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Environmental impacts of renting rangelands: integrating remote sensing and household surveys at the parcel level

Luci Lu[1], **Ping Li**[2,*], **Margaret Kalacska**[1] **and Brian E Robinson**[1]

[1] Department of Geography, McGill University, Montreal, QC H2A 0B9, Canada
[2] Institute of Grassland Research, Chinese Academy of Agricultural Sciences, Hohhot 010010, People's Republic of China
[*] Author to whom any correspondence should be addressed.

E-mail: lipingcau@126.com

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Abstract

Land rental markets are growing worldwide and facilitate efficient utilization of land. However, the short duration of occupancy and limited property rights mean that rental contracts may discourage longer-term sustainable land management. Direct investigation into the relationship between land tenure and ecological outcomes has been hampered by scale-appropriate data on land tenure, resource management, and land outcomes. In this paper, we address these issues with a study design that combines participatory mapping, household surveys, and remote sensing. We analyzed these data in a multilevel statistical model, controlling for environmental and land management influences. Our results show that rented land parcels are associated with worse rangeland outcomes compared to privately held parcels. This study contributes to the literature by documenting important empirical effects of rental markets and presenting a replicable workflow for integrating earth observations and micro-level survey data, which can be adopted by researchers and practitioners in regions where land registry data is unavailable or inaccessible. The results have important implications for incentive and compensatory-based environmental policy.

1. Introduction

Property rights have long been recognized as fundamental to the sustainable management of land resources and are recognized as foundational to global development agendas such as the Sustainable Development Goals and the Paris Climate Agreement. Secure rights allow landholders to be more forward-looking and have greater incentives to invest in longer-term outcomes, often promoting greater care and stewardship of land into the future [1]. While there are number of ways to develop secure right regimes [2, 3], privatization of property is still a dominant policy tool used to combat land degradation [4].

A consequence of land privatization is that it gives landowners the right to allow others to use their land under rental or sub-lease agreements. Rental land as a 'byproduct' of privatization has been largely ignored in the study of social-ecological land system dynamics, despite the robustness and growth of rental markets worldwide in various sectors. For example, the efficiency and equity of agricultural rented markets have been widely documented [5], but how rental markets affect ecosystem and land outcomes has only recently gained attention [6, 7].

Rangeland systems cover 30%-40% of global land surface and are a highly important biome for water, biodiversity, and livestock farming [8]. Rangelands are critical soil carbon sinks and improving management of rangelands is a key measure that can be taken to mitigate climate change [9, 10]. Rental markets for rangelands in particular are experiencing considerable growth [11, 12]. Nevertheless, parcel-level comparisons of outcomes in rented rangelands to those with more complete property rights are exceedingly rare. This is partly explained by the challenges in integrating data on land tenure, rangeland management, and ecological outcomes at a scale appropriate for linking management decisions—i.e. at a parcel or household level [13, 14]. Linking herders to plots of their land at a micro-scale is further complicated by the unique characteristics of rangeland socio-ecological systems [15], such as the influence of highly variable inter- and intra-annual precipitation, the lack of clearly defined property boundaries, widespread informal land agreements, and potentially complex land-use practices.

In this study, we examine how land tenure in rangeland systems, specifically renting rangelands versus privately holding them, affects land outcomes. We address the methodological challenges with a combination of participatory mapping, household surveys, and remote sensing to understand the location and intensity of households' livestock production activities. A combination of the empirical context and innovative field methods allows us to identify differences between rented and privately-held rangelands by linking data on household management, land rights, land use, and remotely sensed rangeland productivity outcomes for 400 parcels that belong to 187 households in Inner Mongolia, China. Leveraging open-access data from multiple satellites, we monitored the rangeland outcomes and the climatic influences of each parcel every September from 2013 to 2019. We statistically test for the influence of a parcel being rented versus privately-held in a multilevel modeling framework. This combination of methods allows us to identify the relationship between parcel-level land tenure and rangeland health and productivity.

2. Methods

2.1. Methodological approach

Tying herder behavior to rangeland outcomes is difficult due to a lack of scale-appropriate (parcel-level) data on land tenure, resource management, and rangeland outcomes over time. To overcome this, we streamlined an analytic process to allow herders to identify individual parcels, describe their herding rights and practices, and then tie these to high-resolution remotely sensed data over time. First, we pre-processed and tiled Sentinel-2 images for use on tablet computers, highlighting fences and other landscape features that allow herders to better identify their parcel boundaries on satellite images (figure 1(a)). Individual herders then identified their parcel boundaries in the field, at which time we additionally asked each herder about land rights and any dedicated use for each parcel through a traditional household survey (i.e. all-season, winter, and summer grazing, lambing, or hay harvesting) (figure 1(b)). After compiling all herder parcels into a spatial database, we used these parcels as 'cookie-cutter' polygons to extract historical Landsat 8 images from 2013 to 2019, from which we calculated metrics of rangeland productivity and abiotic (climatic and topographic) information (figure 1(c); figure 2). Finally, we used statistical models to assess the relative influence of rental tenure on rangeland outcomes, while controlling for well-documented biotic and abiotic factors (figures S1–S3), household characteristics, and township-level unobservable factors (figure 1(d)).

2.2. Study area

Pastoral land in China is often defined as 'quasi-privatized': rangelands are technically collectively owned, but individual households have 30–50 year private contracts over land parcels (here referred to as 'privately held parcels') [16, 17]. In the 1980s, rangelands were contracted first to small groups of herders and later to individual households in the 1990s [18], which were often then fenced. Herders born after the 1990s share their parents' contracted land with siblings. Rental markets thus provide opportunities for younger herders, especially those who lack initial land endowments or other off-farm opportunities, to acquire land from an aging cohort of landholders [19]. China's 'Grassland ecological protection reward-subsidy' policy provides compensatory payments to land contractors to retire from herding or reduce livestock holdings [20]. Retiring and then renting, or allowing renters to receive the payments from this program, are not allowed.

