnerability of the 14 cities. Regression analysis was performed on the SPEI6 for each category of drought impact, and an example is given in Figure 7 which shows the linear regression of DSA with SPEI6 in the 14 cities. It can be surmised that the more serious ~~of~~ the drought impacts for a specific drought severity (as defined by SPEI6), the higher the drought vulnerability. Fuxin, Tieling, Chaoyang, Jinzhou and Shenyang have a higher vulnerability to DSA compared to the other cities.

Similar analyses were performed for all impact types, and Figure 8 displays ~~which~~ the drought impacts each city in Liaoning province is most vulnerable to. It can be seen from Figure 8 that there is little difference between cities in terms of sensitivity to various categories of drought impacts. Considering the various impacts, Chaoyang, Jinzhou, Tieling, Fuxin and Shenyang had the highest drought vulnerability~~, which~~ - these cities are all located in the northwest part of Liaoning province. Dalian was most vulnerable to NLH.

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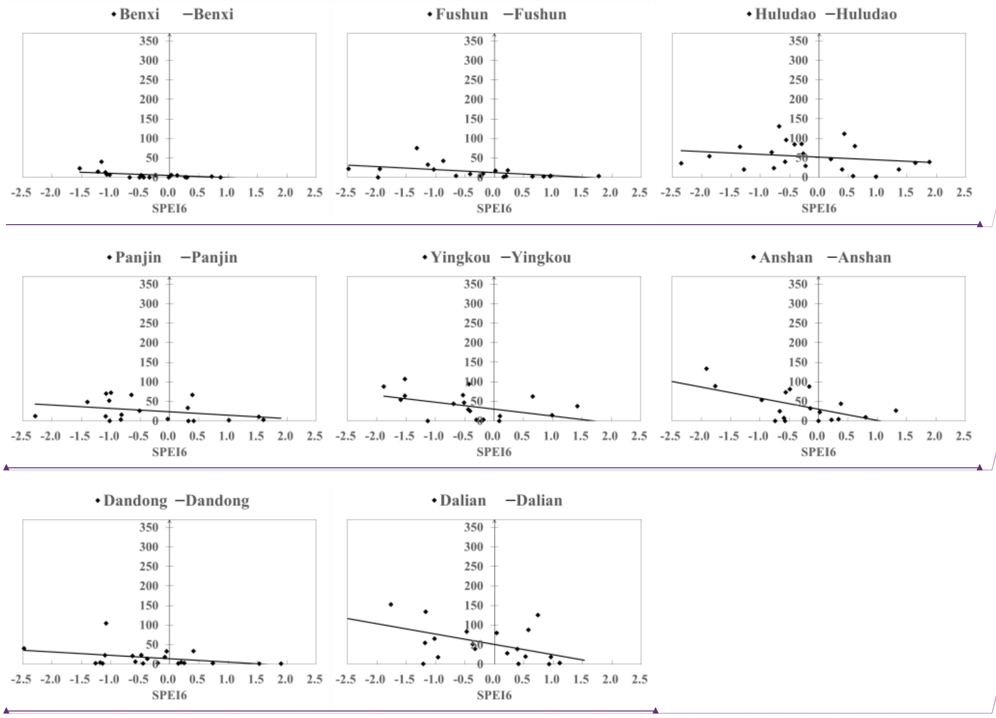


**Figure 7: Linear regression results of drought suffering area (DSA) with SPEI6 in each of the 14 cities in Liaoning Province.**

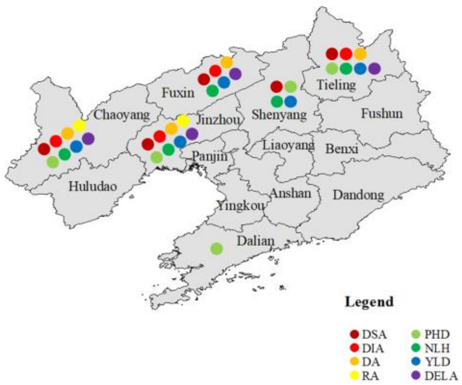


**Figure 8: Map showing ~~which~~ the drought impacts each city in Liaoning province is most vulnerable to, based on the results of the linear regression.**

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### 3.6 Vulnerability analysis

A stepwise regression model was built to explain the variation in each type of Standardised Drought Impact using vulnerability factors (listed in Table 2) as predictors. Drought impacts are symptoms of vulnerability and so can be used to estimate vulnerability to drought (Blauhut et al., 2015a). The vulnerability to drought can be assessed by maintaining a constant severity of drought (i.e. particular drought index values), and comparing the resultant impacts. More serious impacts correspond to higher vulnerability. Thus, the Standardised Drought Impacts corresponding to~~at~~ a ~~moderate~~severe meteorological –drought ~~severity~~ (~~,~~SPEI6 equal to -1.5), were regressed on the standardis~~z~~ed drought vulnerability factors for 2017 to assess drought vulnerability for each drought impact type. Table 3 shows the results of stepwise regression model, demonstrating the contribution of vulnerability factors to each category of drought impact; the results varied for each impact type.

