Response to Editor Decision: Reconsider after major revisions (further review by editor and referees) (27 Dec 2018) by Margreth Keiler

Dear Prof. Keiler

Thank you very much for your consideration of our paper for the potential publication and your suggestions about the major revision. We have carefully revised the manuscript following comments point-by-point, as well as the revision plan we prepared and submitted earlier. We prepared three documents as requested: (1) a point-to-point reviewer response document including original comments/questions, our response, and corresponding revisions made in the manuscript, (2) a track-change manuscript showing all the detailed modifications in the manuscript, and (3) a clear manuscript after revision.

Again, we appreciate your kind help in the reviewing and revision process. We look forward to further updates from you.

Warm regards,

Tao Ye
On behalf of the co-authors

Reponses to Reviewer #1

We greatly appreciate your comments and suggestions. We have revised the manuscript according to what you have pointed out and believe that the quality of this manuscript has been improved as a result of the revision. We have included our detailed responses to each of your comments raised. Your original comments are in bold.

General comments:

Natural hazards that lead to disasters can cause tremendous impacts on societies, the environment, and economic wealth of the affected countries. Climate change will exacerbate existing challenges relating to livestock snow disaster risk. Adapting to climate change is a necessity for sensitive areas and those that are vulnerable to climate change such as the Qinghai-Tibetan Plateau. To investigate and better understand the risk of livestock snow disasters in the Qinghai-Tibetan Plateau is critical to towards sustainability of grassland animal husbandry and livelihood of the herdsmen. This topic fits well with the mission and scope of Natural Hazards and Earth System Sciences. However, there are still many flaws in the current manuscript.

Special comments:

1. There are many abbreviated symbols in the paper such as QTP, PRA, SDD, BRT etc. Because of too many abbreviations, readers often get confused. It is suggested that a separate symbol page should be set up in front of the manuscript.

RE: Thank you for your kind suggestion. We have added list of abbreviation in the appendix as suggested by the editor. Please refer to the first page of appendix for details.

2. At present, there are many good quantitative methods for the study of snow disaster vulnerability and risk in alpine pastoral areas in particular on the Qinghai-Tibetan Plateau and Inner Mongolia Plateau. In the literature review in the "Introduction", the authors review this issue incompletely. The literature covered is also very limited. And main viewpoint may be biased. For example:

Page 2, lines 19-20, "The first type employs an ordinal risk assessment framework in which the risk index is derived by integrating several indices representing different components of risk";
Page 2, lines 12-13, "The other risk assessment approach is quantitative, often called the probabilistic risk assessment (PRA), in which risk is measured with a probability distribution of socioeconomic losses (consequences)";
Page 2, lines 24-32, "However, studies applying PRA to livestock snow disasters have been limited. Bai et al. (2011) published one of the first trials in applying the PRA framework to a livestock snow disaster risk assessment. In their study, winter season (November to April of the preceding year) average daily snow depth was used to describe snow hazard intensity. Physical vulnerability, a function of livestock mortality rate in response to snow depth, was fitted using historical case data. Using annual average snow depth computed from satellite-retrieved data, return-period livestock mortality and mortality rates were derived as the final risk metrics. Based on their method, quantitative livestock snow disaster risks were mapped nationwide in

China (Shi, 2011). The major flaw of this method was the mismatch between the event-based vulnerability function and annual measure of snow hazard. In another work focusing on Mongolia, a vulnerability function trained from a tree-based model was used, but still on an annual basis".

RE: Thank you for your kind suggestion. We did another round of careful literature search and review and found several important articles i.e. (Dong and Sherman, 2015; Miao et al., 2016; Nandintsetseg et al., 2018; Wei et al., 2017; Yeh et al., 2014). We have re-organized our literature review and added these references into the review section following your suggestion and suggestions from Reviewer #2 (comments 1 and 2). Please refer to page 2, lines 5 – page 3 line 5 in the revised clear manuscript for details (or page 2 line 5 – page 3 line 25 in the manuscript with track changes).

References related to this comment:

Dong, S. and Sherman, R.: Enhancing the resilience of coupled human and natural systems of alpine rangelands on the Qinghai-Tibetan Plateau, Rangel. J., 37(1), i–iii, doi:10.1071/RJ14117, 2015.

Miao, L., Fraser, R., Sun, Z., Sneath, D., He, B. and Cui, X.: Climate impact on vegetation and animal husbandry on the Mongolian plateau: a comparative analysis, Nat. Hazards, 80(2), 727–739, doi:10.1007/s11069-015-1992-3, 2016.

Wei, Y., Wang, S., Fang, Y. and Nawaz, Z.: Integrated assessment on the vulnerability of animal husbandry to snow disasters under climate change in the Qinghai-Tibetan Plateau, Glob. Planet. Change, 157(March), 139–152, doi:10.1016/j.gloplacha.2017.08.017, 2017.

Yeh, E. T., Nyima, Y., Hopping, K. A. and Klein, J. A.: Tibetan Pastoralists' Vulnerability to Climate Change: A Political Ecology Analysis of Snowstorm Coping Capacity, Hum. Ecol., 42(1), 61–74, doi:10.1007/s10745-013-9625-5, 2014.

3. Page 3, lines 13-15, "*Worldwide, the QTP suffers from some of the highest livestock snow disasters due to its large area of snow cover area, longlasting snow cover days, and nomadic grazing. This region is also a hot spot in climate change. Quantitative risk assessments for the present day will likely be a significant source of information for disaster risk reduction*". The above sentence should be moved to before line 5 on the second page.
Delete lines 15-16 of the second page, *"In addition, the framework can be adapted for livestock mortality in snow disasters in the context of future climate change analysis, and therefore support climate adaptation planning for local government and herding communities".*

RE: These places has been revised according to your suggestion.

4. In the "Materials and Methods" section, the Qinghai-Tibet Plateau as case area, it is necessary to have a more comprehensive description of the geographical, environmental, social, and economic backgrounds of the QTP, especially the role of livestock in livelihood for local people.

RE: Per your suggestion, we have added a sub-section exclusively introduce the QTP, including its geographical, environmental social and economic backgrounds, with emphasis on the role of livestock in livelihood for local people. Please refer to section 2.1 in the revised manuscript for details.

5. We know the positive intervention of humans on the grassland ecosystem and that the grassland carrying capacity could be elevated with a reduction of harmful human activities (adverse effect), an increase of disaster prevention capacity. For example, the proportion of

fenced pasture area to the total usable grassland (to show the capacity of grassland biomass to regenerate), the warm shed area per unit of livestock (to illustrate the capacity of livestock to prevent freezing disasters) and the proportion of sown grassland area to the total usable grassland (to descript the capacity of balancing forage supply and demand), accessibility of traffic and information (to depict the capacity of disaster response or prevention), if the above key factors are missing, in other words, if the authors do not emphasize the socio-system intervention for livestock snow disaster assessment, it will be very difficult to objectively assess the risk of snowstorms in livestock.

6. Page 4, line 10, "*prevention capacity as measured by gross domestic production (GDP) of the underlying county*", GDP as prevention capacity is not a scientific proxy, indeed, local fiscal revenue and the intensity of infrastructure construction in animal husbandry (including alpine grassland) are the key to reducing vulnerability and risk of livestock snow disaster.

7. Similarly, page 8-9, in "2.4 Loss modelling", as one of loss index, GDP at county level is not consistent with the risk topic of livestock snow disaster. It is suggested that the added value of animal husbandry at county level should be adopted.

RE: Above comments (5, 6, and 7) are related to each other and are responded together.

We totally agree that it needs a thorough understanding of vulnerability to snow disaster before a good risk assessment carries out. You have offered important insights into local herders' coping capacity to snow disasters, and the factors that you mentioned (fenced pasture area, warm shed area, sown grassland, and accessibility) are critical in deciding vulnerability to snow disaster. These variables are valuable, but mostly only available for certain regions and can only be obtained from interview/survey. Per your suggestion, we checked again the statistical yearbooks, including the provincial statistical yearbooks of Qinghai and Tibet which date back to 1989, and the National County (City) Socioeconomic Statistical Yearbook (2000~), but found little data such as fenced pastures, warm shed areas, and sown grassland area.

So we kept the strategy of using a proxy variable to indicate prevention capacity. Following your suggestion, we collected data on "fiscal revenue" (*Fiscal_Rev*) and "added value in animal husbandry" (*Value_Add*), which could be the first-best choices to denote prevention capacity. In addition, we also considered Fiscal Expenditure (*Fiscal_Exp*) and GDP per capita (*GDP_PC*). All these values were turned to 2015 Yuan. These variables were slightly-to-moderately correlated with GDP. The Pearson correlation coefficients between *Value_Add*, *Fiscal_Rev*, *Fiscal_Exp*, *GDP_PC* and *GDP* are: 0.336, 0.760, 0.420 and 0.223, respectively.

We re-ran our generalized additive model (GAM) as shown in Eq (1) by replacing GDP with each of the four variables, and performed model diagnostics to check goodness-of-fit as well as response curves. Summary statistics of model runs are provided as below:

Table R1 Generalized additive model results by using different socioeconomic factors indicating prevention capacity

$\ln LR = s(Duration) + s(Wind) + s(P) +$	R-sq.(adj)	Deviance explained	GCV	N(sample)	Significance level of the socioeconomic factor
$s(GDP)$	0.554	62.1%	2.5105	79	At 0.01 level
$s(Value\_Add)$	0.563	62.5%	2.5508	73	At 0.01 level
$s(Fiscal\_Rev)$	0.516	58.4%	2.8392	73	Not significant

$s(Fiscal\_Exp)$	0.524	58.4%	2.7301	73	At 0.01 level
$s(GDP\_PC)$	0.506	57.2%	2.8561	74	Not significant

As shown in the table, variable *Fiscal_Rev* cannot improve the prediction of ln*LR* (natural logarithm of mortality rate). *Value_Add* is capable of deriving competing results. The response curves of the variables are also similar: ln*LR* showed downward slope with each of the three variables, indicating decreasing loss rate in response to enhanced prevention capacity.

Given above analysis, together with your suggestion, we have decided to use value added of animal husbandry in our vulnerability function, and update all our results throughout the manuscript. Specifically:

1) We have updated the texts describing the vulnerability function
2) We have re-calculated event and annual loss (mortality rate and mortality), and updated the result maps and tables

In the revised manuscript, we have re-organized our description on the vulnerability function to address the changes made according to your suggestion and our additional analysis listed above. Please refer to section "*2.2.2 Vulnerability function*" in the revised manuscript for details. In addition, we have also supplied a supplementary material about the GAM fitting details of the vulnerability function we have used.

8. Page 7, lines 3-6, the authors stated that "*Historical snow disaster event data with the time of each event for each meteorological station were used to train the BRT model. These data were obtained from two sources. Records for 1980–2007 were obtained from W. Wang et al. (2013) while records from 2008–2015 were obtained from the China Meteorological Science Data Sharing Service System (CMSDS, http://data.cma.gov.cn)*." However, are the identification criteria of the two snowstorm records sources consistent?

RE: This comment is high related to Reviewer #2's comment (Page 7 Lines 4-6: Are there no bias between the two data?). According to (Wang et al., 2013), the data for period of 1980-2007 were obtained from the yearbooks of meteorological disasters. Therefore, these data were originally recorded by provincial meteorological administrations officially, and published as a collection in yearbooks. The data for 2008-2015 were directly obtained from China Meteorological Administration in digital format. Therefore, they are both from official records from meteorological administration, the standards in identifying snow disasters are the same according to local Meteorological Administration officials.

In the revision, we have added the information to clarify that the potenail bias between two data is very limited. "*Records for 1980–2007 were a collection of snow disaster records published in 6 provincial meteorological yearbooks neighboring the Plateau (Wang et al., 2013b). Records from 2008–2015 were obtained from the China Meteorological Science Data Sharing Service System (CMSDS, http://data.cma.gov.cn). Records in both datasets are official observations by the meteorological administrations and are consistent with each other in terms of observation standards*." Please refer to page 6, lines 18-22 in the revised manuscript for details (or page 8 lines 6-11in the manuscript with track changes).

9. Page 8, in "2.3 Exposure", the herd size as a critical proxy of exposure, although the spatial

distribution of livestock size can reflect the extent of snowstorm exposure of livestock, it is well known that the Qinghai-Tibetan Plateau has a vast area with obvious spatial differences, and the distribution density of livestock (the number of livestock per unit area) may be more scientifically and accurately describe the spatial feature of snowstorm exposure.

RE: Thank you for your suggestion. We have changed our term from "herd size" to "herd density" where exposure is discussed. In the exposure map we derived (Fig. A2), the unit has already been (Sheep unit/ha). Accordingly, we will update the risk metrics map in terms of mortality (Fig.7) to show the loss measured with sheep units/km^2.

10. Page 9, lines 1-4, I don't understand that *"County level GDP values were assigned to each grid within its boundary. We used constant GDP values for 2015 for two reasons. First, the results can be directly treated as a stationary time series for estimating the probability distribution, as the influence of prevention capacity improvement has been removed. Second, it meets the goal of risk assessment, to estimate the likelihood of potential loss in the near future*". The GDP of each county changes with time. Dynamic GDP should be used instead of static GDP to predict the probability of loss, which is not consistent with reality.

RE: Thanks for your comment. In our vulnerability function, GDP (has been changed to value added of animal husbandry per your comments 5-7) was used as an indicator of prevention capacity. Therefore, whether to use historical dynamic value or a static present value essentially depends on our purpose of analysis.

1) If we are modeling actual historical losses for model calibration and verification purposes, historical dynamic value should be used (for such discussion, please refer to the response to reviewer#2's comment regarding Page 19 Lines 15-16 and Page 19 Lines 27-28).

2) If we are assessing livestock risk (the probability of potential loss) for the next couple of years, then using present-day prevention capacity would be a better choice than using historical prevention capacity. Then, our risk assessment effort tries to answer "if historical events occur in nowadays prevention capacity, how would the probability distribution of the loss will be". Correspondingly, the risk metrics would be meaningful for prevention planning and insurance implications because we are considering the near future given today's situation.

Technically, to fit a probability distribution from samples of loss requires that the sample data must be at least stationary in its mean and variance, so as to remove any technical, environment, or prevention capacity change effects. This is the reason in many risk assessment research, historical loss must be "detrended" before it was fit (Lobell and Burke, 2010; Maddala, 1977; Ye et al., 2015). In our case, as GDP (or value added in animal husbandry) keeps growing along the time, modeled losses based on historical dynamic GDP (or value added of animal husbandry) will contain obvious trend and therefore cannot be used directly to fit any probability distribution.

In order to better explain the difference, we modeled annual winter losses (from September ~ June of the next year) using both historical (dynamic) and static (2015) value added of animal husbandry, and the time series are shown below (Figure R1).

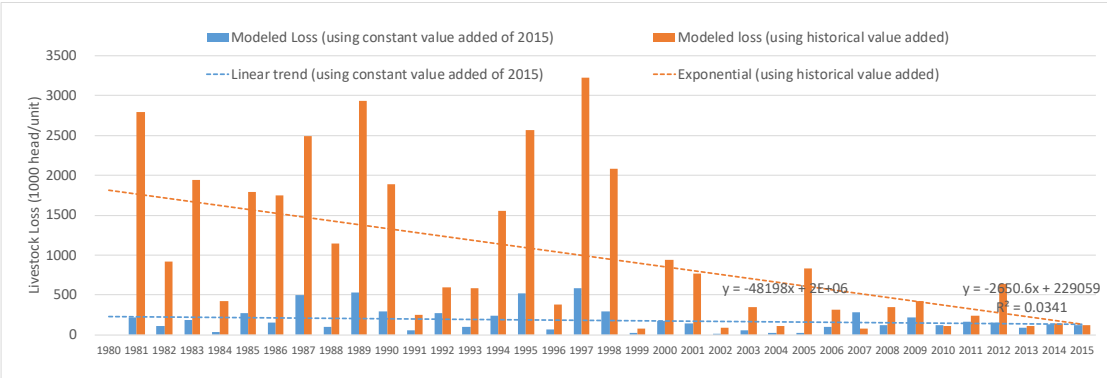

Figure R1 Modeled total livestock loss over the Tibetan Plateau. The blue time series was losses modeled using constant *Value_Add* of year 2015, assuming present-day prevention capacity (static). The orange time series was losses modeled using *Value_Add* of historical values (dynamic), assuming historical prevention capacity. All the losses are for a specific snow disaster season from September to the next June rather than a civil year.

Loss modeled using historical value added of animal husbandry (*Value_Add,* the orange time series in Figure R1) obvious contained trends. It showed an obvious downward trend. Fitting a probability distribution would over-estimate the size of risk. Using a static present value of one recent year, it technically meets the requirement of a stationary time series (the blue trend line is flat in Figure R1). Then losses derived from our event-based model are derived with the prevention level of historical period. Their difference demonstrates the effect of improved prevention capacity (which might echoes the Comment #1 of reviewer2, and provides meaningful discussion for your Comment #11).

In the revision, we have explicitly describe our modeling efforts of modelling annual aggregate losses by using both historical dynamic and 2015-static value added of animal husbandry in "*2.2.4 Loss modelling*". Correspondingly, we have also supplied corresponding results as shown in Figure R1 in the revised manuscript (Figure 6).

11. The discussion part only deals with the content of spatial pattern (4.1 Spatial patterns of livestock snow disaster risk in the QTP). As an important part of risk change, the characteristics of dynamic and temporal variation cannot be absent. Moreover, the authors do not pay attention to the causal relationship between risk and its influencing factors.

RE: Thank you for your comment. We added a new subsection in the result section to show temporal changes of livestock mortality derived from our model, and enrich our discussion by comparing it to historical losses observed. Please refer to the new section "3.1.2 Model-derived annual snow disaster loss, 1980–2015" for details.

The discussion over the causal relationship between risk and its influencing factors can be partly be done by comparing the dynamics of the modeled loss with historical prevention capacity and static present-day prevention capacity, as shown in Figure R1. We have also added discussion about the role of improved prevention capacity in a new section "*4.2 Temporal changes of livestock snow disaster loss and its drivers*".

12. In "4.3 Risk-informed implications" *Page 20, line 22, "Our results imply that the present level of preparedness in local regions are far from sufficient";*
Page 21, line 5, "Due to the difficulty in improving prevention capacity, insurance schemes are

needed to provide relief";
From the perspective of above mentioned sentences, this is not the inspiration of the article analysis, but the main existing problems.

RE: Thank you for your comment. We have revised this part by merging this section into section "*4.3 Advantages of the event-based PRA*". We have deleted the general issues and main existing problems, and tried to concentrate on the unique quantitative information that are offered by the event-based PRA framework, and its implication in risk-informed risk reduction actions.

13. The language of the manuscript is rather deficient and requires the re-editing of native speakers.

RE: We have sent the paper for professional proof-reading service. A proof of the proof-reading service has been included in the re-submission.

Reponses to Reviewer #2

We greatly appreciate your comments and suggestions. We have make a careful plan to revise the manuscript according to what you have pointed out and believe that the quality of this manuscript will be improved as a result of the revision. We have included our detailed responses to each of your comments raised. Your original comments are in bold.

[General comments]

"Probabilistic risk assessment of livestock snow disasters in the Qinghai-Tibetan Plateau" by Ye et al. applies boosted regression tree and general additive modeling methods to the snow disasters in the Qinghai-Tibetan Plateau, as an event-based evaluation, and the results are basically consistent with existing studies. The research topic is within the scope of the journal, but there are some substantial flaws in the study, which should be addressed. The major concerns are:

1: The advantage of event-based evaluation is not clear. Rather than hay preparation based on event-based analysis of this study, that based on annual-based analysis will work well when the intervals between the two events are very short (as time to prepare for the next event is not enough, preparation for annual basis is better, particularly when modeled annual frequency > 1).

Page 19 Sect. 4.2: As "more than one snow disaster a year is unlikely", annual evaluation is enough, isn't it? For me it looks to prepare hay based on annual evaluation is OK.

2. The authors say probabilistic analysis is one of the advantages of the study. However I consider a year-by-year evaluation is more sophisticated, and the probabilistic analysis used here is not necessarily an advantage, but a result of taking a simple evaluation dealing with what should be separately treated as one set of data. An effective PRA would be a result from a probabilistic function, not a result from treating various conditions as one case.

RE: Above questions are inter-related and are therefore responded together.

We totally agree that annual based modeling has its own advantages, but the event-based approach is also very important. By nature, livestock snow disaster can occur multiple times in a winter, and the losses would accumulate event by event. Capturing the details of event occurrence and intensity are important for following aspects:

1) ln*LR* (natural logarithm of loss rate) shows a concave relationship with disaster duration (can be found later in details in response to your comment #4). Therefore, the total loss of one event lasting 30 days and two-event in one winter lasting 15 days each will be different. Knowing only the aggregate duration in a year cannot reflect such important details.

2) Although presently our data shows that historically it has been less likely to have more than 1 snow disaster in a winter for most parts of the Qinghai-Tibet. But if we are considering a method that can be generalized, then we need to consider the possibility of changing frequency and intensity, and the capacity to model it, particularly with the observed and projected slight increase in precipitation on the Plateau (GUO et al., 2018; Kuang and Jiao, 2016). Using the annual loss approach cannot capture such changes.

3) From the perspective of risk-informed actions, annual evaluation (i.e. potential aggregate duration) would be temporarily good for preparedness by the government and community. But it can hardly work for risk-transfer mechanisms as insurance schemes were mostly based on events. This is also the critical reason that catastrophe risk models are mostly built on event-basis (Michel-Kerjan et al., 2013).

For the advantage of this study, we totally agree with you that a year-by-year evaluation is more sophisticated (than a simple statistical analysis). So the advantage should be event-by-event loss modeling, which is even more sophisticated than year-by-year evaluation, rathern than probabilistic analysis. Benefited from your comment, we have added these discussions into the introduction section, page 2 line 29 – page 3 line 4 (or Page 3 Lines 15-25 in the track-change version) and discussion section (section "*4.3 Advantages of the event-based PRA*") to better highlight the advantage of event-based modeling instead of probabilistic analysis.

3: To evaluate livestock number by carrying capacity, and to evaluate carrying capacity by grassland type is questionable. The appropriateness of them should be more carefully discussed.

