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Spatial variation of human influences on grassland biomass on the Qinghai-Tibetan Plateau

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Abstract:

An improved understanding of increased human influence on ecosystems is needed for predicting ecosystem processes and sustainable ecosystem management. We studied spatial variation of human influence on grassland ecosystems at two scales across the Qinghai-Tibetan Plateau (QTP), where increased human activities may have led to ecosystem degradation. At the 10 km scale, we mapped human-influenced spatial patterns based on a hypothesis that spatial patterns of biomass that could not be attributed to environmental variables were likely correlated to human activities. In part this hypothesis could be supported via a positive correlation between biomass unexplained by environmental variables and livestock density. At the 500 m scale, using distance to settlements within a radius of 8 km as a proxy of human-influence intensity, we found both negatively human-influenced areas where biomass decreased closer to settlements (regions with higher livestock density) and positively human-influenced areas where biomass increased closer to settlements (regions with lower livestock density). These results suggest complex relationships between livestock grazing and biomass, varying between spatial scales and regions. Grazing may boost biomass production across the whole QTP at the 10 km scale. However, overgrazing may reduce it near settlements. Our approach of mapping and understanding human influence on ecosystems at different scales could guide pasture management to protect grassland in vulnerable regions on the QTP and beyond.

Keywords —Alpine grasslands, distance to settlements, human influences, livestock density, overgrazing, remote sensing of biomass, spatial-pattern modeling

1. Introduction

More than three-quarters of the terrestrial biosphere has been altered by human activities

(Ellis and Ramankutty, 2008) which has also caused unprecedented changes in many Earth-system processes during the last decades (Chen et al., 2013; Ellis, 2015), including regional and local ecological processes (Ellis and Haff, 2009). It is necessary to understand the consequences of human influence on ecosystems to better explain spatial patterns of ecosystems and their responses to climate and other environmental changes (Ellis, 2015). Ecosystem functioning and services have been most affected in arid and semi-arid areas, where recent degradation has taken place (Chen et al., 2014; Harris, 2010; Wessels et al., 2004). The grassland ecosystems in these areas cover a large portion of the Earths' surface and contain substantial amounts of soil organic carbon. Grassland degradation and land-use changes, including conversion of grassland to cropland, result in a loss of grassland ecosystem carbon stocks (Conant et al., 2017; Guo and Gifford, 2002). This is also the case on the Qinghai-Tibetan Plateau (QTP) (Chen et al., 2013), where vast grassland ecosystems store a large amount of carbon, thus playing a significant role in global carbon cycle (Liu et al., 2016; Ni, 2002).

The grassland ecosystems on the QTP also influence the local (Xu et al., 2009) and even global climate, e.g. by triggering South Asian monsoon activity (Duan and Wu, 2005). In addition, the QTP is the source region of Asia's major rivers (Figure 1), which supply fresh water for a large part of the world's population downstream (Foggin, 2008; Xu et al., 2008). The stability of ecosystems on the QTP is thus not only of regional importance but also of global relevance for water supply, radiation feedbacks and global climatic patterns (Meyer et al., 2013).

The grassland ecosystems on the QTP, characterized by slow plant growth and recovery rate after disturbance (Shang and Long, 2007), are particularly vulnerable to and threatened by pressures from climatic changes and human activities. Degradation of alpine grasslands has indeed been observed on the QTP and led to productivity declines, land desertification and an

increase of noxious weeds (Fassnacht et al., 2015; Lehnert et al., 2014a). Such degradation not only damages the livelihoods of local people but also threatens biodiversity and the ecological services of the QTP at large (Harris, 2010). However, the causes of the grassland degradation on the QTP are still unclear and have been related to warming-caused desiccation and permafrost degradation (Harris, 2010; Lehnert et al., 2016) or to increasing human activities (Harris, 2010; P. Wang et al., 2016; Zhaoli et al., 2005).

Increasing human activities may have affect grassland biomass production on the QTP, which is mostly covered by rangeland and livestock grazing as the main land-use type (Chen et al., 2013). Privatization of rangeland and semi-nomadic pastoralism have caused increasing grazing pressure (Harris, 2010; Meyer et al., 2013; Wang et al., 2017) and overgrazing of winter pastures (Harris et al., 2016, 2015; L. Li et al., 2017). Moreover, infrastructure development such as highways and townships, tourism and mining exert increasing pressure on QTP grassland ecosystems (S. Li et al., 2017). Human activities of grassland conservation programs (L. Li et al., 2017) and nature reserve programs (S. Li et al., 2018), however, have been launched to protect ecosystems and secure biodiversity and ecosystem services. All these human activities happened at different areas and scales. For example, livestock grazing is widely spread across the whole QTP whereas the grazing pressure is higher in low areas and near settlements. Construction works are site-based and ecosystem protection programs are widely located in the "Three-Rivers headwater regions" in the southern part of Qinghai province. These human activities indicate that human influences on grassland ecosystems are spatially heterogeneous and scale-dependent.

The various human activities and land-use intensity on the QTP, combined with clear environmental and productivity gradients (Chen et al., 2015), imply that the grasslands respond differently to diverse human activities on the QTP. For example, the different levels of grassland productivity translate into different carrying capacities for livestock (Miehe et al.,

2008), indicating different levels of resistance to grazing and different grazing effects (Milchunas et al., 1988). Previous studies involved quantifying human influence on grassland dynamics (Chen et al., 2014; Lehnert et al., 2016; L. Li et al., 2018) and mapping of human-influence intensity on the QTP (S. Li et al., 2017). However, quantifying and mapping spatially heterogeneous human influence on grassland ecosystems has not been done so far, yet this would be key to understand how ecosystems respond to environmental changes and to help distinguishing climatic and anthropogenic contributions to spatial variation in grassland biomass. We aimed to map human-influenced spatial patterns of grassland biomass on the QTP at two spatial scales, i.e. at the 10 km scale across the whole QTP and at the 500 m scale near human settlements.