2.3. Household sample

We surveyed herder households in 2019 and selected households for this study via stratified random sampling. We first selected four counties (*banners*) in Xilin Gol prefecture (*league*) that are ecologically representative of the temperate grasslands and have a high percentage of households dependent on herding. Among these four counties, 17 townships (*sumus*) were chosen (table S1) with the goal of maintaining ecological and social representativeness, and a roughly equal number of responses within each county. Households within each township were randomly selected, resulting in a sample of 214 households. We visited each herder household and mapped their land parcels through participatory mapping.

2.4. Data collection

2.4.1. Spatial data: parcel boundaries recorded through participatory mapping

To facilitate participatory mapping, basemaps were derived from the Europe Space Agency's Sentinel-2 images, focusing on Level 2A 'Bottom-Of-Atmosphere' reflectance product. We identified thirteen 100 km^2 tiles that cover the sampled households in Xilin Gol (figure 2). For each tile, we downloaded an image with the least amount of cloud cover in December 2018 and March, June, and September 2019 to help capture the nuanced changes in land features that may be visible by comparing images in different seasons. We displayed the growing season

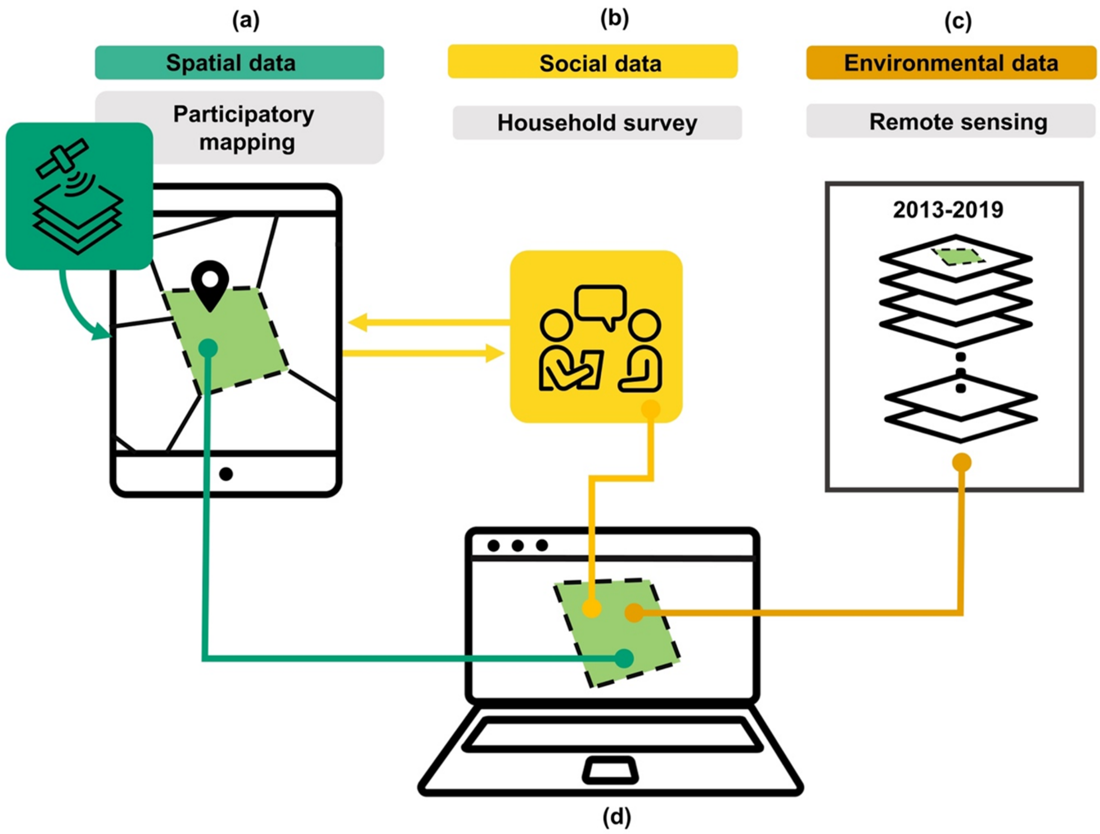

Figure 1. Methodological flowchart. We (a) created Sentinel-2 basemaps and stored them in a tablet computer. We then conducted tablet-based participatory mapping with individual herders to identify their land parcels. We (b) conducted tablet-based surveys with individual herders and collected social data on their rental status, land management, and socioeconomic characteristics, (c) extracted remote sensing derived environmental data from land parcels identified by the herders, and (d) integrated and analyzed remote sensing and household survey data.

images in near-infrared band combination (near-infrared, red, green) and winter images in shortwave infrared band combination (shortwave infrared, near-infrared, red).

These band combinations allow for visualization of wavelength ranges not usually visible to the human eye, which helps us identify fences and property boundaries via spectral differences in lightly and heavily grazed land parcels. Rangeland parcels are often utilized for distinct purposes, durations, and under various intensities, leaving different amounts of standing biomass among parcels. During the growing season, ungrazed or lightly grazed land will have taller and denser grass compared to heavily grazed land, all else being equal (figure 3(d)). A near-infrared band composite accentuates biomass contrasts and helps highlight fences that separate parcels (figure 3(e)). Dry grasses and snow also accumulate along fence edges, thickening the trace of the fence which, in shortwave infrared band composite appears clearly as bright cyan lines (figure 3(f)).

We converted all GeoTIFF satellite images into map tiles using ArcGIS Pro. We displayed these map tiles as offline base maps using ArcGIS Collector and collected spatial data in the field. Collector displays our real-time movement and location on top of the map tiles and allows herders to interact with the tiles by panning and zooming.