The relatively high $R^2$ values demonstrate the ability of the vulnerability factors to explain the variability exhibited by each drought impact. This is particularly the case for DSA, drought suffering area, and PHD, population with difficulty in accessing drinking water, which had associated $R^2$ values of 0.894 and 0.805, respectively. Population, crop cultivated area, and livestock production explained 89.4% of the variation in DSA. Population, in combination with per unit area of fertili~~z~~ser application, and reservoir total storage capacity, also contributed to the DA model, explaining 80.5% of DA variation.

Population, crop cultivated area, and livestock production were identified as significant predictors in four, five, and three models, respectively, more than other vulnerability factors. Crop cultivated area, the most frequently significant predictor of drought impacts, also exhibited relatively high regression coefficients, demonstrating the strong relationship between the areas cultivated for crops, and the vulnerability to drought impacts. These results are paralleled in a composite drought vulnerability tool, which assigns relatively high weighting to area of land irrigated (Quinn, et al. 2014).

Population exhibited negative regression coefficients for three of four drought impacts, suggesting that as the population increased, the vulnerability to drought impacts decreased. However, population exhibits correlation with crop cultivated area, and livestock production. This, paired with potential unaccounted interactions between population and other predictors, may have resulted in inaccurate population coefficient estimation. This is supported by a positive population coefficient for predicting NLH. Population was used exclusively to predict NLH, thus correlation with other predictors, and interaction effects were unable to influence the coefficient. Furthermore, Figure 9 demonstrates that as population increases, DSA, DIA, and DELA increase. The composite drought vulnerability tool of Quinn et al. (2014) does not explicitly account for population, making a direct comparison not possible. However, it does assign a positive relationship between the ratio of rural population and drought vulnerability, which may explain the unexpected negative coefficients presented here.

The number of electromechanical wells also exhibited a positive coefficient, suggesting that as the number of wells increases, drought impacts increase. However, it's possible that electromechanical wells are more prevalent in more drought prone areas~~,~~, thus, the positive coefficient may simply demonstrate an association between ~~electromechnical~~electrometrical wells and RA.

**Whilst drought vulnerability factors were able to explain 47.4-89.4% of the variability in drought impacts, annual per capita water supply, effective irrigation rate, and per unit area of major agricultural products were not identified as significant predictors of any drought impact type. It is important to consider, however, that correlation between these ~~vulnerability factors and~~ other vulnerability factors could result in ~~these vulnerability factors~~them not being identified as ~~not~~ significant, as the information is already contained within other vulnerability factors. T**his is supported by drought impact correlations with per capita water supply, and effective irrigation rate. However, minimal correlations between drought impacts and unit area of major agricultural products were observed, suggesting that the absence of a detected relationship ~~between unit area of major agricultural products and drought impacts~~ may be a true reflection.

~~A further stepwise regression model was built to explain the variation in each type of Standardised Drought Impact using vulnerability factors (listed in Table 2) as predictors. Since dDrought impacts are symptoms of vulnerability and so, it can be used to estimate vulnerability to drought (Blauhut et al., 2015a). FBecause for a specific severity of drought (i.e. particular drought index values), basically, the more serious the impact caused, the more vulnerable the region is. Thus, the regressed Standardizsed Drought Impacts at a moderate drought severity with SPEI6 equal tos -1.5 were applied to measure the drought vulnerability. Table 3 shows the results of stepwise regression model, demonstrating the contribution of vulnerability factors to each category of drought impact;. T the results varied for each impact type.~~