2. Data

2.1 Observed aboveground biomass

Grassland aboveground biomass was assessed using an empirical model based on Landsat-8 satellite data and field-measured data (C. Li et al., 2018). Vegetation with higher biomass shows stronger reflectance in near-infrared bands but lower reflectance in visible bands than grassland with lower biomass. The Normalized Difference Vegetation Index (NDVI) was developed to characterize the vegetation (Tucker, 1979) and has been extensively used to estimate aboveground grassland biomass (Jia et al., 2016; Zhang et al., 2016). The 172 biomass plots were measured in the field during peak growing season (late July to mid-August) in 2015 and 2016. The closest Landsat-8 NDVI values were extracted with respect to the individual field sampling locations and dates. The field-measured biomass data were randomly split into two parts, using three-quarters of the data for model calibration and one-quarter for validation. The developed empirical model ($R^2 = 0.55$, rRMSE = 0.23) was applied to the Landsat-8 NDVI in 2015 to map grassland biomass with the Google Earth Engine (Gorelick et al., 2017) across

the whole QTP.

We rescaled the aboveground biomass map to a spatial resolution of 10 km and 500 m and further mapped human influences on biomass at 10 km and 500 m scale.

2.2 Climatic variables

The climatic variables used to model the contribution of environmental variables to spatial variation in grassland biomass included growing season (June–September) mean air temperature in 2015 and precipitation in 2015. These variables were extracted from the China Meteorological Forcing Dataset with a spatial resolution of 0.1° (Chen et al., 2011). The temperature variable was constructed by merging observations from 740 meteorological stations and corresponding Princeton meteorological forcing data (Sheffield et al., 2006). The precipitation variable was constructed by combining three precipitation data sets, including observations from the same 740 meteorological stations, the Tropical Rainfall Measuring Mission (TRMM) 3B42 precipitation products (Huffman et al., 2007) and the Asian Precipitation-Highly Resolved Observational Data Integration Towards Evaluation of the Water Resources project (APHRODITE) (Yatagai et al., 2009). This climatic dataset has been widely used in soil moisture modeling and ecosystem studies (Guo and Wang, 2013; Liu and Xie, 2013; Wang et al., 2017).

2.3 Soil properties

Soil variables of soil organic matter, available nitrogen and total phosphorus were selected from eight soil variables (available phosphorus, available potassium, available nitrogen, total phosphorus, total potassium, total nitrogen, soil organic matter and soil PH) to estimate aboveground biomass. The selected soil variables have lowest co-linearity (Variance Inflation Factor <10) with other variables (section 3.2). The soil variables were extracted from a 30×30 arcsec resolution gridded soil characteristics dataset (Shangguan et al., 2013). This dataset includes physical and chemical attributes of soils derived from 8979 soil profiles and

the Soil Map of China (1:1,000,000). This soil properties dataset has been widely used in soil and ecological studies (Bi et al., 2016; Maire et al., 2015; Sun et al., 2016; Wang et al., 2015).

2.4 Data on eco-geographical regions

The classification of the QTP into eco-geographical regions (Figure 1) was included as a further environmental explanatory variable for spatial variation in grassland biomass (Section 3.1). The eco-geographical regions have been defined based on a combination of climatic factors and vegetation types (Gao et al., 2009). We included the classification of eco-geographical regions as an explanatory variable because it reflects the effects of broad differences in species composition between vegetation types on biomass (Chuang et al., 2014). The eco-region data were converted from a polygon-shape file to a raster with 10 km using the statistical software R (R Core Team, 2018).

2.5 Indicators of human influences

Two indicators of human influence, livestock density and distance to settlements, were used to explain the potentially human-influenced spatial patterns at the 10 km and 500 m scale. The settlement locations of cities, towns, hamlets and villages in 2017 were extracted from OpenStreetMap (Haklay and Weber, 2008) as spatial points (https://download.geofabrik.de/asia/china.html). The size of settlements was considered when analyzing the correlation between biomass and distance to settlements as described below (section 3.2). The Euclidean distance to the closest of these points was calculated for each grid cell of the QTP (Figure 2).

Pasture is the main land-use type on the QTP. Livestock grazing is an important human-influenced activity. Livestock density can serve as an indicator of such human influence. Livestock density was assessed in terms of the number of sheep, goats and yak per square kilometer reported in the 2015 statistical yearbook from Qinghai, Xizang (National Bureau of Statistics of China, 2015). The absolute numbers of different animal species were converted to

livestock units using conversion factors of 0.6 for yak and 0.1 for sheep and goats (Lehnert et al., 2016). In the end, livestock densities of 100 counties at the county level were calculated (Figure 2) and decreased from the east to the west of the QTP. The livestock density is suitable to evaluate the human influence on grassland biomass via livestock grazing on the whole QTP scale as demonstrated in previous studies (Lehnert et al., 2016; S. Li et al., 2017). The livestock density data were converted from a polygon shape file to 10 km and 500 m raster in ESRI ArcMap software (http://desktop.arcgis.com/en/arcmap/).

3. Methods

3.1 Model for environmental and human-influenced spatial patterns of biomass at 10 km scale

We hypothesized that the human-influenced biomass could be calculated from the difference between potential biomass in the absence of human activities and actual biomass estimated from the satellite data. This hypothesis and framework is widely used to quantify human contribution on ecosystem biomass production both at the global scale (Haberl et al., 2014, 2007; Krausmann et al., 2013) and at the regional scale of the QTP (Chen et al., 2014; Z. Wang et al., 2016). The potential biomass is the biomass that would be predicted solely by environmental factors without the interference of human activities. Here this potential biomass was defined based on a deterministic empirical model with environmental explanatory variables (x) with regression coefficients β (fixed effects). The actual aboveground biomass, which is influenced by both environmental variables and human activities, was measured from remote sensing NDVI data (y). The difference between potential biomass and actual biomass involves a spatial process (h) that is potentially correlated with human influences (random effects) and a residual noise component ε (Eqn 1) (de Jong et al., 2013). This analysis was conducted at the 10 km scale across the whole QTP by rescaling all environmental explanatory

variables to 10 km resolution using the *projectRaster* function in R with bilinear interpolation:

$$h = y - x^T \beta - \varepsilon \qquad \textit{(Eqn 1)}$$

a. Deterministic model (xTβ) attributing biomass to environmental drivers

Temperature, precipitation and soil properties are considered to be the most important variables that may explain spatial biomass variation across the whole QTP (Luo et al., 2004; Sun et al., 2013; Yang et al., 2009). In addition, elevation can account for microclimatic variation and influence grassland biomass (Fisk et al., 1998). Therefore these environmental variables were used to estimate potential biomass.

