Manuscript nhess-2019-310 “Linking drought indices to impacts to support drought risk assessment in Liaoning province, China” – Point by point response to referee 1 comments

We thanks referee #1 for the feedback to our manuscript. We appreciate all the comments and suggestions and it is very useful to improve its quality and readability.

We would like to address the referee’s major concern. We have added a comparison with the paper of Hao et al. (2011), including methods, data and results. The vulnerability assessment method is a little confusing in the former manuscript, and we have added some explanations on how we did the quantitative vulnerability assessment. At the same time, some sentences are reorganized, which makes the manuscript more readable. In the discussion, we have added some comparison with other drought studies, including research data, methods and results. More detailed changes and replies are in bold below.

Line 43, That strongly differs to me 2016, Naumann 2018, Voigt 2019 and Hagenlocher et al 2019; Especially check for the latter-->drought risk and vulnerability review.

We thank the reviewer for this comment. Lots of drought risk assessment methods have been used in different study area. In Julia Urquijo & Veit Blauhut 2016, some reviewed paper defined risk as follows.

R = H x V

Where risk (R) is considered to be a function of hazard (H) and vulnerability (V).

It is similar to the one of the class in this manuscript which drought risk evaluate by drought hazard (drought frequency, severity etc.), vulnerability (including the drought resistance ability) and exposure of affected bodies (density of house, property and so on). Lots of indices were selected to measure the hazard, vulnerability and exposure. Drought risk is calculated by the weighted indices.

R = H x V x E

Where risk (R) is considered to be a function of hazard (H), vulnerability (V) and Exposure.

Another drought risk assessment method was grouped in this manuscript as follows.

$$R = P \times C$$

Where risk (R) used to be considered to be a function of probability of drought (*P*) and potential consequences & impacts (C).

In Blauhut et al. (2016), past drought impacts, drought indices and vulnerability factors were applied to assess drought risk. Blauhut et al. (2015) combine past drought impacts with hazard measurement in order to assess drought risk in pan-European. Probability of drought impact occurrence at five different drought hazard levels was used to measure drought risk. The higher of the probability of drought impact occurrence (potential consequences & impacts) at same drought hazard levels (probability of drought), the higher of the drought risk. In Carrao et al. (2018) (Carrao, Naumann

2018), definitions of risk are commonly probabilistic in nature, referring to the potential impacts from a particular hazard in a future time period.

Essentially, these research assess drought risk from the drought severity and the potential drought impacts. These are similar with another class in this manuscript. We will clarify this in the revised manuscript..

Line 47: Indeed, quite some studies use 'risk' to characterize the hazard of drought (severity, frequency etc.). But the terminology of risk is by definition the likelihood of impacts! I recommend you to highlight this "missuse" a little more.

We agree with the reviewer and highlight this "missues" as suggested. Then we revised the manuscript.

Line 52: Reference?

Thanks for your suggestion and we added a reference here(Erhardt and Czado, 2017).

Line53: Vegetation drought?

We thank the referee for the comments and revised the manuscript to make it clear.

Line 66：I believe Hao et al. 2011 published on this.

We thank the reviewer for this important comment. Hao's et al. (2011) is an important related study in this field to compare with. As mentioned above, we have added a reference to Hao et al in the revised manuscript. .

In Hao's study, drought impact only measured by affected crop area in a 10-day time step at county level, in our research, it is measured by eight types of annual drought impacts, which including the affected crop area at city level. Their result shows that West Liaohe Plain has a high risk. Most parts of Chaoyang and Fuxin are identified the highest vulnerability in our research which are located in West Liaohe Plain.

Line 78 ?   Line 87 Line 94

We modified the reference as suggest.

Line 114: Does this mean from rainfall, recharge or water available for public water supply?

Here, it means the all the freshwater, we have clarified this in the revised paper.

Line 149: Please indicate why you selected these vulnerability factors: prestudies, expert knowledge, data availability, statistical tests?

We thank the reviewer for this comment and we fully agree with him on this point. Then, we added the reason why we selected these vulnerability factors. As mentioned in the response to reviewer 2, we selected these vulnerability factors, as the majority of impacts in Liaoning affected the agricultural sector. We have added some more description of this (and add some relevant previous studies that informed the selection) to the revised manuscript (Junling et al., 2015;Kang et al., 2014).

Line 170 SPI and SPEI are well know these days. Did you then interpolated between the stations, or did you keep stations values? If so why? Did you generalized to administrative border? If so how?

One station in each city was selected and calculated the SPI/SPEI for that one station and used it to represent the city

(this meant the drought indices and drought impact data were at the same spatial scale – we will ensure this is clear in the revised paper.

Line 192 I just stumbled over this term again. You might explain what a city includes for your case. E.g. if you tale about cities in Europe it's only about the highly populated city centers, were actually no agriculture exists.

For this study, the city is divided by the city unit which include urban, town and village in its jurisdiction. We have added this definition to the data section.

Line 224 Where?

We changed the sentence and made clearer.

Line 227 How has this been done? Furthermore is this for a single city? Of are this averaged values? Please be more precise.

We thank the reviewer for this comment. We added a sentence to explain it clear on how we calculated the *sum of SDI*. "*Sum of SDI* is the sum of all types of Standardized Drought Impacts in 14 cities for each year." The standardization of the drought impacts is described in Section 2.2.4 of the methods.

Line 229 visually detected or proven by stats?

It is visually detected and we corrected and made clearer.

Figure 3 Please improve the resolution and use the full terms. How are the class defined.

We thank the reviewer for this comment and we fully agree with him on this point. We used the full terms and a higher resolution in the figure. The threshold is identified by the Natural Breaks (Jenks) method in the Arcmap.

Figure 4 Again, lots of space. present the full term please.

We agree with the reviewer and we present the full term as suggest.

Figure 6 Please increase resolution.

Yes we increased resolution as suggest.

Line 301 Please be more precise here vulnerability analysis is most often a big issue and quantitative approaches are lacking. Hence, readership might be highly interested here (at least I am).

We thank the reviewer for this important comment. We added some explanation on how do we quantitatively assess vulnerability.

Because 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.

For example when SPEI6 is equal to -1.5, the regression result shows that yield loss due to drought is 5 thousand ton in Chaoyang whilst it is 1 thousand ton in Huludao. It means that in the term of the yield loss due to drought, Chaoyang is more vulnerable than Huludao.

Line 316 Please note that Blauhut et al. 2016 did similar, but on the basis of multivariable regression---checking for suitable hazard indices (SPI, SPEI, Soil moisture, VHI, CDI) and also checking trough a long list of vulnerability indices. Furthermore, the results of Hao et al. might be important for comparison.

The reviewer is right. We revised in the manuscript. Also we agree with the reviewer that we need make a comparison with Hao et al. 2011.

'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 at county unit. Their result shows that West Liaohe Plain has a high risk. Chaoyang and Fuxin are identified the highest vulnerability and most part of these two cities are located in West Liaohe Plain.'

Line 335 Here I strongly recommend a comparison to other studies which combined NDVI to impacts! Normally NDVI (or other vegetation health indices) suite very good.

We thank the reviewer for this important comment. We added some comparison with other studies which combined NDVI to impacts.

In other studies NDVI is mainly used to identify vegetation (agriculture) impacts. In this manuscript, affected human and livestock are also collected to measure drought impacts.

Line 339 How did other studies perform with respect to drought risk? In Liaoning province? China? Globally? How good could teh linkage be detected by others? For agriculture?

We thank the referee for the suggestion that we included the comparison in the new version of the manuscript. We added some comparison with other studies which used different method of drought risk assessment.

Line 353: I suggest to prove this statically. Naumann et al. did an easy/brief stats on linking impacts and vulnerability in Africa. Or..you might consider to integrate vulnerability information in your risk model?

We thank the reviewer for this important comment. In Naumann et al. (2014), the tetrachoric correlation was computed between the drought vulnerability indicator and the numbers of persons reported affected to assess how the vulnerability indicators are correlated with drought disasters.

In our manuscript, stepwise regression model was built to compute between each type of Standardised Drought Impact and vulnerability factors to explore the contribution of the vulnerability factors to drought impacts. We will clarify it in the revised paper.

Line 354 This sentence feels a little loose here. What so you mean with this?

Yes, we delete this sentence.

Line 356 ?

Corrected.

Line 360 This is very detailed

We rephrased the sentence and revised the sentence to make it more readable.

Line 363 This is most often not a good idea! Besides that, the selected vulnerability factors limit management possibilities a lot. You might state that, the detection of drivers can support this

The reviewer is right. We changed the expression as suggested.

References

Blauhut, V., Stahl, K., Stagge, J. H., Tallaksen, L. M., De Stefano, L., and Vogt, J.: Estimating drought risk across Europe from reported drought impacts, hazard indicators and vulnerability factors, Hydrology and Earth System Sciences,20,7(2016-07-12), 20, 2779-2800, 2016.

Carrao, H., Naumann, G., and Barbosa, P.: Global projections of drought hazard in a warming climate: a prime for disaster risk management, Climate Dynamics, 50, 2137-2155, 2018.

Erhardt, T. M., and Czado, C.: Standardized drought indices: A novel uni- and multivariate approach, Journal of the Royal Statistical Society, 2017.

Yan, L., Zhang, J., Wang, C., Yan, D., Liu, X., and Tong, Z.: Vulnerability evaluation and regionalization of drought disaster risk of maize in Northwestern Liaoning Province, Chinese Journal of Eco-Agriculture, 20, 788-794, 2012.

Zhang, J. Q., Yan, D. H., Wang, C. Y., Liu, X. P., and Tong, Z. J.: A Study on Risk Assessment and Risk Regionalization of Agricultural Drought Disaster in Northwestern Regions of Liaoning Province, Journal of Disaster Prevention & Mitigation Engineering, 2012.

Manuscript nhess-2019-310 "Linking drought indices to impacts to support drought risk assessment in Liaoning province, China" – Point by point response to referee 2 comments.

We thanks referee #2 for the feedback to our manuscript. We appreciate all the comments and suggestions and it is very useful to improve its quality and readability. The detailed Answer to each comment and suggestion are as follows.

Specific comments

The abstract should be shortened; now it consists of 400 words, while NHESS standards foresee a 100-200 word abstract.127: you said that one representative meteorological site in each city was selected to represent the meteorological condition for the whole city. Which are the criteria you adopted to select the representative station?

We thank the reviewer for this important comment. We made it shorter as suggested.

We considered the data quality, length of the time series and location of the stations to select the representative station. We have added some content to make it clearer.

Line 135-136: NDVI data: you used MODIS data, which are available from 2000 to 2013. Why didn't you consider the NOAA AVHRR data, which span from 1981 to present? In this case you can include in your analysis also the period from 1990 to 2000.

We thank the reviewer for this important comments. Yes, it is true that NOAA AVHRR has a long time series data. But, on the one hand, considered the advanced characteristics of MODIS data with high spatial and spectrum resolution, greatly improved data acquire ability and widespread applied on drought monitoring, etc., we used MODIS data instead. Also, it is easy to get access to the MODIS product of the NDVI.

Can you please specify how you computed the monthly average NDVI?

The monthly average NDVI products are available from the Geospatial Data Cloud (http://www.gscloud.cn/**), and all the products quality were inspected. So we directly downloaded and used the monthly average NDVI products. According to the description of the products, the daily maximum NDVI data were used to represent the monthly average NDVI.**

Line 140: which criteria is adopted to establish the beginning of a drought event or to trigger a drought warning according to the SFDH?

There are several criteria to trigger a drought warning for SFDH according to the local specific Drought Preparedness Plan, , such as meteorological drought monitoring result from the China Meteorological Administration, Soil moisture and hydrological drought monitoring from the Ministry of water resources and drought impacts collected from the county-level in the system. So, basically, the criteria to trigger a drought warning are the integration of multiple factors, and are different with varied places.

Line 244: Figure 2: since it seems that SPEI performs better than SPI, the same graph showed for SPI can be presented for SPEI too.

We thank the reviewer for this comment and we fully agree with him on this point. We presented the SPI for SPEI in figure 2 as suggest.

Line 234: Figure 3: it is not clear to me why at line 231 you say “Figure 3 shows the spatial distribution of the annual average of each drought impact type collected between 1990 and 2016” and in the figure caption you report a different period (1990-2013). Please, correct the wrong one.

Thanks for your suggestion. We corrected this error.

Line 301-302: Can you please clarify why you select SPEI6=-1.5 for the second stepwise regression presented in the paragraph “Vulnerability analysis”?

Firstly, there are a certain amount of drought impacts when SPEI6=-1.5 for all types of drought impacts. If we use the result of regression analysis when SPEI6 is equal to -1, some types of the drought impacts are not be triggered. If we use the result of regression analysis when SPEI6 is equal to -2, due to the serious of drought, there could be serious drought impacts in all cities. Secondly, the results of relative value between cities are consistent when SPEI ranges from -1 to -2. Therefor we select SPEI6=-1.5 as a suitable point to stepwise regression.

Technical corrections

Line 12: I believe there is a typing error: risk assessment (instead of risk assessments).

Yes we corrected it and delete ’s’.

Line 33-35: I would rephrase the sentence in the following way: “Drought is one of the most pervasive natural hazards which can cause huge societal impacts. Drought impacts are mainly non-structural, widespread over large areas, and delayed with respect to the event; therefore, it is still challenging to properly define, quantify and manage drought.”

Yes we rephrased the sentence as suggest.

Line 39: I will substitute “successive” with “consecutive”.

Yes we replaced the “successive” with “consecutive”.

Line 60: I believe there is a typing error: impacts instead of impact.

Corrected.

Line 66: I believe you forgot to insert from: “impacts from a range of sources..”

Corrected.

Line 68: I believe there is a typing error: “at country level”.

The data collection system reports to the national level through different grades of government, county-city-province-nation. Here it describes the data reporting process although this study obtains data from national level.

Line 70-72: please review this sentence, since it is not clear.