**Table 3: The vulnerability factors selected for the stepwise regression model and the $R^2$ of the resulting model for each impact type (identified by the codes in Table 1).**

| Drought Impacts | Predictors vulnerability factors) | Standardised Coefficients | $R^2$ |
|---|---|---|---|
| DSA | Crop cultivated area | 0.814 | 0.894 |
| | Population | -0.476 | |
| | Livestock production | 0.451 | |
| DIA | Crop cultivated area | 1.098 | 0.743 |
| | Population | -0.451 | |
| DA | Livestock production | 0.691 | 0.731 |
| | Per capita gross domestic product | -0.436 | |
| RA | Number of electromechanical wells | 0.629 | 0.541 |
| | Per capita gross domestic product | -0.452 | |
| PHD | Crop cultivated area | 0.949 | 0.805 |
| | Reservoir total storage | 0.472 | |
| | Per unit area of Fertilis~~z~~er application | 0.352 | |
| NLH | Population | 0.720 | 0.474 |
| YLD | Crop cultivated area | 0.798 | 0.606 |
| DELA | Crop cultivated area | 0.556 | 0.786 |
| | Population | -0.879 | |

| | |
|---|---|
| Livestock production | 0.793 |

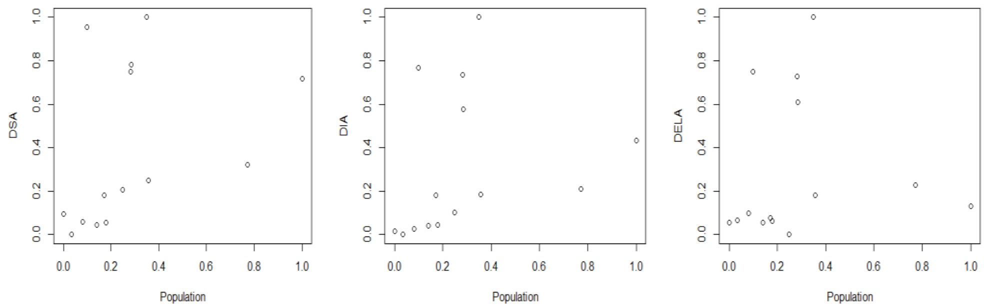


**Figure 9: Scatterplots demonstrating the association between population and drought impact in Liaoning province.**

~~Crop cultivated area had a significant relationship with drought vulnerability for DSA, DIA, PHD, YLD and DELA impact types; and population had a significant relationship with DSA, DIA, NLH and DELA. Population was the only significant predictor identified for DELA, with an $R^2$ of 0.474. Crop cultivated area increases drought vulnerability significantly for 5 out of 8 drought impacts types, while~~ a ~~more~~larger ~~population reduces the drought vulnerability significantly for four drought impact types. With the exception of PHD and NLH, crop cultivated area is directly related to the other drought impact types. Crop cultivated area was the only significant predictor for YLD.~~

## 4 Discussion

The methodology in this research has ~~the~~ a number of distinctive ~~following~~ characteristics in relation to previous drought impact and vulnerability assessments. ~~Firstly, it~~ The method takes many drought impacts, across a range of sectors, into consideration. ~~Secondly, t~~The extensive drought impact data were systematically collected at county level, which is a consistent and reliable data source enabling regional comparisons. The drought impact data used here included impact variables that are rarely available in other ~~studies~~settings: e.g. ~~such as~~ population with difficulty in accessing drinking water, number of livestock with difficulty in accessing drinking water, yield loss due to drought and direct economic ~~loss~~losses in agriculture. ~~Thirdly~~In addition, we not only considered the occurrence of drought ~~events~~impacts, but also the severity of ~~drought~~ impacts and their ~~its~~ spatial ~~extent~~variation between regions. Finally, the relationship between drought indices and drought ~~-~~impacts was explored using different statistical approaches, and this linkage was ~~applied~~ used to assess drought vulnerability in Liaoning province using a range of vulnerability factors.

~~The~~ The study has some important limitations which must be considered in interpreting the outcomes. The biggest challenge