Page 8 Lines 18-20: More careful discussion on the validity of this method is needed. I want to see the scatterplot of observed and estimated values.

Page 8 Lines 21-22: More careful discussion on the validity of this method is needed. I want to see the scatterplot of observed and estimated values.

Page 21 Lines 19-20: More careful evaluation is needed for the performance of herd size estimation.

RE: Thank you very much for your comment. Above comments are related and therefore responded together.

1) The appropriateness of evaluating livestock number by carrying capacity

We first need to clarify that we are trying to use carrying capacity to evaluate livestock number EXPOSED to snow disaster, but not the total livestock number. In the study area, only livestock grazing on grassland in pastoral and agro-pastoral regions (central to western part of Tibet Plateau) are exposed to snow disaster. Livestock kept in ranches or industrial livestock farms in agricultural regions (mostly the eastern and lower altitude parts of the Plateau) are not. When estimating exposure, we were trying to estimate the livestock number grazing on grassland.

The livestock number grazing on grassland is essentially determined by livestock carrying capacity, which exactly defines the maximum livestock number that can graze in a specific area of grassland, given local forage productivity and grazing style. Since 2011, the Tibet Autonomous Region started the program of "subsidy and award policies for grassland ecological conservation efforts" to reduce the number of livestock and conserve grassland. In 2014-15, news articles intensively reported that "Tibet has basically reached forage-livestock balance" (government release, http://www.gov.cn/xinwen/2014-05/12/content_2677946.htm, in Chinese). In other words, the actual livestock number grazing on grassland (and exposed to snow disaster) is highly consistent to the carrying capacity officially designated.

2) The appropriateness of evaluating carrying capacity by grassland type

Evaluating carrying capacity by grassland type is the way that adopted by both official calculation technical manual (*Ministry Standard of Calculation of Rangeland Carrying Capacity issued by Ministry of Agriculture of China*, NY/T 635-2015) and academic studies regarding forage-livestock balance, i.e. (Xin et al., 2011). Grassland type essentially determines

the key values of evaluating carrying capacity, i.e. forage regrowth percentage, proper utilization rate of rangeland (of different grazing seasons), conversion coefficient of standard hay. Using grassland type as an identifier of different carrying capacity is also the widely adopted way of presenting the evaluation results.

3) Verification of livestock number estimated

We obtained official release of carrying capacity by Tibet Autonomous Region from *Statistical Materials of Grassland Resource and Ecology of Tibet Autonomous Region* published by the Department of Agricultural and Pastoral of Tibet Autonomous Region in year 2011. We used zonal statistics to derive county-level carrying capacity estimated by our method, and compared with the official release (Figure R2).

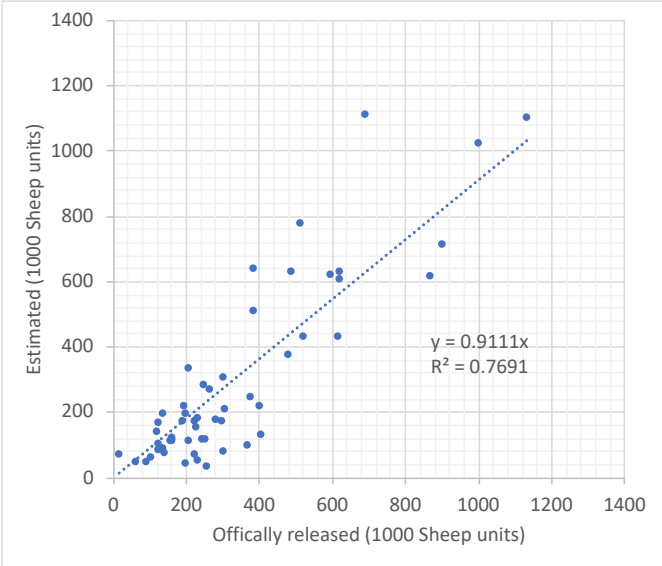

Figure R2 Estimated and officially released livestock carrying capacity in Tibet Autonomous Region

As the above Figure R2 shows, the estimated and officially released livestock carrying capacity basically agree with each other.

In the revision, we have 1) clarified that we are estimating the herd size exposed to snow disaster (livestock number on free grazing) rather than total herd size; and 2) further explained the appropriateness of estimating livestock number of carrying capacity, and estimating carrying capacity by grassland type. Please refer to section "*2.2.3 Exposure*" for more details of the revision.

4. Explanation and discussion on Eq. 1 is not sufficient. The form of functions for each term in the right hand side, and the performance of the equation should be clearly presented.
Page 4 Line 10 (eq 1): Present the detailed forms of s(Duration), s(Wind), s(P) and s(GDP). (all parameters of spline curves)
Page 4 Line 14: More detailed performance check is needed (not for lnLR, but for LR). How large is RMSE? Is the error random or systematic? I want to see the scatterplot of observed and modelled values.

RE: Thank you for these questions and comments. In light of the suggestion from Reviewer #1 (please refer to Reviewer#1 Comments 5,6, and 7), we have updated the model by using value added of animal husbandry of the underlying county instead of GDP as the indicator of prevention capacity. Correspondingly, Eq(1) has been updated to: $\ln LR = s(Duration) + s(Wind) + s(P) + s(Value\_Add)$. Details of the updated model are provided below.