Rephrased.

Line 80: I believe there is a typing error and “whilst” should not have a capital letter.

We corrected it as suggest.

Line 82-86: please review this sentence in order to explain better the concepts.

We rephrased the sentence.

Line 92: I believe there is a typing error: previous studies have BEEN focused.

We corrected it and added 'been'.

Line 115-116: please review the sentence "Thus, Liaoning province is one of the severe water-shortage provinces in northern China".

We changed it as suggest.

Line 125 Remove "including daily precipitation and temperature"; you have already specified this point at the previous line.

We delete it as suggest.

Line 147: Vulnerability factors were collected from the 2017 Liaoning province Statistical Yearbook to explain the drought vulnerability. Please, explain it better.

We thank the reviewer for this comment we made it clearer.

Line 157: I believe there is a typing error: "The WMO recommends: : :"

Corrected.

Line 162-166: Please, review the sentence, since it is not easy to understand.

We have restructured the sentence to make it clear.

Line 170-171: I would change the sentence in the following way: "Precipitation in Liaoning province is concentrated between April and September; this period corresponds to the growing stage of spring maize".

Thanks for your suggestions. We replaced the sentence.

Line 171-172: Please review the sentence in order to explain which SPI6 and SPEI6 values you used in your analysis.

We agree with the reviewer and we added some explanation to make it clearer.

Line 172-173: Please review the sentence in order to explain which SPI and SPEI 12, 15, 18 and 24 values you used in your analysis.

Rephrased.

Line 193-194: I will rephrase the sentence in this way "it can be inferred that the greater the impact caused by droughts of the same severity (measured according to SPI/SPEI), the higher the drought vulnerability of the city."

Thanks for your suggestion and we replaced it as suggest.

Line 207: I believe there is a typing error "where y_i and ^ y_i are the observed drought impacts and the estimated drought impacts".

Corrected.

Line 219: I believe there is a typing error: " and min DI are the maximum"

Yes we corrected this error.

Line 231-233: please, review the sentence to explain better what you have done.

Yes we have rephrased it.

Line 277: I believe there is a typing error, since I cannot find an impact type called "DIS" in Table 1.

We corrected this error.

Line 316: I would change the sentence in the following way: "data was systematically collected at country level".

We have replaced this sentence in the revised paper as suggest.

Line 239: I would change the sentence in the following way "but may not be appropriate.."

Rephrased.

Line 350: I would change the sentence in the following way: "Dalian and Fuxin showed the highest correlation coefficients among drought impacts and drought indices in all cases".

Thanks for your suggestions and we have replaced this sentence.

Line 353-354: please rephrase the sentence.

Thanks for your suggestions. We restructured the sentence to make it clear.

Line 356-360: please, rephrase the sentence, since it is not clear.

We rephrased the sentence to make it clearer.

Line 362: I would change the sentence in the following way: "The drought vulnerability map can be used to support drought risk planning, in order to help decision-makers to implement appropriate drought mitigation activities"

Thanks for your suggestions. We replaced with this sentence.

Line 372: I would substitute "severity" with "severe".

We replaced "severity" with "severe".

Line 377: I would substitute "performance" with "perform".

We have replaced "performance" with "perform" in the revised paper.

Line 387: I believe there is a typing error and "impact" should be used instead of "impacts".

Corrected.

References

Liaoning Province Bureau of Statistical: Liaoning Statistical Yearbook 2016, China Statistics Press, 2017.

Yan, L., Zhang, J., Wang, C., Yan, D., Liu, X., and Tong, Z.: Vulnerability evaluation and regionalization of drought disaster risk of maize in Northwestern Liaoning Province, Chinese Journal of Eco-Agriculture, 20, 788-794, 2012.

Zhang, J. Q., Yan, D. H., Wang, C. Y., Liu, X. P., and Tong, Z. J.: A Study on Risk Assessment and Risk Regionalization of Agricultural Drought Disaster in Northwestern Regions of Liaoning Province, Journal of Disaster Prevention & Mitigation Engineering, 2012.

Manuscript nhess-2019-310 "Linking drought indices to impacts to support drought risk assessment in Liaoning province, China" – Point by point response to referee 3 comments

We thanks referee #3 for the feedback to our manuscript. The comments and suggestions are particularly useful for us to revise the manuscript. Based on the suggestions, we have added the definition of drought and compared with other related studies. We emphasized the link between historical droughts studies and this manuscript, and added more explanations on how we did the quantitative vulnerability studies and how this method can be used in other regions. We have responded to each comment in turn below in bold.

General suggestions

The first suggestion is regarding the absence of a clear drought definition. The sentences in the Introduction [R36-37] are insufficient in describing what kind of 'numerous droughts' China has experienced, and how this study is related to drought studies in China or globally. The specific naming of the 2000-01 event and the frequent occurrence of drought [R118] calls for a rigid definition of a drought. Later in the Introduction, it only becomes clear that this study focuses on meteorological and (soil moisture) agricultural droughts. In my opinion, this should have been stated earlier and clearer.

Thank you for your suggestion. We will extend the drought definition in the Introduction to clarify these points in the revised manuscript. We will also add some explanation of the kind of drought China has experienced, and also add relevant literature to explain the relationship between this study and other related drought studies.

In addition to this, the manuscript gives little explanation of previous meteorological or agricultural drought events, even though multiple authors have described droughts in China on both national and regional level (Wu, et al. 2001; Zou, et al. 2005; Leng, et al. 2015, Xiao-jun, et al. 2012; Wang, et al. 2016). It would be beneficial to the manuscript to explore the link with previous studies and build on other national-scale drought studies to claim further implications of this study. For example, the presented dataset seems unique and unpublished, although the term 'China water resources bulletins' in Xiao-jun, et al. (2012) suggests that there are multiple sources of drought impact data. I would suggest that acknowledging of these relevant studies, as it helps to rightly place this new study in context of previous research and thereby support the claim of further implications of this study [R97-98 and R364-366]. In lines R364-366, it is stated that the method could be applied to other areas, although it remains unexplained how to do so. Results in Figure 3 and 4 suggests that the linking between drought impact data and climate indices is fruitful despite the large climate variability. The results show the strong relation between SPEI6 and Drought suffering area (DSA), SPEI6 and drought impacted area (DIA), and yield reduction and NDVI. These relations could be explored further in the Discussion section (R364-366), if a rigid drought definition is applied and the findings are related to relevant studies. That would increase the outreach of the developed method and would therefore benefit the manuscript significantly. In other words, I would strongly recommend to 1) provide a definition of the studied drought events, 2) relate them to past events –strengthen objective 1- and 3) link the findings to other drought studies in China to show the relevance of this study. Given the current structure of the introduction, I would expect that these suggestions would strengthen both the first, second and sixth paragraph [R87-91].

We thank the reviewer for these comments and we fully agree with him on these points. As the reviewers said, readers will have a lot of confusion without a clear definition of drought. Therefore we have added the definition of drought in the introduction. We explained what kind of drought China has experienced, and also added relevant literature to explain the relationship between this study and other related drought studies.

We have added the relationship analysis with the previous related studies in nation scale, such as the historic drought events, drought indices, and how this method can be applied in other regions. The details are as follows.

‘ In China, many indices were used for types of drought monitoring, such as Palmer drought index, SPEI, SPI, China-Z index, relative soil moisture, vegetation indices and remote sensing indices (Hong et al., 2001;Wang and Chen, 2014;Wu et al., 2012;Yanping et al., 2018), which found that serious drought events occurred in 1972, 1978, 1991 , 1999, 2000 and 2006. Based on previous drought studies, SPI, SPEI, soil moisture and NDVI were selected in this research. ’

‘The methods used here can be applied in other areas to better understand drought impacts and drought vulnerability, since similar data (e.g. drought impacts, meteorological data) can be collected in other regions.’

In addition to suggestion 1, I would suggest to include relevant drought studies in China that have explored a meteorological index (Wu, et al. 2001), agricultural droughts (as referenced) and water resource management strategies (Xiao-jun, et al. 2012). The current overview given in paragraph 6 does not reflect the full spectrum of relevant studies, hence I would strongly suggest for a thorough review of relevant studies in China to emphasise the link between previous studies and these findings. These studies have also performed analysis using multiple sources of information and could therefore strengthen the second paragraph in the discussion R321-335

We thank the reviewer for this important comment. We made some comparison with other related studies in data, method and results. According to your suggestion, we have added the comparison of relevant literature in the introduction and discussion section.

‘In drought monitoring, the index selected in this study is similar to the method in Leng et al. (2015), where the SPI, standardized runoff index (SRI) and standardized soil moisture index (SSWI) were selected to assess droughts from meteorological, agricultural, and hydrologic perspectives. In terms of drought impact data, Xiao-jun et al. (2012) collected drought affected and damaged area, losses in food yield from China water resources bulletins, which is the secondary data.’

‘The above results are also in general agreement with Hao et al. (2011), their study used a higher temporal and spatial resolution for drought impacts. It collected 10-day affected crop area data to assess drought risk in China at county unit. Their result shows that West Liaohe Plain has a high risk, northwestern part of Liaoning province are located at West Liaohe Plain.’

This is consistent with existing research by (Yan et al., 2012;Zhang et al., 2012), which established a drought risk

assessment index system to assess drought risk in northwestern Liaoning. In Zhang et al. (2012), indices such as precipitation, water resources, crop area, irrigation capacity and drought resistance cost are used to measure drought risk, result shows that high drought risk was identified in Fuxin, Chaoyang and Shenyang.

The second suggestion concerns another definition; the use of the term vulnerability and the vulnerability assessment. In the Introduction, the relationship between drought indices, impact, and vulnerability is mentioned [R73-74], although in that same paragraph there is very little background given on the term 'drought vulnerability' or the chosen approach of this study. Later in the manuscript, R147-150, it becomes evident that vulnerability factors are related to agricultural productivity. It would strengthen the claim of 'developing a drought vulnerability evaluation' [R97], if the choice of vulnerability factors was justified earlier in the manuscript, perhaps supported using relevant literature to drought vulnerability.

We will add more background information on drought vulnerability as a term, and improve the definition in the introduction. As for the vulnerability factors, as most of the impacts available for Liaoning Province relate to agriculture and the rural economy, we selected the vulnerability factors to reflect this, also taking guidance from the studies of Junling et al., 2015 and Kang et al., 2014. We will add this information to the revised manuscript.

Also we added more explanation in how do we quantitatively assess drought vulnerability.

The vulnerability factors themselves (Table 2) require some additional adjustment in my opinion. Currently, these factors do not relate to normal conditions, or below-normal conditions, i.e. drought conditions. The standardisation in R215-220 shows that vulnerability factors are a ratio that is relative to the maximum amount measured for an unknown time scale. It remains unknown how these factors are measured or would change over time and since these vulnerability factors are not given as a reduction from normal conditions, it remains unclear to the reader how they represent vulnerability. Without the full understanding of the vulnerability factors, the impact of Figure 8 is limited, as these vulnerability levels do not indicate vulnerability as such, solely a reduction from the maximum number. For example, it remains unclear what 'most vulnerable to' implies in Figure 8, and more explanation is required to understand which factors are in or excluded for which cities. If so, it would require some more explanation regarding the rationale behind these 'most vulnerable to' factors. Once the vulnerability factors are converted into a deviation from the long-term mean (or however a drought is defined), the combined effect of these factors would become clearer. I do not expect the results to change, although the factors will and potentially show the deviation from the mean (or normal) conditions and therefore emphasise the change during droughts. The results might show an amplified effects, which will help to strengthen the claim in R288-289. Along the same lines, I would also change the PHD, NLH and DELA into a percentage or ratio that relates to normal conditions. In the conclusion, relatively strong statements in R288-289 suggest that there is increasing drought vulnerability. However, from Figure 8 or Figure 7, it remains unclear how the vulnerability changes in Liaoning province, and these suggestions might aid the general analysis of the vulnerability factors.

Thank you for your comments. The manuscript may not be clear here before. The vulnerability factor is relative static

to a specific city, which is the characteristics of the city. The maximum value refers to the maximum value among 14 cities in Liaoning Province, not the maximum value of a city for a period. In this paper, we ignore the changes of vulnerability for a period time, mainly emphasizing the difference of the vulnerability factors between cities.

We assumed that these factors was static for a period of time and that are collected by local government.

For each city, we analyze the relationship between vulnerability (measured by types of drought impacts at the same drought severity) and vulnerability factors to explore the contribution of vulnerability factors to each type of drought impacts.

For example when SPEI6 is equal to -1.5, the regression results show that yield loss due to drought is 5 thousand ton in Chaoyang whilst it is 1 thousand ton in Huludao. It means that in the term of the yield loss due to drought, Chaoyang is more vulnerable than Huludao.

Thank you for your suggestion using the percentage of the drought impacts. It would be better if drought impacts are display with percentage. However some drought impacts are difficult to convert to percentage, such as economic losses [0.1b], it's difficult for us to get a value to be divided to obtain the percentage. Similarly, due to the total number of livestock is not available in each city, we can't get the percentage too. Above all, it is difficult to show the impacts in the form of percentage.

The third suggestion is regarding the varying time scale of the multiple datasets. The presented data and analysis combine multiple datasets of varying quality and sources into one product. That in itself is a fine bit of work, although I would suggest to show the applied time scale in the correlation analysis and in the random forest modelling. It is not a major concern, but it would strengthen the manuscript to frame a defined study period that matches all data analysed in the correlation analysis, i.e. 1990-2013. In R191-192 and in R211-212, a short statement is written regarding the limitations of the soil moisture data and the NDVI data. Perhaps, an additional note regarding the applied study period is best written here.

Thank you very much for your suggestion. We agree with the reviewer that we need to add the period. In the method section, we have added the period of time series for each analysis.