~~of this study~~ was the spatial and temporal matching between the drought impacts and indices. The regularity with which impact data are collected is determined by the drought warning level and as such they are not evenly spaced in time; as a result of this, the data were aggregated to annual totals. It was important to match the accumulation period and timing of the selected drought indices to the timescales critical for the drought impacts; for example SPEI6 in September covers the critical maize growth period and is when the majority of precipitation falls. ~~Drought impacts and drought index data are~~ were ~~calculated annually.~~ However, ~~T~~the results may change if we ~~applied~~ used ~~the~~ multi-year drought impacts, as ~~. L~~longer index accumulation periods ~~time scale of indices~~ may ~~has~~ have a ~~better~~ stronger correlation with multi-year drought impacts than single year drought impacts. ~~The regularity with which impact data are collected is determined by the drought warning level and as such they are not evenly spaced in time; as a result of this, the data were aggregated to annual totals. It was important to match the accumulation period and timing of the selected drought indices to the timescales critical for the drought impacts; SPEI6 in September covers the critical maize growth period and when the majority of precipitation falls.~~ Soil moisture data ~~are~~ were collected at a daily resolution, in order to match up soil moisture and impact data,~~;~~ the March to October average soil moisture was used in the correlation analysis. However, short term soil moisture deficits can have serious impacts on crops which are sometimes unrecoverable. The average soil moisture may not have captured these short-term deficits, particularly if soil moisture was, in general, sufficient the rest of the year. Also i~~I~~n some cities, the lack of soil moisture data means that the annual average soil moisture does not reflect the occurrence of typical agricultural drought during the year. For this reason, soil moisture data can be used for real-time drought monitoring applications, but may not appropriate to present drought impacts on an annual scale for risk assessment, as applied here. ~~In some cities, the lack of soil moisture data means that the annual average soil moisture does not reflect the occurrence of typical agricultural drought during the year.~~

NDVI data for the critical growth period of spring maize was used in the analysis with annual drought impacts (i.e. ~~month~~July-month), but again this does not take all drought events during crop ~~growth~~ growing period into account. The correlation coefficients characteri~~z~~sing the relationship between NDVI and drought impacts are both positive and negative; this is likely due to the complexity of NDVI drivers (e.g. diversity of land cover, crop types and growth stages etc.). For this reason, some studies have used the NDVI to identify the impact of drought on vegetation (Miao et al., 2018;Rajpoot and Kumar, 2018;Trigo et al., 2015;Wang et al., 2015).

The results from the correlation analysis were consistent with the results from the RF analysis. Drought suffering area (DSA) and drought impact area (DIA) had strong correlations with all drought indices in Liaoning province, while PHD and NLH have a weak correlation with indices. This was because DSA and DIA are direct impacts of agricultural drought, whilst PHD and NLH are related to many additional factors, such as drinking water source location and the quality of water resources;~~,~~ for example, livestock can drink water from the river directly, but the ~~water~~ quality of the river water means it is not suitable for humans – ~~cannot meet the human drinking needs. F~~for this reason, NLH showed least sensitivity to water deficits.

The random forest algorithms presented in this paper explained an average of 41% of the variance observed within the drought impact data. This is relatively modest, and ~~is~~ may be partially due to~~because of the~~ limitation associated with~~of~~ the impacts data~~, random forest algorithm, and optimiszation such as….~~. The c~~C~~ollinearity of the drought indices (e.g. SPI6 is correlated with SPEI6) is also a potential cause of the low MSE%. The correlation coefficients calculated for drought indices and NLH in Yingkou, and PHD in Fushun were positive. This ~~result is~~was unexpected given the interpretation of these indices as estimations of the drought severity, and the majority of reported correlation coefficients being negative. Therefore, it seems likely this result is not representative of the true relationships between these indices and impacts, and instead is an artifact of imperfect impact data. To explore this, years with the highest numbers of impacts were removed before ~~–~~the correlation coefficients were estimated~~ with the largest impact years removed~~. This resulted in a negative correlation coefficient, providing further evidence for the positive correlation coefficients not being representative of the true relationships in these cities. The availability of more data would enable a better approximation of the true relationships between indices and impacts.

For all the drought impacts, Dalian and Fuxin showed the highest correlation coefficients among drought impacts and drought indices in all cases. The most vulnerable cities were Fuxin, Tieling, Chaoyang, Jinzhou and Shenyang, which are all located in the northwestern part of Liaoning province indicating there is a high drought vulnerability and drought risk in northwestern Liaoning. This is consistent with existing research by Yan et al. (2012) and Zhang et al. (2012), which established a drought risk assessment index system to assess drought risk in northwestern Liaoning. Zhang et al. (2012) used indicators such as precipitation, water resources, crop area, irrigation capacity and drought resistance cost to measure drought risk and~~, they~~ found that Fuxin, Chaoyang and Shenyang ~~have~~ had a high drought risk.

The above results are also in general agreement with Hao et al. (2011), ~~their study~~ who used 10-day affected crop area data as the drought impacts to assess drought risk in China ~~in~~ at the county unit. Their result showed~~s~~ that the West Liaohe Plain ~~has~~ had a high risk. The results presented in ~~this~~our paper identify ~~.~~Chaoyang ~~–~~and Fuxin ~~are identified~~ as having the highest drought vulnerability – the majority of these two cities are located ~~–in this research and most part of these two cities are located in~~on the West Liaohe Plain.