(1) Model-fitting statistic:

```
Family: gaussian
Link function: identity

Formula:
lnLR ~ s(Duration) + s(Value_Add, k = 4) + s(maxWind) + s(P)

Parametric coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)   0.5300     0.1708   3.103  0.00287 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Approximate significance of smooth terms:
               edf Ref.df     F  p-value
s(Duration)  5.626  6.705 9.706 1.96e-08 ***
s(Value_Add) 1.000  1.000 8.878  0.00407 **
s(maxWind)   2.732  3.440 2.747  0.04463 *
s(P)         1.000  1.000 2.809  0.09864 .
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R-sq.(adj) =  0.563   Deviance explained = 62.5%
GCV = 2.5508  Scale est. = 2.1593    n = 74
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Figure R3 Fitting statistic of the updated GAM model

(2) The response curves (spline curves)

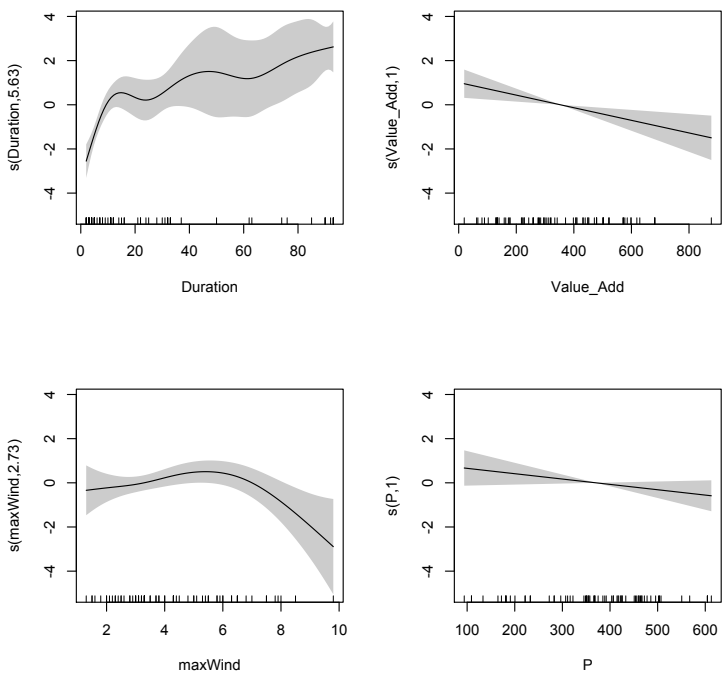

Figure R4 Response curves of the updated GAM model

Its response curves (Figure R4) indicate that: (1) ln*LR* is increasing with snow disaster duration. Duration up to 15-18 d is a critical period that mortality will increase rapidly. (2) ln*LR* decreases with value added of animal husbandry (*Value_Add*), indicating the effect of stronger prevention capacity in reducing mortality, i.e. government expenditure in reserving hay for preparedness, and subsidy to herders to build/enlarge warm sheds. (3) An inverted-U shaped relationship between daily maximum wind speed and ln*LR*. The up-slope part indicates the increasing stress of stronger wind on livestock, but the down-slope part (beyond 5-6 m/s)

indicate herder's reaction to stop free-grazing and keep herds in shelters (Wu et al., 2007). (4) ln*LR* decreases with growing season precipitation. Larger growing season precipitation indicates more abundant food for livestock in summer, and therefore better body-condition in resisting low temperature and lack of food in snow disaster times.

(3) Model performance diagnostics

We performed 10-fold cross validation, and found RMSE, MAE and ME for the model were 1.747, 1.325, and -0.002, respectively.

The performance diagnostics charts of the model (Figure R5) indicate that 1) QQ plot is very close to a straight line, suggesting our distributional assumption of normality about ln*LR* is reasonable. 2) The variance is approximately constant as the mean increases. 3) The histogram of residuals appears approximately consistent with normality. 4) the response against fitted values show a positive linear relationship in the scatter plot.

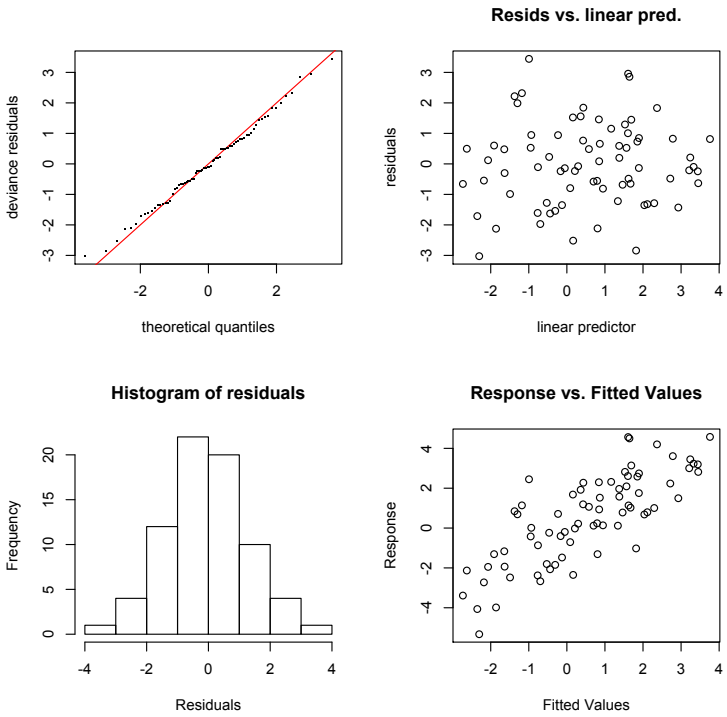

Figure R5 Performance diagnostics charts for the updated GAM model

In the revision, we have supplied more details about the model fitted in to the manuscript. Please refer to section "*2.2.2 Vulnerability function*" for more details. In addition, model details shown here, including the fitting statistics, response curves, and performance diagnostics charts (Figure R3~Figure R5) has been provided as a supplementary material for reference.

[Specific comments]

Page 3 Line 1: Do you mean that the final metrics should always be mortality, not mortality rate? It looks the study considered mortality rate as the final metrics, and I think each study can use its own final metric.

RE: Thank you for your comment. The sentence was misleading. In the revision, we have deleted the latter part of this sentence and kept "*Compared to earlier works, they successfully extended the framework to future climate change analysis*" only.

Page 3 Line 13: Provide the rationale of "some of the highest livestock snow disasters". What is "highest", by the way? Largest damage? Highest frequency?

RE: We intended to say "one of the regions with the highest risk" in terms of both high frequency and large damage. In the revision, we revised this sentence to "*Worldwide, the QTP is a region that has most-suffered from livestock snow disasters due to its large snow cover area, long-lasting snow cover days, and nomadic grazing (Li et al., 2018)*." (page 3, lines 11-12 in the clear version)

Page 3 Line 14: Provide literature for "This region is also a hot spot in climate change".
RE: References will be provided into the text as suggested in the revision, i.e. (Diffenbaugh and Giorgi, 2012; Gu et al., 2014).

Diffenbaugh, N. S. and Giorgi, F.: Climate change hotspots in the CMIP5 global climate model ensemble., Clim. Change, 114(3–4), 813–822, doi:10.1007/s10584-012-0570-x, 2012.
Gu, H., Yu, Z., Wang, J., Ju, Q., Yang, C. and Fan, C.: Climate change hotspots identification in China through the CMIP5 global climate model ensemble, Adv. Meteorol., 2014, doi:10.1155/2014/963196, 2014.

Page 4 Fig 1: It is difficult to understand the relationship between Timing, and Duration and Wind speed from the figure.
Page 4 Sect. 2.1: Fig 1 indicates GDP part is the vulnerability function, while Sect. 2.1 reads Eq. 1 (to derive mortality rate from GDP as well as hazard indicators). Which is true?
RE: Above questions are related and are therefore responded together.

The figure presented in the online document was not complete due to unknown technical reasons when generating .pdf files. The correct figure should be:

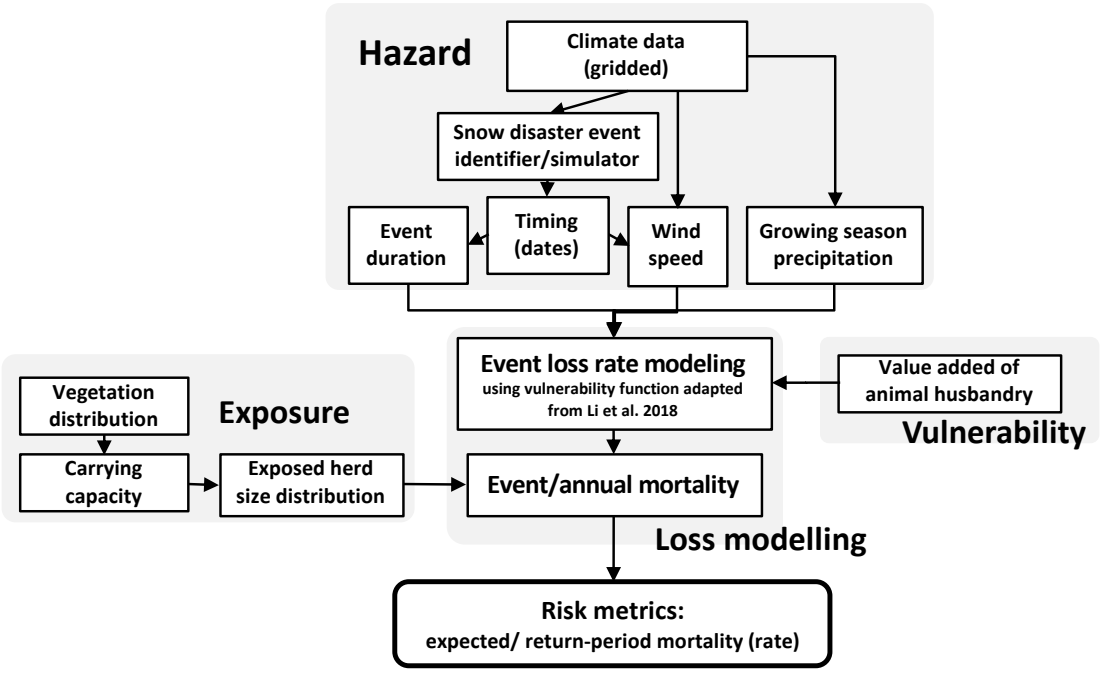

Figure R6 Corrected technical flow of the study (Fig 1 in the manuscript)

In the modeling process, we derive timing (both starting and ending dates) from the "snow disaster event identifier/ simulator". Then the duration of the event (days between the starting

and ending dates) and the wind speed during this period can be derived (as we have daily wind speed data).

GDP (has been replaced by value added of animal husbandry) was one out of the four inputs of the vulnerability function (others were hazard indicators), which was used to indicate prevention capacity. In the revision, we have corrected and updated Fig. 1 in the manuscript by moving the vulnerability function into box "Event loss rate modeling" to keep it consistent with Eq. 1.

Page 5 Line 19: How the data of the previous days are used?
Page 6 Line 14: Why since the last snow fall day?
RE: The two comments are related and are therefore responded together.

We used average daily precipitation (snowfall) since the last snowfall day (the last day with effective precipitation) to represent the diminishing impact/pressure from snowfall as time elapses. In general, the larger amount of snowfall, the longer the impact of the snowfall would be given identical temperature conditions – it would take longer time to thaw. Similarly, the closer a day to the snowfall day, the more likely it would be identified as a "snow disaster" day. It worked especially for deciding whether two snow fall days should be regarded as parts of one single event or two independent events.

Page 6 Lines 12-13: How do you compromise when the two standards are different with each other?
RE: Thank you for your comment. The two standards, although designed for different regions, are not conflicting with each other on the key indicators (Table R2), but shares similar indicators (i.e. continuous days of perpetual snow cover, or number of consecutive snow fall days since the last snow fall day).

Table R2 Variables considered in national and industrial standards for snow disaster

Snow Disaster Grades in Grazing Regions of China (GB/T20482-2017)	Meteorological Grades of Urban Snow Hazards (QX/T 178-2013)
Snow depth (cm) Grass height (cm) Continuous days of snow cover (d) % of grassland covered by snow (%)	Cumulative snowfall (mm) Maximum daily snowfall (mm) Snow depth (cm) Number of consecutive snowfall days (since the last snowfall day) Daily lowest temperature (degree C) Windspeed (m/s) Minimum relative humidity *(%)

We have also clarified this point in the revised manuscript (page 6 line 10 in the clear version, or page 7 line 13 in the track-change version).

Page 7 Lines 1-2: This sentence dose not explain why satellite is not used here.
RE: Thank you for your comment. Data need from satellite imagery is mainly the daily snow cover ("yes/no" data) and snow cover rate (% area covered by snow). One of the major purpose of this study is to develop a probabilistic risk assessment framework for risk assessment future climate change scenarios. For such a purpose, our input variables used in the framework must

be available in climate projections. As far as we know, there are no projections of daily snow cover for the future. This is one of the main reasons that we did not consider it.

In the revision, we have tried to make this point clear to the readers. "*Daily snow cover data were not considered as they were absent in future climate projections. Because our goal is to develop a model framework that can assess both present-day and future risk with climate projections, we refrained from using variables absent in future climate projections.*" Please refer to page 6 lines 13-16 (or page 8, lines 1-5 in the track-change version) for details.

Page 7 Lines 4-6: Are there no bias between the two data?

RE: A similar question has been raised by Reviewer #1 (comment #8). According to (Wang et al., 2013), the data for period of 1980-2007 were obtained from the yearbooks of meteorological disasters. Therefore, these data were originally recorded officially by provincial meteorological administrations, and published as a collection in books. The data for 2008-2015 were directly obtained form China Meteorological Administration in digital format. Therefore they are both from official records from meteorological administration, and the standards in identifying snow disasters are the same. However, we cannot perform a bias check as the data from two different sources do not share any overlapping period.

In the revision, we have added information to clarify that the potenail bias between two data is very limited. "*Records for 1980–2007 were a collection of snow disaster records published in 6 provincial meteorological yearbooks neighboring the Plateau (Wang et al., 2013b). Records from 2008–2015 were obtained from the China Meteorological Science Data Sharing Service System (CMSDS, http://data.cma.gov.cn). Records in both datasets are official observations by the meteorological administrations and are consistent with each other in terms of observation standards*." Please refer to page 6, lines 18-22 in the revised manuscript for details (or page 8 lines 6-11in the manuscript with track changes).

Page 7 Line 11: Explain the meanings of lr and tc.

RE: Boosted Regression Trees have two important parameters that need to be specified by the user. Tree complexity (*tc*) controls the number of splits in each tree. A *tc* value of 1 results in trees with only 1 split, and means that the model does not take into account interactions between environmental variables. A *tc* value of 2 results in two splits and so on. Learning rate (*lr*) determines the contribution of each tree to the growing model. As small value of *lr* results in many trees to be built. These two parameters together determine the number of trees that is required for optimal prediction. The aim is to find the combination of parameters that results in the minimum error for predictions.

In the revision, we have supplied these information into the text (page 6 lines 26-28, or page 8 lines 15-17 in the track-change version).

Page 7 Lines 13-14: How the number of the variables and prediction power is weighted? Any kind of criteria like AIC or BIC is used?

Page 10 Line 4: Why SD, minWind and Pre were excluded?

RE: SD, minWind and Pre were excluded as they were least important in explaining the response variable. BRT uses a process of variable selection analogous to backward selection in regression. It drops the least important (in terms of relative influence) predictor, then re-fits the model and sequentially repeating the process (Elith et al., 2008). In each step, after the removal of one predictor, the change in predictive deviance is computed relative to that obtained when

using all predictors. Finally, a list containing the mean change in deviance and its standard error as a function of the number of variables removed will be returned (Hijmans et al., 2011). From the list, the optimal number of variables to drop can be identified, i.e. the number of variables that yield the minimum predictive deviance.

In the revision, we have supplied these information about the mechanism of variable selection and model simplification. Please refer to page 6 lines 31-34 (or page 8 lines 20-24 in the track-change version) for details.

Page 7 Line 14: The cross validation is how many fold?
RE: We used a 10-fold cross-validation. This information has been supplied in the revision (page 6 line 34).

Page 7 Line 20: Is "prediction error" random? If they are systematic, to take average may not be a good solution.
RE: The CV estimates of prediction error (predictive deviance in BRT models, Elith et al. 2008) of our BRT model indicates that the error is random.

Page 9 Line 9: How good is the performance of the equation?
RE: This equation is derived using logic reasoning: if a share of livestock died in one event, then the actual herd size exposed to the next event should be reduced correspondingly. As we rarely have two or more subsequent events in one year and one place in our historical records, we cannot evaluate the performance of this equation. We can only say that it is logically correct.

Page 10 Line 7: How relative contribution is calculated?
RE: In BRT, the relative importance is calculated based on the number of times a variable is selected for splitting, weighted by the squared improvement to the model as a result of each split, and averaged over all trees. The relative importance for each variable is scaled so that the sum adds to 100 (Elith et al., 2008). We have added this information as a footnote (page 11).

Page 10 Line 19 "well captured": p-values of 0.118 and 0.189 are not necessarily good (not statistically significant with 10% level). To check the model's representability more carefully, let us see not cumulative but probability density function before accumulation.
RE: We agree with your that we may not use "well captured". But we want to double confirm about the meaning of "not statistically significant with 10% level". The null hypothesis of the Two-sample Kolmogorov–Smirnov test is: "The two samples come from a common distribution", and the alternative hypothesis is: "The two samples do not come from a common distribution" (https://www.itl.nist.gov/div898/software/dataplot/refman1/auxillar/ks2samp.htm). Our test statistics indicated "not statistically significant at 10% level", and therefore we failed to reject the null hypothesis and had to believe that the two samples (observed and predicted) were from a common distribution. It said that our prediction had captured the statistical feature of the observed duration (both event and annual). We posted the probability densities of these variables below, and actually they showed similar thing with the cumulative density function:

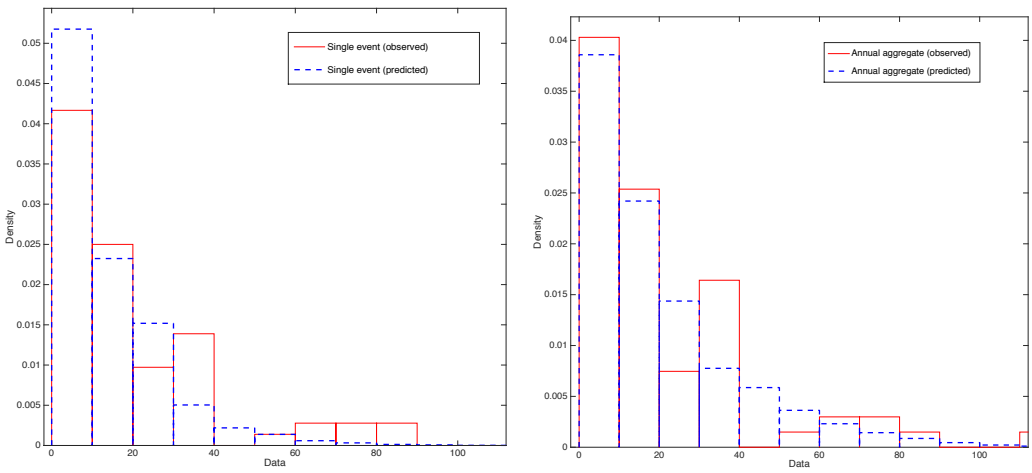

Figure R7 probability densities of observed and predicted snow disaster durations

In the revision, we have changed "well captured" to "captured" following your suggestion.

Page 12 Fig. 5: Better to present the annual total number of SDDs.
Page 13 Line 13: Fig 5b shows annual aggregate snow disaster duration? But the caption says "mean event duration".
RE: Two questions above are related and responded together.

We believe that you have been discussing Fig. 5 (b). In the revision, we have followed your suggestion and present the mean annual aggregate duration (mean annual total number of SDDs). Correspondingly, its corresponding description has been updated to keep consistency with the figure (page 12 line 13-18).

Page 13 Line 11 (also for Page 18 Line 1): It is obvious when the Gaussian approximation is used.