For consistency, I would also emphasise the applied time period for the random forest algorithm (as introduced in the third section of the Methods). In the current manuscript, the applied time period remains unknown for the Random Forest algorithm. In fact, to enhance clarity, a brief summary of the work of Bachmair, et al. (2016) would be beneficial for readers that are less familiar with this algorithm. Again, minor adjustments in the text would enhance the understanding of applied methods and therefore improve the manuscript.

We will add some more background to the approach in the revised manuscript and as mentioned above clarify the time periods over which the random forest analysis was conducted. We have added some explanation of MSE%, also we've added an example to explain the MSE% to make it clear.

Last correction I would suggest is the text along with Figure 5. In the figure, the coloured matrix gives the mean squared error in percentage. Firstly, I would strongly suggest to adjust the colour scheme to allow a non-experienced reader to see the difference between positive and negative percentage changes. Secondly, the change in MSE % suggests given a certain impact factor changes the error. If I read it correctly in R209, the change shows how much the accuracy decreases given the effect of the variable. This can be explained better than just one line of text, as a positive change in MSE% would imply not more MSE, but a more accurate model. Given the colour scale and the limited information available, the findings are somewhat hidden in this Figure despite the quality of the work. Hence, I would argue to change the colour scale accordingly and elaborate more in the text, i.e. give some examples.

We thank the reviewer for this comment and we fully agree with him on this point. According to reviewer's suggestion, we tried other color schemes, including blue, gray, brown, etc. to highlight the difference between positive and negative values. Finally, according to the visual effect and other references, we changed the color scheme.

Specific comments

Regarding the aggregation of impact data to an annual time scale, I would suggest to dedicate a short paragraph in the Discussion [R340-349] to show if results change for a multi-year drought (2000-01) or for a one year drought (2009). You might be better placed to identify example drought events, but it would strengthen statements in R334-346.

Thank you for your suggestion. We have added some explanations about the difference between the results of multi-year drought and single year drought.

The NDVI results show both positive and negative correlations. In lines R334-335, it is stated that this could be due to diversity of land cover, but given the detailed vulnerability factors, I would assume that there could be a more elaborate answer to these correlations. It would strengthen the discussion section to highlight some of correlations to plausible explanation regarding, e.g. land cover, change of cropping, use of perennial crops, etc.

We thank the reviewer for this important comment. According to reviewer's suggestion, we will add some detailed explanation. In other studies NDVI is mainly used to identify vegetation (agriculture) impacts. In this research, affected human and livestock are also collected to measure drought impacts.

Given the large spatial and temporal variability in precipitation [R108-110], it would be relevant to indicate the difference in water resources in addition to the variability in precipitation. The current annual average volume [R114-115] might not be relevant to drought conditions or vulnerability to droughts. The deviation from normal (annual average conditions) is relevant for drought research, how these droughts relate to the already water stressed areas might be detected by the climate indices.

We agree with the reviewer that the spatial and temporal variability in water resources need to be detected, we added the distribution characteristics of water resources in Liaoning Province.

The skewed distribution of water resources might play a part in the results of the DSA and DIA. It would be useful to indicate the deviation from mean, or the difference in source of water, rather than the amount that is available [R336-339]. In 358-360, the source and diversity of water sources is again linked to the vulnerability. This statement could benefit from an example case, where the source or variability in water resources indeed increased the vulnerability, as your results show.

We thank the reviewer for this important comment. We have added some examples the difference of water sources between NLH and PHD. To illustrate the importance of different water sources as you suggest.

Change the layout of Table 1 so that the vulnerability factors are easier readable. This would shift the focus from being on the spatial variability (which would be better shown in a map than a table) to the different vulnerability factors

We thank the reviewer for this comment and we fully agree with him on this point. It would be better shown in a map than a table. We have tried to plot a map to display the vulnerability factors. There will be ten maps (one for each type of drought impact), more space needed for these maps. Also the threshold of each type of drought impacts need be identified. Therefor we used table to show the vulnerability factors.

Depending on the applied drought definition (see general comment 1), mark this in Figure 2 to show the identified droughts. That will make it easier for the reader to deduct how the authors come to their findings in R128.

We agree with the reviewer and we added the definition of drought as suggest. In Figure 2, we use the SPEI as an example to illustrate the historical drought situation in Liaoning Province.

Change the current volumes and amount in [0.1b] yuan of drought impact in percentages. For a reader that is not familiar with current production levels in Liaoning province, it is hard to grasp the loss of 1.89 million tons, or the impact of an economic loss 1.87 billion yuan when the normal conditions are not provided [R120-121]

Thank you for your suggestion. We agree with the reviewer that it is more readable using percentages. Some drought impacts are difficult to express as a percentage, such as economic losses [0.1b], it's difficult for us to get a value to be divided to obtain the percentage. Also, due to the total number of livestock is not available in each city, we can't get the percentage value. As similar with Yield loss due to drought. Above all, it is difficult to show the impacts in percentage since "normal conditions" means there is no drought occurred with no drought impacts.

Repeat the abbreviations in Table 1 in the text and perhaps in Figure 3,4, and 5. The abbreviations are used throughout the result sections, but are only fully explained in Table 1. I would suggest to repeat the abbreviations in the text to enhance the readability. For example, include (DI) in R124 and (SDI) R218. Same for the vulnerability factors NLH and PHD [R223]. It would be better to first write them full, before abbreviating even though these are given in table 1

We thank the reviewer for this comment and we fully agree with him on this point. For Figure 3, figure 4 and figure 5, we have added the full name of the drought impact rather than abbreviations to enhance the readability.

Also we have used the full terms in Discussion and Conclusion when it is first appear.

Need to support claims in drought mitigation strategies (e.g. sinking(?) more wells to enhance resilience to drought) R362-363.

We agree with the reviewer and we have added more drought mitigation strategies.

Could the authors clarify that the drought vulnerability map [R361] is indeed Figure 8?

Based on the results of the vulnerability analysis, figure 8 shows which cities have a higher vulnerability to which drought impacts. It displays that which city is vulnerable to what kinds of drought impacts.

Other than in the abstract (R29-31), no findings are related to future applications for other regions in China. Please revise the abstract, as these statements cannot be supported given the current manuscript.

We thank the reviewer for this comment and we revised the abstract as suggest.

In R124 the meteorological data is introduced, I assume that this data is obtained from all stations in Figure 1, please indicate which stations were use, or refer to the figure in R124. The same holds for the soil moisture data in [R129]

Thank you for your suggestion. We added explanatory text to explain all the sites in Figure 1 were used.

Explain the difference between the applied SPEI using the log-logistic probability distribution (Yu, et al. 2014) [R165-166] and the often used method of Vicente-Serrano, et al. 2010).

Thank you very much for your suggestion, we changed the references.

Timeframe in R231 is 1990-2013 not 2016. Or, perhaps there is a mistake in the Figure 3 legend

Yes, thank you for your suggestion. We have corrected it.

Rephrase line 158-159

Yes we rephrased the sentence to make it clearer.

Rephrase line 286-288

Yes we have rephrased the sentence to make it clearer.

Rephrase line 314-316

Yes, the sentence has been corrected and made clearer.

Add 'of RF' in R356

Corrected.

Rephrase line 358-360

Rephrased.

References

Hao, L., Zhang, X., and Liu, S.: Risk assessment to China's agricultural drought disaster in county unit, Natural Hazards, 61, 785-801, 2011.

Yan, L., Zhang, J., Wang, C., Yan, D., Liu, X., and Tong, Z.: Vulnerability evaluation and regionalization of drought disaster risk of maize in Northwestern Liaoning Province, Chinese Journal of Eco-Agriculture, 20, 788-794, 2012.

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Jinhua, C., Weiguo, Y., Ruina, L., Wei, Y., and Xi, C.: Daily standardized antecedent precipitation evapotranspiration index(SAPEI) and its adaptability in Anhui Province, Chinese Journal of Eco-Agriculture, 2019.

Yu, M., Li, Q., Lu, G., Wang, H., and Li, P.: Development and application of a short- /long-term composited drought index in the upper Huaihe River basin, China, 369, 103-108, 2015.

List of all relevant changes made in the manuscript

Line 7 ‘Centre for Ecology & Hydrology, Oxfordshire’ →‘The UK Centre for Ecology & Hydrology, Oxfordshire’

Line 12 ‘risk assessments;’→ ‘risk assessment’

Line 14-16 we deleted the sentence :‘They can be used to demonstrate whether drought indices (used for monitoring or risk assessment) are relevant for identifying impacts, thus highlighting if an area is vulnerable to drought of a given severity.’

Line 18-22 we deleted ‘. Using multiple drought indices – Standardized Precipitation Index (SPI), Standardized Precipitation Evapotranspiration Index (SPEI), Soil Moisture (SoilM) and the Normalized Difference Vegetation Index (NDVI) – and drought impact data (on crop yield, livestock, rural people and the economy) correlation and random forest analysis were used’

Line 22-24 we deleted the sentence ‘the relationship varies between different categories of drought impacts and between cities.’

Line 23 ‘SPEI’ → ‘Standardized Precipitation Evapotranspiration Index’

Line 26-27 we deleted the sentence ‘Based on the linkage, drought vulnerability was analyzed using various vulnerability factors. Crop cultivated area was positively correlated to the drought vulnerability for five out of the eight categories of drought impacts, while the total population had a strong negative relationship with drought vulnerability for half the drought impact categories.’

Line 29-30 ‘region, and provides a methodology for application for other regions of China (and other countries) in the future, as well as providing’ →‘region and provide ’

Line 33-36 ‘Drought is one of the most pervasive natural hazards with some of the greatest societal impacts (Belal et al., 2014), but is challenging to understand, quantify and manage. These challenges arise from the typically wide spatial extent of droughts, their frequent occurrence and the non-structural, diffuse and delayed nature of drought impacts.’ → ‘Drought is one of the most pervasive natural hazards which can cause huge societal impacts. Drought impacts are mainly non-structural, widespread over large areas, and delayed with respect to the event; therefore, it is challenging to properly define, quantify and manage drought’

Line 36 we added the definition of drought: ‘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). Then other types of drought can follow this definition.'

Line 36 'economic losses' → 'impact in many sectors'

Line 39 'successive'→ 'consecutive'

Line 42 -45 we deleted the sentence 'There are numerous approaches to drought risk assessment, and these can be grouped into two broad classes: one based on the definition of drought risk, which combines the frequency of drought and the possible drought impacts. The other is an assessment method for establishing indices to measure the hazard, vulnerability and exposure of drought (Jin et al., 2016).'

Line 47 'To adequately define'→ 'However, to adequately assess drought'

Line 51-52 we deleted the sentence 'the selected index should reflect the type of drought one wishes to monitor and manage.'

Line 53 we added 'different types of drought which can be monitored, e.g., meteorological, hydrological and agricultural (Erhardt and Czado, 2017). '

Line 57 we added the comparison of the related drought studies '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 (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 emphasize on difference of timescales. Wu et al. (2013) developed an Integrated Surface Drought Index for agricultural drought monitoring in mid-eastern China. Drought indices are focus on meteorological and agricultural drought monitoring in China. Based on previous drought studies, SPI, SPEI, soil moisture and NDVI were selected in this research for meteorological and agricultural drought.'

Line 60 'drought impact'→ 'drought impacts'

Line 61 '(Bachmair et al., 2016b)' → ' (Bachmair et al., 2016a;Bachmair et al., 2016b)'

Line 66 ' impacts a'→ ' impacts from a'

Line 71 'informative;' → 'instructive and'

Line 78 'Bachmair et al. (2014) and Bachmair (2016b) used drought impacts'→ 'Stagge et al. (2014) and Bachmair (2016b) used drought impacts'

Line 80 'Whilst Blauhut et al. (2015) developed' →'whilst Blauhut et al. (2015a) and Blauhut et al. (2015b) '

Line 82 ‘They assumed drought impacts were only measured by the drought impact occurrence, meaning that all drought impacts have equal weight without considering the duration, intensity or spatial extent of the impacts;’ → ‘However, they assumed drought impacts were only measured by the drought impact occurrence (i.e. whether there was, or was not, an impact in a given month), meaning that all drought impacts had an equal weight without considering the duration, intensity or spatial extent of the impacts.’

Line 83 we deleted ‘; a similar logistic regression approach was also used by Stagge (Stagge et al., 2014).’

Line 87 ‘In China, previous studies have also focused on agricultural drought. ’→ ‘In China, previous studies have also focused on agricultural drought risk assessment. ’

Line 87 we added ‘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.’

Line 91 we added a comparison with previous drought impact studies in China

‘In drought impacts studies, 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 only measured by affected crop area in a 10-day time step in county level. In our research, eight types of drought impacts are collected to measure drought impacts in city 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 92 ‘have focused’→ ‘have been focused’

Line 94 ‘Blauhut et al. (2015), ’→ ‘Blauhut et al. (2015a) and Blauhut et al. (2016)’

Line 114 ‘water resources’→ ‘freshwater resources’

Line 115 ‘Thus, Liaoning is one of the severe water-shortage provinces in northern 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.’

