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From Pixels to Mobile Pastoral Households: Scale Mismatch, Exposure Measurement, and Inference in Mongolian Rangeland Research

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From Pixels to Mobile Pastoral Households: Scale Mismatch, Exposure Measurement, and Inference in Mongolian Rangeland Research

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Abstract

Spatially explicit Earth-observation products and machine-learning models increasingly support detailed monitoring of vegetation productivity and land-surface dynamics across Mongolia. Yet the spatial unit observed by a satellite, the area actually grazed by a mobile herd, the administrative unit used in official statistics, and the household unit used in socioeconomic surveys are rarely identical. This methodological study formalizes that scale mismatch as a source of exposure-measurement and inferential error in linked rangeland–livelihood research. It develops a pixel-to-household framework that separates five objects: remotely sensed environmental signals, ecological interpretation, seasonal grazing locations, mobility-weighted household exposure, and livestock or household outcomes. The framework identifies four recurrent mismatches—pixel-to-pasture, residence-to-grazing-area, temporal aggregation, and administrative-boundary mismatch—and specifies alternative procedures for constructing exposure weights using GPS tracks, participatory mapping, seasonal-location surveys, livestock-unit weighting, and probabilistic exposure surfaces. Using Mongolian rangeland research as the application domain, the study shows why strong predictive agreement with a remotely sensed productivity proxy does not by itself establish household-level exposure or causality. The resulting design standards emphasize explicit spatial and temporal support, structured validation, exposure uncertainty, and sensitivity to alternative linkage rules. The framework is intended as a technical design tool for remote-sensing, ecological, livestock, and socioeconomic studies in mobile pastoral systems.

Keywords: Mongolia; rangelands; remote sensing; pastoral mobility; ecological exposure; spatial scale; machine learning; household panel; causal inference; grazing systems

1. Introduction

Mongolia is an unusually demanding setting for integrated rangeland research. Extensive pastoral production depends on ecological conditions that vary sharply across space and time, while herders can respond by moving animals, changing seasonal camps, altering herd composition, purchasing feed, selling livestock, or drawing on non-livestock income. At the same time, satellite remote sensing increasingly provides high-frequency, spatially continuous information on vegetation and climate. The apparent complementarity is compelling: if ecological

conditions can be observed from space and household outcomes can be surveyed on the ground, the two should be linkable.

The central difficulty is that they are often observed at different scales. A satellite pixel is not a grazing territory. A household residence is not necessarily the location where its animals forage. A soum average can conceal large within-soum variation. Annual household income can integrate outcomes from several seasonal grazing locations and from shocks occurring at different points in the livestock cycle. When these units are matched mechanically, the resulting dataset can look precise while ecological exposure is measured with substantial error.

This problem is now more important because the technical accuracy of environmental prediction is improving. Sodnomdavaa (2026), for example, combined Sentinel-2 features, climate variables, and machine learning to obtain strong predictive agreement with a MODIS-derived grassland GPP proxy, while explicitly distinguishing proxy agreement from absolute ground-truth validation. Such models are useful for environmental monitoring, but a high-performing pixel-level model still does not establish which pixels represent the exposure of a particular mobile household. The remaining challenge is not only prediction; it is linkage.

A second reason for focusing on linkage is the changing evidence on drivers of Mongolian rangeland productivity. The systematic review by Sainnemekh et al. (2022) documented wide variation in definitions and estimates of degradation and emphasized that grazing and climate effects vary across ecological zones. Long-term field evidence also shows that total biomass or cover can remain comparatively stable while species composition and richness change (Khishigbayar et al., 2015). More recently, Purevjav et al. (2025), using nationwide spatially disaggregated data from 1984–2024 and seasonal variation in grazing locations, estimated that weather effects on primary productivity were an order of magnitude larger than contemporaneous herd-size effects, while long-run temperature effects dominated at decadal scale. These results reinforce a basic identification principle: ecological exposure must be measured at the scale at which climate, grazing, and mobility operate.

Recent conceptual work has already made an important distinction among ecological productivity, rangeland condition, soil carbon, livestock production, value capture, and household welfare. Ariunsukh (2026) formalized these distinctions in the Productivity, Condition, Carbon, and Livelihood (PCCL) framework and emphasized explicit inference boundaries among measurement, prediction, association, and causality. The present paper takes that logic as a starting point rather than claiming it as a new contribution. The unresolved problem addressed here is different: even when the outcome domains are correctly separated, how should researchers assign ecological exposure to a household whose animals move through space and season?