Page 13 Lines 18-19: If "The distribution of annual average mortality rate is extremely positively skewed", the Gaussian kernel function (Page 9 lines 21-22) is not appropriate, is it? BTW, is it related to the dependent variable in Eq .1 is lnLR, not LR?
RE: Thank you for your question. The two comments are related and are responded together. There are three points to clarify:

1) We did not use Gaussian approximation over the simulated annual loss rates, which is a parametric and symmetric distribution function. Instead, we used a non-parametric approach called kernel density function (Page 9 lines 21-24) with a Gaussian kernel function (Silverman 1986). The kernel density approach does not specify any functional form of the entire distribution and therefore is flexible to capture probability densities of different degrees of skewness. A simple explanation about the method can also be found in Ker and Goodwin (2000, American Journal of Agricultural Economics).
2) Page 13 Lines 18-19 was describing the distribution of annual average mortality rate of different grids (spatial locations), but not the distribution of annual mortality rate for any specific location. "Extremely positively skewed" means that the grids/regions of high mortality risk take only a small portion of all places on the Plateau, but their annual average

mortality rates were much higher than those of other grids. It is not related to the distributional assumption of dependent variable LR.

3) LR is also positively skewed. Only its natural logarithm (lnLR) exhibits normality.

Page 18 Table 1: What is the trend of actual herd size in QTP? To consider a static herd size is reasonable?

RE: The trend of herd size as a total of Qinghai and Tibet is provided below in Figure R8. As shown in the figure, number of cattle has not changed much for both regions. Number of sheep in Qinghai has not changed much since 2006, but that of Tibet has been decreasing for recent years, mainly due to the forage-livestock balance policy. In terms of aggregate size (1 cattle = 5 sheep units), Qinghai remains quite stable since 2006, and Tibet keeps dropping rapidly up to year 2014. Once it drops to the upper limit of carrying-capacity, it is very likely to keep nearly constant (please also refer to the discussion on your comment #3).

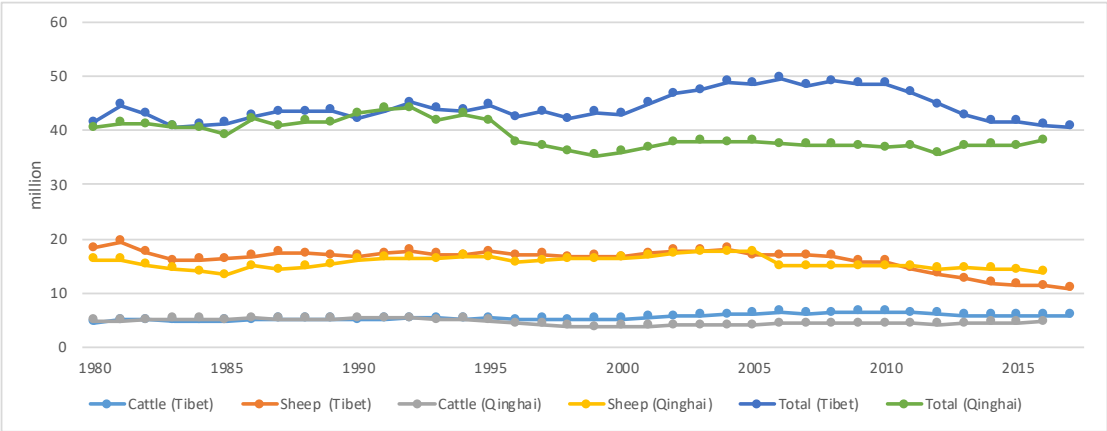

Figure R8 Change of herd size summed from Qinghai and Tibet

In our results, we have added discussion regarding the use of static exposure into the limitation section. Please refer to page 23 lines 23-26 for details (or page 32 line 33 – page 33 line 4 in the track-change version).

Page 18 Line 8: Why mortality becomes small by the constraint of herd size by carrying capacity?

RE: This sentence was misleading. We intended to say that the mortality (sheep units) was small (mostly below 10 per grid), and the main reason was that the estimated carrying capacity was small. In the revision, we will change this sentence to: "*Mortality appears small in Fig. 8, generally several sheep units/km^2. However, when aggregated at the prefecture level, mortality remained considerable (Table 1).*" (page 20 lines 4-5, clear version)

Page 19 Lines 15-16: It is better to compare the modeled mortality with observed (historical) ones.

Page 19 Lines 27-28: Is there no possibility that this study overestimates?

RE: The two questions above are related to each other and are responded together.

To further test the performance of the model, we have re-run the model using historical value added of animal husbandry. For the two specific cases as mentioned in our previous manuscript, our modeled aggregate livestock loss for event (a) in 1996 in Yushu and Guoluo

prefectures was approximately 1.20 million heads/units (turned from 2.64 million sheep units modeled given the cattle-to-sheep ratio in Qinghai Province), and the historical record was 1.48 million[1] livestock recorded), and for event (b) in 1998 in Naqu Prefecture was 0.72 million head/unit (turned from 1.59 million sheep units), compared to 0.82 million livestock. Therefore, our model result did capture the loss of major events in specific regions, although it still suffered from uncertainty.

In our revision, we have added the temporal changes of livestock loss in section "*3.1.2 Model-derived annual snow disaster loss, 1980-2015*", in which model-derived historical losses were presented, and compared with recorded historical loss. In addition, model-derived loss of the two individual events were supplied to the second paragraph of section "4.1. Spatial patterns of livestock snow disaster risk in the QTP" (page 19 lines 21 – 28, clear version; or page 29 line 24 – page 30 line 5, track-change version)

Page 21 Line 8 "two critical indices": Is this presented in the Result section?

RE: The "two critical indices" were referring to disaster duration and growing season aggregate precipitation, two variables that critically determines livestock mortality rate in our vulnerability function.

In the revision, we have deleted this part per the comment of reveiwer#1 comment 12.

Page 22 Line 18: How the study can be applied for future? I consider that the method used here is not suitable when the climate is changing.

RE: Thank you for your question. In our modeling process, we have been trying to make our model framework capable of incorporating the changing climate and socioeconomic development. Following the existing work of climate change risk assessment (Carleton and Hsiang, 2016; Kinoshita et al., 2018; Tachiiri and Shinoda, 2012; Winsemius et al., 2016), our model consists of a set of response relationships: 1) a hazard module defines the relationship between daily weather condition and the occurrence (identification) of snow disasters; 2) a vulnerability function defines the relationship between even mortality rate and hazard intensity (duration, wind speed, growing season precipitation) and prevention capacity (as proxied by socioeconomic variable); 3) exposure in terms of herd size is used only in a multiplicative way to derive the final risk metrics in terms of sheep units.

In such a structure, climate condition and socioeconomic condition are merely inputs to our model, rather than a part of the model. Climate change will lead to changes in model input, and correspondingly model output. And that is why we want the model to have the capability to capture: in the short-term future, will the changing climate lead to more or less frequent snow disasters, with shorter or longer duration? Together with projected prevention capacity, will the mortality risk increase or decrease correspondingly? For the first question, our hazard module is capable of identifying/simulating snow disaster days based on climate inputs mimicking meteorological observers' decision using machine learning algorithm: given daily maximum, mean and minimum temperatures, precipitation, and maximum and mean wind speed, the module can exactly derive corresponding snow disaster event set. Applying it to future climate scenario can then generate future event set and investigate the change of disaster event

[1] The figure 1.08 million in the previous manuscript was from a literature, but unfortunately it is not consistent with those reported in the books. We have corrected it.

frequency and intensity (duration) in the future. For instance, in a warmer climate we may expect snow disaster events with less frequency and shorter duration.

In summary, climate change will not influence the model structure, but certainly it (model input) will change the model results. That is how the climate changing is taken into account in our model.

As reviewer #1 has raised similar comment (comment#3), we have refrained from claiming so strongly in the current manuscript but decided to conduct future risk assessment using the framework presented here in our next study.

[Technical corrections]

Page 1 Lines 20,22: 1/20a -> 20 years (also for all similar expressions).

RE: Thanks for pointing this out. We have corrected it throughout the manuscript and in the figures.

Pages 14-15 Fig 6: To be multi-colored like Fig 7 would be more reader-friendly.

RE: Thanks for the suggestion. We have updated the figures to use multi-color in the map.

Page 9 Line 7: “although unlikely” should be rephrased with better expression.

RE: Thanks for the suggestion. We have removed the phrase from the text.

Page 5 Lines 4-6: Hard to understand. Too many “and”s. “its needs” -> “it needs”? Delete one of the two “provide”s?

Page 10 Line 14: Fig. 3 -> Fig. 4?

Page 13 Line 2: topology -> topography?

Page 19 Line 22: There is no Table 2.

Page 19 Line 26 (also in Page 21 Line 28): higher -> longer.

Page 20 Line 8: Fig A2 -> A3?

RE: Above comments are related to typos. We have revised/corrected them as suggested.

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Event-based Probabilistic Risk Assessment of Livestock Snow Disasters in the Qinghai-Tibetan Plateau

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Abstract. Understanding risk using a quantitative risk assessment offers critical information for risk-informed reduction actions, investing in building resilience, and planning for adaptation. This study develops an event-based probabilistic risk assessment model for livestock snow disasters in the Qinghai-Tibetan Plateau (QTP) region and derives risk assessment results based on historical climate conditions (1980–2015) and present-day prevention capacity. In the model a hazard module was developed to identify/simulate individual snow disaster events based on boosted regression trees. Together with a fitted quantitative vulnerability function, and exposure derived from vegetation type and grassland carrying capacity, risk metrics based on livestock mortality and mortality rate were estimated. In our results, high risk regions include the Nyainqêntanglha Range, Tanggula Range, Bayankhar Mountains and the region between the Kailas Range and neighbouring Himalayas. In these regions, annual livestock mortality rates were estimated as > 2% and mortality was estimated as >2 sheep unit/km^2 at a return period of 1/20 a20-year. Prefectures identified with extremely high risk included Yushu Guoluo in Qinghai Province and Naqu, and Shigatse, Linzhi, and Nagri in the Tibet Autonomous Region. In these prefectures, a snow disaster event with return period of 1/20 a20-year or higher can easily claim a total loss of more than 200500,000 sheep units. Our event-based PRA results provide a quantitative reference for preparedness and insurance solutions in reducing mortality risk. The methodology developed here can be further adapted to future climate change risk analyses and provide important information for planning climate change adaption in the QTP region.

1 Introduction

Livestock snow disasters are serious winter extreme weather events that widely occur in central-to-east Asian temperate steppe and alpine steppes (Li et al., 2018; Tachiiri et al., 2008). In the pastoral areas of these regions, heavy snow fall leads to thick and long-lasting snow cover, making forage unavailable or inaccessible (Fernández-Giménez et al., 2015). Together with

extremely low temperature and strong wind, it severely inhibits natural grazing, claims considerable livestock mortality, and brings devastating impacts to the livelihoods of local herders, even threatening their survival (Wang et al., 2013a). In response to threats from livestock snow disasters, great efforts have been devoted to understanding their mechanism as a complicated interaction between precipitation, vegetation, livestock, and herding communities (Nandintsetseg et al., 2018; Shang et al., 2012; Sternberg, 2017); the major drivers of (socioeconomic) vulnerability (Fernández-Giménez et al., 2012; Wang et al., 2014; Wei et al., 2017; Yeh et al., 2014); and key factors that could foster adaptive capacity and community resilience (Dong and Sherman, 2015; Fernández-Giménez et al., 2015). Attempts have been made to develop techniques, such as snow disaster monitoring, forecasting, and rapid assessment, to provide critical information for prevention and addressing emergencies (Wang et al., 2013b; Yin et al., 2017). Quantitative analysis have also been carried out to derive the relationship between livestock loss, snow hazard, and various environmental stressors (Li et al., 2018; Mukund Palat et al., 2015).

Disaster risk is a measure of uncertain consequences. The Sendai Framework outlines the importance of risk assessment as a critical means of understanding disaster risk and a prerequisite for other actions, such as risk-based investment for resilience and adaptation (UNISDR, 2015). ~~For livestock snow disasters, researchers have followed~~ Following the mainstreaming risk assessment ~~methodology~~ framework ~~by framing risk as the product of hazard, vulnerability, and exposure,~~of Risk = Hazard × Exposure × Vulnerability ~~(Jongman et al., 2015; Kinoshita et al., 2018; Shi and Kasperson, 2015).~~ (Jongman et al., 2015). ~~However, two very different approaches can be used, which derive quite different risk metrics. The first type employs an ordinal risk assessment framework in which the risk index is derived by integrating several indices representing different components of risk (e.g., the world risk report; Birkmann and Welle, 2016). S~~several ordinal risk assessment studies have been conducted for livestock snow disasters in Inner Mongolia and the QTP of China (Li et al., 2014; Liu et al., 2014a; Wu et al., 2007). They in general drive the measure of risk as an ordinal index by integrating ~~several~~ indices representing different components of risk (e.g., the world risk report; Birkmann and Welle, 2016). This ordinal ~~approach for~~ risk assessment approach ~~is flawed in its output: it~~ offers only rankings but no quantitative information of the underlying risk, i.e. the uncertainty of consequences. Consequently, it can be valuable for policy-making but can hardly support risk - informed decisions, e.g. insurance pricing or cost-benefit analysis.

Researchers have also been trying to derive ~~The other risk assessment approach is quantitative, often called the~~ probabilistic risk assessment (PRA) results for livestock snow disaster~~probabilistic risk assessment (PRA),~~. ~~in~~ In such a framework, ~~which~~ risk ~~is measured with~~measured as a probability distribution of socioeconomic losses (consequences) are generally derived with the probability distribution of hazard intensity, and the dose-response relationships between hazard intensity and socioeconomic losses (Carleton and Hsiang, 2016; Michel-Kerjan and Kousky, 2010; Shi and Kasperson, 2015). ~~In the state-of-the-art PRA framework, risk can be estimated by projecting/translating the probability distribution of a hazard via a "dose-response" function (the vulnerability function) (Carleton and Hsiang, 2016). Such a projection/translating can be conducted using analytical methods, or in a more popular sense, carried out via discrete simulation, an approach widely used in catastrophic risk models (Michel-Kerjan et al., 2013). However, studies applying PRA to livestock snow disasters have been limited.~~ Bai et al. (2011)~~published one of the first trials in applying~~ applied the PRA framework to a livestock snow disaster risk assessment in Qinghai Province of China. ~~In their study, winter season (November to April of the preceding year) average~~