Line 123 ‘1)’→ ‘2.2.1’

Line 125 we deleted ‘, including daily precipitation and temperature’

Line 127 we added ‘(shown in Figure 1) ’ after ‘city’

Line 129 ‘2)’→ ‘2.2.2’

Line 130 ‘ province ’→ ‘ province (shown in Figure 1) ’

Line 134 ‘3)’→ ‘2.2.3’

Line 137 ‘4)’→ ‘2.2.4’

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

Line 154 ‘1)’→ ‘2.3.1’

Line 157 ‘monitoring applications’→ ‘monitoring applications around the world’

Line 157 ‘and the World Meteorological Organization recommend the use of the SPI to ’→ ‘and the SPI is recommended by World Meteorological Organization to ’

Line 158-159 ‘This is due to the relatively simple calculation, flexibility of calculation at different time scales, and the fact it can be compared across time and space.’→ ‘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’

Line 162-163 ‘The SPEI is a very similar concept, using the climatic water balance (that is, precipitation minus potential evapotranspiration, PE). Here, PE is calculated ’→ ‘The SPEI uses the same standardization concept using the climatic water balance (that is, precipitation minus potential evapotranspiration; PET) instead of precipitation. Here, PET is calculated’

Line 165 ‘SPEI ’→ ‘The SPEI ’

Line 165-466 ‘Yu et al. 2014’ → ‘Vicente-Serrano et al., 2010’

Line 170-171 ‘In Liaoning province, precipitation is concentrated between April and September; this is also when the growth stage of spring maize occurs. ’→ ‘Generally, precipitation in Liaoning province is concentrated between April and September; this period corresponds to the growing stage of spring maize’

Line 173 we added ‘during 1990 to 2013’ after ‘drought impacts’

Line 185 we added ‘during 1990 to 2006’ after ‘impact data’

Line 188 we added ‘during 2000 to 2013’ after ‘drought impacts’

Line 189 ‘2)’→ ‘2.3.2’

Line 192 ‘ It can be inferred that the greater impact caused by the same severity of drought (as measured by the relevant index e.g. SPI/SPEI), the higher drought vulnerability of the city.’→ ‘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.’

Line 195 ‘3)’→ ‘2.3.3’

Line 204 ‘Eq. (1)’→ ‘Eq. (3)’

Line 207 ‘each’→ ‘observed’

Line 207 ‘and estimated’→ ‘and the estimated’

Line 210 we added ‘(i.e. if the SPEI6 is excluded from the model, the MSE% of the model may increase)’

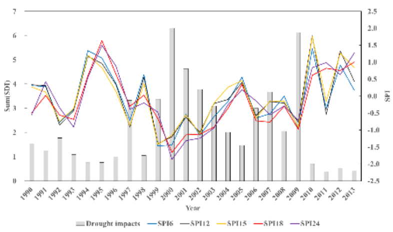
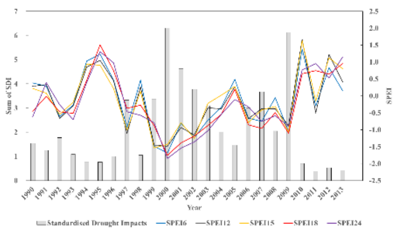
Line 211 ‘the value’→’MSE%’

Line 213 ‘4)’→ ‘2.3.4’

Line 215 ‘Eq. (3) and Eq. (4)’→ ‘Eq. (4) and Eq. (5)’

Line 219 ‘is’→ ‘are’

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

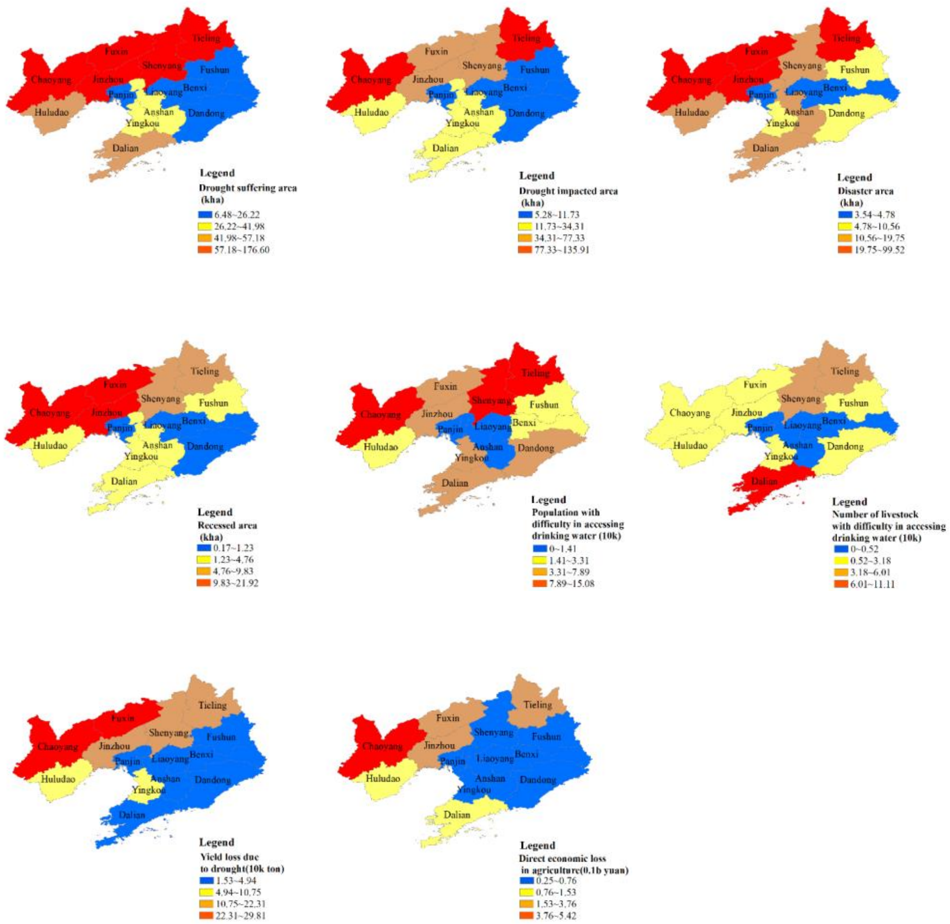
Figure 2  → 

Line 226 ‘Standardized Precipitation Index (SPI)’ → ‘Standardized Precipitation Evapotranspiration Index (SPEI)’

Line 229 ‘The largest’ → ‘From a visual inspection, the largest’

Line 232 ‘ that all categories of drought impacts, more drought impacts ’ → ‘that more serious drought impacts’

Figure 3 replace with the following Figure:



Line 235 '1990-2013 '→ '1990-2016 '

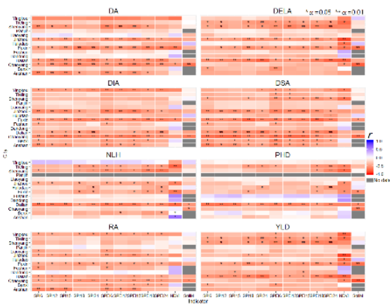
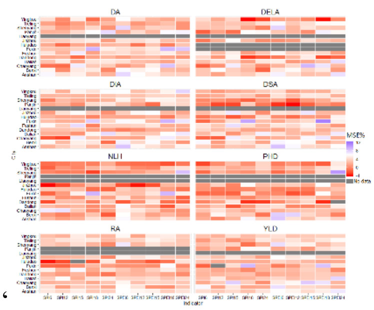
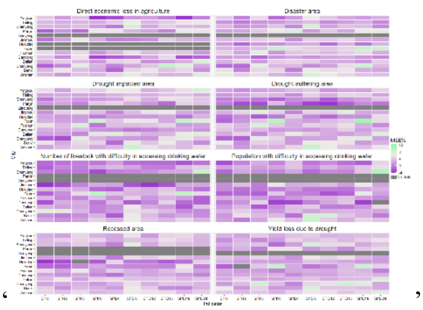
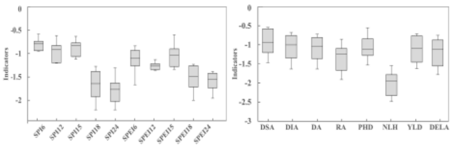
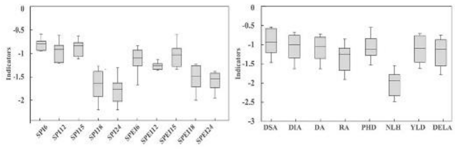
Figure 4 '  '→ '  '

Figure 5 '  '→ '  '

Line 227 'DIS'→ 'DIA'

Figure 6 ‘ 

’→ ‘ 

’

Line 287-289 ‘It can be surmised, for practical purposes, that the worse the drought impacts associated with a given drought severity (defined by SPEI6), the higher drought vulnerability of the city to the given impact. Fuxin, Tieling, Chaoyang, Jinzhou and Shenyang have a higher vulnerability to DSA compared to the other cities.’→ ‘ It can be surmised that the more serious of drought impacts for a specific drought severity (as defined by SPEI6), the higher drought vulnerability. Fuxin, Tieling, Chaoyang, Jinzhou and Shenyang have a higher vulnerability to DSA compared to the other cities.’

Line 290 ‘Similar analyses were conducted for all impact types, and Figure 8 summarises which drought impacts each city was the most vulnerable to. ’→ ‘Similar analyses were performed for all impact types, and Figure 8 displays which drought impacts each city in Liaoning province is most vulnerable to’

Line 296 ‘DSA ’ → ‘drought suffering area (DSA)’

Line 301 we deleted ‘ where SPEI6 is equal to -1.5,’

Line 302 we added ‘ Because 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.’

Line 314-315 we deleted ‘combines multiple sources of data such as remote sensing data (NDVI data), soil moisture and meteorological data, and’

Line 316 ‘data was systematically collected from the county level’→ ‘data were systematically collected at county level,’

Line 318 ‘PHD, NLH, YLD and DELA.’→ ‘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 in agriculture.’

Line 321 we added ‘Drought impacts and drought index data are calculated annually. The results may change if we applied the multi-year drought impacts. Longer time scale of indices may has a better correlation with multi-year drought impacts than single year drought impacts.’

Line 334 ‘This is likely due to the complexity of NDVI drivers (e.g. diversity of land cover). ’→ ‘; this is likely due to the complexity of NDVI drivers (e.g. diversity of land cover and crop types 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). '

Line 336 'DSA and DIA' → 'Drought suffering area (DSA) and drought impact area (DIA) '

Line 339 'the amount of water resources available'→ 'the quality of water resources, 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. '

Line 350 'Dalian and Fuxin had the highest correlation coefficient for all drought impact types and indices.' → 'Dalian and Fuxin showed the highest correlation coefficients among drought impacts and drought indices in all cases'

Line 353 'with existing research by (Yan et al., 2012;Zhang et al., 2012)' → 'with existing research by Yan et al. (2012) and Zhang et al. (2012'

Line 354-355 we deleted 'The number of electromechanical wells is associated with low drought vulnerability, this is the critical water source for irrigation and human drinking.'

Line 355 '. In Zhang et al. (2012), indices such as precipitation, water resources, crop area, irrigation capacity and drought resistance cost are used to measure drought risk, result shows that high drought risk was identified in Fuxin, Chaoyang and Shenyang.'→ ' Zhang et al. (2012) used indicators such as precipitation, water resources, crop area, irrigation capacity and drought resistance cost to measure drought risk, they found Fuxin, Chaoyang and Shenyang have a high drought risk. '

Line 356 we added '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. Their result shows that West Liaohe Plain has a high risk. Chaoyang and Fuxin are identified the highest vulnerability in this research and most part of these two cities are located in West Liaohe Plain.'

Line 358 ' it caused yield loss by 80% or more, compared to 10% and 30% for DIA and DA, respectively.' → 'it caused more yield loss compared to DIA and DA. '

Line 356 'The first splitting value tended to decrease as the accumulation periods increase, ' → 'As the accumulation period increased, the first splitting value extracted from the random forest model tended to decrease'

Line 359 we deleted ' amount of impact'

Line 359-360 'compare to human and lot of water source available for livestock. '→ 'compare to human, for example, livestock can drink water from the river directly, but the water quality of the river cannot meet the human drinking needs. ’

Line 361-363 ‘The drought vulnerability map can be used to support drought risk planning, helping decision makers to inform drought mitigation activities (e.g. sinking more wells to enhance resilience to drought). ’→ ‘The drought vulnerability map can be used to support drought risk planning, in order to help decision-makers to implement appropriate drought mitigation activities (e.g. the detection of drivers can support to sink more wells to enhance resilience to drought, allocation of drought mitigation materials and water transport). ’

Line 364 we added ‘, since similar data (e.g. drought impacts, meteorological data) can be collected in other regions.’

Line 372 ‘When and where the most severity drought and impact occurred in study area ’→ ‘When and where the most severe droughts occurred between 1990 and 2013 in Liaoning province’

Line 377 ‘Whether there is an obvious link between drought impact data and drought indices. Which index or set of indices performance best in study area ’→ ‘Which drought indices best link to drought impacts in Liaoning province’

Line 383 have a high ’→ ‘ has a higher ’

Line 387 ‘impacts ’→ ‘impact’

Line 388 ‘ contribute most to’ → ‘have a higher contribution to ’

We added: 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 and daily meteorological data).

Line 404 ‘ 2017YFC1502404’ → ‘ 2017YFC1502402’

Line 405 ‘JZ0145B592016’→ ‘JZ0145B592016, JZ0145B582017’

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

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Abstract. Drought is a ubiquitous and reoccurring hazard that has wide ranging impacts on society, agriculture and the environment. Drought indices are vital for characterizing 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~~s~~. 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.~~ They can be used to demonstrate whether drought indices (used for monitoring or risk assessment) are relevant for identifying impacts, thus highlighting if an area is vulnerable to drought of a given severity.~~ 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)~~. Using multiple drought indices – Standardized Precipitation Index (SPI), Standardized Precipitation Evapotranspiration Index (SPEI), Soil Moisture (SoilM) and the Normalized Difference Vegetation Index (NDVI) – and drought impact data (on crop yield, livestock, rural people and the economy) correlation and random forest analysis were used~~ to identify which indices link best to the recorded drought impacts for cities in Liaoning. The results show that~~ the relationship varies between different categories of drought impacts and between cities.~~ Standardized Precipitation Evapotranspiration Index~~SPEI~~ with a 6-month accumulation (SPEI6) had a strong correlation with all categories of drought impacts, while 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. ~~Based on the linkage, drought vulnerability was analyzed using various vulnerability factors. Crop cultivated area was positively correlated to the drought vulnerability for five out of the eight categories of drought impacts, while the total population had a strong negative relationship with drought vulnerability for half the drought impact categories.~~ This study can support drought planning efforts in the region~~,~~ and~~ provides a methodology for application for other regions of China (and other countries) in the future, as well as providing~~ provide context for the indices used in drought

monitoring applications, so enabling improved preparedness for drought impacts.