We used each environmental variable's Variance Inflation Factor (VIF) to quantify co-linearity between variables. VIFs are positive values representing the overall correlation of each predictor with all others in a model. Generally, VIF >10 indicate "severe" co-linearity (Neter et al., 1996; Smith et al., 2009). In the end, six environmental variables including temperature, precipitation, available soil nitrogen, total soil phosphorus, soil organic matter, elevation (Table I) and eco-regions (multi-level factor) were used to develop a multiple linear regression model to predict potential biomass. The VIF of selected environmental variables was 2.4 showing low co-linearity.

A bootstrapping method was applied when estimating model coefficients to avoid spatial dependency in the training data (de Jong et al., 2013). Five thousand samples were randomly selected from 13574 observations to estimate model coefficients. Three-quarter the samples were used for model calibration and one-quarter of samples were used for model validation. This sampling step was repeated five thousand times to include all data into the model. The relative Root-Mean-Square Errors (rRMSEs (%)), that is the ratio between RMSE and the mean of actual biomass, were averaged to estimate model accuracy. Finally, model coefficients were averaged to estimate environmental-driven biomass at the 10 km scale. In addition, to quantify the relative contribution of each variable to biomass, the relative importance of each

198 environmental variables in the multiple linear regressions was investigated using hierarchical
199 variation partitioning as implemented in the R package *relaimpo* (Grömping, 2006) (Table I).

200 **b. Spatial process (*h*) and residuals** (ε)

201 We used a Gaussian random field (GRF) to model the spatial patterns of unexplained effects
202 (de Jong et al., 2013). A GRF is described by three elements: 1) a mean function, 2) a range
203 that determines the length scale of the spatial dependency and 3) a sill that determines the
204 marginal variance. The estimated parameter set was used to model the spatial field *h*. The
205 detailed description of the model can be found in de Jong et al. (2013). Based on our assumption,
206 the modeled spatial patterns are correlated to human activities. We further tested the spatial
207 patterns (h) for correlations with the human-influenced variable livestock density at the county
208 level.

209 The residual component ε contains the remaining spatial variation of biomass that was neither
210 captured by the environmental variables (fixed-effects components fitted in the first step) nor
211 by the spatial process (random-effect components fitted in the second step). In the ideal case,
212 these residuals are spatially uncorrelated (de Jong et al., 2013). This component may contain
213 small-scale human interventions (de Jong et al., 2013; Zhou et al., 2001). To find out whether
214 potential small-scale human interventions could be visible, we also related the residuals to the
215 human-influence variable livestock density (county level).

216 **3.2 Model for human-influenced variation of biomass at the 500 m scale**

217 At the 500 m scale, we used distance to settlements as a proxy of human-influence intensity.
218 Distances to watering points or settlements have been widely used as proxies for grazing
219 intensity in various grassland systems with long pastoral histories (Fernandez-Gimenez and
220 Allen-Diaz, 2001; Manthey and Peper, 2010; Wang et al., 2017). On the QTP, the grazing
221 pressure increased over the past three decades near to the settlements because pasture
222 management was transferred from nomadic to semi-nomadic pastoralism or privatized (Meyer

et al., 2013; Wang et al., 2017). Therefore, areas closer to settlements experience more intensive human activities, including higher grazing density, construction work and tourism activities.

Human influences on biomass were analyzed within 8-km neighborhoods around settlements at a spatial resolution of 500 m based on previous findings that human influence can be neglected beyond 8 km on the QTP (Liu et al., 2006; Wang et al., 2015). This limit was determined in a breakpoint analysis (see next paragraph). Human activities of grazing, trampling and infrastructure near settlements can directly influence grassland biomass by removal or disturbance, although this may be conterbalanced by compensatory regrowth. Within the range of distances from 0–8 km, a positive correlation between biomass and distance to settlements indicates that biomass is lower near settlements, which suggests a negative human influence on biomass. In contrast, a negative correlation indicates that biomass is higher near settlements, suggesting a positive human influence on biomass. If biomass stays stable along distance to settlements this indicates that human activities do not have a profound influence on biomass. However, beyond the limit distance of 8 km to settlements, the direct human influence on grassland biomass should be small (Liu et al., 2006). Nevertheless, biomass may tend to decrease beyond the limit distance because people avoid areas where potential biomass is low due to harsh environmental conditions (Figure S1). Figure 3 illustrates the above scenarios of changes of biomass along distance to settlements. A supplementary video (supplementary 2) shows examples of changes of biomass along distance to settlements, where a turning point can be observed showing the potential human influential distance and indicating a breakpoint in the relationship between biomass and distance to settlements. The influence of human activities on biomass at the 500 m scale was mapped based on these scenarios.

In order to find the specific human influential distance, the *breakpoints* function and *F*

248 statistics test in the R package strucchange were applied (Zeileis et al., 2003), which have been
249 widely used for detecting and monitoring structural changes in (linear) regression models
250 (Zeileis et al., 2003). We configured the algorithm to detect the one most influential breakpoint
251 for each pixel using a moving-window method. We assumed that the maximum human
252 influential distance could be as large as 15 km, according to the 12 km of human influential
253 distance reported from an area in the east of the QTP (Liu et al., 2006). The detected breakpoint
254 distances were averaged across all pixels to get a single estimate for the entire QTP. This
255 yielded the above-mentioned limit distance of 8 km to settlements beyond which direct human
256 influence related to settlements could no longer be detected (Figure 4).
257 To detect the spatial variation of human influence on biomass at the 500 m scale, a moving-
258 window method was applied between distance to settlements and biomass. Specifically, we
259 used local Pearson moving-window regression to show positive and negative influences of
260 human activities on biomass. The selected window size with a radius of 8 km for the local
261 Pearson regression was based on the breakpoint analysis explained above. The area covered by
262 settlements has no biomass value and was therefore excluded from the analysis, that is, human
263 influential distance was calculated to the boundary of a settlement, not an inside point. We
264 finally linked the local Pearson correlation coefficients that represent the human-influenced
265 spatial patterns at the 500 m scale with livestock density. Figure 5 summarizes all data and
266 processing steps as a flowchart.