The paper makes three methodological contributions. First, it identifies four recurrent forms of scale mismatch in rangeland–livelihood studies: pixel-to-pasture, residence-to-grazing-area, temporal aggregation, and administrative-boundary mismatch. Second, it formalizes a mobility-weighted ecological exposure operator that can be implemented with GPS tracks, participatory maps, seasonal-location modules, livestock-unit weights, or probabilistic grazing weights. Third, it translates these ideas into practical design and reporting standards for linked remote-sensing, livestock, and household panels. The contribution is methodological rather than empirical: this

technical framework is intended to improve the validity of the bridge between environmental monitoring and household-level inference without presenting new empirical estimates.

2. Positioning the Contribution: From Inference Boundaries to Exposure Linkage

2.1 What is already established

The conceptual distinction between remotely observed productivity and broader sustainability outcomes should no longer be treated as novel. Ariunsukh (2026) explicitly separates productivity, condition, carbon, livestock production, value capture, and household welfare. Likewise, the empirical studies motivating the present synthesis already impose important boundaries. Sodnomdavaa (2026) describes the target as a remote-sensing-based GPP proxy and does not equate predictive agreement with ground-measured ecosystem productivity. Davaatseren et al. (2026) combine Sentinel-2 NDVI, soil organic carbon, and a household panel in Öndörshireet Soum, but explicitly restrict causal and geographic generalization from a single pastoral system.

2.2 The unresolved linkage problem

Correctly distinguishing outcome domains does not solve the problem of assigning ecological conditions to mobile decision-makers. A household panel typically contains a stable household identifier and a residence or administrative location. Remote sensing contains spatially explicit observations. Pastoral exposure, however, is generated by herd movement through multiple locations over time. If the exposure assigned to household i in year t is simply the pixel at the residence, or the average vegetation index of the soum, the implicit assumption is that this spatial unit represents the grazing conditions relevant to the household's livestock. That assumption can be false even when both data sources are measured accurately.

$$Residence_i \neq Seasonal\ grazing\ locations_i \neq Ecological\ exposure_i$$

The inferential consequence is an exposure-measurement and change-of-support problem that is often hidden: misalignment can attenuate associations, distort spatial gradients, or confound ecological effects with administrative or market characteristics (Gotway & Young, 2002, 2007; Kyriakidis, 2004; Zeger et al., 2000).

2.3 Framework development

The framework is developed through a structured methodological synthesis of three bodies of work already used in this paper: spatial scale and change-of-support research, pastoral mobility and rangeland ecology, and remote-sensing-household data linkage. The synthesis is not presented as a systematic review. Instead, it uses established spatial-statistical principles on incompatible supports and measurement error (Gotway & Young, 2002, 2007; Kyriakidis, 2004; Waller & Gotway, 2004; Zeger et al., 2000), empirical evidence on mobile grazing behavior in Mongolia (Michler et al., 2022, 2023), and structured validation principles for spatially and temporally dependent environmental prediction (Roberts et al., 2017) to define the linkage problem.

Framework construction proceeds in three steps. First, the spatial and temporal support of the environmental measurement is distinguished from the support of the livestock or household outcome. Second, recurrent support mismatches are classified according to whether they arise from pixels, residence locations, temporal aggregation, or administrative boundaries. Third, these

mismatches are represented through an exposure operator that assigns ecological conditions to a household according to where and when its livestock are plausibly exposed. This sequence turns the scale problem into an auditable design choice that can be examined before model estimation and subjected to sensitivity analysis afterward.

3. Four Forms of Scale Mismatch

3.1 Pixel-to-pasture mismatch

Satellite products are measured on grids whose spatial resolution depends on sensor and processing. Pastoral use is organized around grazing routes, camps, water points, seasonal reserves, and accessible forage. A pixel can contain vegetation that is technically productive but unavailable to a particular herd because of distance, terrain, water access, ownership arrangements, snow conditions, or seasonal timing. Conversely, a herd can utilize multiple pixels within a short period. Therefore, pixel-level environmental accuracy is a necessary input but not a sufficient definition of livestock exposure.

The distinction becomes especially important when environmental prediction is downscaled. Higher spatial resolution creates more detailed maps, but it does not automatically identify the relevant support of the exposure variable. Change-of-support methods show that point, pixel, and areal quantities have different statistical properties and cannot be interchanged without assumptions about spatial aggregation (Gotway & Young, 2007; Kyriakidis, 2004). Statistical precision can increase while substantive misalignment remains.