~~daily snow depth was used to describe snow hazard intensity. Physical vulnerability, a~~A function of livestock mortality rate in response to snowing season (November to April of the preceding year) daily average snow depth~~,~~ was fitted using historical disaster records~~ease data~~. ~~Using~~ Together with ~~annual~~ historically annual average snow depth computed from satellite-retrieved data, return-period livestock mortality and mortality rates were derived as the final risk metrics. Based on their method, quantitative livestock snow disaster risk were mapped nationwide in China (Shi, 2011). Tachiiri and Shinoda (2012) successfully extended the framework to future climate change analysis. ~~The major flaw of this method was the mismatch between the event-based vulnerability function and annual measure of snow hazard. In another work focusing on Mongolia~~They trained a tree-based model to~~, a vulnerability function~~ link annual livestock loss rate and October to April snow water equivalence and normalized difference vegetation index. Then they used ~~trained from a tree-based model was used, but still on an annual basis. They inputted~~projected snow water equivalence in climate scenarios ~~-~~to estimate the frequency of anomalous livestock loss rates >5% or >17% for 2010–2099~~ (Tachiiri and Shinoda, 2012)~~. ~~Compared to earlier works, they successfully extended the framework to future climate change analysis, but they did not report many details describing the final risk metrics.~~ Ye et al. (2017) further extended the PRA framework to support insurance design and pricing using snowing season cumulated snow-cover days. ~~They focused on the risk of economic stress to local herders due to increased feeding expenditures induced by long-lasting thick snow cover in eastern Inner Mongolia but did not analyze livestock mortality issues.~~ Earlier studies have mostly developed their PRA model using annual variables. In this study, we tried to develop~~ed~~ an event-based PRA method for present and future livestock snow disaster risk assessments for the QTP region. The event-based PRA approach has several important features as compared to earlier studies using annual variables. 1) From the modeling perspective, the even-based framework retains the capability to accommodate multiple events in a year, which is a nature of snow disaster. This is important for snow disaster as earlier studies has demonstrated that livestock mortality rate exhibits concave relationship with disaster duration (Li et al., 2018). The losses of one event lasting for 30 days and two-event lasting for 15 days each will be totally different. In addition, modelling events allows to capture the change of event frequency and intensity in response to environmental change such as climate change. 2) From the risk-informed action perspective, annual evaluation (i.e. potential aggregate duration) can hardly work for risk-transfer mechanisms as insurance that works in nature on event basis, although it might be temporarily fine for annual planning of preparedness. This is also the critical reason that catastrophe risk models are mostly built on event-basis (Michel-Kerjan et al., 2013).

There are three major aims of this study: 1) Develop a hazard module that can identify/capture snow disaster event based on daily weather data. It is the basis for any event-based modelling attempts, and is particularly important for regions where historical records are absent and for future risk assessment where observations and records are not yet available and variabilities from future climate change will exist. 2) Set up an event-based PRA framework for livestock snow disaster risk assessment by integrating snow disaster event (hazards), livestock vulnerability, and exposure together to derive a probabilistic quantification of risk. 3) Derive the risk metrics for livestock mortality risk in the QTP and offer risk-informed reduction implications.

Worldwide, the QTP is one of the regions that has ~~suffer~~suffered the most ~~s~~ from ~~some of the highest~~ livestock snow disasters due to its large area of snow cover area, long-lasting snow cover days, and nomadic grazing (Li et al. 2018). This region is

also a hot spot in climate change (Diffenbaugh and Giorgi, 2012; Gu et al., 2014). Quantitative risk assessments for the present day will likely be a significant source of information for disaster risk reduction. In addition, the framework can be adapted for livestock mortality in snow disasters in the context of future climate change analysis, and therefore support climate adaptation planning for local government and herding communities.

2. Materials and methods

2.1 Study area

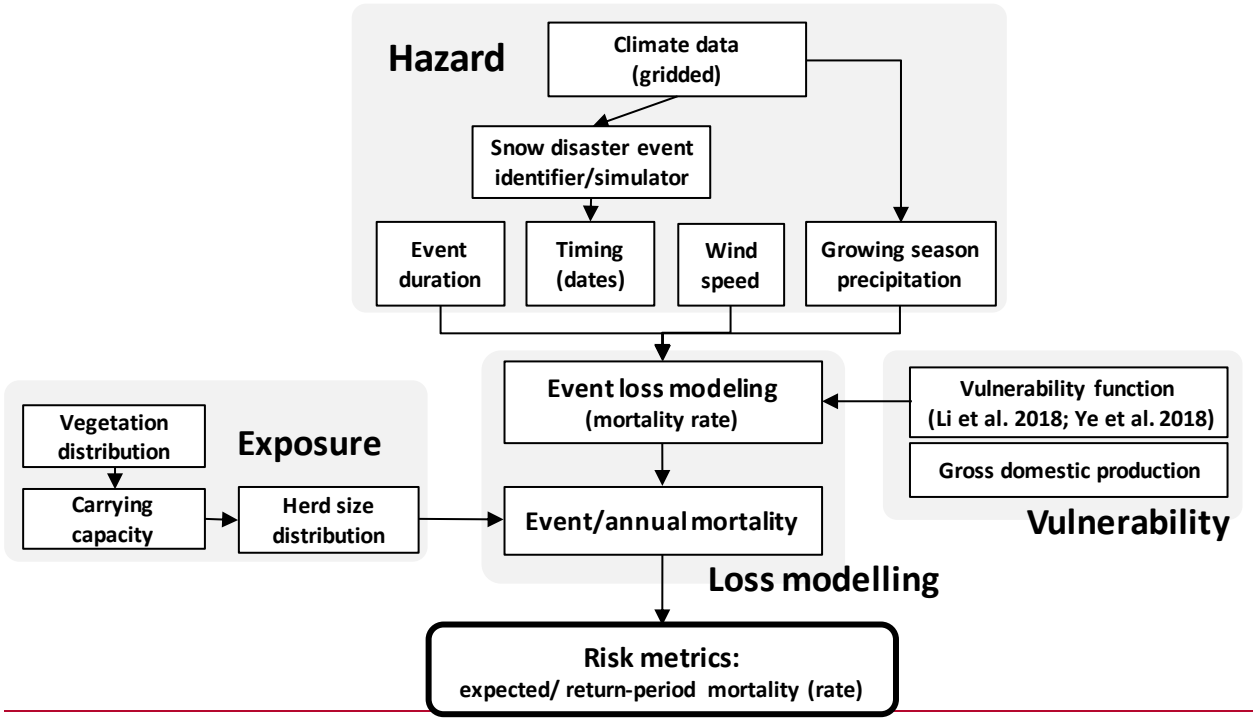
The QTP contains the world's highest pastoral area (Wang et al., 2016). It has extremely enriched grassland resources, with a total alpine grassland cover of 1.57 × 10^6 km^2, supporting the livelihood of approximately 2 million pastoralists and 3 million agro-pastoralists (Miller, 2005). In 2014, the QTP housed a total of 38.03 million livestock, and animal husbandry production reached 23.85 billion RMB yuan[1]. A typical nomadic way of grazing has been used for centuries and even today, it is still the most popular way of raising livestock (Wang et al., 2014). Local herders rely heavily on open-air free grazing and possess poor infrastructure (such as thermal sheds), lacking the sense to prepare hay and fodder for potentially harsh winters. Provincial and local governments have been investing to improve prevention capacity and snow disaster resilience for local communities, but further efforts are still needed to reach a satisfactory solution due to economic and conventional constraints (Shang et al., 2012; Ye et al. 2018)

The Tibetan Plateau is one of the three major snowfall regions in China (Yin et al., 2017; Qin et al. 2015). On average, the snow cover can attain 0.61 × 10^6 km^2 in the winter season (Duo et al., 2014) and persist for over 240 days (Basang et al., 2017). A large snow cover area, long-lasting snow cover days, together with the nomadic way of grazing, make this area one of the regions that suffers most from livestock snow disasters. A total of 18 million livestock died in snow disasters during the 1974–2009 period in the eastern part of the Tibetan Plateau (Wang et al., 2016). In the snowing season of 1995-1996, consecutive snow disaster events in total killed 1.29 million livestock (Wen 2008). The 1997-1998 snow season in Naqu, central Tibetan Plateau, led to the loss of 0.82 million livestock, and threatened the lives of 100,000 local people (Wen 2008b).

2.2 Methods

In this study, an event-based PRA framework was developed for livestock snow disaster (Fig. 1~~Fig. 1~~). We followed the PRA approach proposed by Carleton and Hsiang (2016), and applied the concept of event-based modelling in catastrophic risk models (Michel-Kerjan et al., 2013). The event-based modelling approach was framed using state-of-the-art three-element risk modelling, hazard, exposure, and vulnerability (Kinoshita et al., 2018; Muis et al., 2015) to model losses claimed by individual events. Then PRA was achieved through repetition of individual event modelling, in which a large number of events were drawn from the full distribution of hazards, given the predicted losses/consequences from individual events, from which a full distribution of disaster loss can be obtained. ~~(Fig. 1).~~

[1] 1 yuan = 0.146 USD as of Dec 27, 2018



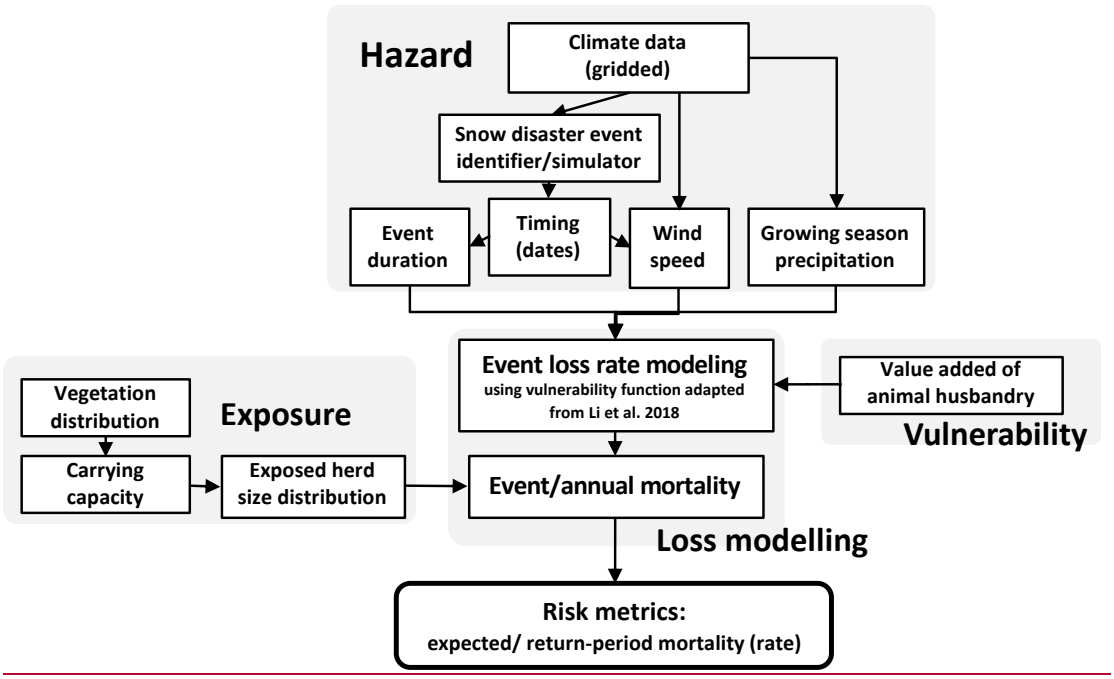


Fig. 1 Event-based **Probablistic Risk Assessment Framework for Livestock Snow Disasters in the Qinghai-Tibetan Plateau** ~~(QTP)~~ **region**

2.2.1 Hazard

In our event-based PRA method, the Hazard module ~~is critical in our event-based PRA method, and its~~ needs to identify individual snow disaster events ~~, and~~ to provide ~~provide the exact timing (starting and ending dates) of each event,~~ event duration ~~based on which~~(~~-~~*Duration*) and during event wind speed (*Wind*), two important inputs to model event loss using the vulnerability function ~~can be derived~~. It requires to obtain the exact timing (starting and ending dates) of each event. ~~Such information~~The timing of each individual event, nevertheless, ~~are~~ is not so straightforward to obtain. For the historical period, there are no ready-to-use snow disaster event datasets at the grid level. The number of meteorological stations capable of observing snowfall in QTP is limited and are primarily located to the eastern and southern part of the region. For future risk assessment, no projections of snow disaster events are provided in climate scenario datasets, although models have been developed to simulate daily snow depth (Yuan et al., 2016). Therefore, a snow disaster event identifier/simulator was developed here to identifying/simulating snow disasters.

A snow disaster is a weather process with snow fall, low temperature, and snow cover, with certain length of durations, according to the Chinese national standard for *Snow Disaster Grades in Grazing Regions of China* (GB/T20482-2017) and China Meteorological Administration (CMA) standard for *Meteorological Grades of Urban Snow Hazards* (QX/T 178-2013). A snow disaster event designation largely depends on the snow weather process and observer's decision (manual record). To mimic a meteorological observer's decision to designate a snow disaster event, our snow disaster event identifier/simulator has considered two major questions. First, whether a specific day would be regarded as a snow-disaster-day (SDD) given weather information of the day and previous days. The key is the modelling the binary response variables (Yes/No), which can be conducted with either regression or classification methods. Second, whether two SDDs, exactly neighbouring or a couple of days away from each other, should be regarded as one snow disaster event. The key is to assemble many single SDDs into snow disaster events, which can be accomplished using smoothing and filtering. In response, three major steps were considered (Fig. 2~~Fig. 2~~, Fig. A1):

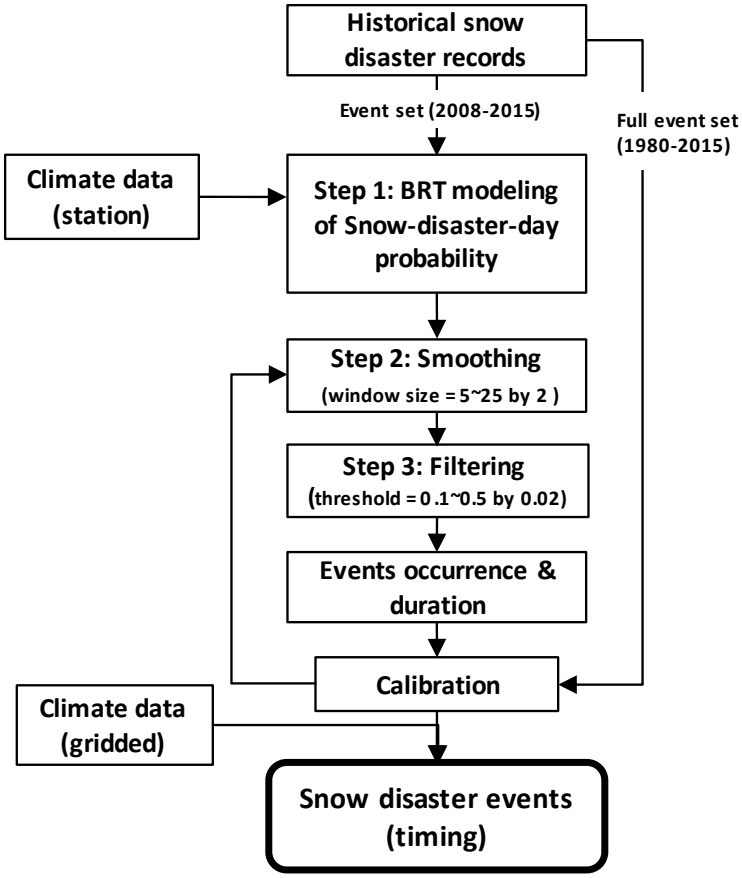


Fig. 2 Technical flow of the snow disaster event identifier/simulator

(1) Step 1: modelling the SDD probability for each single day

For this step, boosted regression tree (BRT) modelling was used to establish a multi-variate and non-linear relationship between SDD and various weather information. BRT modelling methodology was chosen due to its promising power for both explanatory and predictor purpose in many ecological and environmental modelling scenarios (Elith et al., 2008; Hastie et al., 2009). Other machine learning methods such as random forest can also be used here but less likely to outperform BRT according to the literature (Oppel et al., 2012; Youssef et al., 2016). To fit a BRT model, historical snow disasters were first turned into SDD flags, if a date was included in a historical snow disaster it was flagged with "1", and "0" otherwise. Variables used to explain and predict days that would be considered SDD was inspired by the two standards, GB/T20482-2017 and QX/T 178-2013. Both standards agree well on each other about the important indicators that define a snow disaster. We included daily snow depth (*SD*, cm), daily maximum (*maxWind*), mean (*meanWind*) and minimum wind (*minWind*) speed (m/s), daily maximum (*maxT*), mean (*meanT*), and minimum (*minT*) temperature (℃), daily precipitation (*Pre,* mm), and average daily precipitation since the last snow fall day (precipitation > 0.1 mm) (*aveP*, mm/d). *aveP* was used to denote the diminishing

impact/pressure from snowfall as time elapsed. Daily ~~Snow~~ snow cover data were not considered as they were absent in future climate projections~~obtained from satellite imagery data was not considered because it is unavailable for future periods and predicting disasters~~. As we have aimed to develop a model framework that can assess not only present-day risk, but also future risk with climate projections, we refrained from using variables absent in future climate projection~~, although, in this study, we used only historical data~~.

Historical snow disaster event data with the time of each event for each meteorological station were used to train the BRT model. These data were obtained from two sources. Records for 1980–2007 were a collection of snow disaster records published in 6 provincial meteorological yearbooks on the Plateau ~~obtained from W. Wang et al. (2013)~~ (Wang et al., 2013b). ~~while r~~Records from 2008–2015 were obtained from the China Meteorological Science Data Sharing Service System (CMSDS, http://data.cma.gov.cn). Records in both datasets are official releases of snow disaster records by the meteorological administrations and are consistent with each other in terms of observation standards. Data for the predictors were also obtained from CMSDS, including 106 national reference stations in the region. The dataset contains daily observations of maximum, mean and minimum temperature, maximum and mean wind speed, and precipitation.

BRT model fitting was conducted using the package *dismo* (Hijmans et al., 2011) in R 3.3.3. Given the type of response variable, the Bernoulli distribution family was used. BRT model has two important parameters to specify to obtain the optimal prediction, tree complexity (*tc*), the number of splits in each tree, which controls whether interactions are fitted, and learning rate (*lr*) that determines the contribution of each tree to the growing model (Elith et al., 2008). To identify the best combination of model parameters, we compared the combinations of *lr* = (0.01, 0.005, 0.001) and *tc* = (1, 2, 3, 5), as recommended by Anderson *et al* (2016). The maximum number of trees was set to ~~10~~20,000, which proved sufficient for convergence. For each combination of parameters, we applied the predictor selection process using the *gbm.simplify* function~~ to best obtain a balance between prediction power and number of predictors requested~~. It uses a process of variable selection analogous to backward selection in regression. It drops the least important predictor, then re-fits the model and sequentially repeating the process (Elith et al., 2008), until some stopping criteria, i.e. the reduction in predictive performance exceeds some threshold (Elith et al., 2008, Appendix S2). We used a 10-fold cross-validation, and t~~T~~he result with the least cross-validation deviance was retained. To achieve the most promising goodness-of-fit, historical snow disaster records obtained from CMSDS (2008–2015) were used for fitting. ~~This part of the data exactly matched the CMSDS record and most precisely followed CMA's definition of a snow disaster.~~ Records for 1980–2007 were used later for validation and calibration purposes.

(2) Steps 2 and 3: assembling single SDDs to events by smoothing and filtering

A fitted BRT model can help predict the probability of a single day being judged as a SDD. To predict/rebuild snow disaster events, these single day probabilities must be deemed snow disaster events, an ensemble of multiple SDDs. Because the explicit output from the BRT suffered from prediction errors, simply using a threshold to turn probabilities into "0/1" values would yield a set of "busy" snow disaster events, e.g., high frequency but small duration (Fig. A1, "Step 1"). Therefore, a smoothing treatment is needed to filter out isolated single SDDs and fill the small gaps between two neighbouring events. There are two parameters essential to changing the frequency and duration of identified snow disaster events: the smoothing window size and filtering threshold. In general, using larger window size for smoothing can filter out noises and reduce the frequency of

events, while using lower threshold can increase the duration of single events. In order to best match the annual occurrence and the duration of single events, the two parameters were tuned through calibration using the full dataset of historical records between 1980 to 2015. We considered moving averages with window sizes from 5 d (minimum duration of a single disaster as defined by CMA) to 31 d (one month) in steps of 2 days, in combination with thresholds of 0.10 – 0.5 in steps of 0.02. The timing and duration of events derived from our model for any given pairs of window size and threshold were compared with historical records, including the frequency distribution of annual occurrence of single events, the frequency distribution of single event duration, and the timing of each single event. Through tuning, the combination of parameters that yielded the best matches were recorded.