267 # 4. Results

268 ## 4.1 Spatial variation in biomass attributed to environmental drivers at the 10 km scale

269 The biomass data derived from the Landsat-8 NDVI data showed a decreasing gradient from
270 the east to the west of the QTP and additionally varied strongly within the gradient (Figure 6a).
271 The overall spatial variation in biomass across the QTP was decomposed into three parts: 1)

variation explained by environmental variables (Figure 6b), 2) variation due to spatial autocorrelation unexplained by environmental variables but potentially correlated with variation in human influences (Figure 6c and Section 4.2) and 3) residual variation neither explained by environmental variables nor by spatial autocorrelation (Figure S2).

The model developed from environmental variables including climatic variables, soil properties, topographical variables and eco-regions explained 70% (coefficients of determination $R^2 = 0.70$) of the spatial biomass variation with an accuracy of 27% as measured by the rRMSE. The biomass predicted by these environmental variables clearly showed the decreasing trend towards the west described in the previous paragraph. Among different environmental variables, elevation played the most important role in explaining biomass variation, followed by precipitation and soil available nitrogen (Table I). The relatively lower importance of temperature than elevation was probably due to the higher temperature but low biomass in the Qaidam basin, which was opposite to the general trend of decreasing temperature and biomass along increasing elevation (Figure S5).

The biomass predicted by environmental variables shows a sharp transition from high to low biomass along the east-to-west gradient (Figure 6b). This sharp transition was caused by eco-region boundaries and showed the relevance of including eco-regions in the model.

4.2 Spatial variation in biomass potentially due to human-influence at the 10 km scale

The random effects component accounting for spatial autocorrelation in biomass at the 10 km scale, which could not be attributed to variation in environmental variables was potentially related to variation in human influences. This spatial autocorrelation component accounts for 16% of the spatial variation of biomass. Negative spatial autocorrelations in biomass values occurred on the northern part of Qinghai-lake and in the southern part of the QTP. Positive spatial autocorrelations were mainly found in the eastern part of the QTP (Figure 6c). Both the positive and the negative autocorrelations were clearer in the eastern part of the QTP where

297 human activities are more intense (Figure 2 and Figure 6c). A weak positive correlation (R^2 =
298 0.1) was found between the spatial autocorrelation in biomass and the human-influence
299 variable livestock density (Figure 7). No further correlation was found between residuals and
300 livestock density (Figure S3).

301 **4.3 Human-influenced spatial patterns of biomass at the 500 m scale**

302 The influences of human activities on biomass at the 500 m scale were mapped by analyzing
303 biomass along distance to settlements using a moving window radius of 8 km. The map (Figure
304 8) shows both biomass decreases and biomass increases near settlements, indicating positive
305 and negative human influences. Strong negative signals were detected in the Yellow River–
306 Huangshui River Valley and around the southeastern part of Qinghai-lake, Xinghai and Tongde
307 counties (Figure 8 (1)), in the Yarlung Zangbo River valley and in the central Tibetan counties
308 of Doilungdeeqeen, Lasa and Dagze (Figure 8 (3)). In all these areas biomass decreased with
309 proximity to settlements. Positive signals were detected for example in the southeastern part of
310 the QTP, i.e. Baima and Jigzhi counties, where the biomass increased with proximity to
311 settlements (Figure 8 (2)).

312 Across the QTP, positive signals, i.e. higher biomass values closer to settlements, occurred
313 in areas with low livestock density at the 10 km scale. In contrast, the negative signals were
314 correlated with high livestock density, and prevailing negative signals were detected when the
315 regional livestock density was higher than about 22 livestock units per square kilometer (Figure
316 9), even though these regions are also the ones with more productive ecosystems (Figure S4).
317 In general, biomass was actually larger near settlements in areas with low livestock density,
318 whereas biomass was lower near settlements in more productive areas with higher livestock
319 density.

5. Discussion

5.1 Spatial variation in biomass attributed to environmental drivers at the 10 km scale

The model developed from environmental variables explained most of the spatial variation of biomass (70%). Uncertainties of the model might stem from the limited number of environmental variables used and uncertainties within the environmental variable data, which might affect the potential biomass estimation accuracy. The influence of environmental variables such as soil moisture, soil temperature (X. Wang et al., 2016) and solar radiation (Piao et al., 2006) on biomass has become more important to affect biomass on the QTP under climate change, which should be considered in the future studies. Nevertheless, the environmental variables estimated the potential biomass without the inference of human activities. The difference between the potential biomass and actual biomass are here assumed to be linked with human-influenced variables (Haberl et al., 2007; Pan et al., 2017).

5.2 Human-influenced spatial patterns of biomass at the 10 km scale across the whole QTP

A continuing increase in intensity and diversity of human activities exerts spatially heterogeneous influences on grasslands on the QTP. The spatial patterns of human influence on grassland are unknown on the QTP, which are important to understand how different human activities are impacting the ecosystems and how these respond to environmental change. We mapped spatial patterns at two spatial scales and studied whether the patterns can be explained by livestock grazing density.

At the 10 km scale, we found that livestock density was positively correlated with the human-influenced spatial pattern of grassland biomass, which indicated that at large scale grazing and biomass have a positive relationship. The QTP has served as pastoral land for thousands of years (Klein et al., 2007; Lu et al., 2017). Grassland ecosystems can become adapted to grazing

(Miehe et al., 2009) and major plant species are grazing-resilient (Miehe et al., 2013, 2011). Moderate grazing intensity can promote nutrient recycling and ecosystem production (Lu et al., 2017; Luo et al., 2012). Consistent with these finding, we observed that the potential biomass predicted using only environmental variables was lower than the biomass estimated from the satellite data especially in the eastern part of the QTP, where livestock grazing is the common land use. Appropriate grazing management can affect species composition and facilitate mineral uptake and hydrological processes (Schrama et al., 2013). These effects potentially boost the biomass production, especially in ecosystems that are more productive and more resilient to grazing (Milchunas and Lauenroth, 1993; Wang and Wesche, 2016), which seems to be the case in the eastern and the southeastern part of the QTP (Figure 6c). In summary, positive grazing effects might explain the positive correlation between livestock density and human-influenced spatial patterns in grassland biomass. The opposite causality, i.e. that livestock density is higher where biomass — unexplained by environmental variables — is higher, seems less plausible unless these higher biomass values were caused by unmeasured environmental variables.