3.2 Residence-to-grazing-area mismatch

A second mismatch arises when the household residence or registered administrative location is used as a proxy for ecological exposure. Mobility evidence from the Dzungarian Gobi shows why this can be problematic. Michler et al. (2022) followed 19 herds for 20 months and reported repeated camp changes, with biomass availability influencing movement decisions and large seasonal distances between camps. Follow-up analysis of the same pastoral system further showed that camp-use duration and daily herd movement respond to biomass, season, and local environmental conditions (Michler et al., 2023). These results demonstrate that ecological exposure is generated by a trajectory, not by a point location.

For mobile households, the meaningful environmental unit is therefore closer to a time-weighted grazing footprint than to a residential coordinate. This is not merely a cartographic refinement. If households with greater mobility systematically differ in herd size, wealth, market access, or adaptive capacity, residence-based exposure error can be endogenous to the outcome being studied.

3.3 Temporal aggregation mismatch

Environmental and household processes also operate at different temporal frequencies. Vegetation indices may be available every few days; GPP products may be composited; livestock mortality can be concentrated in a short winter shock; household income may be recorded annually; and herd-management decisions can respond within weeks. Aggregating all variables to a calendar-year mean can therefore erase the biologically relevant sequence of exposure and response.

A growing-season vegetation anomaly, for example, may affect pre-winter body condition and forage reserves before a dzud. The economic loss may then appear in winter mortality, spring sales, or subsequent-year income. A contemporaneous annual regression can misalign cause and consequence even if the spatial match is correct.

3.4 Administrative-boundary mismatch

Administrative units are convenient for statistics and policy, but ecological processes do not follow soum boundaries. Climate gradients, ecological zones, seasonal pasture use, and market access can cross administrative borders. Aggregating environmental exposure to a soum can therefore generate the modifiable areal unit problem: statistical relationships may change when the same underlying spatial information is summarized at different geographic partitions (Openshaw, 1984; Waller & Gotway, 2004). In pastoral applications, this risk is compounded when livestock move across those partitions.

Table 1. Recurrent scale mismatches in rangeland–livelihood linkage and their inferential consequences.

Mismatch	Typical shortcut	Primary inferential risk	Preferred design response
Pixel-to-pasture	Use the environmental value of one pixel or a simple local buffer as herd exposure.	The pixel may contain inaccessible, unused, or seasonally irrelevant vegetation; finer resolution does not guarantee correct exposure support.	Aggregate environmental data over observed or plausibly used grazing footprints and retain sensor resolution and aggregation metadata.
Residence-to-grazing area	Assign exposure from the household residence or registered location.	Mobile herds may graze far from the residence; error may be endogenous if mobility is related to wealth, herd size, or adaptive capacity.	Use GPS tracks, seasonal camp locations, participatory maps, or mobility-informed probabilistic weights.
Temporal aggregation	Match annual household outcomes to annual mean vegetation or climate indicators.	Biologically relevant exposure windows and lagged responses are obscured; exposure and outcome timing may be reversed or diluted.	Define seasonal/event exposure windows and use lags consistent with forage, winter mortality, sales, and income mechanisms.
Administrative boundary	Use soum- or district-level environmental averages as household exposure.	Within-area heterogeneity and cross-boundary grazing create change-of-support and MAUP sensitivity.	Test alternative spatial supports and, where possible, assign exposure from actual grazing areas rather than administrative units.

Table 1 converts the four conceptual mismatches into explicit design choices that can be audited before model estimation.

4. A Mobility-Weighted Ecological Exposure Framework

The key design object is household-specific ecological exposure. Let i index households, j index spatial cells or grazing locations, t index the household outcome period (for example, year), and s index a season or biologically meaningful exposure window within t . Define E_{jst} as an ecological signal at location j during window s of period t , such as vegetation productivity, biomass, snow burden, drought intensity, or an ecologically validated condition indicator. Let w_{ijst} represent the share of the household's effective grazing exposure occurring in location j during window s . Household exposure can then be represented as:

$$X_i = \sum_s \sum_j w_{ijst} E_{jst}, \text{ with } w_{ijst} \geq 0 \wedge \sum_s \sum_j w_{ijst} = 1$$

The weights need not be interpreted literally as time shares in every application. They can represent grazing duration, herd-days, livestock-unit-days, utilization intensity, distance-decay weights, or posterior probabilities of pasture use. The seasonal index allows exposure to preserve the ordering of growing-season, winter, and other biologically relevant windows rather than collapsing them mechanically into an annual mean. The essential requirement is that the

exposure definition reflects where and when livestock actually interact with ecological conditions.