As the accumulation period increased, the first splitting value extracted from the random forest model tended to decrease, suggesting that at longer accumulation periods, ~~higher~~ larger water deficits are required for ~~the same~~equivalent impacts to occur~~ at longer accumulation periods~~. There is a ~~more~~ severe water deficits of RA occurrence since it caused more yield loss compared to DIA and DA. Drinking water for l~~L~~ivestock ~~drinking water~~ requires lower water quality compared to that for humans, for example, livestock can drink water from the river directly, but the water quality of the river cannot meet the human drinking needs. For this reason, NLH showed least sensitivity to water deficits.

The relationships analysed in this research support the ~~development~~ use of drought indices as~~of~~ a predictor of drought impacts ~~a drought impacts predictor~~ and t~~. T~~he impact thresholds identified can also support improved drought warning and planning.

The drought vulnerability map (Figure 8) can be used to support drought risk planning, helping decision-makers to implement appropriate drought mitigation activities through an improved understanding of the drivers of drought vulnerability – for example, by sinking more wells to enhance resilience to drought~~t~~ (noting of course, that this measure has potential longer-term ~~implicatons~~implications, for example, on groundwater exploitation e.g. Changming et al. (2001)~~ADD REFERENCE HERE~~). ~~). The impact thresholds identified can also support improved drought warning and planning.~~ The methods used here can be applied in other areas to better understand drought impacts and drought vulnerability, ~~since~~ where similar data (e.g. drought impacts, meteorological data) ~~can be~~are collected~~ in other regions~~. While systematic, statistical archives of drought impact are comparatively rare, globally, there are numerous other potential sources of impact data that could be used (e.g. see Bachmair et al. 2016b).

## 5 Conclusion

This study used correlation analysis and random forest methods to explore the ~~linkage~~ relationship between drought indices and drought impacts. It assessed drought risk in Liaoning province, and proposes a drought vulnerability assessment method which is applied to study the contribution of various socioeconomic factors to drought vulnerability. Here, we return to the original objectives of the study to summarise the key findings.

1. ~~1:~~ When and where the most severe droughts occurred between 1990 and 2013 in Liaoning province?

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

2. ~~2:~~ Which drought indices best link to drought impacts in Liaoning province?

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

3. ~~3.~~ Which city or areas has a higher drought vulnerability in Liaoning province?

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

4. ~~4:~~ Which vulnerability factor or set of vulnerability factors have a higher contribution to drought vulnerability?

Population and crop cultivated area ~~had~~ were strongly associated~~a strong negative relationship~~ with drought vulnerability, ~~whilst crop cultivated area was positively correlated with drought vulnerability~~, suggesting these factors are good indicators of drought vulnerability. However, the complexities of these relationships with drought vulnerability require further investigation.

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

## Data availability

Some data, used during the study are proprietary or confidential in nature and may only be provided with restrictions (e.g. drought impacts data, soil moisture ~~and~~ ~~and daily meteorological data~~) Daily meteorological data can be explored at http://data.cma.cn/ but access to data is restricted. NDVI data can be obtained from the Geospatial Data Cloud (http://www.gscloud.cn/). Vulnerability data were from the Liaoning Statistical Yearbook which can be obtained from ~~….. (or note if it is not available)~~ Liaoning Province Bureau of Statistics (http://www.ln.stats.gov.cn/).

## Author Contributions

Yaxu Wang, Juan Lv, Jamie Hannaford, Yicheng Wang and Lucy Barker discussed and developed the aims of the paper. Yaxu Wang was responsible for the data analysis, visuali~~z~~sation and prepared the original manuscript, with contributions from Hongquan Sun, Lucy Barker, Jamie Hannaford, Miaomiao Ma, Zhicheng Su and Michael Eastman.

## Competing interests

The authors declare they have no conflict of interest.

## Acknowledgements

The authors gratefully acknowledge funding support for these researches provided by the National Key Research and Development Project (No. 2017YFC1502402), and Fund of China Institute of Water Resources and Hydropower Research (JZ0145B592016, JZ0145B582017) and China Scholarship Council. Jamie Hannaford, Lucy Barker and Michael Eastman were supported by the NERC National Capability Official Development Assistance project SUNRISE ("Sustainable Use of Natural Resources to Improve Human Health and Support Economic Development") [NE/R000131/1].

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