1 Introduction

Drought is one of the most pervasive natural hazards which can cause huge societal impacts. Drought impacts are mainly non-structural, widespread over large areas, and delayed with respect to the event; therefore, it is challenging to properly define, quantify and manage drought~~Drought is one of the most pervasive natural hazards with some of the greatest societal impacts (Belal et al., 2014), but is challenging to understand, quantify and manage. These challenges arise from the typically wide spatial extent of droughts, their frequent occurrence and the non-structural, diffuse and delayed nature of drought impacts~~ (Mishra and Singh, 2010)~~(Mishra and Singh, 2010b, a) (National Soil Census Office, 1993;Mishra and Singh, 2010b).~~. 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). Then other types of drought can follow this definition. China has experienced numerous droughts, which have caused great impact in ~~economic losses~~many sectors since the 1950s, especially in Liaoning province in the dry northeast of the country (Zhang, 2004). 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~~successive~~ years of drought (Chen et al., 2016)~~(Chen et al., 2016a, b) (Chen et al., 2016b)~~.

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), providing methods to predict the potential drought risk to society and the environment. ~~There are numerous approaches to drought risk assessment, and these can be grouped into two broad classes: one based on the definition of drought risk, which combines the frequency of drought and the possible drought impacts. The other is an assessment method for establishing indices to measure the hazard, vulnerability and exposure of drought (Jin et al., 2016).~~ The majority of risk assessment efforts focus primarily on meteorological indices of drought, e.g. assessing the risk of a given severity of meteorological drought using historical precipitation data. However, it is just drought severity evaluation, rather than drought risk assessment. ~~t~~To adequately ~~define~~ assess drought risk it is also necessary to characterize the consequences of drought occurrence, i.e. the impacts of drought on society, the economy and the environment.

A wealth of drought indices have been used in the literature (Lloyd-Hughes, 2014), although predominantly for drought monitoring and early warning (e.g. the review of Bachmair et al. 2016b) rather than risk assessment. The range of drought indices reflects the different types of drought which can be monitored, e.g., meteorological, hydrological and agricultural ~~; the selected index should reflect the type of drought one wishes to monitor and manage~~(Erhardt and Czado, 2017)~~(Erhardt and Czado, 2017a, b)~~. Many indices, such as the Standardized 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 for 12 or 24 months are normally applied to hydrological drought monitoring (Hong et al., 2001;Seiler et al., 2002). 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 (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 emphasize on difference of timescales. Wu et al. (2013) developed an Integrated Surface Drought Index for agricultural drought monitoring in mid-eastern China. Drought indices are focus on meteorological and agricultural drought in China. Based on previous drought studies, SPI, SPEI, soil moisture and NDVI were selected in this research for meteorological and agricultural drought. The relationship between drought indices and drought impacts, established by a correlation or some other similar analysis (e.g. 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 provide a proxy for vulnerability by demonstrating adverse consequences of a given drought severity (Stahl et al., 2016)~~(Stahl et al., 2016a;Stahl et al., 2016b)~~.

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., 2016a;Bachmair et al., 2016b)~~(Bachmair et al., 2016a;Bachmair et al., 2016c)~~. Some countries and regions have established drought impact recording systems to analyze 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)~~(Stahl et al., 2016a;Stahl et al., 2016b)~~. Such databases are an important step forward, but the information in them is necessarily partial and biased, 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 formalized network of reporters, who collect drought impacts statistics 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~~informative;~~ 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, linking generally indices like the SPI/SPEI and crop yield. Examples appraising multi-sectoral impacts are much sparser – recent studies tend to be in Europe, utilizing the EDII. Stagge et al. (2014)~~Stagge et al. (2014);Shi (2016)~~ and ~~Bachmair 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. w~~W~~hilst Blauhut et al. (2015a)~~Blauhut et al. (2015b);Blauhut et al. (2015c)(Blauhut et al., 2015c);Blauhut et al. (2015b)~~ and Blauhut et al. (2015b) developed a quantitative relationship between drought impact occurrence and SPEI using logistic regression in four European regions. However, they assumed drought impacts were only measured by the drought impact occurrence (i.e. whether there was, or was not, an impact in a given month), meaning that all drought impacts had an~~They assumed drought impacts were only measured by the drought impact occurrence, meaning that all drought impacts have~~ equal weight without considering the duration, intensity or spatial extent of the impacts~~; a similar logistic regression approach was also used by Stagge (Stagge et al., 2014)~~. Karavitis et al. (2014) described drought impacts transformed into monetary losses to measure drought impacts in Greece. However, it is challenging to transform all drought impacts into monetary units – especially the indirect impacts of droughts.

In China, p(Hong et al.;Wang and Chen;Wu et al., 2013;Yanping et al., 2018)~~previous~~ revious studies have also focused on agricultural drought risk assessment. Hao et al. (2011) ~~Lu and Liu (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. Jia et al. (2011) used the water stress coefficient and duration to establish a drought index. Li et al. (2009) analyzed 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, 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 only measured by affected crop area in a 10-day time step in county level. In our research, eight factors are collected to measure drought impacts in city 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.

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)~~Blauhut et al. (2016);Blauhut et al. (2015a)~~, 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 vulnerability, as quantified in objective 3.

2 Materials

2.1 Study area

Located in the northeastern of China, Liaoning province, comprised of 14 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.

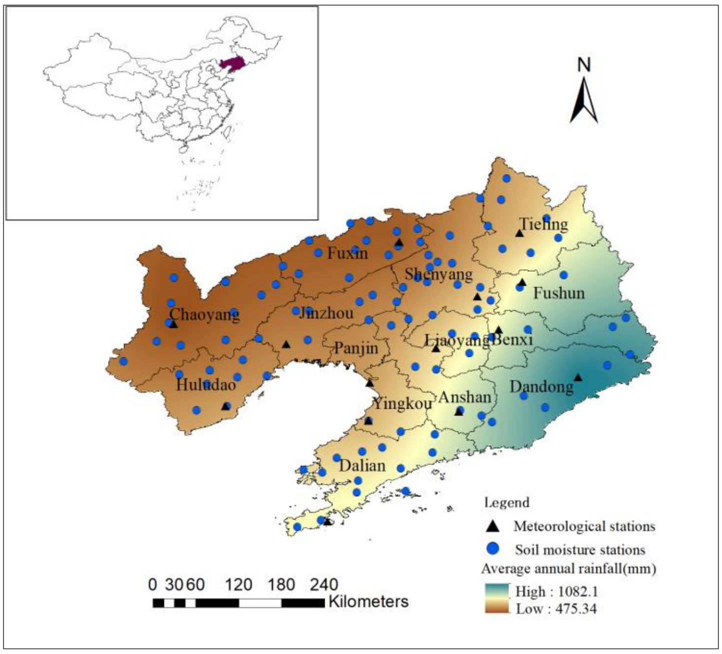


Figure 1: Map showing the 14 cities, the distribution of meteorological and soil moisture stations and the average annual precipitation in Liaoning province.

The annual average volume of freshwater resources 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 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~~Thus, Liaoning is one of the severe water-shortage provinces in northern China~~. Liaoning province is also a highly productive area for agriculture. 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

~~1)~~ 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/)~~, including daily precipitation and temperature~~. 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)~~2.2.2 ~~–~~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 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.

~~3)~~2.2.3 Normalised Difference Vegetation Index (NDVI) data

Monthly MODIS 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.

~~4)~~2.2.4 Impact data

In contrast to many other countries, China has a systematic, centralized 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, the impact types used are listed in Table 1.

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

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

5) Vulnerability factors

~~Vulnerability factors were collected from the 2017 Liaoning province Statistical Yearbook to explain the drought vulnerability (Liaoning Province Bureau of Statistical, 2017).~~ The drought impacts described in Section 2.2.4~~above~~ are mainly focused on agriculture~~, rural populations, agricultural productivity and the agricultural economy~~ sector. As a result of this, ~~;~~the availability of data~~therefore~~ and the findings of Junling et al. (2015) and Kang et al. (2014)~~(Junling et al., 2015;Kang et al., 2014),~~, vulnerability factors relevant to these impacts~~factors relevant to these sectors~~ were selected. Vulnerability factors were collected from the 2017 Liaoning province Statistical Yearbook to assess their contribution to the drought vulnerability (Liaoning Province Bureau of Statistical, 2017). ~~The selected vulnerability factors and data from the 2017 Liaoning Statistical Yearbook are~~ shown in Table 2.

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

City	Per capita gross domestic product(k yuan)	Population (10k)	Crop cultivated area(kha)	Annual per capita water supply(m³)	Per unit area of Fertilizer application(kg/ha)	Effective irrigation rate (%)	Number of electromechanical wells(k)	Reservoir total storage capacity(m m³)	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

~~1)~~2.3.1 Drought indices

Two meteorological indices were selected, Standardized Precipitation Index (SPI; McKee et al., 1993) and Standardized Precipitation Evapotranspiration Index (SPEI;Vicente-Serrano et al., 2010). These standardized indices are widely used in drought monitoring applications around the world, and the SPI is recommended by –World Meteorological Organization ~~recommend the use of the SPI~~ 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~~This is due to the relatively simple calculation, flexibility of calculation at different time scales, and the fact 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 normalization, 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 standardization concept using the climatic water balance (that is, precipitation minus potential evapotranspiration; PET) instead of precipitation. Here, PET~~The SPEI is a very similar concept, using the climatic water balance (that is, precipitation minus potential evapotranspiration, PE). Here, PE~~ is calculated by the Thornthwaite method (Thornthwaite, 1948), using observed temperature and sunlight hours (estimated from latitude) as inputs. The SPEI are calculated by normalizing the climatic water balance using a log-logistic probability distribution (Vicente-Serrano et al., 2010)~~(Vicente-Serrano et al., 2010;Yu et al., 2014)~~. SPI and SPEI are easily calculated and can fit a wide range of time scales (e.g. 1, 3, 12, 24, 72 months) of interest (Edwards, 1997). SPEI has the added advantages of characterizing 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). Generally, precipitation in Liaoning province is concentrated between April and September; this period corresponds to the growing stage of spring maize~~In Liaoning province, precipitation is concentrated between April and September; this is also when the growth stage of spring maize occurs~~. Considering the climatology and crop growth period, SPI6 and SPEI6 ending in September were selected, i.e. calculated using precipitation during April to September. The 12, 15, 18 and 24 months SPI and SPEI in ending December– were analyzed 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).

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

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

Where θ_i is the soil moisture of the *i*-th layer (i=1, 2, 3). θ_{10}, θ_{20} and θ_{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 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 analyzed with the annual drought impact data during 1990 to 2006. 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.

~~2)~~2.3.2 Correlation analysis

The Pearson correlation method was used to characterize the correlation between indices and various 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. 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 ~~It can be inferred that the greater impact caused by the same severity of drought (as measured by the relevant index e.g. SPI/SPEI), the higher drought vulnerability of the city~~.

~~3)~~2.3.3 Random forest modeling

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. (~~1~~3), was used to evaluate the importance of each index:

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

Where y_i and $\hat{y}_i$ are the ~~each~~ 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 ~~the value~~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.

~~4)~~2.3.4 Standardization of drought impacts and vulnerability factors

To ensure comparability and to facilitate the visualization of the drought impacts and vulnerability factors, they were standardized to a value from 0 to 1 using Eq. (~~3~~4) and Eq. (~~4~~5) (Below et al., 2007)~~(Below et al., 2007b;Below et al., 2007a)~~.

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

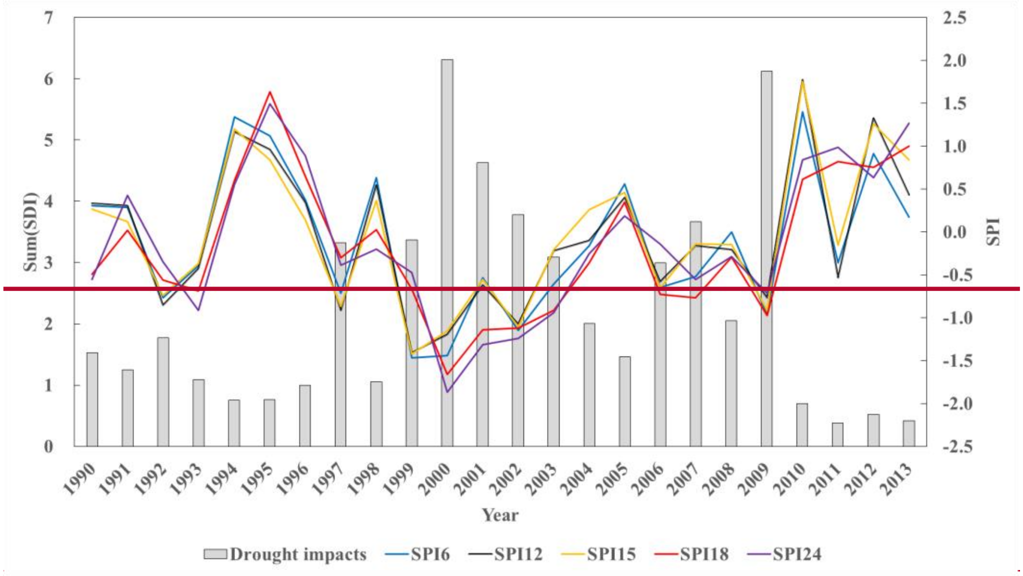
$$SVF_j = \frac{VF_j - \min VF}{\max VF - \min VF} \qquad (5)$$

Where SDI_i and DI_i are the Standardized Drought Impacts and drought impacts of year *i* in Liaoning province, respectively. max *DI* and min *DI* are~~is~~ 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~~ high consistency between~~ 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.