Except for livestock grazing effects, other human activities including ongoing ecosystem restoration projects and infrastructure development might explain potential human-influenced spatial pattern in grassland biomass (Fig. 6 (b)). This is especially the case in the eastern and central areas of the QTP because in these areas human activities of land-use changes and grazing density are more widespread and more intense (S. Li et al., 2017), whereas in the northwestern part of the QTP human activities are less widespread and less intense (Figure 2).

5.3 Human-influenced spatial patterns of biomass at the 500 m scale

The mobility of pastoralists has decreased and they have become more sedentary across Africa, Asia, the Middle East and the Americas (Sayre et al., 2017), which leads to increased grazing intensity near settlements (Batjargal, 1997; Vanselow et al., 2012). Distance to

settlements could potentially serve as a proxy of human-influence intensity in pastoral ecosystems (Fernandez-Gimenez and Allen-Diaz, 2001; Manthey and Peper, 2010), including the QTP (Wang et al., 2017). Thus, recent studies report that livestock-grazing pressure has been increased around settlements on the QTP (Dorji et al., 2013; Hafner et al., 2012; Lehnert et al., 2014b). Here we analyzed how distance to settlements as a proxy of human-influence intensity correlated with grassland biomass across the entire QTP.

Increased biomass closer to settlements might suggest positive grazing effects, including effects of increased input of nutrients with cattle manure (Lehnert et al., 2014a). On the other hand, implemented ecosystem restoration projects may also contribute to increased biomass near settlements in some areas, for example in the area of south Sanjiangyuan Jigzhi and Baima County, where positive biomass signals close to settlements were observed (Figure 8 (4) and previous studies of Cai et al., 2015; Xu et al., 2011). However, negative biomass signals close to human settlements were observed in the Xinghai and Tongde County in spite of ecosystem restoration projects in these areas (Figure 8 (1)).

Typically, reduced biomass near settlements is taken as an indication of negative human influences due to overgrazing (Hafner et al., 2012). Overgrazing can lead to the reduction of vegetative cover and soil erosion (Papanastasis, 2009; Thornes, 2007), which might be the case in the two regions of the Yarlung Zangbo River valley and the Yellow River-Huangshui River Valley, where we observed negative biomass signals close to human settlements (Figure 8). These regions are characterized by high human population density, livestock-grazing intensity, land use and infrastructure pressure (S. Li et al., 2017). That overgrazing could be one of the main reasons for negative biomass signals near settlements in our study is supported by the fact that these negative signals occurred mainly in areas with high livestock density (Figure 9).

The influence of grazing on ecosystem degradation on the QTP is still a topic of debate. Some studies found that heavy grazing causes severe rangeland degradation or even

desertification (Song et al., 2009; Wang et al., 2012), whereas other studies found that grazing improved forage quality and extended the growing season (Chen et al., 2013; Harris, 2010; Klein et al., 2007). In the study, we argue that both situations occur on the QTP, depending on the study area and the study scale. Across the whole QTP, grazing is positively related to biomass production at the 10 km scale. However, because of the limited mobility of local herders (Wang et al., 2017), overgrazing occurs near settlements in areas with high livestock density. The overgrazed area might be more vulnerable and more sensitive to climate change, which requires further attention in future ecosystem protection projects.

However, the changes of biomass with distance to settlements may also be influenced by other, unmeasured human-influence variables than only by grazing intensity and it may furthermore interact with other environmental variables such as soil properties (Papanastasis, 2009). Therefore, the observed spatial patterns need further understanding and validation by combining detailed human activity-indicators with environmental variables. In addition**,** our study is a single snapshot in time, assessing the human-influenced spatial patterns in grassland biomass in 2015. Future studies should also assess changes over time in these human-influenced spatial patterns.

6. Conclusions

Increased human-influenced activities including livestock grazing and township development exert spatially complex influences on grassland biomass on the QTP. Our study on spatial variation of human influences on grassland biomass on the QTP helps us to understand how these ecosystems may respond to environmental change. At the 10 km scale across the whole QTP we estimated spatial variation of human-influenced biomass by measuring the difference between the potential aboveground biomass without the interference of human actives and actual biomass estimated from the remote sensing data. We found both positive and negative human-influenced spatial patterns across the whole QTP. These patterns

positively linked to the livestock density at the county level. At the 500 m scale, we analyzed the human influence on grassland biomass as a function of distance to settlements, used as a proxy of human-influence intensity. This was done because the socioeconomic changes of privatization of pasture land and of sedentarization of nomadic herders was assumed to have increased livestock grazing and other pressures near settlements. We detected hotspots where the biomass decreased or increased towards settlements within a radius of 8 km, indicating both negative and positive human influences on biomass. In particular, we found that biomass decreased near settlements in areas with high livestock density at county level. Overall, our study showed both positive and negative human influences on grassland biomass at two spatial scales, demonstrating the complexity of the relationship between human-influence intensity and grassland biomass, leading to large spatial variation in the relationship across the entire QTP. As a broad generalization we conclude that livestock grazing so far had positive effects on grassland biomass across the whole QTP but overgrazing near settlements now represents a threat to the future biomass production and stability of these ecosystems.

7. Acknowledgements

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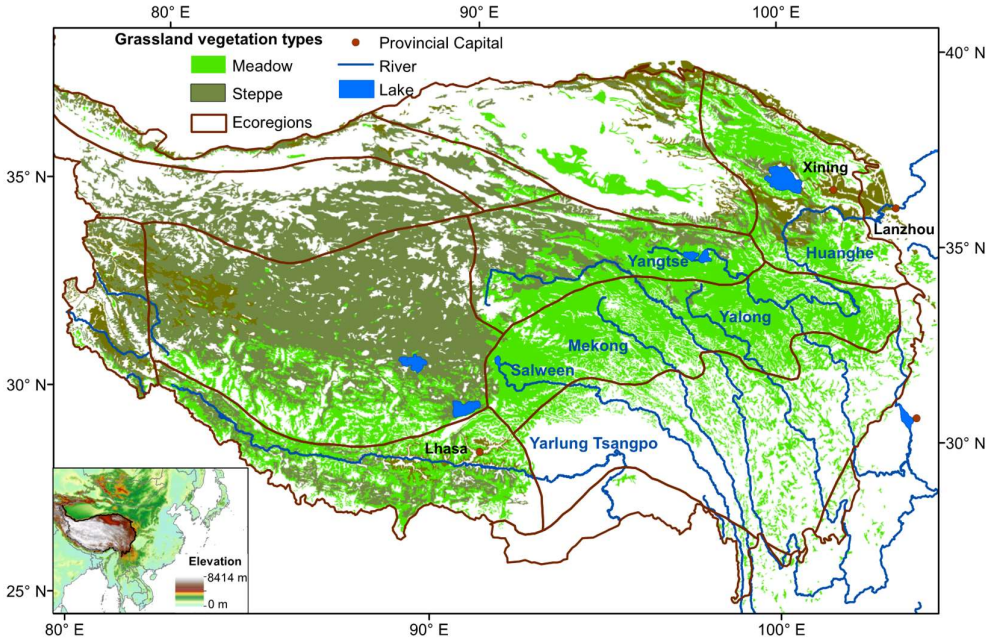
718 Table I. Environmental variable's Variance Inflation Factor (VIF) and their relative importance for explaining
719 biomass