To further verify whether a land parcel is used and inquire about parcel-based land management information, we conducted participatory mapping with herders. To bridge herders' *first-person* spatial knowledge with a 2-dimensional *bird's eye* satellite image [21], we identified visible land features while viewing maps with herders. To verify the parcel identified on the basemap was the same that the herder was thinking of, we checked the herder's reported parcel geometry [22] and spatial relationship among features [23] against what we measured using the ArcGIS Collector. We followed a 3-step process to identify land parcels with herders:

(1) We oriented herders to cardinal directions on the landscape. We arranged the tablet towards the north and invited the herder to orient themselves with the satellite imagery. We continually reinforced the cardinal directions during the mapping process.
(2) We presented herders with three options for identifying their land parcels based on their comfort and digital literacy: through satellite

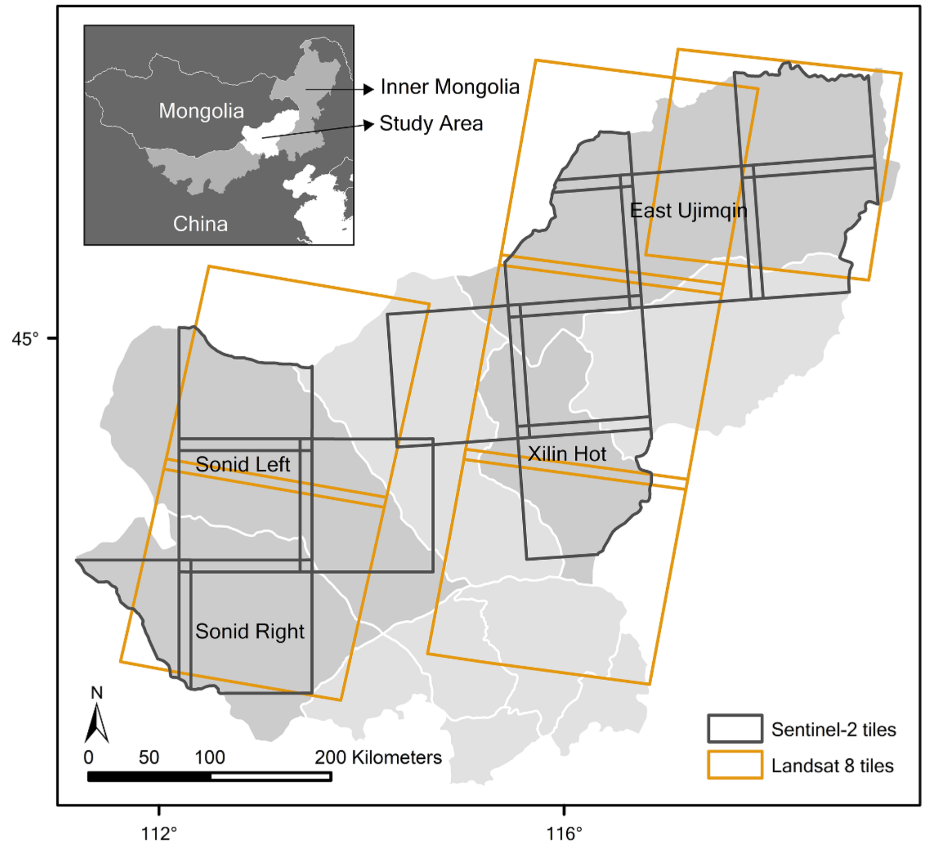

Figure 2. Map of the study area. Boxes represent tiles from satellite imagery. Sentinel-2 tiles were used to create basemaps for participatory mapping. Landsat 8 tiles were used for obtaining data on rangeland greenness—the outcome examined in the analysis.

imagery on the tablet, a sketch map drawn by the investigator with the basic land features (e.g. communal wells, motorcycle paths, concrete roads, gates, etc), or blank sketching paper with cardinal directions indicated.

(3) To verify each land parcel, we asked herders questions about the parcel's geometry (e.g. size, shape, and edge length) and the parcel or herder's spatial relationships (e.g. direction and distance) with key land features. We then compare herders' responses with our measurements derived from ArcGIS Collector (see detailed steps in figures S4 and S5). We also intentionally asked about land features that did not belong to the herder to make sure the respondent disagreed.

Of the 512 parcels initially identified, 415 passed the verification steps (step 2 and 3 above). Of parcels that did not pass, only a partial fence was recognizable in the basemap or we could not reconcile a parcel's satellite-observed geometry and the herder's description. Among the fully recognized parcels, we excluded nine because they were primarily covered by saline-alkali marshes or gravel pits and another six that were solely reserved for times of severe drought (figure 3(d)). In all this reduced our sample by 27 households giving us, in the end, 400 fully recognizable parcels from 187 households are included in our analysis.

For each parcel identified, we asked the herder detailed land management and property rights questions including the rental situation, land use purpose, and duration. Participatory mapping was accompanied by a standard household survey that recorded demographic and livelihood information.

2.4.2. Social data: rental status, land management and socioeconomic variables collected via survey

We used a household survey to collect household social data and land management actions. Our main interest is whether a parcel is rented or privately held each year affects rangeland outcomes from 2013 to 2019. A 'rented' parcel is defined as a parcel for which the tenant has paid a landlord for use rights over the rangeland and has some form of contractual agreement (informal or formal). We also differentiated renting from 'otor', a traditional Mongol drought-coping practice where land may be borrowed or rented in a time of need, but is generally much shorter in duration [24] (see table S2 for detailed comparisons).