Finally, the fitted BRT model together with the tuned parameters of smoothing and filtering was applied to generate all snow disaster events during 1980-2015 by grid. The China meteorological forcing dataset (He and Yang, 2011) obtained from the Scientific Data Centre of Cold and Arid Regions http://westdc.westgis.ac.cn/data/7a35329c-c53f-4267-aa07-e0037d913a21 was used. It offers variables, including precipitation, air temperature, wind speed, and sunshine duration at spatial resolution of 0.1° × 0.1° and temporal resolution of 3 h. We used this dataset because it focuses on the cold and arid regions in western China, and the QTP has been used as a focus region for validation (Chen et al., 2011; Yang et al., 2010). The 3-h dataset was aggregated to daily for input to the BRT model to rebuild gridded snow disaster events. Based on the identified events, the variables *Duration* and *Wind* were computed as inputs to the vulnerability function. From the 35 winters' events identified, we calculated the annual frequency and mean (single) event duration of snow disasters, as well as their return period values (Fig. A3).

2.2.2 Vulnerability function

Vulnerability is the critical function that links dose (hazard inputs) and response (loss estimates) (Carleton and Hsiang, 2016). For livestock snow disasters, a set of vulnerability functions have been estimated linking livestock mortality (rate) to snow disaster duration, during disaster environmental stress, summer season vegetation productivity, and disaster prevention capacity (Fang et al., 2016; Wang et al., 2016). To fulfil the goal of event-based modelling, the vulnerability relationship must be built on event basis. Using generalized additive models, (Li et al., 2018) have derived the quantitative relationship among livestock mortality (rate), snow disaster event duration, during disaster wind speed, pre-winter vegetation condition and time index. Using identical dataset, we tried to include disaster prevention capacity as proxied by socioeconomic indicators into analysis, and followed Li et al. (2018)'s approach to derive the model with best predictive power. We tried different socioeconomic indicators including gross domestic production, value added of animal husbandry, fiscal revenue, fiscal expenditure, and gross domestic production per capita, following the suggestion from the literature (Wei et al., 2017) and one of the reviewer. We found the model using value added of animal husbandry yielded the best fitting result, having a deviance-based R^2 of 0.625 (More details of the model, including model fit statistics, response curves and model performance diagnostics, are provided in supplementary material S1). Therefore, following~~Therefore, the results from (Li et al., 2018; Ye et al., 2018) were considered. Following their suggestion from the multi-method comparison, we chose the predictive~~ version of the generalized additive model was considered in further analysis,

$$\ln LR = s(Duration) + s(Wind) + s(P) + s(\cancel{GDP}Value\_Add)\ , \quad (1)$$

where, livestock mortality rate induced by a snow disaster is determined by disaster duration (*Duration*), during disaster maximum daily mean wind speed (*Wind*), growing season (May-Sep) aggregate precipitation (*P*), and prevention capacity as measured by ~~gross domestic production~~value added of animal husbandry (~~*GDP*~~*Value_Add*) of the underlying county. *Duration* was used as the key indicator of hazard intensity. *Wind* and *P* were used to denote during disaster and pre-season environmental stressors, respectively (Li et al., 2018). *Value_Add* was used to indicate disaster prevention capability, which explicitly measures the size of animal husbandry, and implicitly represents prevention infrastructure and capability of risk management (Wei et al., 2017). ~~The predictive function has a deviance-based R^2 of 0.672, and good predictive power compared to random forest and boosted regression tree models.~~

Given such a relationship, the vulnerability is a truly dose-response function between livestock mortality rate (mortality/herd size) and snow hazard intensity together with other environmental stressors and prevention capacity, as proposed by (Carleton and Hsiang, 2016). Different from simply defining vulnerability as the loss rate (Jongman et al., 2015; Kinoshita et al., 2018), the potential influence from socioeconomic development is embedded in the vulnerability function.

2.2.3 Exposure

Exposure measures the distribution of assets or population exposed to hazards (Kinoshita et al., 2018). In our framework, it should provide the spatial distribution of herd size exposed to snow disaster, and help turn the outputs from event loss modelling and livestock mortality rate (the response variable in the modelled vulnerability function) into mortality (death toll). According to its definition (Fernández-Giménez et al., 2012), livestock in nomadic grazing are prone-to snow disaster the most as they obtain food mostly from grassland. Livestock raised in ranches or industrial livestock farms in agricultural regions, by contrast, are much less exposed as they have steady food supply from crop by-products and are well protected by infrastructure. Therefore, it is to estimate the number of livestock grazing on grassland to estimate livestock exposure to snow disaster.

A full gridded distribution map of herd size grazing on grassland in the QTP ~~remains unavailable~~is not directly available, but it can be derived ~~. The derivation of its spatial distribution was supported by~~according to the rule-of-thumb for "forage-livestock balance~~,~~". ~~as written in the~~According to the *Forage-livestock Balance Management Approach*~~. The *Approach* was~~ issued by the Ministry of Agriculture of China in 2006 to mitigate severe over-grazing in the pastoral areas of China (Shang et al., 2012)~~. Using the *Approach*~~, herd size grazing on grassland at the county level ~~was~~ must be strictly controlled under carrying capacity. ~~computed according to a thorough investigation of local grassland resources.~~ Therefore, a gridded carrying capacity map can be a good approximation of the actual herd size distribution exposed to snow disaster.

There are several factors deciding the carrying capacity of a given region, but the most important one is grassland type, according the *Ministry Standard of Calculation of Rangeland Carrying Capacity* issued by Ministry of Agriculture of China (NY/T 635-2015). In the standard, grassland type was used as the key identifier that essentially determines forage regrowth percentage, proper utilization rate of rangeland (of different grazing seasons), conversion coefficient of standard hay. Therefore, ~~We~~ we tried to estimate~~d~~ the spatial distribution of ~~herd size~~exposure by turning grassland distribution data with the look-up

table for grassland-type to carrying-capacity relationship. For the look-up table, we adapted the plan of Xin et al. (2011) for Qinghai. For Tibet, we reviewed various criteria (Zhang et al., 2014) -and ~~criteria outlined~~ followed the official release of the Autonomous Region government ~~by the Land Management Administration of Tibet Autonomous Region~~ (Land Management Administration of Tibet Autonomous Region, 1994; Department of Agricultural and Pastoral of Tibet Autonomous Region, 2011) ~~for Tibet after reviewing various criteria (Zhang et al., 2014)~~ The final look-up table was supplied in Appendix (Table A1). For grassland distribution, we used the Vegetation Map of the People's Republic of China (1:1 million) (Editorial Committee of Vegetation Map of China and Chinese Academy of Science, 2007), which offers detailed information about the spatial distribution of 11 vegetation type groups, 55 vegetation types, 960 plant formations, and more than 2000 dominant species in vector data. To match the look-up table and map information, we merged some vegetation types and used only the major grassland types (percentage area >0.5%) according to the survey from food and agriculture organization of the united nations ~~FAO survey~~ (FAO, 2005) (Fig. A2; Table A1). The estimated carrying capacity was aggregated to county-level and compared to the official release of Tibet Autonomous Region. The two datasets showed good agreement with a correlation coefficient of 0.769. Therefore, the estimated carrying capacity was used as exposure to turn mortaility rate into mortaility.

2.2.4 Loss modelling

Snow disaster event losses measured with livestock mortality rate (death toll/ herd size) were modelled by taking requested inputs into the vulnerability function. *Duration* and *Wind* were outputs from the hazard module. Growing season aggregate precipitation *P* was computed from the climate forcing data. ~~For~~ Year-end county-level ~~*GDP*~~*Value_Add* were obtained from the statistical year books of Qinghai, Tibet, Sichuan, Gansu, and Xinjiang. County level *Value_Add* values were assigned to each grid within its boundary. When modelling losses, we considered two cases:

1) Loss based on historical prevention capacity: For modelling actual historical loss for model calibration and validation purpose, we used the actual county-level *Value_Add* of the study area during 1980-2015. As *Value_Add* increases along the time, it indicates the enhancing prevention capacity, and therefore reducing livestock mortality (rate) along the time.
2) Loss based on present prevention capacity: For risk assessment purpose, we used the ~~fixed~~ constant value of *Value_Add* ~~for~~ of year 2015 ~~obtained~~instead ~~from the statistical year books of Qinghai, Tibet, Sichuan, Gansu, and Xinjiang. County level GDP values were assigned to each grid within its boundary~~. ~~We used constant GDP values for 2015 for~~There are two reasons. First, we will need to fit probability distributions over the modelled loss to derive final risk metrics, and the process requires that the underlying loss samples must be at least stationary in their means and variances. Using a constant *Value_Add* value for 2015 avoids to bring any trend inherent within *Value_Add* into the modelled loss as the *Value_Add* has been growing. ~~the results can be directly treated as a stationary time series for estimating the probability distribution, as the influence of prevention capacity improvement has been removed.~~ Second, ~~it meets the goal of risk assessment~~as we have assumed that *Value_Add* is a proxy of prevention capacity, using *Value_Add* value for 2015 in loss modelling helps estimate the potential loss given very recent prevention capacity (year 2015) rather than those of the 1980s or 1990s. Then the derived risk metrics can be helpful for prevention planning and insurance implications for near future. ~~to estimate the~~

~~likelihood of potential loss in the near future given present day prevention capacity (prevention capacity equivalent to year 2015).~~

The searching of snow disaster event and modelling of loss starts in every August and ends in June of the next year. Event mortality rates were then aggregated into annual mortality rates, considering the possibility of multiple events per location annually, although unlikely. In aggregation, we assumed that the second snow disaster event can only have an impact on livestock surviving from the first event, and so on. Therefore, the annual aggregate loss rate in a given grid is $\Delta = 1 - \prod_{i=1}^{N}\left(1-\delta_i\right)$, i = 1,2,…, N, in which δ_i is the modelled loss rate of the ith event in a year, and N is the total number of events. The annual aggregate mortality rate can finally be turned into a death toll by multiplying exposure, the herd size in a given grid.

Event/annual mortality (death toll) can then be derived by multiplying event/annual loss rate in any given location by its herd size. For each grid, 35 annual loss records were modelled (there are 35 winters in 36 years), including both mortality and mortality rate figures. The number of event loss records differ by location, depending on the identified number of events for each grid.

2.2.5 Risk metrics

In the risk metrics, modelled losses of discrete event/annual losses were turned into probability distribution of losses. We followed standard risk metrics by deriving the average and return period values (Michel-Kerjan et al., 2013; Shi and Kasperson, 2015) of annual mortality rate and death toll for each grid. Model-derived annual mortality rates based on constant *Value_Add* of year 2015 were used to derive risk metrics. Due to our limited time span of repetition, return periods of ~~1/10~~ 10 years~~a~~ (~~once in ten years,~~ the 90th percentile of the distribution), ~~1/20 a~~20 years, and ~~1/50~~50 years ~~a~~ were considered while 100-year~~1/100 a~~ usually used in flood/ earthquake studies (Kinoshita et al., 2018) was not considered. The kernel density method was employed to fit non-parametric distributions to derive those return period values by grid. We used the Gaussian kernel function and its corresponding optimal window width in the fitting process according to the "rule-of-thumb" for optimality (Deng et al., 2007; Silverman, 1986). In addition, aggregate mortality rate and death tolls at municipal level were also derived using zonal statistics, so as to better validate the result with historical losses, and provide policy implications.

3. Results

3.1 Modelled ~~predicted~~ snow disaster duration, frequency and annual loss

3.~~2~~1.1 The trained BRT model and tuned parameters in rebuilding snow disaster events

The trained BRT model retained six variables but excluded *SD*, *minWind*, and *Pre* as the result of the predictor selection process. In the final model, we used lr = 0.001 and tc = 5. It had a training data Area-Under-the-Curve (AUC) score of 0.948, and a cross-validation AUC of 0.909, indicating good predicting performance (Youssef et al., 2016). For the six variables

entered in the final model (Fig. 3~~Fig. 3~~), *maxT* has the highest relative contribution[2] (32.77%), while *meanWind* has the lowest (5.78%).

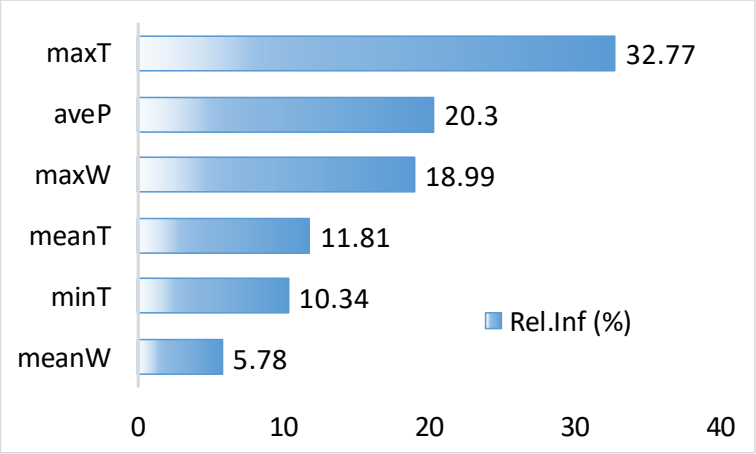


Fig. 3 Relative influence of variables predicting a snow-disaster-day. Blue bars are relative importance of each factor, and the sum of relative importance is 100%.

After tuning the window size with the moving average and threshold, we found the best results with a window size of 21 and a threshold of 0.18. The derived results ~~well~~ captured the timing of occurrence of historical events (**Fig. A1**) and matched the empirical cumulative density functions (ECDF) for historical durations (Fig. 4~~Fig. 4~~), for both event and annual aggregate durations. In historical records, two or more events in a single year at a single location are rare. Therefore, ECDFs for historical single event duration and annual aggreation duration were quite close to each other in Fig. 3. Two-sample Kolmogorov–Smirnov tests were also conducted to verify the degree of agreement between ECDFs. For single event duration (observed vs. predicted) the test statistics was 0.138, and its corresponding p-value was 0.118. The annual aggregate duration (observed vs. predicted) test statistics was 0.131, and its corresponding p-value was 0.189. Therefore, the prediction model well captured statistical features of historical snow disaster duration and the predicted results can be used for event loss ~~modeling~~modelling.

[2] In BRT, the relative importance are calculated based on the number of times a variable is selected for splitting, weighted by the squared improvement to the model as a result of each split, and averaged over all trees. The relative importance for each variable is scaled so that the sum adds to 100 (Elith et al. 2008).

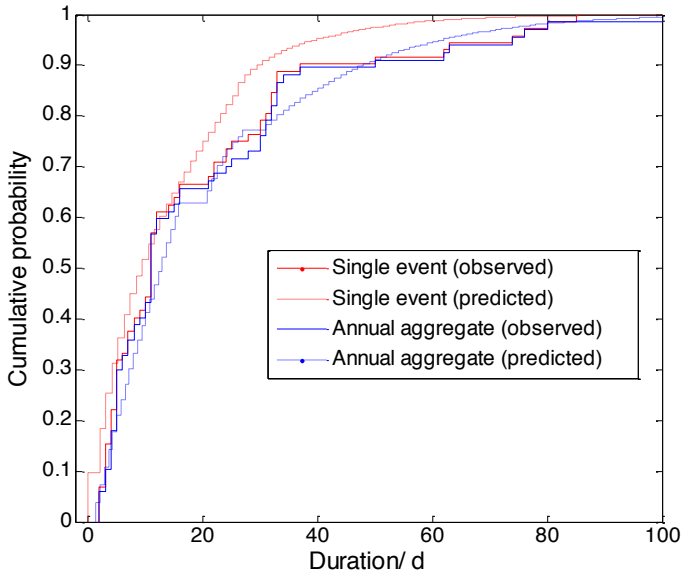