Parameter	Unit	VIF	Relative importance
Elevation	m	3.95	0.32
Precipitation	mm	2.59	0.23
Available N	g/100g	2.78	0.23
Soil organic matter	g/100g	2.62	0.13
Temperature	℃	2.30	0.06
Total P	g/100g	1.57	0.03

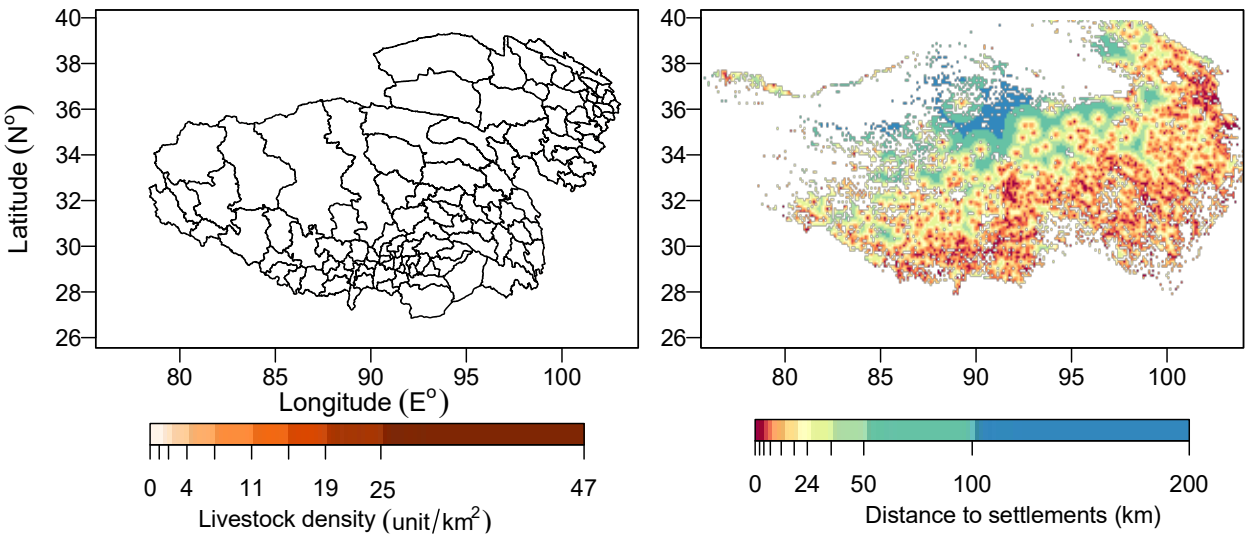
720

721 Figure 1. Distribution of main grassland vegetation types, eco-regions and major rivers (with names) on the
722 Qinghai-Tibetan Plateau (QTP). Inset indicates elevation data of the extended area based on the NASA Shuttle
723 Radar Topographic Mission (SRTM Version 4; Farr et al., 2007).

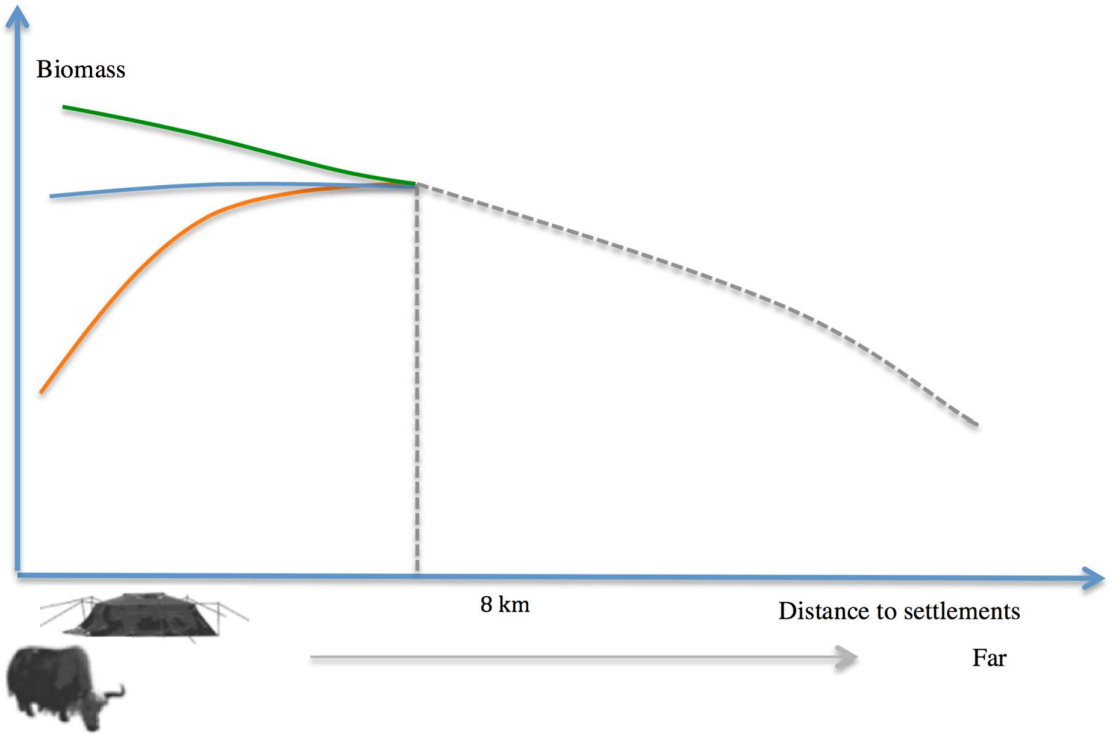


724

Figure 2. Livestock density at county level and distance to settlements at the 500 m scale on the Qinghai-Tibetan Plateau.