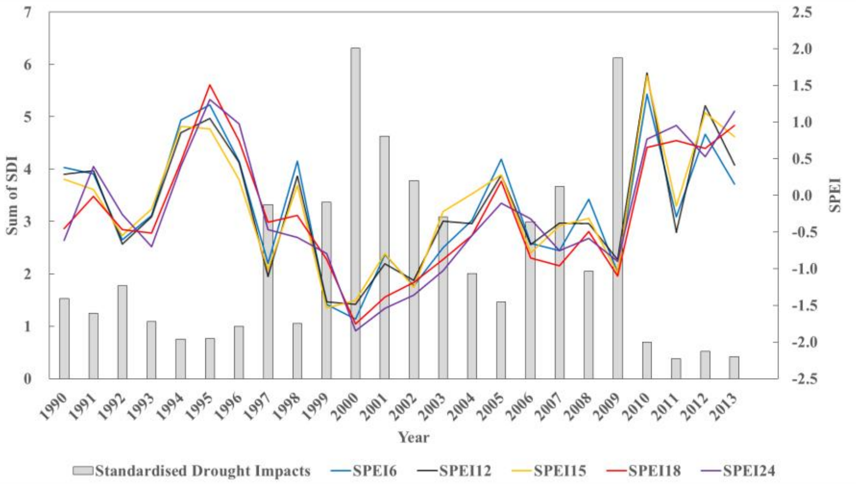
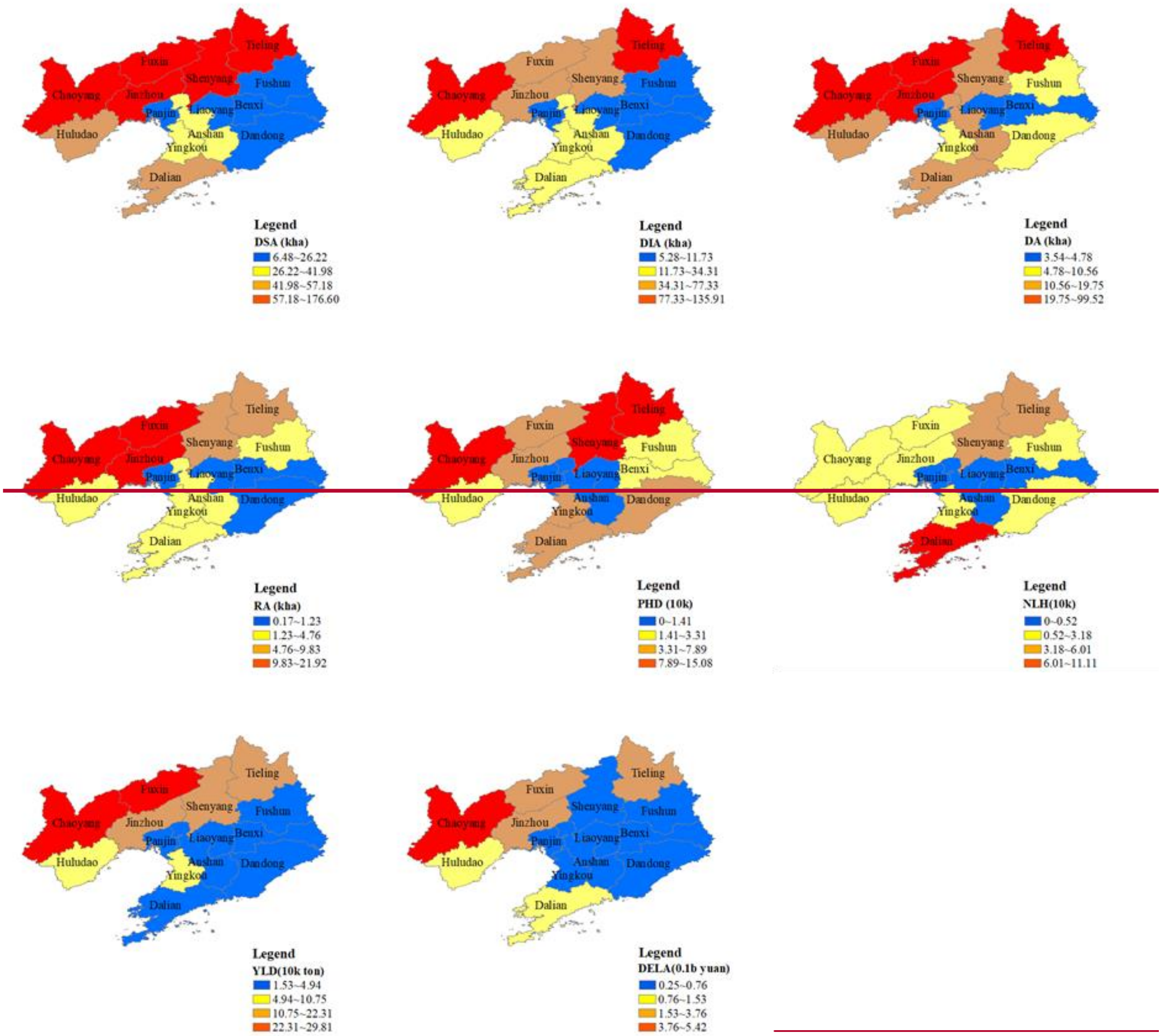
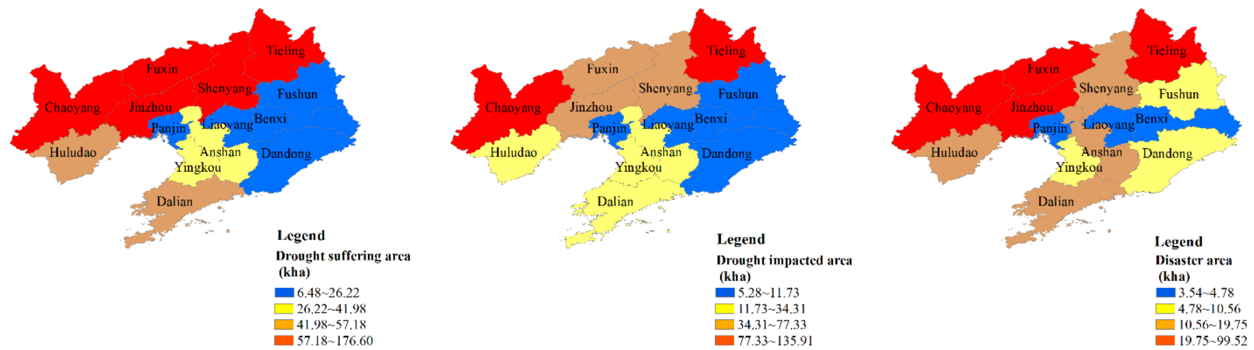


Figure 2: Standardized Precipitation Evapotranspiration Index (SPEI) for 6-, 12-, 15-, 18- and 24-month accumulation periods and the sum of the Standardised Drought Impacts (SDI) for each impact type listed in Table 1 for Liaoning province from 1990 to 2013.

The 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, ~~T~~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 this will be explored quantitatively in the next sections.

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


Legend
DSA (kha)
6.48~26.22
26.22~41.98
41.98~57.18
57.18~176.60
Legend
DIA (kha)
5.28~11.73
11.73~34.31
34.31~77.33
77.33~135.91
Legend
DA (kha)
3.54~4.78
4.78~10.56
10.56~19.75
19.75~99.52
Legend
RA (kha)
0.17~1.23
1.23~4.76
4.76~9.83
9.83~21.92
Legend
PHD (10k)
0~1.41
1.41~3.31
3.31~7.89
7.89~15.08
Legend
NLH(10k)
0~0.52
0.52~3.18
3.18~6.01
6.01~11.11
Legend
YLD(10k ton)
1.53~4.94
4.94~10.75
10.75~22.31
22.31~29.81
Legend
DELA(0.1b yuan)
0.25~0.76
0.76~1.53
1.53~3.76
3.76~5.42


Legend
Drought suffering area (kha)
6.48~26.22
26.22~41.98
41.98~57.18
57.18~176.60
Legend
Drought impacted area (kha)
5.28~11.73
11.73~34.31
34.31~77.33
77.33~135.91
Legend
Disaster area (kha)
3.54~4.78
4.78~10.56
10.56~19.75
19.75~99.52

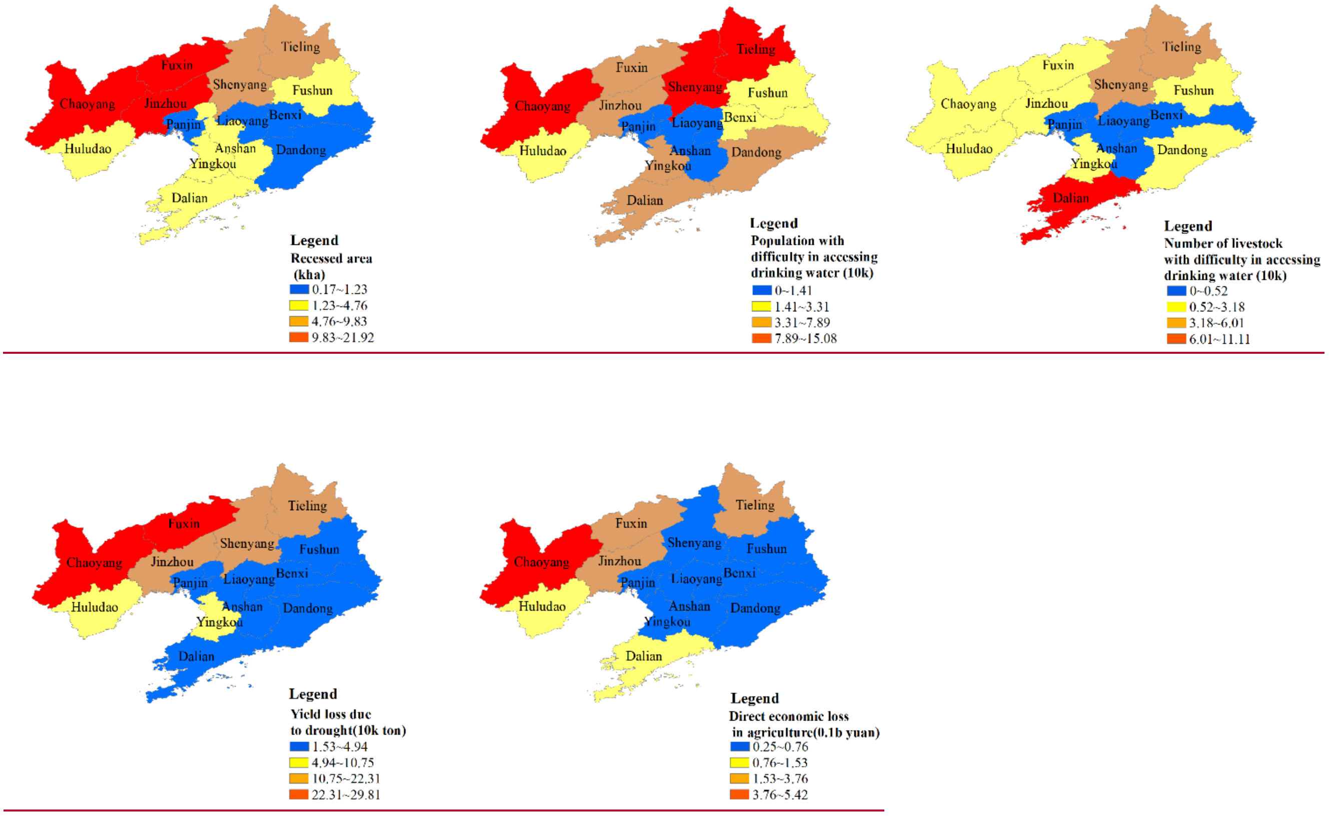
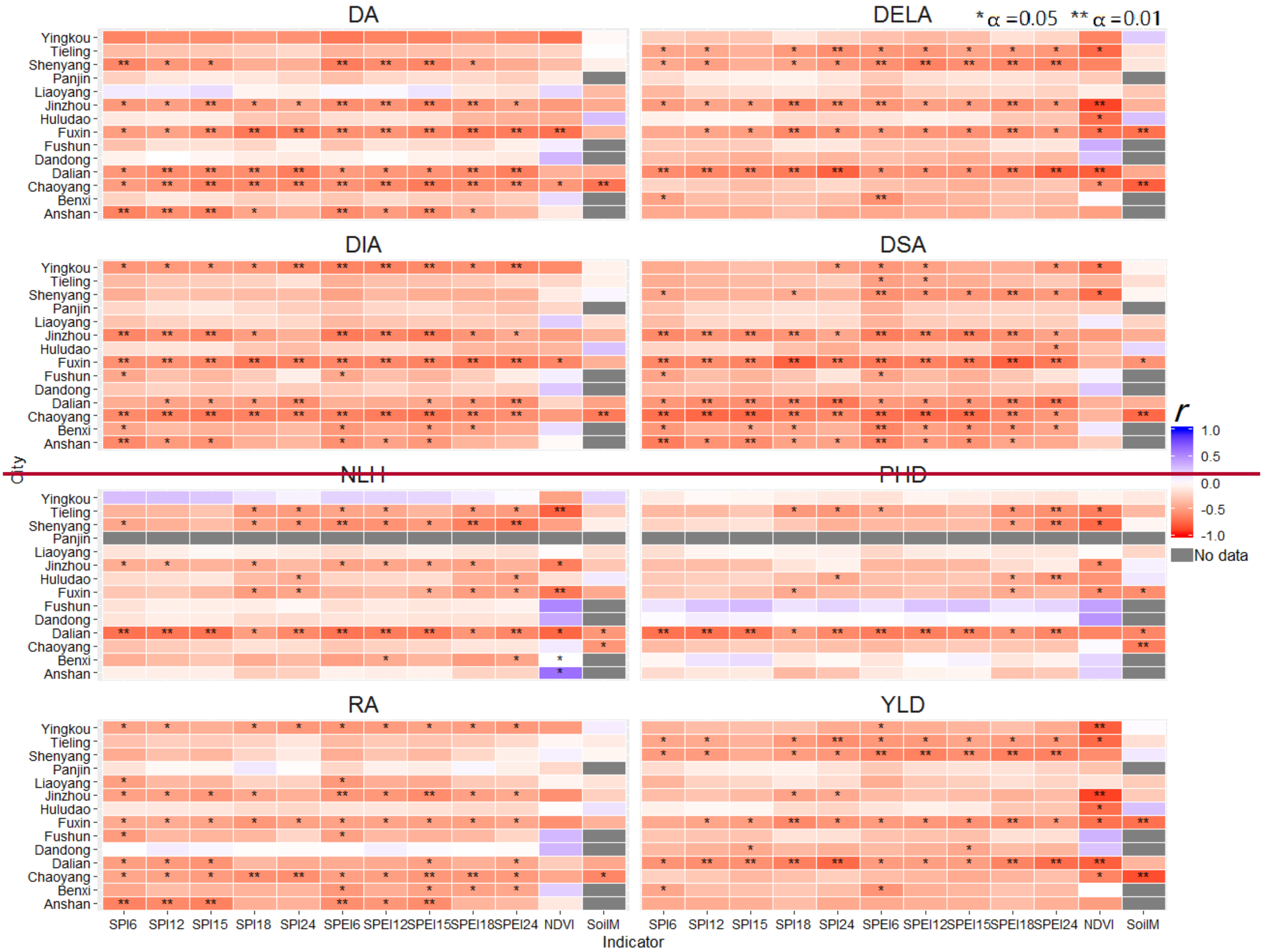


Figure 3: Distribution of average drought impacts (for each impact type, identified by the codes in Table 1) for the period 1990-2016~~3~~ in Liaoning province.