We used a household's stocking rate and annual fodder expenditure to measure herders' land management intensity. The stocking rate proxies herders' dependence on the natural grassland while

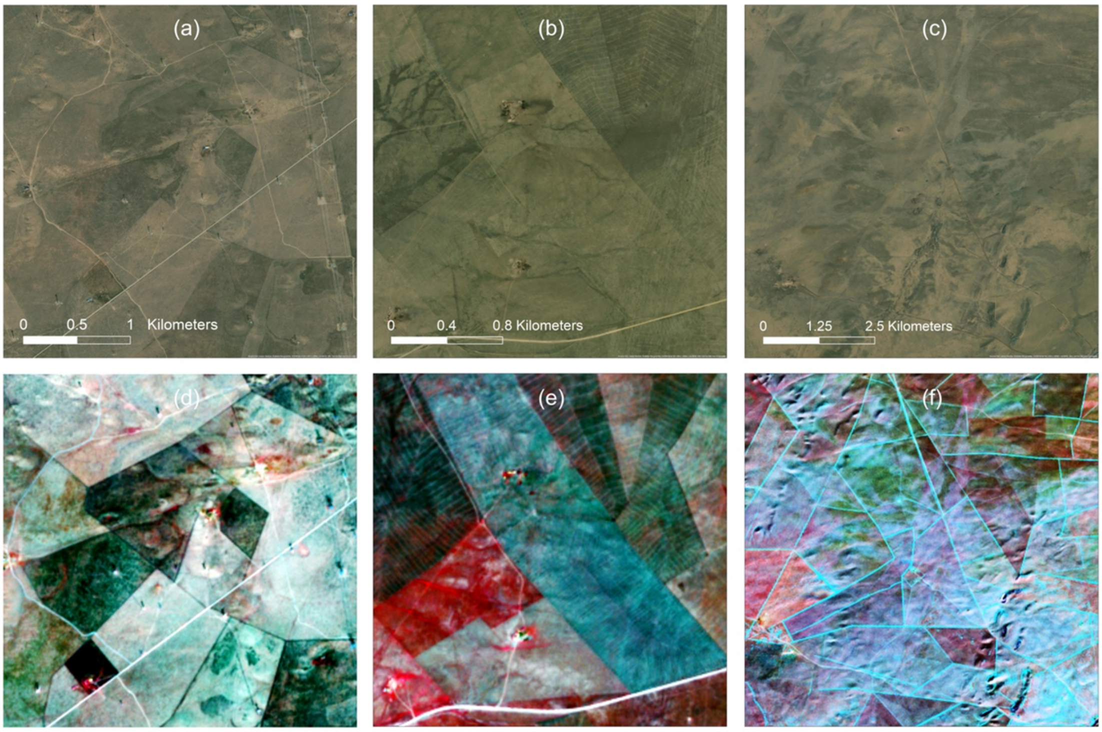

Figure 3. The comparison of three ArcMap's default high-resolution 'World Imagery' basemap images (a), (b), (c), and the same images in near-infrared (near infrared, red and green) and shortwave infrared (shortwave infrared, near infrared, and red) band combination (d), (e), (f). The near-infrared composite of the satellite image (d) captured in September 2019 shows a strong contrast between the brighter parcels that have already been used for summer grazing and the darker parcels reserved for winter. The darkest square parcel located at the bottom left of image (d) is an enclosure kept ungrazed for years, often reserved for extreme drought. Image (e) shows the contrast between different intensities of hay harvesting (dark and light green parcels with stripes) and grazing (white and red parcel) among two households. The shortwave infrared band combination (f) shows how land parcel boundaries that are difficult to discern in 'natural color' maps become more visible.

fodder indicates herders' acquisition of external food resources that would offset the reliance on natural grassland for livestock consumption. Stocking rate is the most commonly used indicator for grazing intensity, generally measured in 'standard sheep units' (SSUs) per hectare. SSU allows for other livestock to be converted to a common unit (sheep) according to their daily consumption needs relative to a representative ewe. Following the Chinese Agricultural Industry Standard issued by the Ministry of Agriculture [25], we used the following conversion factors to calculate SSU: 0.8 for goats, 5 for local breeds of cattle, 8 for crossbred cattle, 5.5 for local horses, and 9 for camels. All lambs and calves are converted to 0.5 of their corresponding adult livestock. In this study, we use a household's *de facto* landholding to calculate stocking rate (instead of the *de jure* land that herders often reported to standard census surveys) to accurately capture intensity of grassland use. *De facto* land can also include land formally held by (absentee) siblings, parents, children, or relatives who live and work in urban areas. All land was included, regardless of being formal or informally held. Fodder expenditure is normalized by SSU, which includes expenditure on hay, hay pellets, grain (corn and oats), corn silage, and straw. We also controlled for respondent and household characteristics including years of herding, years of education, ethnicity, gender, household size, herding labor, and distance to city.

2.4.3. Environmental data: greenness, climatic, and topographic variables obtained through remote sensing

We use remotely sensed images to gather temporally appropriate environmental data for each parcel. We used soil-adjusted vegetation index (VI) as a proxy of relative vegetation greenness and vigor. Although VIs are dimensionless and do not measure biomass quality or quantity directly, previous literature has established robust relationships between VIs and rangeland biophysical parameters such as the fraction of absorbed photosynthetically active radiation and leaf area index [26, 27]. The most widely used VI, normalized difference vegetation index (NDVI) utilizes vegetation's unique spectral characteristic on near-infrared and red wavelength regions and measures relative photosynthesis activities as:

$$\mathrm{NDVI} = (\rho\mathrm{NIR} - \rho\mathrm{Red}) / (\rho\mathrm{NIR} + \rho\mathrm{Red})$$

One shortcoming of NDVI is that it can be influenced by soil background reflectance when the vegetation canopy does not fully cover a pixel [28]. Consequently, soil-adjusted VIs such as the soil adjusted vegetation index (SAVI) and the modified soil adjusted vegetation index (MSAVI) have been developed to minimize the impact of soil on vegetation reflectance properties. Because SAVI requires prior knowledge of a fixed soil brightness adjusting factor, we chose MSAVI for this study because MSAVI uses an inductive method to reduce soil influence and is suitable for our landscape scale that has heterogeneous soil properties [29], and has been used in past work in the Xilin Gol prefecture in Inner Mongolia [30]. MSAVI is calculated as:

$$\mathrm{MSAVI} = \left(2 * \rho\mathrm{NIR} + 1 - \sqrt{(2 * \rho\mathrm{NIR} + 1)^2 - 8 * (\rho\mathrm{NIR} - \rho\mathrm{Red})}\right) \Big/ 2$$

We used the atmospherically corrected Landsat 8 surface reflectance dataset in Google Earth Engine to calculate MSAVI [31]. Landsat 8 was chosen over other satellite data because it offers moderate spatial resolution at 30 m and, importantly, provides a consistent annual source from 2013. A total of 400 parcels giving us 2800 parcel-year observations are available over the 7 year period. Among these, 306 parcel-years were covered by clouds and an additional 215 were classified as having an 'unknown' rental status. We labeled a parcel's tenure status as 'unknown' when, e.g. a parcel was rented by our respondent from 2015 to 2019 but before 2015 it was not tied to our respondent (table S3). In the end, our sample contains 2279 parcel-year observations.