This framework also permits species-specific exposure. Different livestock species may use terrain and forage differently, so weights can be indexed by species k :

$$X_{ikt} = \sum_s \sum_j w_{ijkst} E_{jst}$$

For household welfare analysis, the ecological exposure can then enter a transmission model through livestock outcomes rather than being assumed to affect income directly:

$$Ecology_i \rightarrow Livestock\ response_i \rightarrow Market/asset\ response_i \rightarrow Household\ outcome_i$$

This sequence is intentionally compatible with the inference boundaries emphasized by Ariunsukh (2026). The additional contribution is that each ecological term is household-specific only after a defensible exposure operator has been defined.

4.1 Practical ways to construct exposure weights

- GPS-based tracking: direct movement data from herds or herders can approximate grazing trajectories and duration.
- Participatory mapping: seasonal camp locations, reserve pastures, water points, and routes can be recorded retrospectively or prospectively.
- Seasonal-location survey modules: household panels can record primary and secondary grazing areas by season, even when exact tracks are unavailable.
- Livestock-unit weighting: exposure can be weighted by herd composition or standardized livestock units rather than treating all animals equally.
- Probabilistic exposure surfaces: when movement data are incomplete, weights can be estimated from distance, water, terrain, vegetation, known camps, and observed mobility behavior, with uncertainty retained.

Table 2. Practical exposure-weighting strategies for mobile pastoral households.

Weighting strategy	Required data	Interpretation of w	Main strength	Main limitation
GPS tracking	Time-stamped herd or herder locations	Observed share of time/herd-days in each cell and period	Closest approximation to realized movement and timing	Cost, battery failure, selective participation, and incomplete tracking
Participatory mapping	Seasonal camps, routes, reserve pastures, water points	Mapped use intensity or season-specific area weights	Captures local knowledge and areas not continuously tracked	Recall and delineation error; intensity may be approximate
Seasonal-location survey	Repeated household survey with locations by season	Equal or reported-duration weights across seasonal sites	Low-cost option for panel surveys; directly links to household IDs	Coarser than GPS and sensitive to reporting precision
Livestock-unit weighting	Location plus herd composition and animal counts	Exposure weighted by livestock-unit-days or species-specific use	More biologically meaningful when species use forage differently	Requires detailed herd movement by species and conversion assumptions
Probabilistic exposure surface	Known camps plus distance, water, terrain, vegetation, mobility model	Posterior probability that a herd used each location-period	Useful when movement is only partially observed; preserves uncertainty	Model-dependent and vulnerable to misspecified movement behavior

4.2 Exposure uncertainty should be explicit

A mobility-weighted exposure measure can still be wrong. Pastoral movement records may be incomplete, GPS samples can be selective, and recalled seasonal locations can be imprecise. Spatial data also involve uncertainty about support, aggregation, and linkage across sources (Zhang & Goodchild, 2002; Gotway & Young, 2002). The appropriate response is not to return to

static residence proxies without qualification, but to quantify uncertainty. Sensitivity analysis can compare residence-based exposure, soum-average exposure, equal-weight seasonal exposure, and mobility-weighted exposure. If substantive conclusions change materially across these definitions, the result itself is evidence that scale choice is consequential.

4.3 Illustrative implementation of the exposure operator

A simple hypothetical example shows how the operator works. Suppose a household uses three grazing cells during a biologically relevant exposure window, with mobility weights $w = (0.20, 0.50, 0.30)$ and normalized ecological signals $E = (0.40, 0.70, 0.20)$. The mobility-weighted exposure is then $X_{it} = 0.20(0.40) + 0.50(0.70) + 0.30(0.20) = 0.49$.

If the household were instead assigned only the ecological value of its residence pixel, and that pixel had $E = 0.40$, the residence-based exposure would be $X_{it}(\text{residence}) = 0.40$. The difference, $\Delta X_{it} = 0.09$, arises solely from the exposure-linkage rule; it does not require any error in the underlying satellite observation.