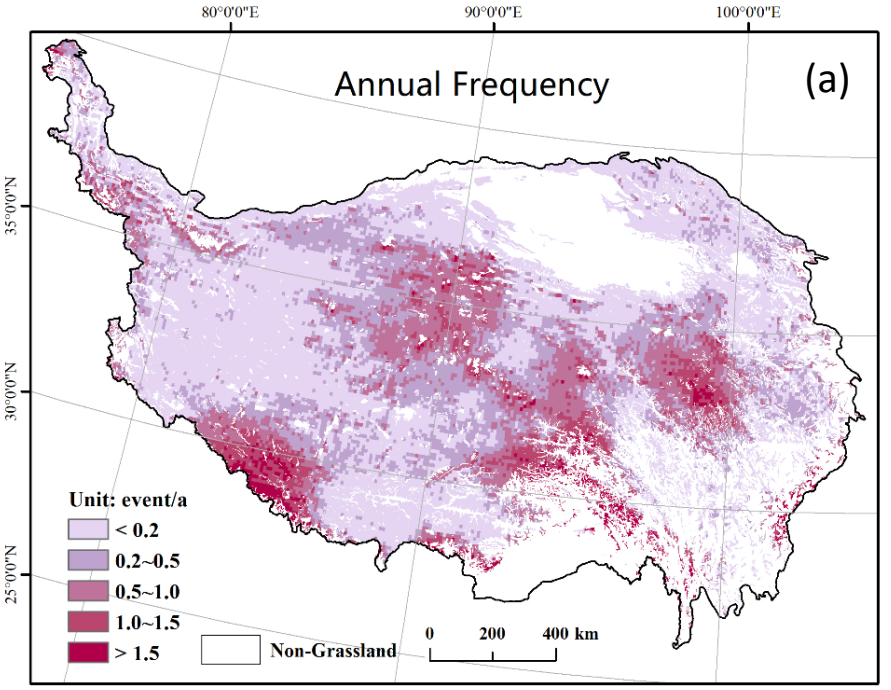
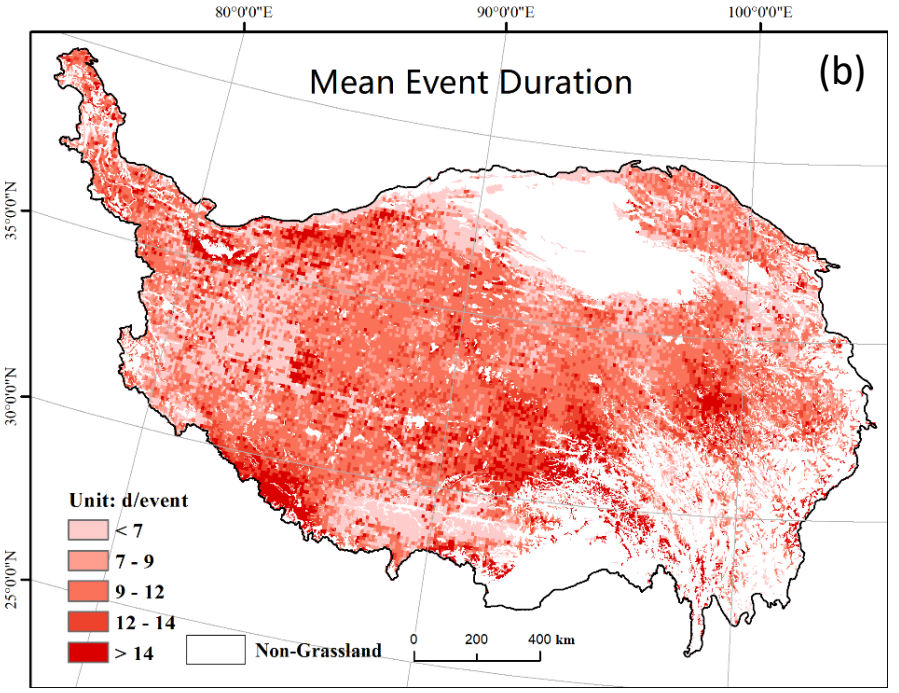


Fig. 4 Empirical cumulative density functions for historical and model-predicted snow disaster duration

3.~~2~~1.~~1~~ 2 Model-derived snow disaster events, 1980–2015

With the tuned model, the timing of snow disaster events were identified in the historical period 1980–2015. Correspondingly, the annual occurrence frequency and duration of snow disaster events were derived (Fig. 5~~Fig. 5~~). In the figure, non-grassland areas, including permanent snow areas, were masked using the vegetation map. Across the entire plateau, the annual average frequency was below 0.2 in most regions, i.e., on average, snow disasters occur every 5 years in these regions. Higher frequency regions were primarily located in major mountains, including the Tanggula Range and Nyainqêntanglha Range in the central part of the plateau, and the Kailas Range and neighboring Himalayas. These regions are higher elevation and spatially close to permanent snow-covered areas. For major pastoral production regions, i.e., the Naqu prefecture in the central QTP, the annual average frequency was 0.2 to 1, echoing the local proverb, “small disaster once in 3 years, and a major disaster once in 5 years” (Ye et al., 2017b).


80°0'0"E
90°0'0"E
100°0'0"E
35°0'0"N
30°0'0"N
25°0'0"N
Annual Frequency
(a)
Unit: event/a
< 0.2
0.2~0.5
0.5~1.0
1.0~1.5
> 1.5
Non-Grassland
0
200
400 km


80°0'0"E
90°0'0"E
100°0'0"E
35°0'0"N
30°0'0"N
25°0'0"N
Mean Event Duration
(b)
Unit: d/event
< 7
7 - 9
9 - 12
12 - 14
> 14
Non-Grassland
0
200
400 km

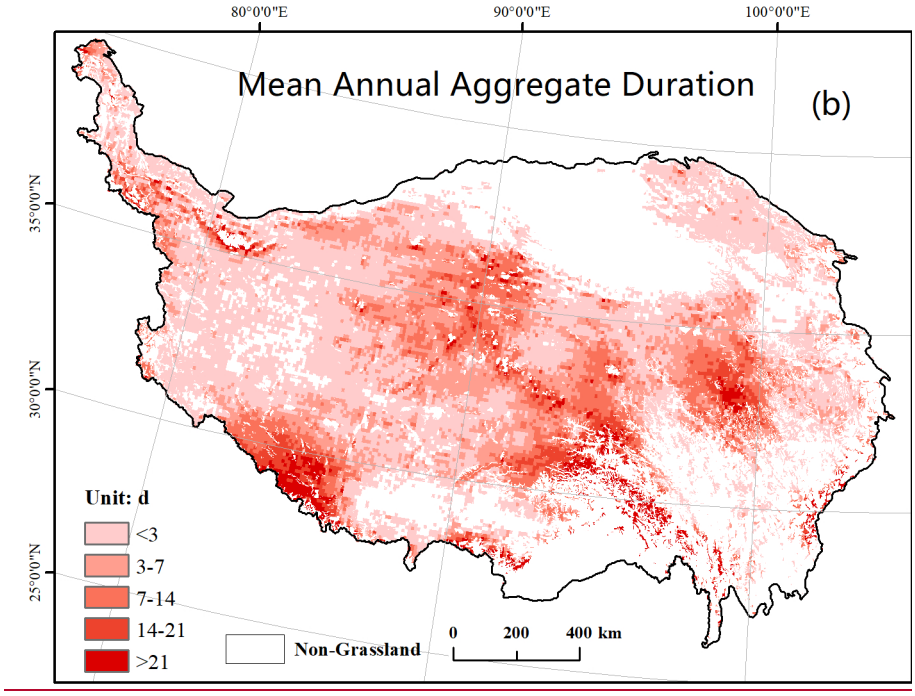


Fig. 5 Gridded annual frequency/ annual average occurrence (a) and mean ~~mean event~~annual aggregate duration (b) of snow disasters from model predictions

The distribution of mean ~~event~~ annual aggregate duration of snow disasters was consistent with annual frequency, indicating strong controls from elevation and topology. For most regions, mean annual aggregate ~~event~~ duration was below ~~7~~ 3 d. For typical pastoral regions, i.e., Naqu Prefecture, a snow disaster can last for more than ~~12~~ 14 d on average. Mean annual aggregate~~event~~ duration can last for more than ~~14~~ 21 d in high elevation mountainous areas, including the Himalayas in the southwest and alpine meadows to the east end of Bayankhar mountains, which is nearly 10% of the total grids with valid values.

3.1.2 Model-derived annual snow disaster loss, 1980–2015

Model-derived annual snow disaster losses (1980-2015) were supplied in Fig. 6~~6~~. In the figure, the orange time series was losses modelled using *Value_Add* of historical values (dynamic), assuming historical prevention capacity. The blue time series was losses modelled using constant *Value_Add* of year 2015, assuming present-day prevention capacity. All the losses are for a specific snow disaster season from August to the next June rather than a civil year.

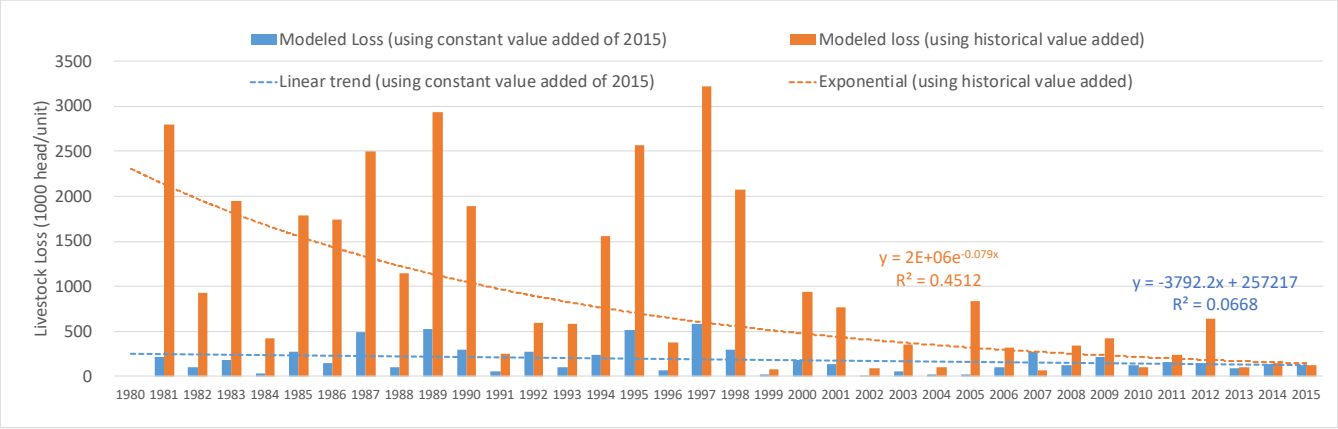


Fig. 6 model-derived annual livestock loss in snow disaster in the QTP (1980-2015). The unit of modeled loss has been converted from sheep units to heads/units by dividing 2.2 (total sheep units ≈ 2.2×herd size by heads/units according to the cattle/sheep structure in the QTP).

In order to measure model performance, historical losses over the QTP during 1980-2015 were collected from China Meteorological Disaster Catalogic (Wen 2008) (for 1980-2000) and China Meteorological Disaster Yearbook (2004-2016) (China Meteorological Administration, 2004-2016). The model result did capture the interannual variation of losses. The correlation coefficient of the modelled loss and recorded historical loss was 0.688, and the root-mean-square-error was 250,841. Our model also captured most of the years that experienced severe snow disaster loss (major loss years, annual aggregate loss of over 500,000 heads/units). These years include 1981 (referring to 1981 snow season, August to June of the next year), 1982, 1985, 1986, 1988, 1989, 1992-1995, 1997, 2007 and 2012. The correlation coefficient of the modelled loss and recorded historical loss of these years was 0.779, the root-mean-square-error was 400671, and the mean-absolute-percentage-error was 37%. For the peak loss years (annual aggregate > 2million), model results were also good. The modelled loss vs. recorded loss were 2.79 and 2.48 million for year 1981, 2.07 and 2.93 million for 1989, 2.94 and 2.57 million for 1995, and 2.79 and 3.22 million for 1997, respectively.

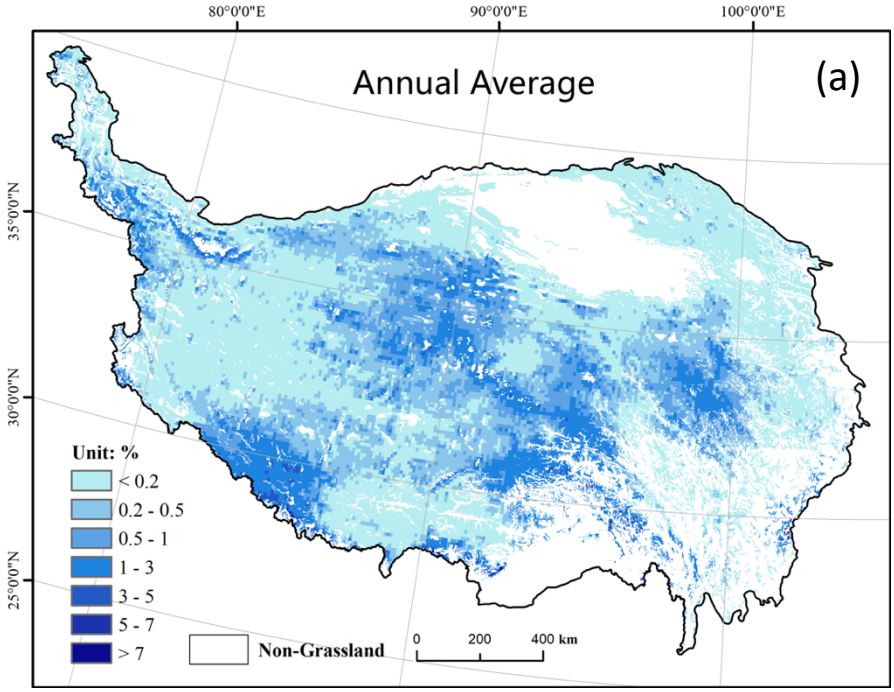
The modelled historical loss also exhibited an obvious decreasing trend as compared to the modelled loss associated with present day prevention capacity (the blue series). The difference indicates that the improved prevention capacity as proxied by value added of animal husbandry did play important role in reducing livestock loss in snow disasters. In addition, it also confirmed that the modelled historical loss cannot be used for fitting probability distribution of loss directly due to its pronounced trend. Instead, the modelled loss associated with present day prevention capacity is appropriate.

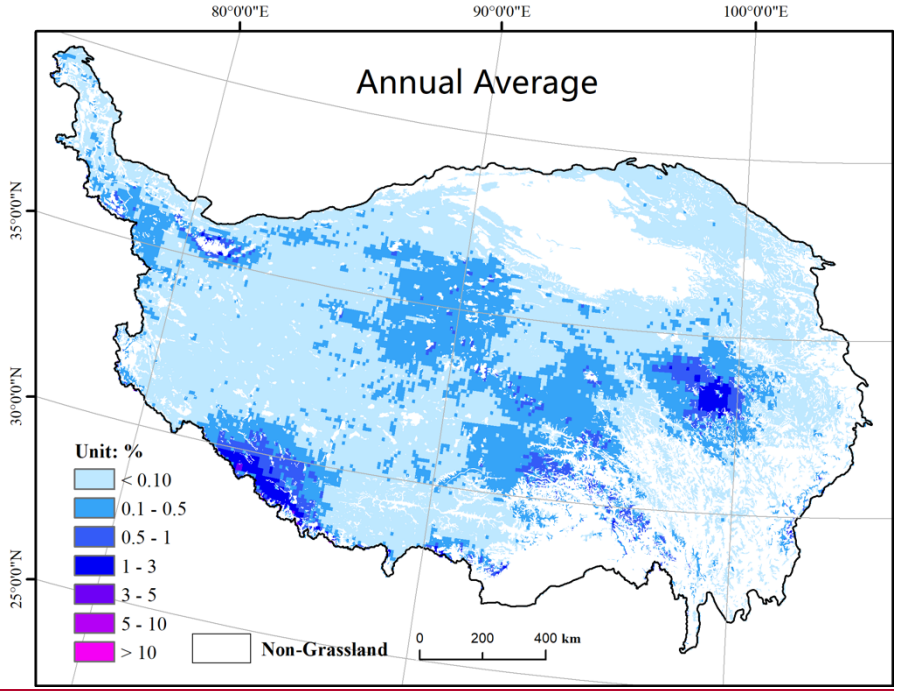
3.2 Probabilistic risk assessment results

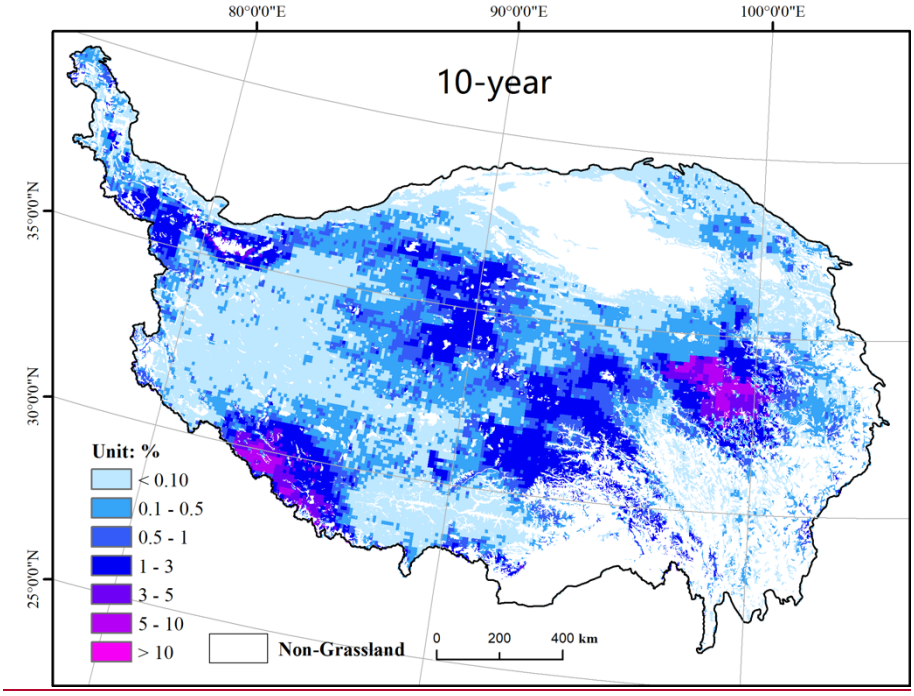
3.2.1 Risk in terms of livestock mortality rate

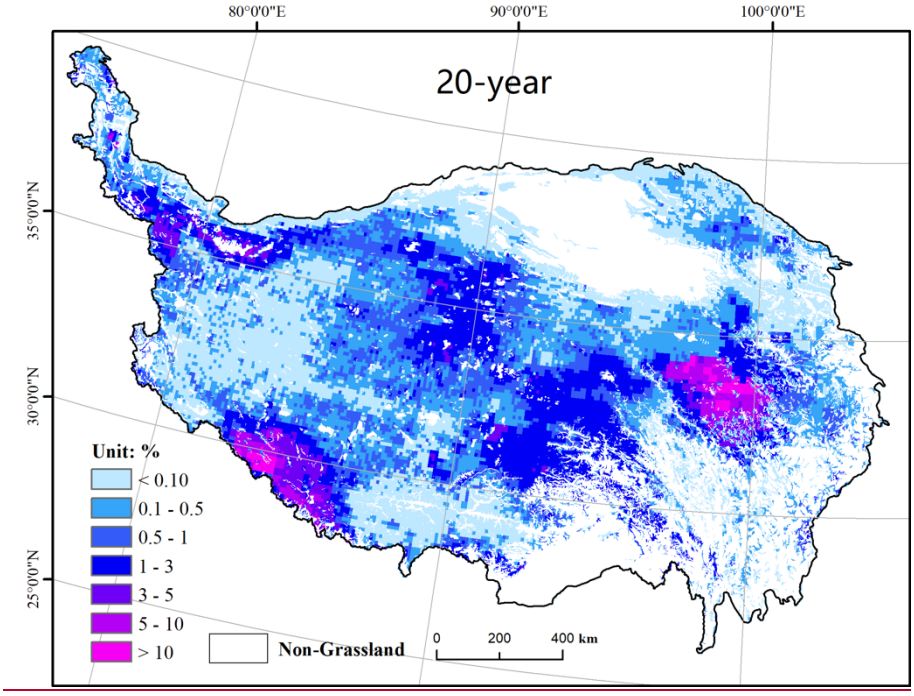
The assessed livestock snow disaster risk measured by annual mortality rate is presented in Fig. 7~~Fig. 7~~. As presenting the full probability distribution of livestock mortality rate by grid is not viable, these figures include the annual average and three return-period mortality rate maps (~~1/~~10-year~~a~~, 20-year~~1/20a~~, and 50-year~~1/50a~~), upon which the non-pasture areas were masked.

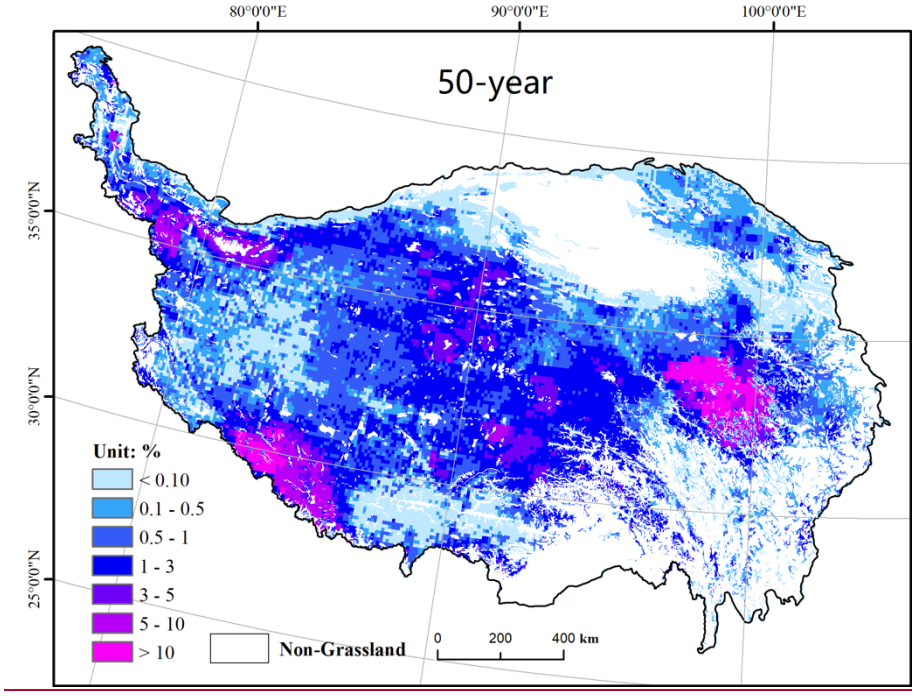
Spatial distributions of mortality rate at different return-periods are highly consistent (Fig. 7~~Fig. 7~~). The pattern is very similar to the pattern of annual aggregate snow disaster duration (Fig. 5~~Fig. 5~~), confirming the dominant influence of snow disaster duration. High-mortality rate regions are primarily located in the major mountainous areas, including the Tanggula Range and Nyainqêntanglha Range in the central QTP, the Kailas Range and neighboring Himalayas in the southwest QTP, Bayankhar mountains in the east QTP, and southern part of the Kalakoram Range and the west-end of the Kunlun Mountains in the northwest corner of the QTP. Classified by administrative districts, high mortality rate regions include the Yushu and Guoluo prefectures in Qinghai Province and Naqu, southwest Ngari, and Northwest ~~Linzhi~~ Shigatse Prefectures in the Tibet Autonomous Region. In these regions, the annual average mortality rate is up ~~ranges from 0.5%~~ to ~~7.6~~10%. In some parts of Guoluo and Shigatse, the 50-year mortality rate can reach more than 10%.~~The distribution of annual average mortality rate is extremely positively skewed. The cumulative percentage of grids with annual average mortality rates <0.5%, 1%, 2%, and 5% are 50%, 68%, 80%, and 98%, respectively. At return period of 1/20 a, estimated mortality rates range from 0.09% to 23%. The cumulative percentage of grids with 1/20 a mortality rates <0.5%, 1%, 2%, and 5% are 12%, 24%, 45%, and 89%, respectively.~~

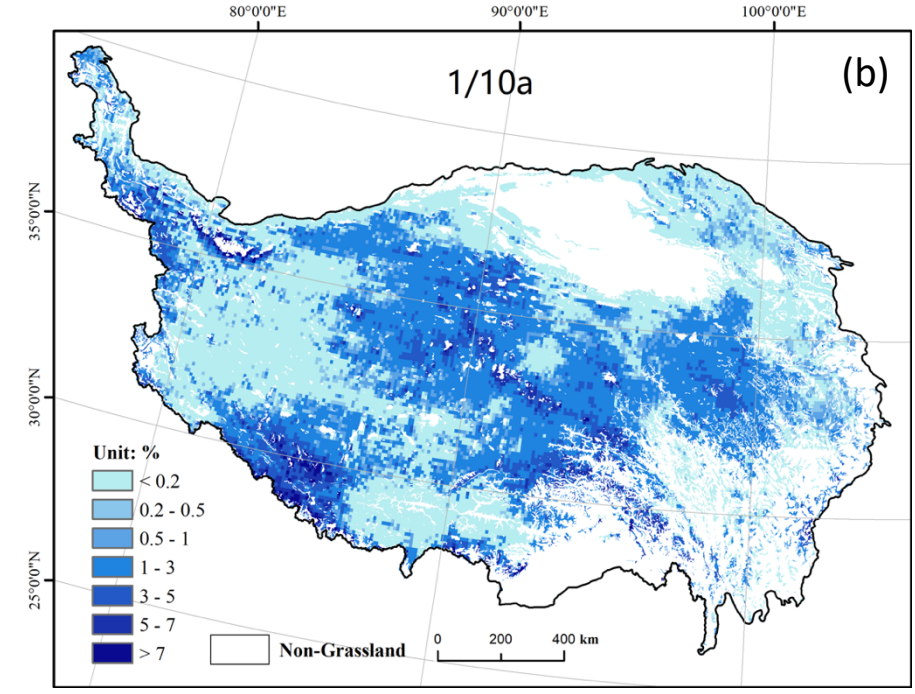

80°0'0"E
90°0'0"E
100°0'0"E
Annual Average
(a)
35°0'0"N
30°0'0"N
25°0'0"N
Unit: %
< 0.2
0.2 - 0.5
0.5 - 1
1 - 3
3 - 5
5 - 7
> 7
Non-Grassland
0
200
400 km


80°0'0"E
90°0'0"E
100°0'0"E
Annual Average
35°0'0"N
30°0'0"N
25°0'0"N
Unit: %
< 0.10
0.1 - 0.5
0.5 - 1
1 - 3
3 - 5
5 - 10
> 10
Non-Grassland
0
200
400 km


10-year
80°0'0"E
90°0'0"E
100°0'0"E
35°0'0"N
30°0'0"N
25°0'0"N
Unit: %
< 0.10
0.1 - 0.5
0.5 - 1
1 - 3
3 - 5
5 - 10
> 10
Non-Grassland
0
200
400 km


20-year
80°0'0"E
90°0'0"E
100°0'0"E
35°0'0"N
30°0'0"N
25°0'0"N
Unit: %
< 0.10
0.1 - 0.5
0.5 - 1
1 - 3
3 - 5
5 - 10
> 10
Non-Grassland
0
200
400 km


80°0'0"E
90°0'0"E
100°0'0"E
50-year
35°0'0"N
30°0'0"N
25°0'0"N
Unit: %
< 0.10
0.1 - 0.5
0.5 - 1
1 - 3
3 - 5
5 - 10
> 10
Non-Grassland
0
200
400 km


80°0'0"E
90°0'0"E
100°0'0"E
1/10a
(b)
35°0'0"N
30°0'0"N
25°0'0"N
Unit: %
< 0.2
0.2 - 0.5
0.5 - 1
1 - 3
3 - 5
5 - 7
> 7
Non-Grassland
0
200
400 km

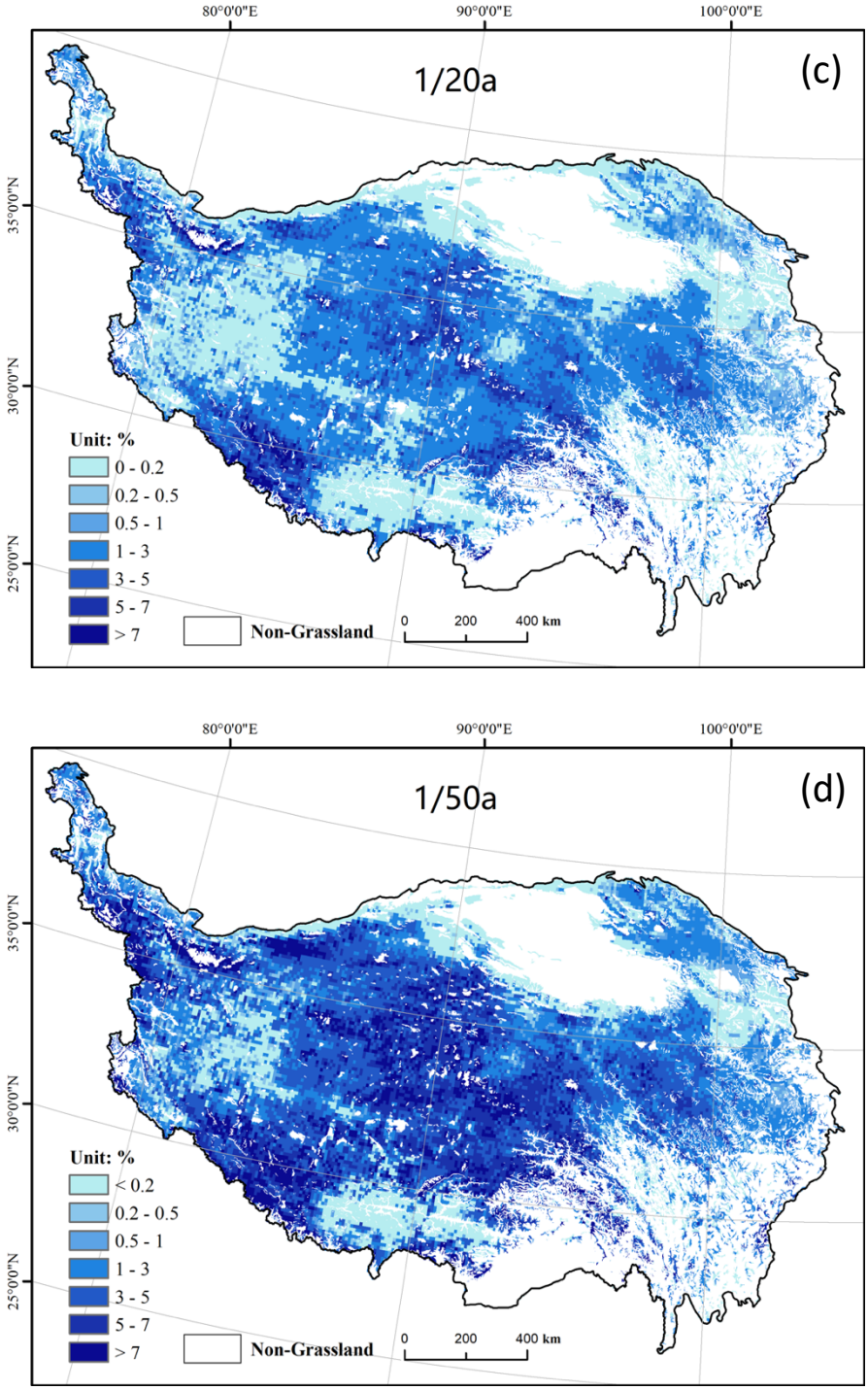
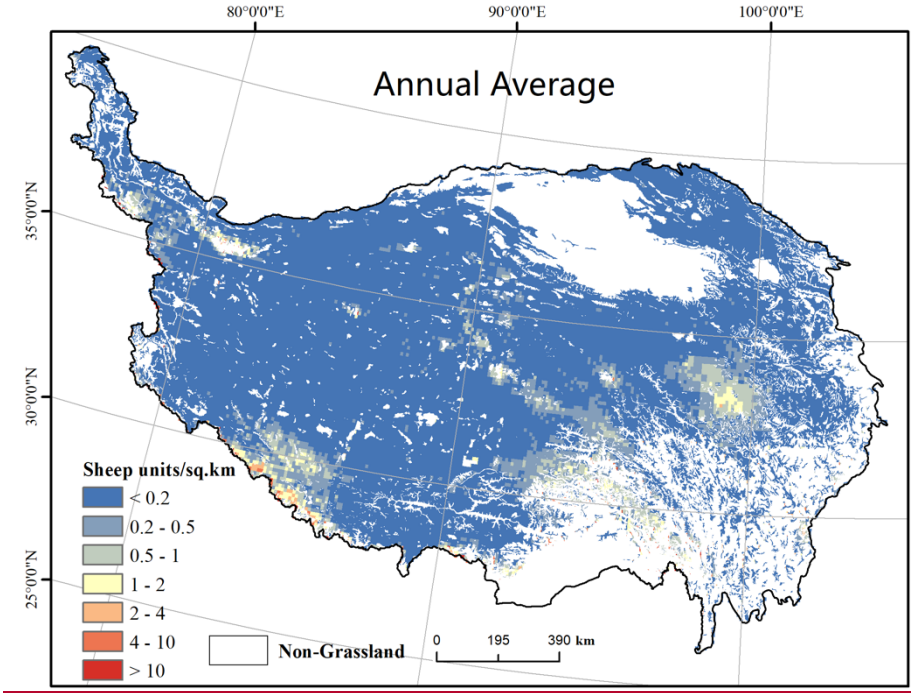
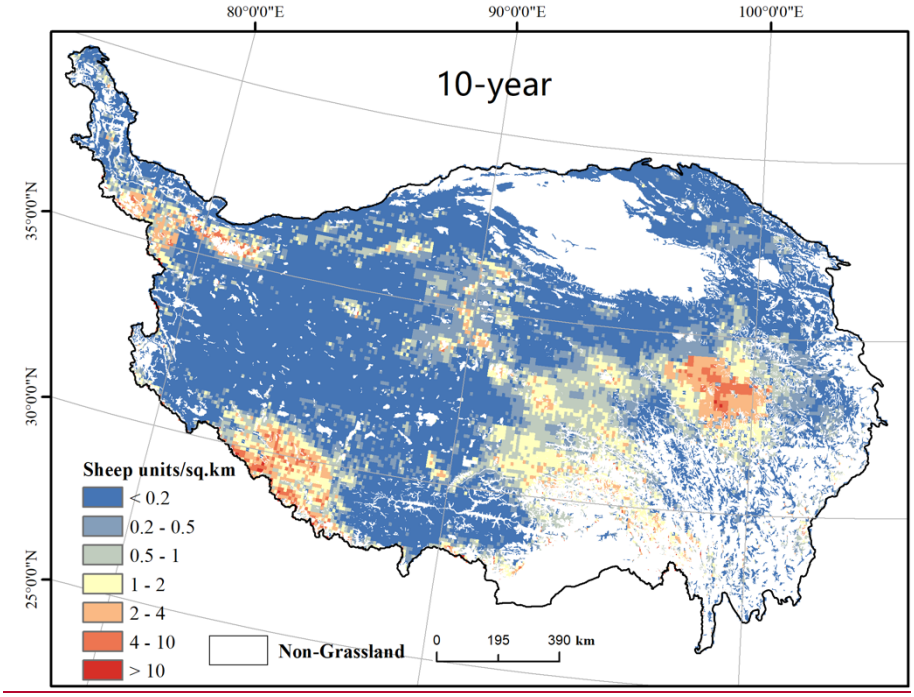


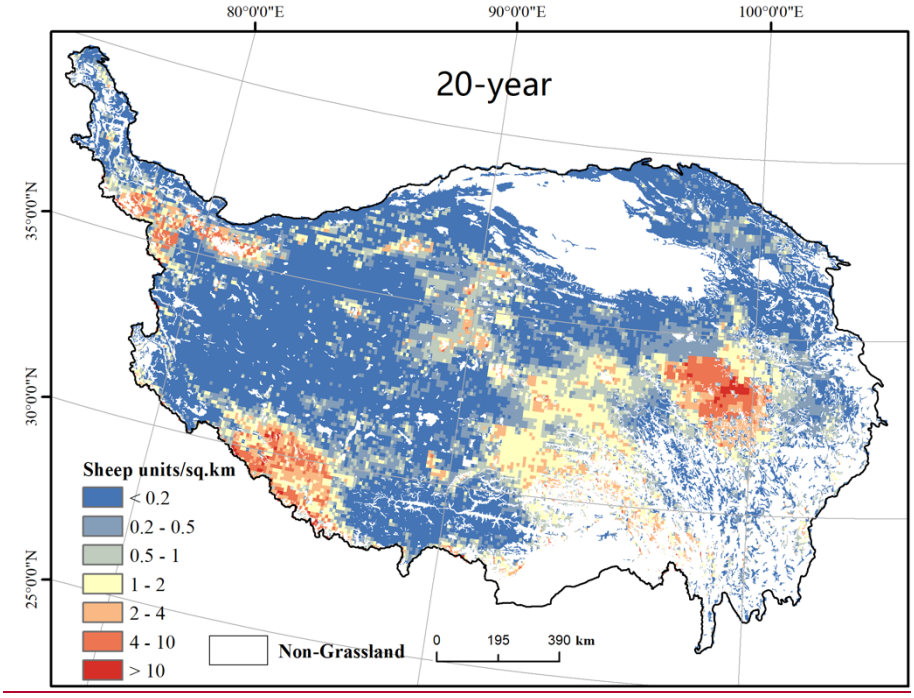
Fig. 7 Gridded livestock snow disaster risk in terms of mortality rate (%) in annual average values ~~(a)~~, and 10-year, 20-year and 50-yar return-period values ~~of 1/10a (b), 1/20a (c) and 1/50a (d)~~. The grid size is 0.1° × 0.1°.

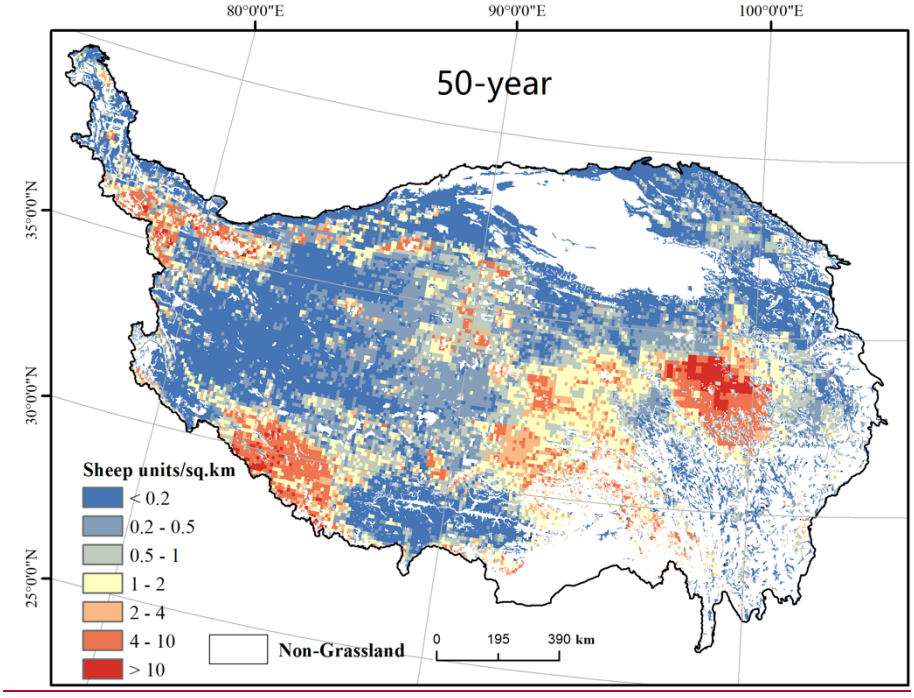
~~3.2.2 Risk in terms of livestock mortality~~

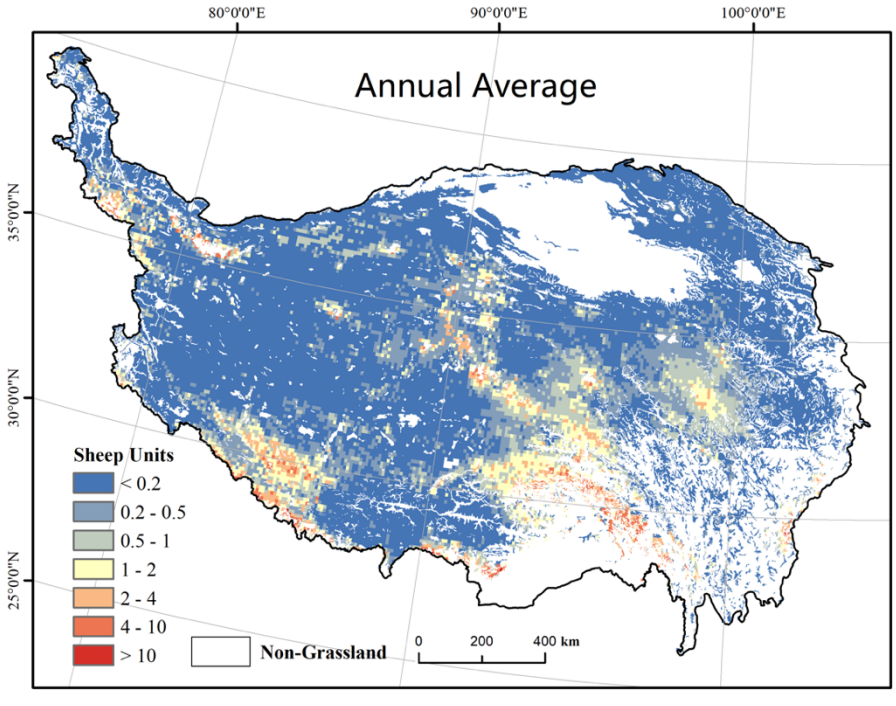
~~Risk metrics in terms of livestock mortality were then derived by multiplying the mortality rate by exposure (**Fig. 8**). Again, annual average mortality, and the mortality at 1/10 a, 1/20 a, and 1/50 a were all reported.~~

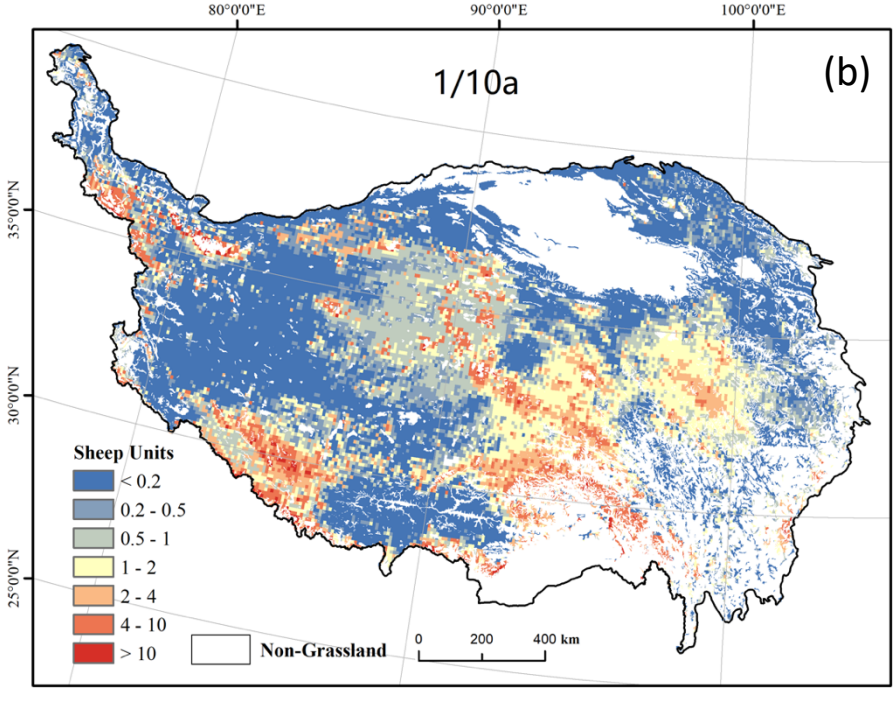

Annual Average
80°0'0"E
90°0'0"E
100°0'0"E
35°0'0"N
30°0'0"N
25°0'0"N
Sheep units/sq.km
< 0.2
0.2 - 0.5
0.5 - 1
1 - 2
2 - 4
4 - 10
> 10
Non-Grassland
0
195
390 km


10-year
80°0'0"E
90°0'0"E
100°0'0"E
35°0'0"N
30°0'0"N
25°0'0"N
Sheep units/sq.km
< 0.2
0.2 - 0.5
0.5 - 1
1 - 2
2 - 4
4 - 10
> 10
Non-Grassland
0
195
390 km


80°0'0"E
90°0'0"E
100°0'0"E
35°0'0"N
30°0'0"N
25°0'0"N
20-year
Sheep units/sq.km
< 0.2
0.2 - 0.5
0.5 - 1
1 - 2
2 - 4
4 - 10
> 10
Non-Grassland
0
195
390 km


80°0'0"E
90°0'0"E
100°0'0"E
35°0'0"N
30°0'0"N
25°0'0"N
50-year
Sheep units/sq.km
< 0.2
0.2 - 0.5
0.5 - 1
1 - 2
2 - 4
4 - 10
> 10
Non-Grassland
0
195
390 km


80°0'0"E
90°0'0"E
100°0'0"E
Annual Average
(a)
35°0'0"N
30°0'0"N
25°0'0"N
Sheep Units
< 0.2
0.2 - 0.5
0.5 - 1
1 - 2
2 - 4
4 - 10
> 10
Non-Grassland
0
200
400 km


80°0'0"E
90°0'0"E
100°0'0"E
1/10a
(b)
35°0'0"N
30°0'0"N
25°0'0"N
Sheep Units
< 0.2
0.2 - 0.5
0.5 - 1
1 - 2
2 - 4
4 - 10
> 10
Non-Grassland
0
200
400 km

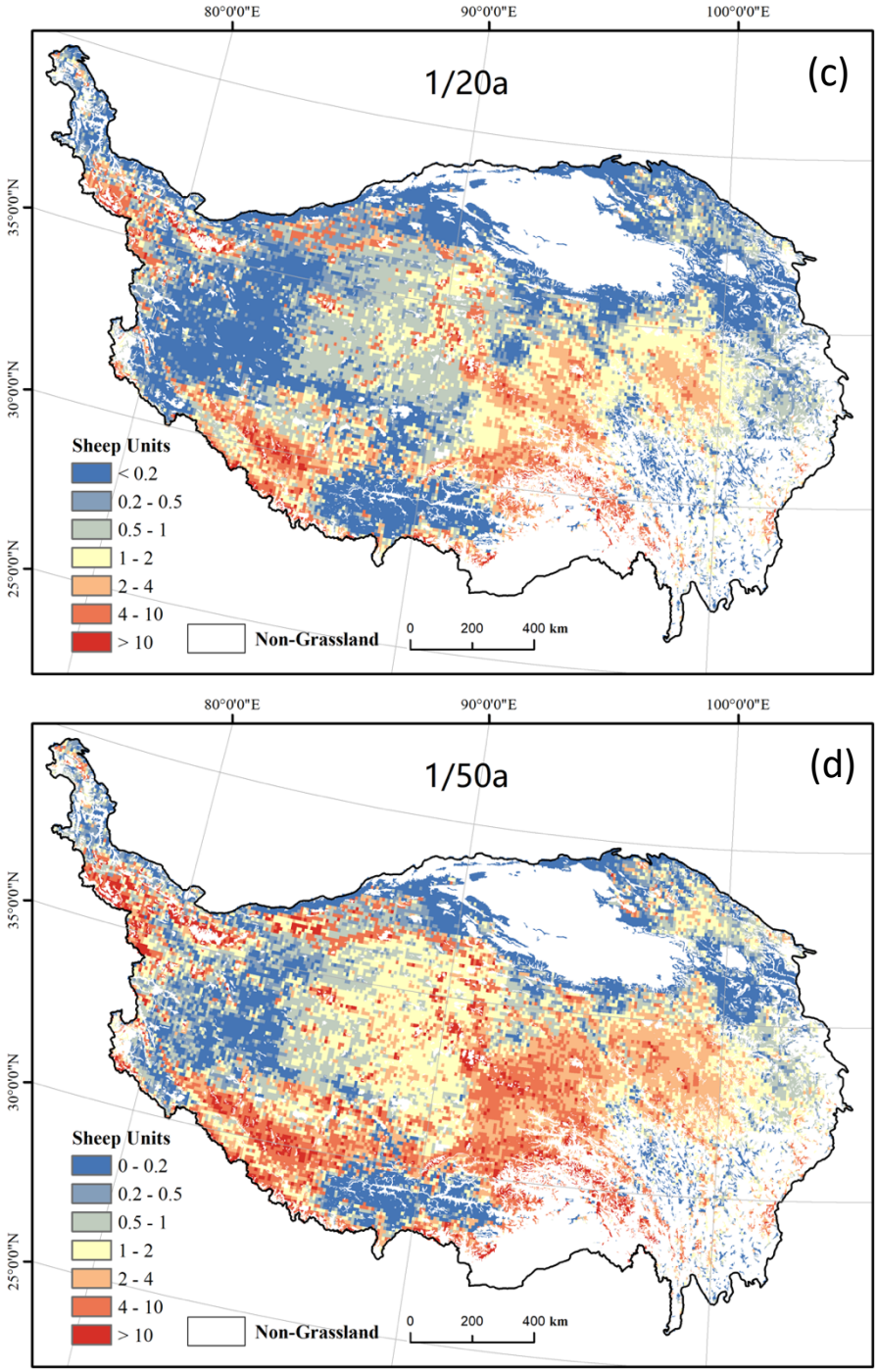


Fig. 8 Gridded livestock snow disaster risk in terms of mortality (sheept units/km^2) in annual average values ~~(a)~~, and 10-year, 20-year and 50-yar return-period values.~~and return-period values of 1/10a (b), 1/20a (c) and 1/50a (d).~~ The grid size is 0.1° × 0.1°.

3.2.2 Risk in terms of livestock mortality

Risk metrics in terms of livestock mortality were then derived by multiplying the mortality rate by exposure (**Fig. 8**). Again, annual average mortality, and the mortality at 10-year, 20-year, and 50-year return periods were all reported.

Mortality appears small in Fig. 8~~Fig. 8~~, ~~mainly due to the herd size constrained by carrying capacity~~generally several sheep units/km^2. However, ~~When~~ when aggregated at the prefecture level, mortality remained considerable (Table 1~~Table 1~~). Zonal statistics results identified high risk prefectures, including Guoluo and Yushu in Qinghai Province and Naqu, Shigatse, ~~Changdu,~~ and Nagri in Tibet Autonomous Region. In these prefectures annual mortality with a return period of ~~1/20~~20-year ~~a~~ was mostly greater than ~~100~~200,000 sheep units (the threshold for an ~~severe~~ extremely severe livestock snow disaster, as defined in GB/T20482-2017). Among them, ~~Yushu~~Guoluo, Naqu, and Shigatse~~, and Nagri~~ are of extremely high risk. Their 20-year~~1/20 a~~ mortality was all >~~200~~500,000 sheep units~~(the threshold for an extremely severe livestock snow disaster, as defined in GB/T20482-2017)~~.

Table 1 Livestock snow disaster risk in terms of mortality (1,000 sheep units) by prefecture

Prefecture	Herd size exposed (estimated)	Mortality (annual average)	Mortality (~~1/20 a~~20-year)	Mortality (~~1/50 a~~50-year)
Xining	283.4	0.1 ~~0.1~~	3.9 ~~0.8~~	5.6 ~~2.1~~
Haidong	437.2	1.3 ~~0.2~~	6.3 ~~1.0~~	13.1 ~~2.1~~
Haibei	2036	1.0 ~~1.9~~	26.5 ~~13.3~~	37.9 ~~26.6~~
Huangnan	1080.2	0.6 ~~1.0~~	13.8 ~~6.1~~	19.4 ~~13.1~~
Hainan	1692.7	0.8 ~~1.4~~	23.7 ~~8.0~~	34.2 ~~16.9~~
Guoluo	5160.7	84.9 ~~32.2~~	1098.1 ~~111.7~~	1962.5 ~~170.6~~
Yushu	12720.9	28.8 ~~69.0~~	492.1 ~~305.8~~	771.2 ~~535.6~~
Haixi	10659.2	6.7 ~~32.5~~	129.0 ~~45.3~~	187.3 ~~102.0~~
Lahsa	1802.1	0.4 ~~9.0~~	9.6 ~~41.2~~	13.9 ~~85.3~~
Changdu	4217.4	12.7 ~~70.8~~	155.6 ~~188.8~~	219.4 ~~281.8~~
Shannan	2607.5	0.2 ~~32.7~~	5.6 ~~89.7~~	7.9 ~~142.8~~
Shigatse	12245.4	110.9 ~~117.1~~	932.4 ~~393.9~~	1470.7 ~~608.9~~
Naqu	17877.2	48.7 ~~129.2~~	646.8 ~~530.1~~	952.6 ~~956.7~~

Ngari	12970.8	12.8 ~~47.3~~	218.8 ~~243.6~~	334.3 ~~504.6~~
Linzhi	2743.9	9.4 ~~101.2~~	120.2 ~~244.4~~	166.9 ~~339.3~~

Note: Only prefectures with a majority of land mass within the QTP are listed. Statistics reported in the table only refer to areas within the QTP.

4. Discussion

4.1 Spatial patterns of livestock snow disaster risk in the QTP

Our results illustrate the spatial distribution and offer quantitative metrics of risk in terms of livestock mortality and mortality rate due to snow disasters in the QTP. The spatial pattern of risk agrees with earlier studies covering this region quite well. From an empirical perspective, the literature frequently mentions Easter Inner Mongolia, the Northern Tianshan Mountains in Xinjiang, and Northeastern QTP as centers of snow disaster around China (Gao, 2016; Hao et al., 2002). Within the QTP, high frequency snow disaster regions that are mentioned repeatedly in the literature include Yushu, Guoluo, Naqu, Shigates, and Nagri (Bai et al., 2011), which have all been identified in our study. As for risk assessment, our results also agree well with earlier studies. For instance, regions between the Kailas Range and neighboring Himalayas, southern Qinghai Province (mainly Yushu and Guoluo), and the northwestern corner of the QTP are all considered as higher risk regions in both qualitative (Liu et al., 2014b) and quantitative (Shi, 2011; p.106-107) risk assessment results. In northern and western Naqu Prefecture, and the central-to-western end of the Nyainqêntanglha Range, our results are consistent with the national snow disaster risk map (Shi, 2011; hereafter termed risk maps), which are of higher-to-the-highest risk. Nevertheless, these regions are considered the lowest of lower risk in the results presented by Fenggui Liu et al. (2014).

For the magnitude of annual average mortality rate, our results were smaller than those in the risk maps of China (Shi, 2011; p.104-107); in general, our results had values about half those previously reported. For the high-risk regions, annual average mortality rates were generally ≥ 2% in our results, but ≥ 4% in the risk map results. Our result had a vast low risk region with annual average mortality rates <0.5%, but the threshold was 1~3% in the risk maps. In terms of mortality, our results matched historical records better. For instance, the most severe snow disaster in southern Qinghai Province since 1960 was in 1995-1996 snow season, mostly in Guoluo and Yushu (Bai et al., 2011), the deadliest disaster in nearly 65 years. It claimed a loss of 1.~~08~~ 20 million livestock (Wen 2008) ~~(equivalent to 1.5~2 × 10^6 sheep units, assuming the local herd structure for 2016)~~. According to our model-derived historical loss, in 1996 in Yushu and Guoluo prefectures the mortality was approximately 1.20 million heads/units (turned from 2.64 million sheep units modelled given the cattle-to-sheep ratio in Qinghai Province)~~our risk metrics, an annual loss of 2 × 10^6 (summing Guoluo and Yushu) would have a return period over 100 years (Table 2)~~. Another example is the 1997–1998 snow disaster in Naqu, the most severe snow disaster since 1960, leading to a loss of 0.82 × 10^6 livestock ~~(equivalent to have 1.2 × 10^6 sheep units, assuming the local herd structure for 2016)~~ (Wen, 2008). ~~Again~~Our