We queried the full Landsat 8 Image Collection from 2013 to 2019 to only select the image tiles covering our area and date of interest. All households surveyed were located within six Landsat tiles on three swaths, namely two tiles in row 29 and 30 of path 126 (which covers our targeted households in Sonid Left and Sonid Right county), three tiles in row 28, 29, and 30 of path 124, and one tile in row 28 of path 123 (which covers our targeted households of Xilin Hot and East Ujimqin county) (figure 2). These tiles on paths 126, 124 and 123 also roughly encompass desert steppe, typical steppe, and meadow steppe, respectively. Within each path, all parcels were visited on the same date. Observations on path 126 were always visited two days earlier than those on path 124, and five days later than those on path 123 due to Landsat's north-south orbital pattern.

We selected September (the end of productive grassland growth for the year) over other months as the period over which to sample images (see figure S6 for the specific date chosen for this study) for several reasons. First, this period provides a good estimate of a final outcome that relates to the season's land use. While sampling earlier in the season could better capture rangeland growth, the timing of some end-of-year practices like haying harvesting is uncertain throughout August and would dramatically affect greenness, contaminating our ability to tie rangeland outcomes to its rental status (during participatory mapping we capture such parcel-based practices, so are able to develop robustness checks for this in our analysis as well). Second, our analysis aims to estimate whether rental properties remove more biomass within a season than privately held properties (all else equal) as an indicator of which tenure system puts more pressure on the rangeland. Even still, greenness throughout September naturally varies by location and across years. In our analysis (see section 2.5 below), we thus standardize the log(MSAVI) by demeaning the measure by county and by year. As such we compare relative greenness across parcels, controlling for differences in location and years. Pragmatically, September also offers more cloud-free observations (89.07% of the total 2800 observations remain cloudless) allowing for more consistency in measurement across all years. Before any indices were calculated, we applied a function to mask clouds and shadows to the image collection's pixel quality band.

There is a lag between climatic factors' occurrence and when they influence vegetation greenness [32], so we measured the average value of three different climatic variables (land surface temperature, precipitation, and incoming shortwave radiation) from Google Earth Engine during the 14 d in advance of the VI retrieval date each year (see table S4 for detailed data description). For example, the VI measured on 17th September 2017 of path 126 is paired with the average value of our climatic variables between 3rd September and 16th 2017.

Daily land surface temperature data come from the moderate resolution imaging spectroradiometer MOD11A1 dataset [33]. Daily precipitation was calculated using the Global Satellite Mapping of Precipitation (GSMaP) hourly gauge-adjusted data [34], which has been shown to offer the most accurate daily precipitation estimation for China [35]. Downward shortwave radiation comes from the Global Land Data Assimilation System dataset (GLDAS-2.1) [36], from which we chose the maximum radiation value every day at 14:00 local time.

Topographic variables for each parcel include average elevation (meters), slope (degrees), and aspect northing ('northness'), all derived from the 30 m resolution Shuttle Radar Topography Mission digital elevation dataset [37]. We converted degrees to radians and calculated aspect northing as the cosine of radians, which ranges from −1 (due south) to 1 (due north), with 0 indicating east or west.

2.5. Statistical analysis: multilevel modeling

To assess the relationship between land tenure and rangeland outcomes, we build several statistical models that take into account known abiotic and household management factors that influence rangeland outcomes. Multilevel analysis is chosen because we have repeated measures for each parcel over time, and there is clustering in parcels' greenness that is possibly correlated with other nearby parcels. Therefore, observations on a given parcel may share similar characteristics with other geographically or temporally proximate observations. Our multilevel framework follows the form:

$$\mathrm{VI}_{ijkt} = \beta_0 + \beta_1 C_{ijkt} + \beta_2 T_{ijk} + \beta_3 M_{jk} + \beta_4 Z_{jk} + \beta_5 R_{ijkt} + \mu_k + \varepsilon_{ijkt}$$

where VI_{ijkt} is the satellite-image derived VI for land parcel i belonging to household j in township k at time t. For each land parcel, we measured its VI, abiotic influence, and rental situation (rented or privately held) at time period t (a specific day in September of each year from 2013 to 2019). C_{ijkt} represents time-variant climatic factors that constrain VI_{ijkt} at the parcel level, and T_{ijk} are time-constant topographic factors. M_{jk} represents rangeland management factors stocking rate and fodder expenditure, and Z_{jk} represents household demographic or socioeconomic characteristics. The impact of interest is R_{ijkt}, the impact of land being rented (vs privately held) on rangeland outcomes. The random intercept μ_k captures time-invariant unobservable at the township level (level 1), and ε_{ijkt} are the residuals at the observation (parcel) level (level 0). To help control for time and differences in vegetation productivity by county, we de-meaned (centered) the log-transformed VI by county and year. All analyses were performed using Stata 15 [38].

3. Results

3.1. Household and parcel characteristics

Our data were collected from herding households across four counties in Xilin Gol prefecture of Inner Mongolia, China. Of the 187 herder households for whom we successfully identified at least one of their land parcels, 74 households grazed only on their own privately held parcels between 2013 and 2019, 108 used a combination of rented and privately held parcels, and 5 households are only renters (table 1). Among the 400 parcels identified, 90 were rented and 310 were privately held for at least one year between 2013 and 2019 (table 2). Although at the household level, 60.5% of the surveyed households ($n = 113$) grazed on a rented parcel at some time, some of these could be tens of kilometers from the respondent's homes and therefore were not able to be captured through participatory mapping.