This example is illustrative and is not an empirical estimate for Mongolia. Its purpose is to demonstrate that the proposed operator is directly implementable and that residence-based and mobility-weighted assignments can differ even when the environmental data themselves are measured consistently. In empirical applications, the same calculation can be repeated across seasons, species, and alternative weight definitions, with uncertainty propagated through sensitivity analysis.

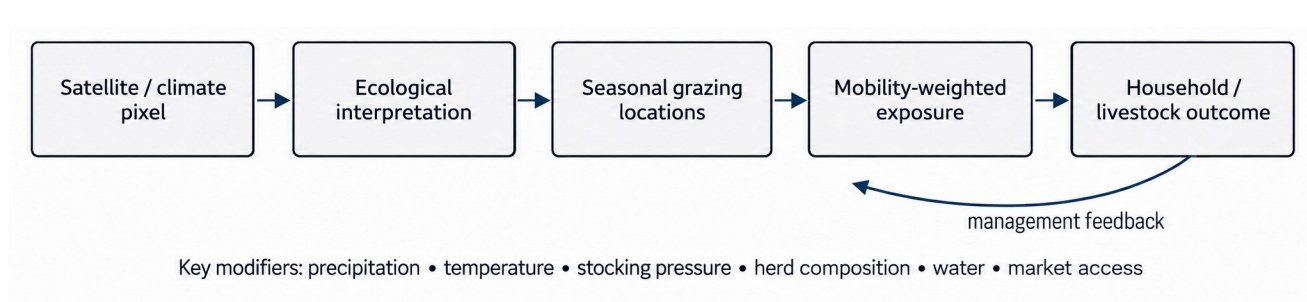


Figure 1. Pixel-to-household exposure framework. The distinct contribution is the linkage between environmental observations and the spatially mobile exposure of households; feedback from household management to grazing pressure prevents the system from being interpreted as a one-way causal pipeline.

5. Why the Problem Matters in Mongolia

5.1 Climate, grazing, and the scale of identification

Mongolian evidence increasingly demonstrates that climate and grazing effects depend on scale. Ahlborn et al. (2020) found that climate–grazing interactions differ along a large environmental gradient and across equilibrium and non-equilibrium conditions. Sainnemekh et al. (2022) similarly concluded that the relative importance of grazing and climate varies across ecological zones. Purevjav et al. (2025) provide particularly strong evidence because their nationwide design explicitly exploits seasonal variation in grazing locations. They estimate a modest negative interannual effect of herd size on primary productivity but substantially larger weather effects, with temperature dominating long-run change. The methodological lesson is that causal

interpretation improves when exposure and variation are aligned with actual grazing geography and time.

5.2 Mobility is adaptation, not noise

Pastoral mobility is sometimes treated as a nuisance that complicates data matching. It should instead be modeled as part of the adaptation process. Michler et al. (2022) show that biomass availability influences camp movement, while winter shelter and other constraints also matter. Because movement responds to environmental conditions, mobility can reduce ecological exposure to local shocks. This creates selection: the households observed in a degraded or drought-affected location at a particular time may not be representative of all households initially exposed to that area.

5.3 Predictive maps and household panels answer different questions

The value of high-resolution remote sensing is clear. Sodnomdavaa (2026) demonstrates that multi-source satellite and climate variables can generate strong out-of-sample agreement with a GPP proxy under spatial and leave-one-year-out validation. Roberts et al. (2017) explain why such structured validation is preferable to random splitting when observations are spatially or temporally dependent. Yet even a well-validated map answers a mapping question: what is the estimated environmental state at this place and time? A household panel asks a different question: what ecological conditions did this household's herd experience, and how were outcomes affected? The second question requires a linkage model in addition to a prediction model.

5.4 Single-site household evidence remains valuable—but scale must be explicit

Davaatseren et al. (2026) provide multi-source evidence within one pastoral system by combining vegetation dynamics, soil information, and repeated household observations. Such local integration is valuable because ecological and economic variables are observed within a coherent setting. Its limitation is the reverse of national remote sensing: geographic coverage is narrower, and generalization is constrained. A future research program should therefore combine the strengths of both approaches—national or regional environmental coverage with household-specific exposure definitions and repeated socioeconomic measurement.

6. Design Standards for Linked Satellite–Livestock–Household Research

6.1 Define the unit of exposure before choosing the model

The first design decision should be substantive rather than algorithmic. Researchers should specify what geographic and temporal unit plausibly affects the livestock or household outcome. Only after this step should pixels be aggregated, lags selected, or machine-learning features constructed. Choosing the model first and defining exposure afterward risks optimizing prediction around an arbitrary spatial support (Waller & Gotway, 2004; Gotway & Young, 2007).