model-derived mortality for this event was 0.72 million head/unit (turned from 1.59 million sheep units)~~, an annual loss of 1.2 × 10⁶ sheep units has a return period of 50 to 70 years according to our metrics~~. ~~As we have assumed stronger prevention capacity using the GDP values for 2015, it is natural to have a higher return period than empirical values.~~ The 1995-1996 Yushu and Guoluo snow disaster would have a return period over 50-year, and the 1997-1998 Naqu snow disaster would have a return period of 80 to 100-year according to our metrics (Table 1). If the mortality rate estimated in risk maps were used instead, then the corresponding return-period could be underestimated~~ by approximately 1/20 a~~, and consequently, snow disaster risk would be exacerbated.

4.2 Temporal changes of livestock snow disaster loss and its drivers

Our results rebuilt a complete list of annual livestock snow disaster loss for period 1980-2015 (Fig. 5). The modelled loss has shown a clear declining trend. Major and peak loss years occurred frequently before year 2000, but rarely after that. Using a different historical data set, Wei et al. (2017) has suggested that over the period of 1960-2015, the loss was increase in the long run. However, if focusing on the later part of the period (i.e. 1980-2015) that they covered, similar results of downward trend would have been derived from their dataset.

Our results indicate that, both climate change and improved prevention capacity have contributed to the declining trend in annual livestock loss. The effect of climate change is revealed by the model- derived historical loss using constant value added of animal husbandry (the blue series in Fig. 6). It has a very modest declining trend, -3792 head/unit per year, or equivalently -1.8% per year if an exponential trend was applied. Such a modest declining trend after controlling for prevention capacity is supported by the literature. Earlier studies has reported uniform increase in temperature (Kuang and Jiao, 2016), reduced snow cover area (Duo et al., 2014), snow depth, and snow cover days (You et al., 2011), and increased growing precipitation and improved vegetation (Pang et al., 2017) in the QTP. All these factors contribute to smaller event frequency, shorter duration, and less environmental stress during and before the snow season.

Improved prevention capacity plays a much more significant role in the declining annual livestock loss. This can be evidenced by the difference of the two model-derived annual loss series in Fig. 6, for they shared identical historical snow disaster event set, and differed only in prevention capacity. For model-derived historical loss (orange series in Fig. 6), the exponential trend indicates that annual livestock loss reduces 7.9% per year, or equivalently 57349 head/unit per year if a linear trend was applied. Therefore, improving prevention capacity has accounted for approximately 6.1% reduction in annual livestock loss per year if exponential trends are assumed, or – 53557/a if linear trends are assumed. The contribution can be supported by the reported government investment in infrastructure such as thermal barns/sheds and fenced grassland, and improved preparedness such as winter season hay and forage storage, although there are still much potential for further improvement(Shang et al., 2012; Wang et al., 2013b; Wei et al., 2017).

4.~~2~~ 3 Advantages of the event-based PRA

Our study differ from the existing literature largely in its event-based PRA framework. Such a framework derives unique information that can hardly be obtained by earlier methods that are based on annual basis, which are important for preparedness

decisions and insurance solutions. With the event-based PRA framework, following information have been derived for better risk reduction.

1) ~~For instance, t~~The event-based framework enables the estimation of frequency distribution of the occurrence ~~and duration~~ of single disaster events. Overall, our analysis indicates that snow disasters are frequent in terms of annual occurrence but more than one snow disaster a year is unlikely (Fig. 5~~Fig. 5~~). Given this finding, prior counter-measures should be implemented to build prevention capacity to handle the one event in every year (Mechler et al., 2010). In addition, the framework can be further applied to climate change analysis. Our snow disaster event identifier can help reveal the changes in frequency and intensity (mainly *Duration*) of snow disasters in response to climate change, and therefore provide information for adaptation.

2) Our results for single event duration provide important quantitative references for hay and fodder storage, which were not achieved by earlier annual basis analyses. For the majority of higher-risk regions, once a snow disaster occurred, on average it lasted for 12 d (Fig. 5~~Fig. 5~~). At return periods of ~~1/~~10~~-a~~-year and ~~1/~~20~~-a~~-year, the durations of single events were up to 21 days and 28 days, respectively (Fig. A2). At return periods of ~~1/~~50-year~~-a~~, single events could even last for more than 40–50 days. The regional average duration of a ~~1/~~20-year~~-a~~ event in Naqu, Yushu, Guoluo, and south Ngari, was estimated to be 24, 22, 26, and 26 days, respectively. From a preparedness perspective, the amount of hay and fodder storage needed, from combined herder households and local government reserves, can be readily estimated from our results once their goal of preparedness capacity is set, i.e., capable of managing a ~~1/~~10-year~~-a~~ event. Alternatively, our results can also help local regions measure their preparedness capacity given their amount of hay and fodder storage. For instance, according to the authors' survey (Ye et al., 2017b), the total amount of hay bought can only support supplementary feeding of county-wide livestock for at most 3~5 days in some counties in central Naqu Prefecture. Such a level of preparedness can only endure a snow disaster with return period less than 5-year.

3) Our event-based PRA results can also provide solid technical support for insurance solutions. Earlier studies that assess risk on annual basis using annual aggregate snow-cover days, or snow depth variables are not capable of doing so as insurance indemnities must be clearly triggered by specific events. The capability of finding the frequency distribution of event occurrence and event duration provides necessary information to help the design of insurance trigger schemes. The insurance product could be conventional (indemnity-based), where the post-disaster loss-adjustment is conducted on herder household bases. Meanwhile, our results can readily support the calculation of actuarially fair premium rates and cat-risk loadings by applying deductible conditions to turn event loss records into event-based insurance losses~~, and then calculating annual average and return period insurance loss-cost ratios~~ (Wang and Zhang, 2003; Ye et al., 2017a).

~~**4.3 Risk-informed implications**~~

~~Our results imply that the present level of preparedness in local regions are far from sufficient. According to our local survey data, a sheep unit, even under the minimum level of supplementary feeding, consumes 1 kg of hay and 0.5 kg of fodder (Ye et al., 2017b). Nyainrong County in central Naqu Prefecture prepared a 4.4 million yuan fund to prepare winter storage of hay and fodder in 2016. The total amount of hay bought (460 ton) can only support supplementary feeding of county-wide livestock~~

~~(1167.6 thousand sheep units) for at most 3~5 days. Such a level of preparedness can only endure a snow disaster with return period less than 1/5 a. This discrepancy also explains the frequent losses from snow disasters in these regions.~~

~~It is not straightforward to improve such preparation capacity to manage higher return period events. As the herd size has mostly reached the defined carrying capacity, hay harvests for winter seasons from local grassland are much less feasible (Shang et al., 2012). Agro-pastoral regions, i.e., the northeast, southeast, and southern parts of the QTP, mostly the agro-pastoral regions in Qinghai, Gansu, Sichuan, and Shigatse in Tibet, can obtain some support from crop straws. Pure pastoral regions, i.e., Naqu and Nagri, are problematic, due to the lack of local resources, and the high transportation cost to import from other regions. To enhance preparedness capacity, inter-prefecture overall planning will be needed to arrange support from agro-pastoral regions, e.g. Shigatse and Lhasa, to pastoral regions. In addition, forage harvesting bases within small parts of pastoral regions with relatively large precipitation and grassland productivity will also be favoured. However, it remains less likely that local regions will be able to provide sufficient hay and fodder to endure long lasting events, i.e. > 14 d or an equivalent event with a return period larger than 10 a.~~

~~Due to the difficulty in improving prevention capacity, insurance schemes are needed to provide relief (Mechler et al., 2010). The insurance product could be conventional (indemnity-based), where the post-disaster loss adjustment is conducted on herder household bases. A more favourable choice is to adopt an index-based structure using livestock mortality rate as predicted by our model, in which disaster duration and growing season aggregate precipitation are two critical indices. The index-based structure is much more efficient in vast and sparsely populated regions by expediting the loss-adjustment process, and consequently, should save considerable associated costs (Ye et al., 2017b). Furthermore, using a model-predicted mortality rate can encourage local communities to invest in prevention and preparedness, and reduce moral hazards (Miranda and Farrin, 2012).~~

4.4 Limitations

Several limitations in our risk assessment model must be mentioned. First, our hazard module to rebuild/predict snow disaster still suffers from uncertainty. We obtained a good AUC score from the BRT model for identifying snow disaster days, and also good agreement in timing of occurrence and distribution of duration for longer-duration events. However, the performance in capturing small disasters of short-duration, i.e., < 5 d, still needs improvement.

Due to the lack of exact spatial distribution of sheep units, the exposure data was derived according to the computed carrying capacity by grassland types. The total herd sizes computed differ within 20% to those ~~reported in the statistical yearbooks at the prefecture levels for pastoral regions~~officially released. ~~The difference for agro-pastoral prefectures in the eastern QTP was much larger, as agriculture provides extra foodstuff for raising livestock and supports livestock farms in addition to free grazing. Fortunately, as snow disaster threats have little impact on livestock kept on farms, our result is less likely to severe underestimate mortality in these locations. For prefectures in the central and western part of the region, our result is of practical significance for use as a reference for livestock mortality under the long-run forage-livestock balance, irrespective of the present true herder size~~ In addition, for historical period when the forage-livestock balance policy that have not come into practice, the actual herdsize exposed would be larger than carrying capacity due to over-grazing . Therefore, our model-derived

historical loss was conservative due to the potentially larger grazing herd size than estimated. However, for risk assessment purpose, using present day exposure is reasonable to estimate livestock loss distribution in the next couple of years. For short and mid-range future risk assessment, then a projection of exposure will be needed. It then requires to project future grassland structure and productivity changes (Gao et al., 2016).

Finally, our risk metrics were derived from events rebuilt from historical climate data, but not from stochastic simulations. Consequently, we have a limited number of events and annual loss records. We are only confident for risk metrics less than 1/35 a. Metrics for any higher return periods were derived from extrapolation and must be used with caution. This limitation can be resolved by inputting stochastic climate datasets using a stochastic weather simulator.

5. Conclusions

Quantitative risk metrics derived under a probabilistic risk assessment framework are critical for understanding disaster risks and providing quantitative evidence for risk-informed decision-making and resilience-building. In this study, we developed an event-based PRA approach for livestock snow disaster in the QTP region and derived risk metrics for livestock mortality and mortality rate. Our assessment results show that the spatial distributions for mortality rate and mortality size are quite similar. Hazard intensity, in terms of disaster duration, was the major driver of spatial differences in livestock mortality, while the influence from exposure in terms of herd size was quite modest. High risk regions include the Nyainqêntanglha Range, Tanggula Range, Bayankhar mountains, and the region between the Kailas Range and neighboring Himalayas. At a return period of 20-year, the annual livestock mortality rate was estimated to be > 2% and mortality was estimated to be > 2 sheep unit/km^2. At prefecture levels, the most important animal husbandry bases were identified as high risk regions, including Guoluo in Qinghai Province and Naqu, and Shigatse in the Tibet Autonomous Region. In these prefectures, a snow disaster event with return period of ~~1/20~~20-year a or higher can easily claim a total loss of more than 500,000 sheep units. Our results of return-period mortality rate and death toll show better agreement with historical losses than those reported earlier. Compared to earlier results, our approach relies on the prediction/simulation of snow disaster events, and correspondingly the modelled livestock losses are on event basis. In addition, our quantitative results for the return-period disaster duration are valuable for preparing hay and fodder reserves and designing insurance protection. The methodology developed here can be further adapted to future climate change risk analysis and providing risk-informed adaption suggestions for the QTP region.

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Appendix

List of Abbreviations

AUC	Area-Under-the-Curve
BRT	boosted regression tree
CMA	China Meteorological Administration
CMSDS	China Meteorological Science Data Sharing Service System
PRA	probabilistic risk assessment
QTP	Qinghai-Tibetan Plateau
SDD	snow-disaster-day

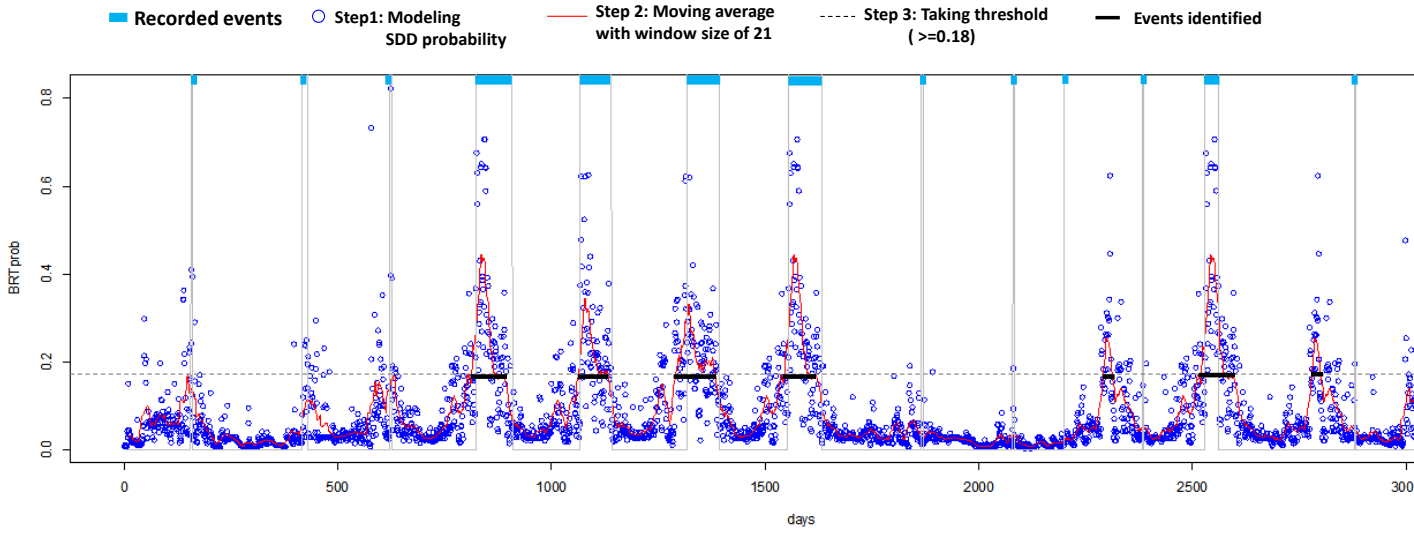

Fig. A1 Illustrative chart of the procedure for identifying snow disaster events, and its calibration with historical records. The time series is
of days in the winter season (October 1 to May 31) with snow disaster records after 2008. In total, this includes 13 station•winter and 3168 single
shows that the procedure is capability of accurately capturing major historical events with relatively longer duration in terms of both timing of
duration.

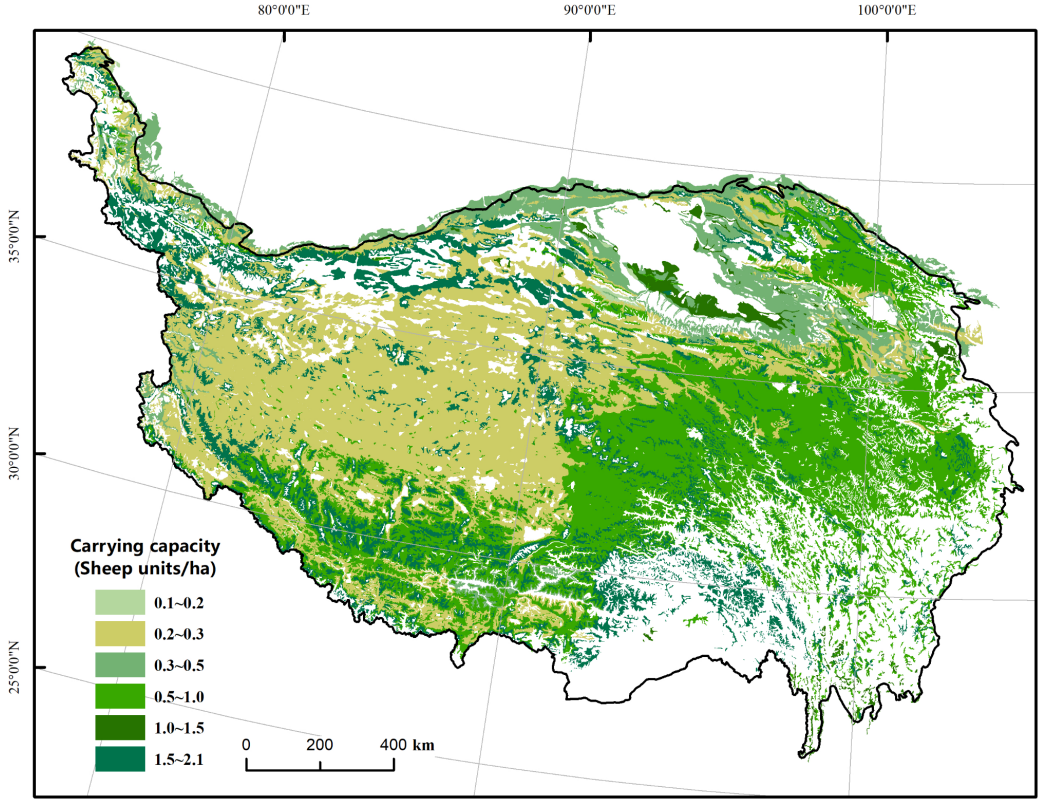

Fig. A2 Spatial distribution of livestock exposure estimated from vegetation distribution

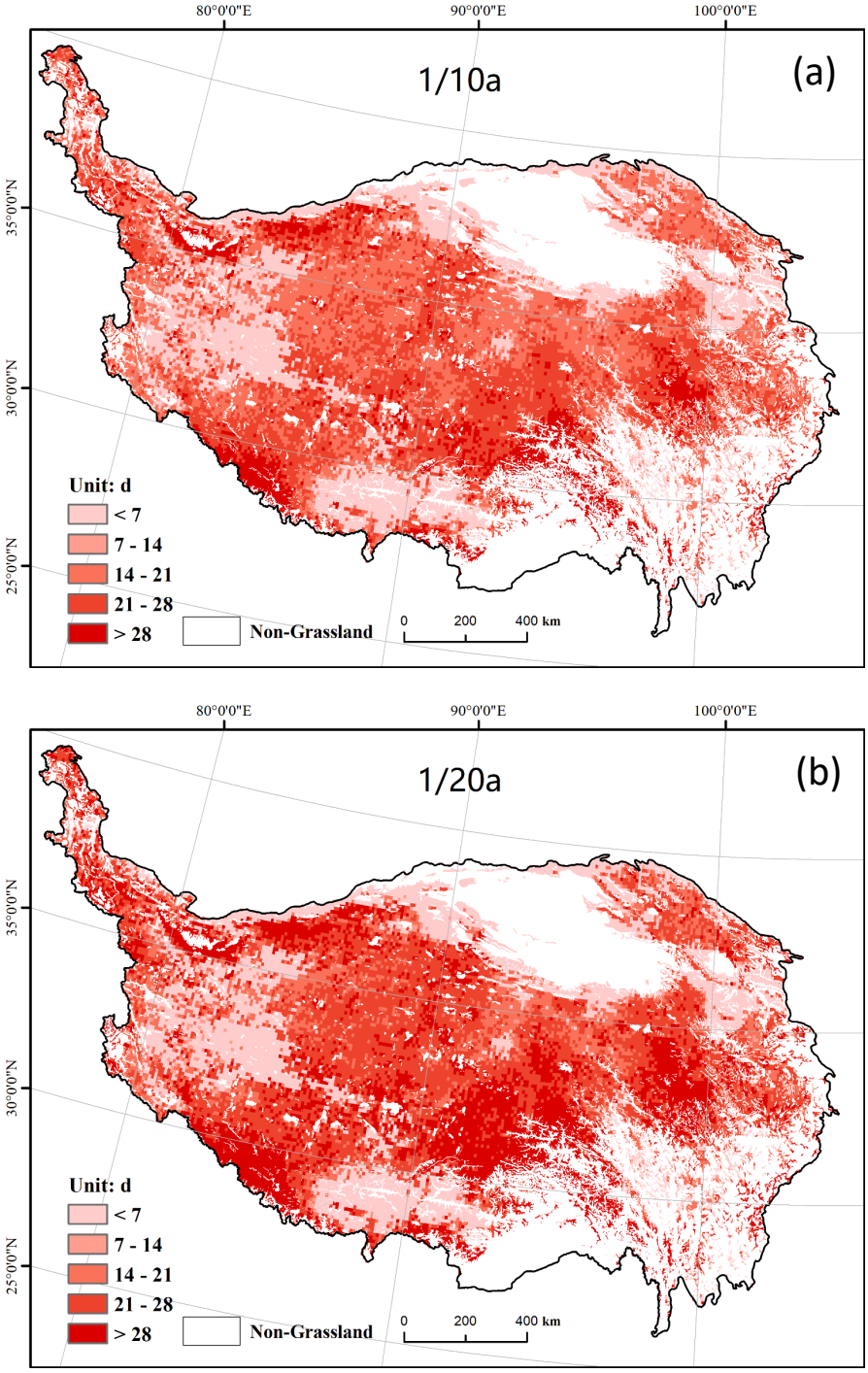

Fig. A3 Gridded duration of a single disaster event by return period: (a) 1/10a; (b) 1/20a

Table A1 Look-up table of carrying capacity by grassland type in the QTP

Grassland type	Fresh grass yield (kg/ha)	Annual grazing rate (%)	Grassland required per sheep unit (ha/unit)	Carrying capacity (sheep unit/ha)
Alpine meadow	1452	50	305.70	0.74
Alpine steppe	677	40	819.30	0.27
Apline meadow-steppe	689	45	745.20	0.30
Alpine desert-steppe	554	35	1077.30	0.21
Apline desert	519	30	988.95	0.23
Temperate steppe	3018	40	170.10	1.32
Temperate desert	683	30	1183.50	0.19
Temperate desert-steppe	611	35	840.75	0.27
Lowland meadow	3498	50	127.50	1.76
Mountain meadow	3879	55	132.30	1.70

Note: Figures were adapted from (Xin et al., 2011) and (Land Management Administration of Tibet Autonomous Region, 1994)