3.2. Rental impact

We estimated a number of models to assess predictors of grassland greenness (MSAVI). Figure 4 shows results for our preferred multilevel model that estimates rangeland greenness as a function of climatic, topographic, land tenure, land management, and socioeconomic influences (see table S6 for numeric results). The model suggests rented land is significantly associated with lower greenness. MSAVI-greenness is measured on a −1 to 1 scale with no real-world analog, limiting the interpretability of effect sizes. Still, the model suggest that a rented parcel has, on average, about a 2% lower value relative to a privately held parcel in the same year and county, all other factors being equal.

3.3. Other factors related to greenness

The climatic (temperature, precipitation, and solar radiation) and topographic (elevation, slope, and aspect) variables used in the model influence primary productivity. These variables show a strong correlation with our VI in directions expected with previous literature [39, 40]. The magnitude of the coefficient estimates are a function of the units of the data, so cannot be directly compared in an absolute sense.

Land management factors are also important in helping explain greenness in our model, with stocking rate and fodder expenditure showing non-linear associations with greenness. The initial positive livestock-vegetation relationship weakens and reverses as livestock per hectare increases (figure 5). Thus, in our sample low stocking rates are positively associated with grassland health, but greater numbers of sheep units per hectare relate to worse grassland outcomes, as we would expect. Herders' expenditure on fodder (reliance on external resources) generally has an increasing positive effect on greenness that stabilizes as fodder expenditure increases—suggesting that greater amounts of feed coming from external markets puts less pressure on local grassland resources.

Other household characteristics are mainly included as control variables, but also provide some insight into rangeland dynamics in the region. Parcels more distant from urban areas, associated with male respondents, and with larger household sizes are more likely to be greener, all else equal. Parcels managed by those with longer experience, somewhat counterintuitively, are likely to be less green. This may be due to many elderly herders working less productive areas, a source of potential bias that we cannot readily control for in this study.

We conducted a number of robustness checks on the model above, including a model that uses a 7 day window to measure climatic influences (table S7), one that uses NDVI to measure greenness (table S8),

Table 1. Descriptive statistics of household-level data.

Variable	Unit	Typical and meadow steppe ($N = 109$[a])						Desert steppe ($N = 78$)					
		East Ujimqin ($N = 50$)			Xilin hot ($N = 59$)			Sonid left ($N = 15$)			Sonid right ($N = 63$)		
		Privately held[b] ($N = 13$)	Rent ($N = 37$)		Privately held ($N = 17$)	Rent ($N = 42$)		Privately held ($N = 6$)	Rent ($N = 9$)		Privately held ($N = 38$)	Rent ($N = 25$)	
Land management													
Stocking rate (avg)	Sheep unit ha^{-1}	1.47 (0.54)	1.22 (0.53)		1.77 (0.81)	1.49 (0.65)		0.72 (0.34)	0.77 (0.38)		0.90 (0.43)	0.74 (0.33)	
Fodder expenditure (avg)	100 yuan /sheep unit	0.44 (0.34)	0.42 (0.36)		1.09 (0.56)	1.65 (1.2)		0.91 (0.58)	1.68 (1.10)		1.30 (1.14)	1.93 (1.31)*	
Household characteristics													
Distance to city (avg)	10 km	8.92 (6.95)	7.41 (5.61)		7.49 (2.17)	6.10 (2.67)		4.75 (2.36)	5.33 (2.15)		3.83 (2.64)	2.80 (2.18)	
Decades herding (avg)	10 years	2.08 (1.46)	2.22 (1.06)		2.19 (1.25)	2.71 (1.02)		1.63 (1.50)	2.36 (0.65)		2.73 (1.24)	2.51 (1.32)	
Education (avg)	Years	9.38 (3.43)	8.76 (3.74)		9.65 (3.44)	8.98 (3.10)		10.83 (5.95)	10.00 (1.50)		7.74 (2.93)	7.92 (2.43)	
Gender (N)[c]													
Female		2	6	$\chi^2(1) = 0.01$	4	8	$\chi^2(1) = 0.15$	4	1	$\chi^2(1) = 5^*$	6	5	$\chi^2(1) = 0.19$
Male		11	31		13	34		2	8		32	20	
Ethnicity (N)													
Han		0	7	$\chi^2(1) = 2.86$	2	18	$\chi^2(1) = 5.22^*$	1	5	$\chi^2(1) = 2.27$	9	15	$\chi^2(1) = 8.43^{**}$
Mongol		13	30		15	24		5	4		29	10	
Household size (avg)	# of people	3.92(0.86)	3.95(1.25)		3.29(0.92)	3.74(1.15)		4.33(1.03)	3.56(1.13)		3.71(1.33)	3.32(0.85)	
Herding labor (avg)	# of people	2.54(0.66)	2.08(0.68)		2.00(0.79)	1.93(0.71)		2.50(0.84)	1.78(0.67)		2.13(0.84)	2.08(0.57)	

Standard deviations in parenthesis. *, **, *** indicates significance at 0.05, 0.01, 0.001 from a 2-sided t-test assessing the difference between variable means of households that grazed only on privately held land vs households that grazed on at least one rented parcel in the same county. χ^2 tests indicate whether there are differences between genders or ethnicities for privately holdinging vs. renting land.

[a] N indicates number of households.

[b] 'Privately held' indicates the household grazed only on privately held land, while 'rent' refers to households that used at least one rented land parcel between 2013 and 2019.

[c] Gender of the respondent who primarily makes decisions around herding.

Table 2. Descriptive statistics of parcel-level data.