6.2 Report at least two plausible exposure definitions

Whenever mobility data are incomplete, studies should report sensitivity to alternative exposure definitions. A minimum comparison could include: (1) residential or centroid exposure, (2) administrative-area mean exposure, and (3) seasonal or mobility-informed exposure. Agreement across definitions strengthens robustness; disagreement reveals that spatial linkage is a substantive source of uncertainty (Gotway & Young, 2002; Zeger et al., 2000).

6.3 Respect temporal ordering

Exposure windows should be tied to biological and economic mechanisms. Growing-season vegetation may affect winter condition; winter severity may affect mortality; mortality may affect next-season sales or income. Distributed lags, seasonal summaries, or event-time designs are preferable to mechanically matching annual averages when mechanisms imply timing.

6.4 Use structured validation for environmental models

Environmental prediction should use validation that reflects deployment. Spatial block validation, leave-one-year-out tests, ecological-zone holdouts, and extreme-event validation are more informative than random splits when neighboring observations are dependent. Strong predictive metrics under random splitting should not be treated as evidence of transferability across years, regions, or shocks (Roberts et al., 2017).

6.5 Separate prediction, explanation, and causality

Machine-learning feature importance can help diagnose prediction, but it does not identify causal drivers. SHAP, for example, attributes model predictions to features within a fitted predictive system (Lundberg & Lee, 2017). A high SHAP contribution of precipitation, coordinates, or vegetation indices does not establish that changing the feature would change household income. Causal claims require a design that addresses confounding, reverse causality, selection, and spatial dependence or interference where relevant (Reich et al., 2021)—including mobility selection.

6.6 Preserve ecological provenance

Every derived variable should retain information about its source, resolution, time window, aggregation rule, and validation target. “NDVI,” “GPP,” “biomass,” and “rangeland condition” should not be treated as interchangeable labels. Geographical information can carry uncertainty from measurement, representation, scale, and spatial transformation (Zhang & Goodchild, 2002). Provenance is especially important when an exposure measure is constructed from a modeled remote-sensing target rather than direct field observation.

Table 3. Minimum reporting standards for linked satellite–livestock–household studies.

Design element	Minimum reporting requirement	Robustness check	Failure mode if omitted
Exposure unit	State the spatial unit that plausibly affects the livestock/household outcome and why.	Re-estimate with at least one alternative spatial support.	High predictive precision can be attached to the wrong ecological exposure.
Temporal support	Report exposure window, season, aggregation, and lag relative to the outcome.	Compare plausible seasonal or lag structures.	Annual averaging can mask biologically relevant sequencing.
Mobility linkage	Explain how household IDs are linked to grazing locations over time.	Compare residence-, administrative-, and mobility-informed exposure.	Residence or registry location may be treated as actual exposure.
Environmental provenance	Report sensor/product, resolution, target, preprocessing, and validation design.	Use structured spatial/temporal validation where feasible.	NDVI, GPP, biomass, and ecological condition may be conflated.
Exposure uncertainty	Quantify uncertainty in movement or assignment, not only in the environmental model.	Sensitivity bands, bootstrap, or alternative weight definitions.	Confidence in pixel prediction is mistaken for confidence in household exposure.
Causal interpretation	Specify confounders, selection mechanisms, reverse causality, and identification assumptions.	Pre-specify scale/exposure for causal analyses; test mobility-related selection.	Prediction or feature attribution may be misreported as causal evidence.

7. Implications for Decision Support

7.1 Early warning

Early-warning systems can benefit from environmental maps, but household targeting should distinguish hazard from exposure. A vegetation or snow anomaly identifies a hazardous environmental condition. Household exposure depends on where animals are actually located, and vulnerability depends on herd structure, feed reserves, wealth, debt, mobility options, and market access. A household should not be classified as highly affected solely because its registered residence falls within an anomalous pixel or administrative area.

7.2 Grazing and restoration policy

Scale-aware exposure also changes how grazing pressure is interpreted. Localized vegetation decline near camps or water points can coexist with broader climate-driven productivity change. Restoration targeting should therefore combine ecological persistence, use intensity, recovery potential, and actual seasonal use. National productivity maps are useful for screening; local management decisions require finer ecological and mobility information.