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 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 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.


DA
DELA
* α =0.05 ** α =0.01
DIA
DSA
NLH
PHD
RA
YLD
Yingkou
Tieling
Shenyang
Panjin
Liaoyang
Jinzhou
Huludao
Fuxin
Fushun
Dandong
Dalian
Chaoyang
Benxi
Anshan
City
SPI6 SPI12 SPI15 SPI18 SPI24 SPEI6 SPEI12 SPEI15 SPEI18 SPEI24 NDVI SoilM
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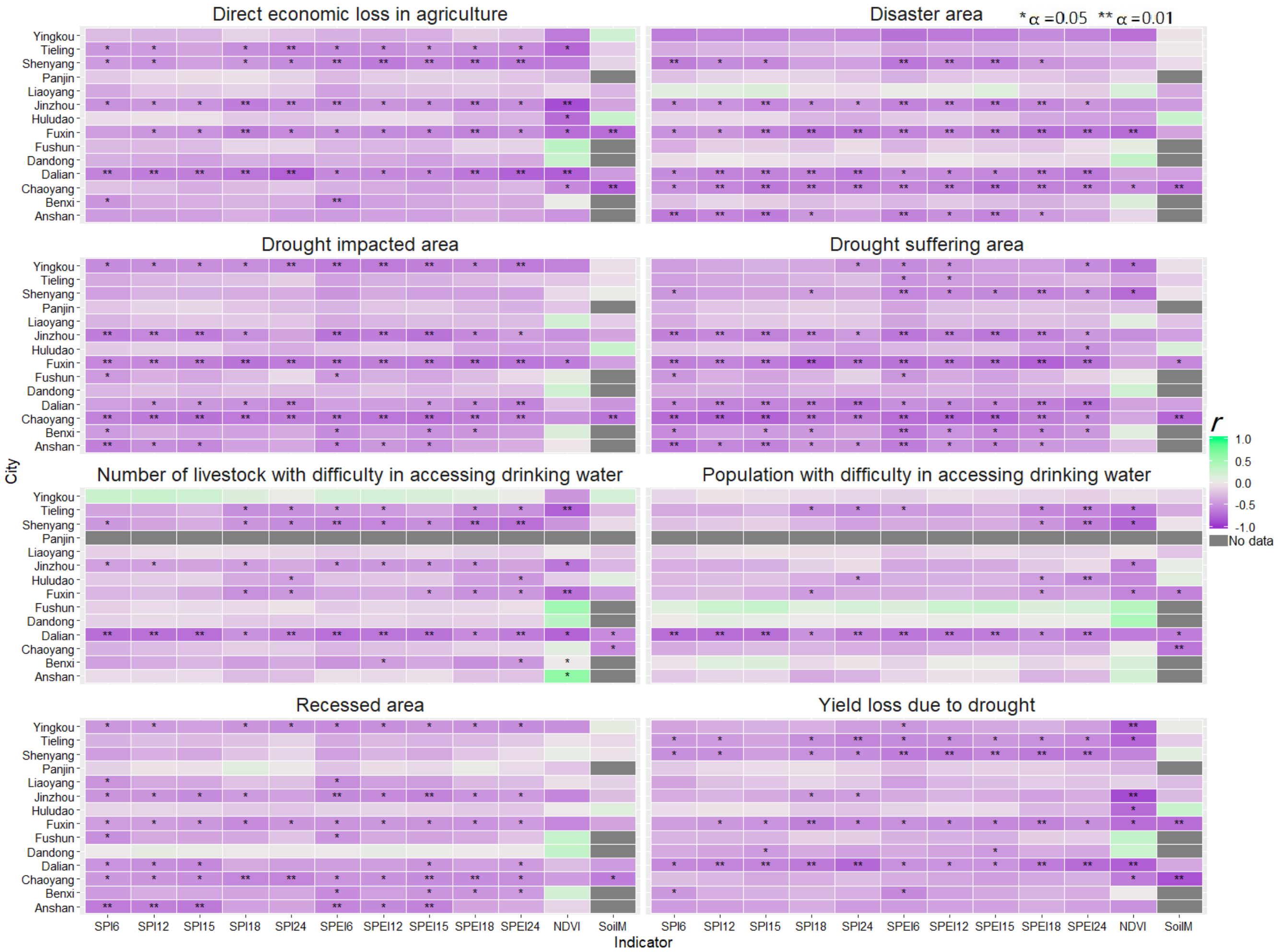


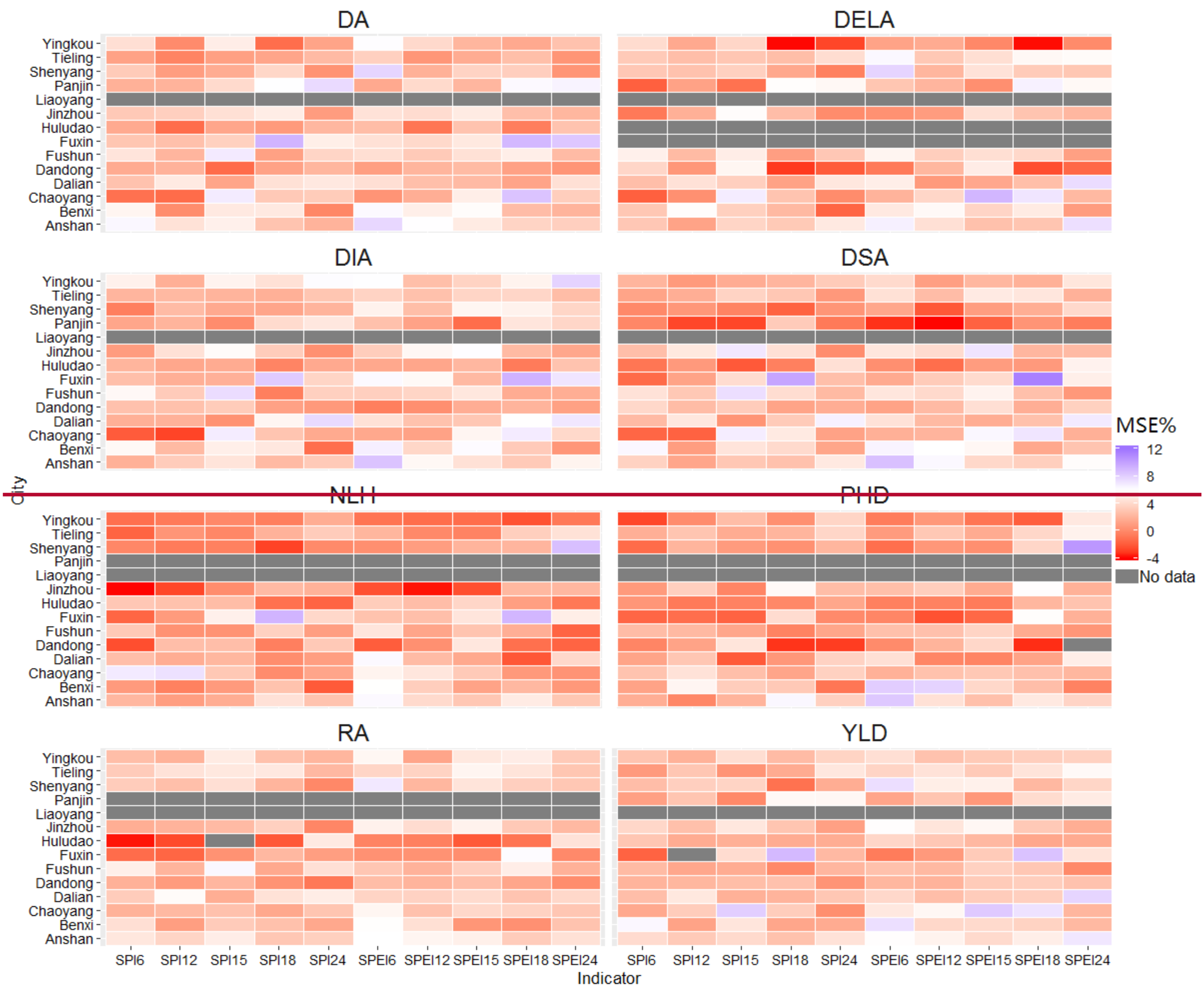
Figure 4: Correlation coefficient (*r*) between drought indices (SPI, SPEI, NDVI and SoilM) and drought impacts for different impact types (identified by the codes in Table 1) in Liaoning province. The significance level of the correlation is indicated using asterisks.

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 (α=0.01), whilst other cities were not significantly correlated.

3.4 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 drought impacts. Indices had a higher importance with impacts in Anshan and Dalian and lower importance in Yingkou and Dandong.



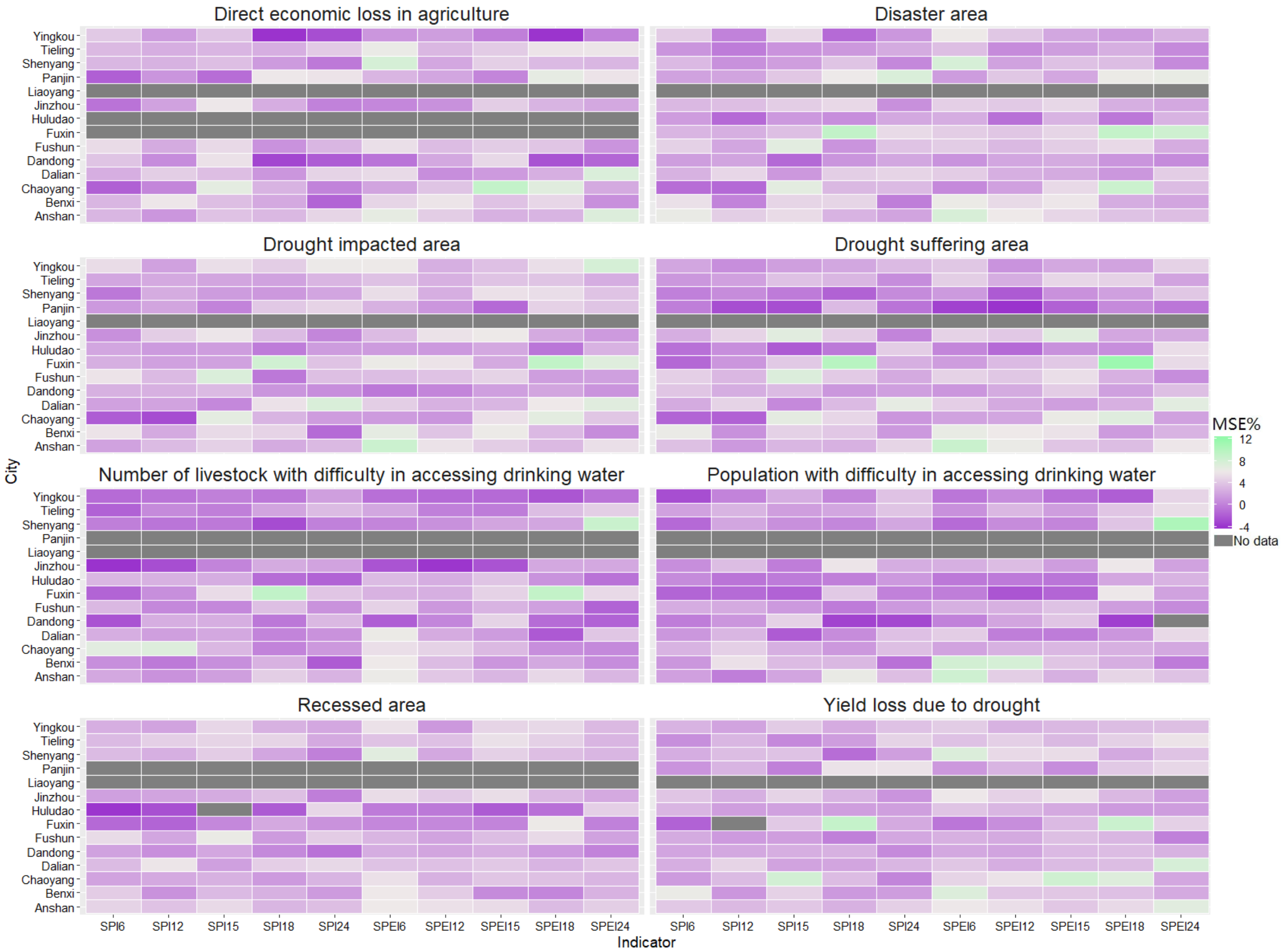
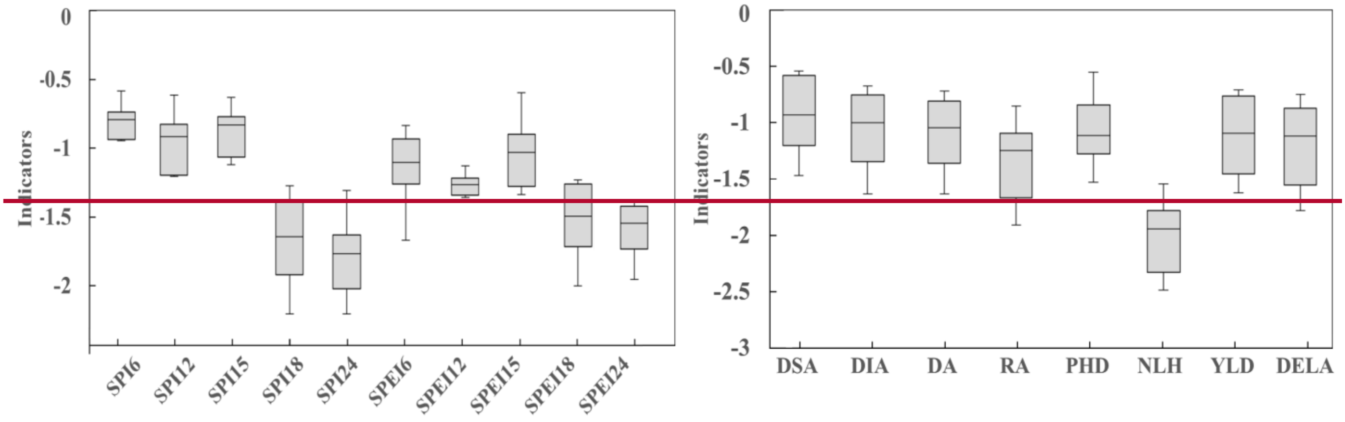