		Typical and meadow steppe ($n = 258$[a])				Desert steppe ($n = 142$)			
		East Ujimqin ($n = 115$[a])		Xilin hot ($n = 143$)		Sonid left ($n = 29$)		Sonid right ($n = 113$)	
Variable	Unit	Privately held ($n = 91$)	Rent ($n = 24$)	Privately held ($n = 102$)	Rent ($n = 41$)	Privately held ($n = 23$)	Rent ($n = 6$)	Privately held ($n = 94$)	Rent ($n = 19$)
Climatic[b] (*14 d average*)									
Land surface temperature	Celsius	27.34 (1.01)	27.51 (0.92)	29.40 (1.05)	28.63 (1.16)***	31.95 (0.64)	32.07 (0.66)	31.6 (0.56)	31.78 (0.46)
Precipitation	mm	1.91 (0.15)	1.96 (0.15)	1.45 (0.06)	1.46 (0.05)	0.74 (0.03)	0.76 (0.03)	1.26 (0.19)	1.33 (0.14)
Solar radiation	W m^{-2}	568.72 (10.72)	565.84 (11.01)	576.78 (9.15)	584.03 (9.11)***	611.92 (5.43)	610.65 (5.18)	623.09 (5.55)	621.92 (4.44)
Topographic									
Elevation	Meter	908.48 (54.24)	920.08 (50.84)	1082.30 (157.2)	1173.67 (154.56)**	967.92 (35.64)	971.57 (30.49)	1107.02 (39.88)	1116.36 (19.96)
Slope	Degree	3.03 (0.99)	3.04 (0.78)	2.71 (1.36)	3.10 (1.46)	2.60 (0.28)	2.60 (0.23)	2.41 (0.36)	2.32 (0.24)
Aspect northing[c]	[−1, 1]	−0.09 (0.29)	−0.12 (0.29)	0.11 (0.22)	0.21 (0.22)*	0.03 (0.07)	0.03 (0.12)	0.09 (0.11)	0.08 (0.15)

Standard deviations in parenthesis. *, **, *** indicates significance at 0.05, 0.01, 0.001 from a 2-sided t-test assessing the difference between variable means of privately held vs rented parcels in the same county.

[a] n indicates number of parcels.

[b] Climatic variables are calculated as the mean of 7 years (2013–2019).

[c] Aspect northing shows whether a parcel is 'north facing' or 'south facing'. It ranges from −1 (due south) to 1 (due north).

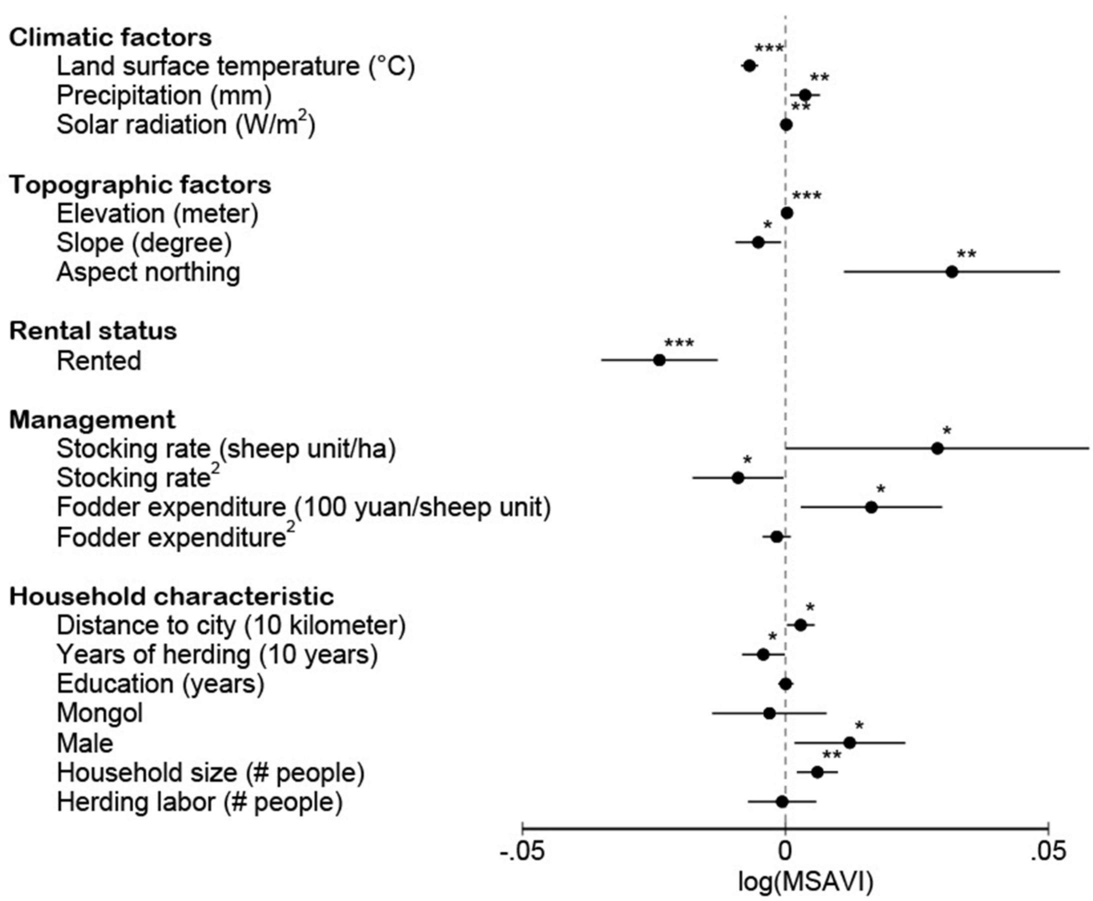

Figure 4. The effect of rented tenure on rangeland outcomes in a multilevel framework. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