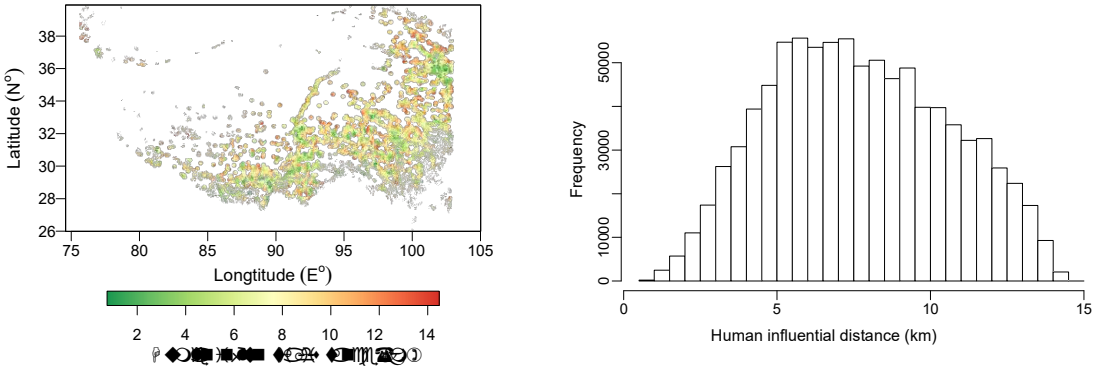


728 Figure 3. Three scenarios of relationships between distance to settlements and grassland biomass: 1 (orange) –
729 biomass decreases near settlements potentially showing a negative human influence on biomass, 2 (blue) – no
730 clear human influence on biomass and 3 (green) – biomass increases near settlements suggesting a positive human
731 influence on biomass. All scenarios hold up to a certain distance (8 km) after which the relationship between
732 biomass and distance tends to be negative (see Figure S1).



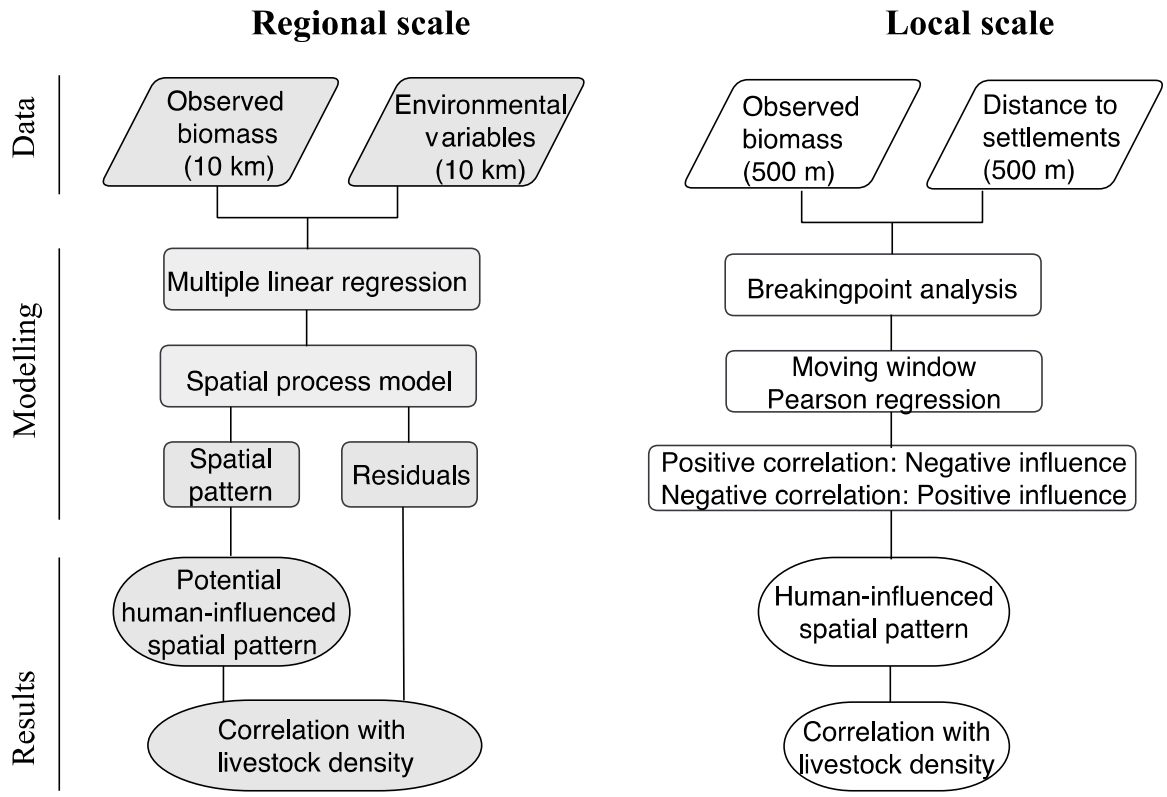
733

Figure 4. The human influential distances on the Qinghai-Tibetan Plateau (a) and their distribution (b). The distances were calculated for local areas using *breakpoints* analysis in R (see Methods). The histogram shows that the average human influential distance is about 8 km.



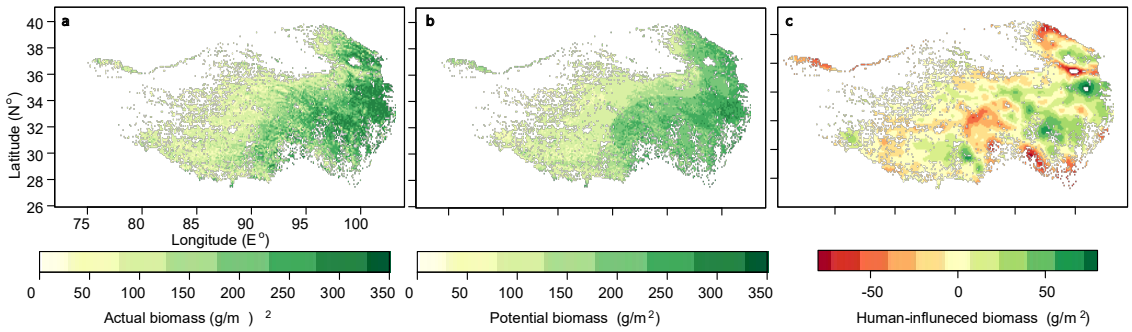
738 Figure 5. Flowchart displaying data and methods used to map the influence of human activities on biomass at 10

739 km ("Regional") and 500 m ("Local") scales.