Figure 5: The MSE% of drought indices (SPI and SPEI) with drought impacts (identified by the codes in Table 1) in Liaoning province using random forest.

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 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, DI~~S~~A, 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.



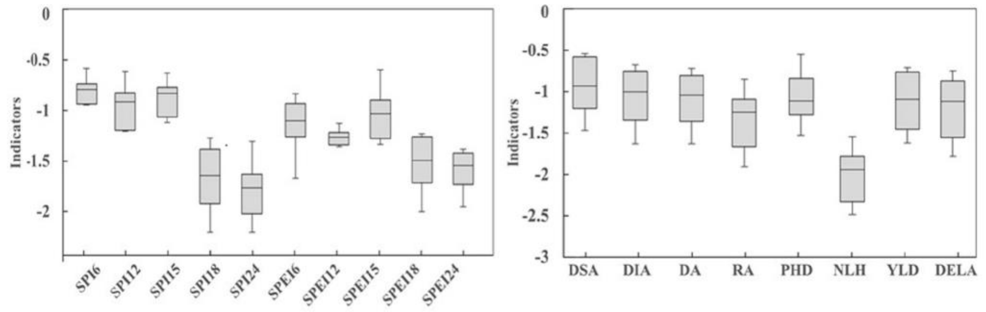


Figure 6: Box plots showing the splitting value (i.e. the thresholds of impacts) in random forest construction across all impact types for each index (left), and across all indices for each impact type (right) in Liaoning province.

3.5 Drought vulnerability evaluation

The results of correlation analysis and random forest show that in most parts of Liaoning province, SPEI at 6-month accumulation period had the strongest correlation 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.~~cities. It can be surmised that the more serious of 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. ~~It can be surmised, for practical purposes, that the worse the drought impacts associated with a given drought severity (defined by SPEI6), the higher drought vulnerability of the city to the given impact. Fuxin, Tieling, Chaoyang, Jinzhou and Shenyang have a higher vulnerability to DSA compared to the other cities.~~

Similar analyses were performed~~conducted~~ for all impact types, and Figure 8 ~~summarises~~displays which drought impacts each city in Liaoning province is most vulnerable to ~~which drought impacts each city was the 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 are all located in the northwest part of Liaoning province. Dalian was most vulnerable to NLH.

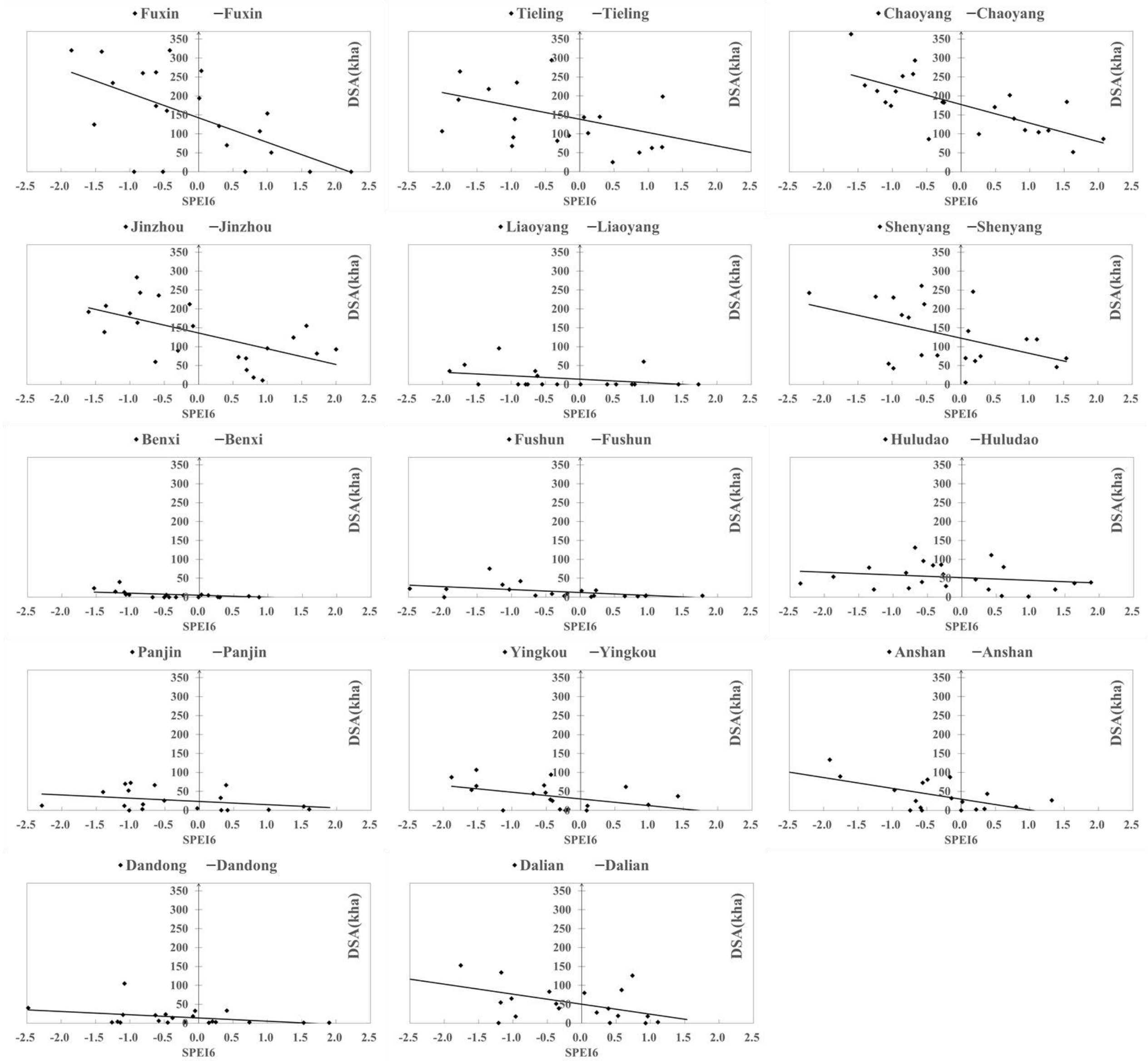


Figure 7: Linear regression results of ~~DSA~~ drought suffering area (DSA) with SPEI6 in each of the 14 cities in Liaoning Province.

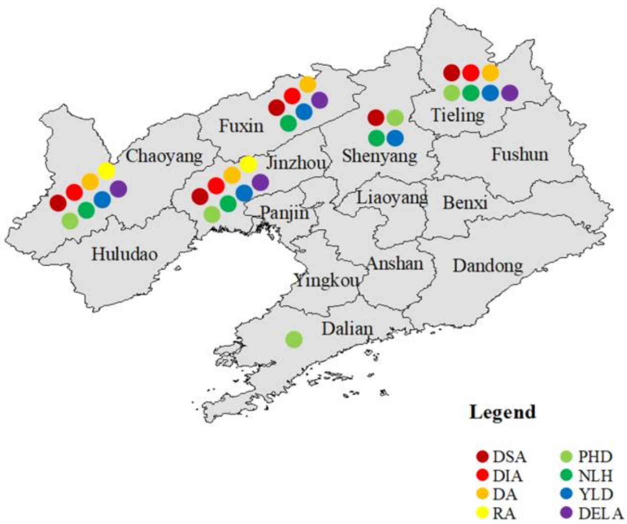


Figure 8: Map showing which drought impacts each city in Liaoning province is most vulnerable to based on the results of the linear regression.

3.6 Vulnerability analysis

A further stepwise regression model was built to explain the variation in each type of Standardised Drought Impact ~~where SPEI6 is equal to -1.5,~~ using vulnerability factors (listed in Table 2) as predictors. Because 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.

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

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 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 following characteristics. Firstly, it ~~combines multiple sources of data such as remote sensing data (NDVI data), soil moisture and meteorological data, and~~ takes many drought impacts, across a range of sectors, into consideration. Secondly, the extensive drought impact data were systematically collected at~~data was systematically collected from the~~ 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 such as population with difficulty in accessing drinking water~~PHD~~, number of livestock with difficulty in accessing drinking water~~NLH~~, yield loss due to drought~~YLD~~ and direct economic loss in agriculture~~DELA~~. Thirdly, we not only considered the occurrence of drought events, but also the severity of drought and its spatial extent. Finally, the drought indices-impacts linkage was applied to assess drought vulnerability in Liaoning province.

The biggest challenge of this study was the spatial and temporal matching between the drought impacts and indices. Drought impacts and drought index data are calculated annually. The results may change if we applied the multi-year drought impacts. Longer time scale of indices may has a better 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 collected at a daily resolution, in order to match up soil moisture and impact data, the March to October average 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. 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, but again this does not take all drought events during crop growth period into account. The correlation coefficients characterizing 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).~~This is likely due to the complexity of NDVI drivers (e.g. diversity of land cover). (Miao et al., 2018;Rajpoot and Kumar, 2018;Trigo et al., 2015;Wang et al., 2015)~~

~~Leng et al. (2015)Xiao-jun et al. (2012)Hao et al. (2011)~~

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 factors, such as drinking water source location and the quality~~amount~~ of water resources~~ available~~, 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 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, because of the limitation of the impacts data. Collinearity of the drought indices (e.g. SPI6 is correlated with SPEI6) is~~ a~~ 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 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 an artifact of imperfect data. To explore this 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. 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~~Dalian and Fuxin had the highest correlation coefficient for all drought impact types and indices~~. 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)~~(Yan et al., 2012;Zhang et al., 2012)~~, which established a drought risk assessment index system to assess drought risk in northwestern Liaoning~~. The number of electromechanical wells is associated with low drought vulnerability – this is the critical water source for irrigation and human drinking~~. Zhang et al. (2012) used indicators such as precipitation, water resources, crop area, irrigation capacity and drought resistance cost to measure drought risk, they found Fuxin, Chaoyang and Shenyang have a high drought risk.

The above results are also in general agreement with Hao et al. (2011)~~Lu and Liu (2011)Lu and Liu (2011)Lu and Liu (2011)Lu and Liu (2011)~~, their study used 10-day affected crop area data as the drought impacts to assess drought risk in China in county unit. Their result shows that West Liaohe Plain has a high risk. Chaoyang and Fuxin are identified the highest vulnerability in this research and most part of these two cities are located in West Liaohe Plain~~Hao et al. (2011)~~.

As the accumulation period increased, ~~T~~the first splitting value extracted from the random forest model tended to decrease~~ as the accumulation periods increase~~, suggesting that higher water deficits are required for the same~~ amount of~~ impact at longer accumulation periods. There is a more severe water deficits of RA occurrence since it caused more yield loss ~~by 80% or more,~~ compared to~~ 10% and 30% for~~ DIA and DA~~, respectively~~. Livestock drinking water requires lower water quality compared to that for human~~s and lot of water source available for livestock~~, 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 of a drought impacts predictor. 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~~The drought vulnerability map can be used to support drought risk planning, helping decision makers to inform drought mitigation activities~~ for example, by sinking more wells to enhance resilience to drought~~(e.g. sinking more wells to enhance resilience to drought~~). 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 similar data (e.g. drought impacts, meteorological data) can be 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. 2016).

5 Conclusion

This study used correlation analysis and random forest methods to explore the linkage 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: When and where the most severe droughts occurred between 1990 and 2013 in Liaoning province~~When and where the most severity drought and impact occurred in study area~~?

Based on the drought monitoring results of SPI, severe drought 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 with the recorded drought impacts.

2： Which drought indices best link to drought impacts in Liaoning province~~Whether there is an obvious link between drought impact data and drought indices. Which index or set of indices performance best in study area~~?

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. Which city or areas ~~have~~ 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~~s~~ data.

4: Which vulnerability factor or set of vulnerability factors have a higher contribut~~e~~ion ~~most~~ to drought vulnerability?

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

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 and daily meteorological data).

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, visualization 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.

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