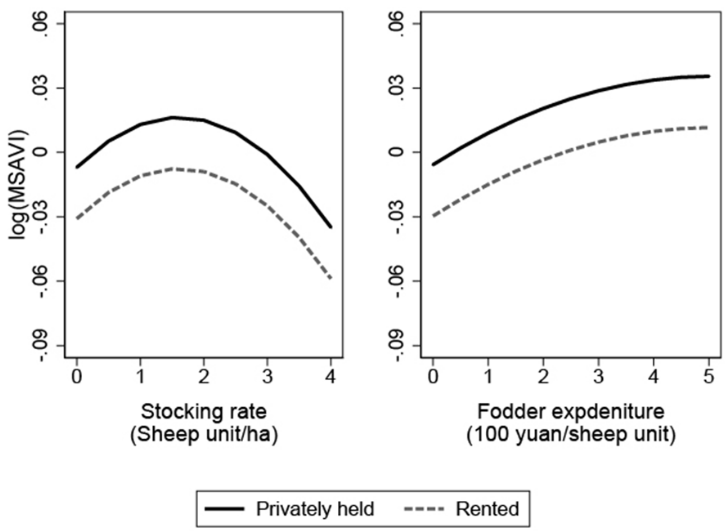

Figure 5. Predicted percentage change in log MSAVI corresponding to 1 unit increase in stocking rate and fodder expenditure for rented versus privately held land. Greenness is measured by the percentage change in modified soil-adjusted vegetation index (MSAVI) centered at a cluster (year and county) mean.

and a model that specifies each parcel's primary use as designated by the herder (i.e. all-season, winter, and summer grazing, lambing, or hay harvesting) (tables S5 and S9). We also estimated a model that excludes the county of Xilin Gol (table S10), which is the only county in our sample where rental and privately held parcel characteristics appear to have some differences (table 2). All results from these checks are qualitatively consistent with those presented in figure 4. We ideally would have liked to perform a 'counterfactual' test for whether moving from being rented to being privately managed improved a parcel's greenness. However, we did not observe any such case in the dataset, making this not statistically possible but show the overwhelming growth in the Inner Mongolian rental market in this region.

4. Discussion

With a multilevel statistical model that controls for climatic, topographic, land management, and household-level socioeconomic influences, our result shows that rented parcels are associated with plots that are less green compared to long-term privately held parcels. Given the growth in rental markets worldwide, our results suggest an increasing need for policy attention on the active management of rented land.

Renter-operated land is common across the globe. Approximately 40% of all farmlands in the United States are managed by renters [41] while in the Czech Republic and the European Union 83% [42] and 53% [43] of the agricultural lands are under leasehold, respectively. Rental of agricultural land is increasing in Africa and Asia as well, especially in countries such as Ethiopia and China, where permanent land transfer is infeasible [5, 44]. Rental allows for flexible distribution of land utilization based on comparative returns to labor. Yet, our study suggests there is a conflict between sustainable land management and the potential efficiency gains that can come through land rental markets.

Rental tenure can also hamper the effectiveness of market-based conservation instruments such as payment for ecosystem services. Policies that aim to incentivize land management lack clear mechanisms to connect to land operators in rental markets. Since most current incentive payments are offered to the *de jure* instead of the *de facto* landholders, such an incentive loses salience in the rental context because it has little influence on the renters' land use decisions and thus the ecosystem services provided. For example, Inner Mongolia's 'Grassland ecological protection reward-subsidy policy' has provided payments to 12 million herding households over the past decade to limit livestock and consequent grazing pressure [45]. However, as only the *de jure* landholders have the rights to receive compensation, compensation flows to absentee landlords instead of feeding back into renters' land management practices [46]. Incentivizing the renters directly may be better, but still transaction costs for identifying, monitoring, and enforcing payment for ecosystem contracts with short-term renters are often too high to implement proper incentives. As payment for ecosystem services and similar programs gain popularity [47], creativity is needed to deal with this rental paradox in incentive-based land management policies.

Despite developing a unique approach to temporal-spatial vegetation analysis at the parcel level, our study is still constrained by the limitations of open-access satellite data and cross-sectional surveys. Multispectral satellite-derived vegetation indices handle rangeland compositional change poorly (e.g. transitions from native to invasive plants) [48, 49], thus our results assume that greener pastures are indeed 'better.' Hyperspectral data may offer ways to identify and map the compositional change based on plant species' unique spectra [50], though there are technical difficulties of conducting a landscape-scale hyperspectral analysis for all surveyed households. Finally, our socio-economic data are constructed from a cross-sectional survey, and therefore may not reflect, for example, unforeseen shocks (e.g. loss of a family member, financial crisis) that could influence land use decisions [49, 51]. Future studies can benefit from pairing biophysical time series with longitudinal survey data.

5. Conclusions

In this study, we investigated the impact of rangeland rental tenure on land outcomes through detailed measurement of land tenure over rangeland parcels and parcel-level vegetation change from 2013 to 2019. Methodologically, our study shows that more comprehensive land-use models can be constructed by linking remote sensing and household survey data at the parcel level. Remote sensing allows us to reconstruct and analyze longer-term vegetation dynamics and their abiotic influences, while household surveys and participatory mapping enables us to explore the underlying drivers of change such as land management and land-use intensity. Empirically we found that rented land parcels have large and consistent negative effects on rangeland greenness relative to privately-held parcels. The findings of this study have significant implications for the design of land management strategies and policies on land under short-term rental arrangements. In addition to rented parcels having short management time horizons, renters also lack of the right to receive compensation or incentives in market-based programs. Both these issues should be recognized and better incorporated into policies that aim to incentivize sustainable rangeland management.

Data availability statement

The data that support the findings of this study are available upon reasonable request from the authors.

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Conflict of interest

The authors declare no competing interest.

Ethical statement

The research protocol was reviewed and approved by McGill's Research Ethics Board (#37-0619). Informed consent was obtained from each participant in this study.

ORCID iDs

Luci Lu https://orcid.org/0000-0003-2943-4032
Ping Li https://orcid.org/0000-0003-3761-1262
Margaret Kalacska https://orcid.org/0000-0002-1676-481X
Brian E Robinson https://orcid.org/0000-0002-8972-8318

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