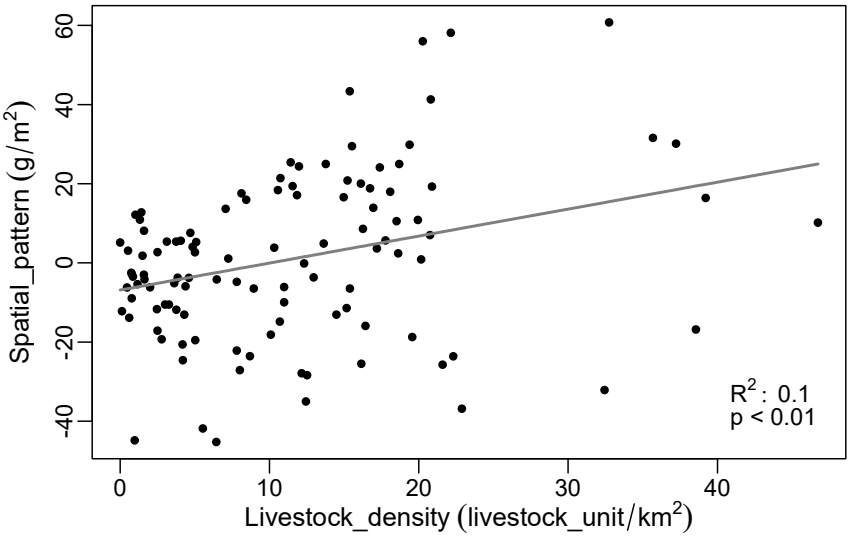


740

Figure 6. Observed biomass using Landsat-8 NDVI vegetation index (a). Biomass predicted using environmental variables (b). Spatial autocorrelation of biomass that could not be explained by environmental variables but possibly human-influence variables (c). Positive hotspots of human influences are indicated with numbers. The circle represents a positive hotspot with a positive human influence at the 500 m scale (Figure 7), whereas the two squares represent positive hotspots with a negative human influence at the 500 m scale.



748 Figure 7. Scatterplot between human-influenced spatial pattern of grassland biomass (y) and livestock density (x).



749

Figure 8. Correlation coefficients between biomass and distance to settlements (within 8 km) at grid cells of 500 m × 500 m (top left panel). A positive correlation shows biomass decreases near settlements and indicates negative human influences and vise versa. Some hotspots of negative and positive human influences area are shown in panels (1), (2), (4).

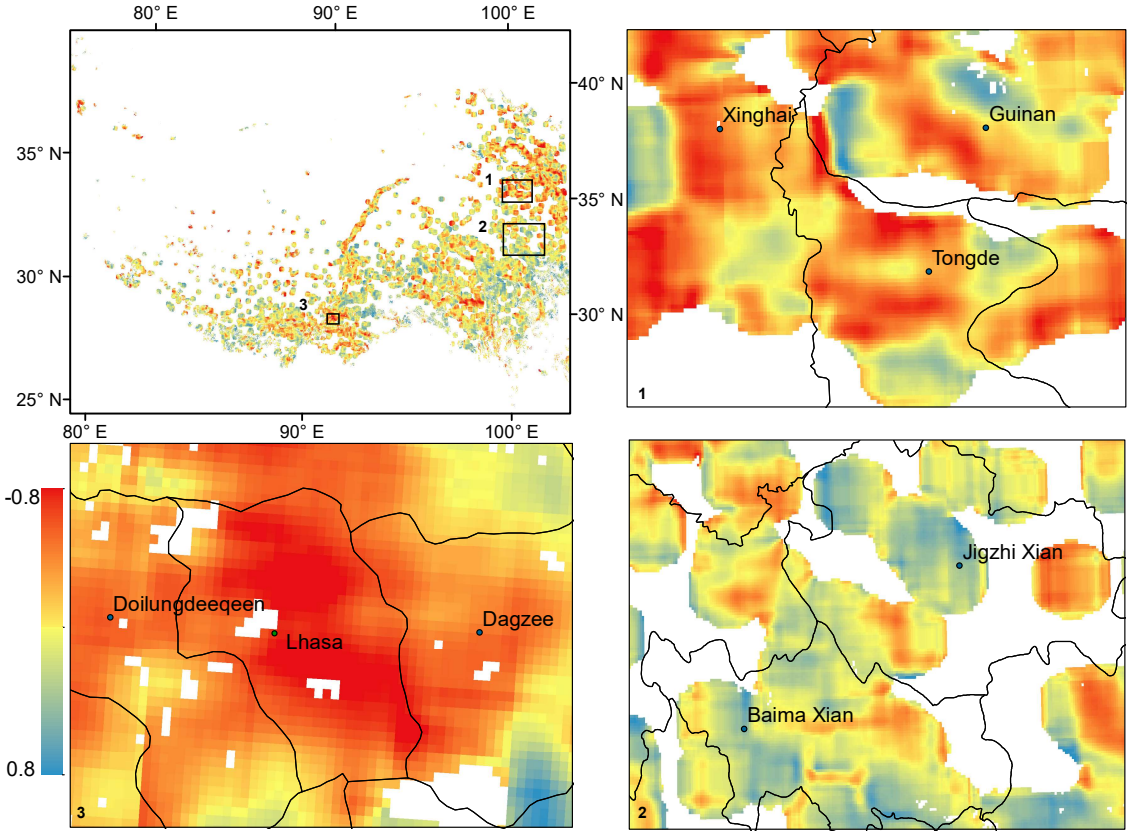


Figure 9. Scatterplot between human-influenced spatial biomass pattern at the 500 m scale (y) and livestock density at the 10 km scale (x). Note that a positive human-influenced spatial biomass pattern reflects a negative correlation between local biomass and distance to settlements, i.e. higher biomass close to settlements, and vise versa. The human-influenced spatial biomass pattern was averaged per county and then regressed on the livestock density per county. The dashed line indicates the division between positive and negative human influences on local biomass.