7.3 Insurance and compensation

The same principle applies to index-based insurance and shock compensation. Basis risk increases when the index is measured at a scale that differs from the insured household's actual exposure. Environmental indicators can complement mortality or weather indices, but their benefit depends on whether they improve household-level alignment rather than merely spatial resolution.

8. Research Agenda

8.1 Build spatially explicit household panels

The highest-value data improvement is conceptually simple: repeated household surveys should record seasonal grazing locations. Exact continuous GPS is not essential in every study. A structured module that records spring, summer, autumn, and winter camps, approximate dates, major reserve areas, and movement distances would materially improve exposure assignment.

8.2 Link movement to livestock units

Future data systems should record which animals moved where. Species and age composition influence forage use, vulnerability, and economic response. Household exposure measures weighted by livestock-unit-days would be more biologically meaningful than unweighted household locations.

8.3 Study adaptive mobility as an endogenous response

Mobility should enter causal models as a behavior that responds to ecological conditions and household capacity. This creates both mediation and selection. Designs that compare movers and non-movers without accounting for these determinants can misattribute the effect of mobility or ecological exposure (Michler et al., 2023; Reich et al., 2021).

8.4 Integrate field ecology with remote sensing at calibration sites

Field observations remain essential for distinguishing productivity, forage quality, species composition, soil condition, and recovery state. National mapping need not measure every

variable everywhere; strategically located calibration and validation sites can anchor remote-sensing products and clarify what environmental signals mean ecologically.

8.5 Propagate uncertainty through the linkage chain

Future studies should report uncertainty not only for the environmental prediction but also for exposure assignment. Confidence in a pixel estimate does not imply confidence that the pixel represents a household's grazing conditions. Uncertainty maps, alternative exposure weights, bootstrap procedures, and sensitivity bands can make this distinction visible (Zhang & Goodchild, 2002; Waller & Gotway, 2004).

8.6 Pre-register the scale and exposure definition in causal studies

Where causal effects are the objective, the exposure definition and its spatial and temporal support should be specified before outcome modeling. This reduces analytical flexibility and makes clear whether identification derives from climate shocks, grazing variation, movement, policy changes, or other sources (Reich et al., 2021).

9. Discussion

The central methodological proposition is narrow but consequential: the quality of rangeland-livelihood inference depends on alignment between the environmental unit observed and the pastoral unit exposed. Mongolia's increasingly rich environmental data make this issue more visible, not less important. Better sensors and more accurate machine learning can reduce measurement error in environmental states while leaving household exposure error untouched.

The proposed framework therefore differs from approaches that primarily distinguish sustainability domains. The PCCL framework of Ariunsukh (2026) correctly warns against equating productivity, condition, carbon, livestock production, value capture, and welfare. The present contribution asks what happens one level earlier in the empirical design: before estimating a relationship between an ecological variable and a household outcome, has the ecological variable been assigned to the household at the correct spatial and temporal scale?

The distinction also helps reconcile seemingly different findings. A national study can show strong climate effects on primary productivity while a local household study finds income associated with vegetation condition. These results do not necessarily conflict because they operate at different scales, on different outcomes, and with different exposure definitions. Purevjav et al. (2025) estimate productivity responses using spatially disaggregated nationwide data and seasonal grazing-location variation. Davaatseren et al. (2026) analyze a specific pastoral system with repeated household observations and local ecological measures. Their inferences should be compared through the structure of their measurement and exposure, not reduced to a single coefficient or narrative.

There is also a practical implication for AI-enabled decision systems. The temptation is to integrate satellite imagery, machine learning, household registries, and dashboards into a single "smart" platform. Such systems can be useful, but integration is not equivalent to identification. If the household-to-environment linkage is wrong, additional computational sophistication can automate the wrong exposure assignment at scale. The first requirement for trustworthy pastoral AI is therefore not model complexity but defensible spatial and temporal correspondence (Roberts et al., 2017; Reich et al., 2021; Waller & Gotway, 2004).

10. Conclusion

Remote sensing and machine learning have substantially improved the ability to characterize environmental conditions across Mongolian rangelands. The next methodological bottleneck is the linkage from those environmental observations to the livestock and households that experience them. In mobile pastoral systems, residence, administrative boundaries, satellite pixels, and actual grazing exposure are not interchangeable.

This paper proposed a pixel-to-household framework in which household ecological exposure is constructed from the locations and timing of grazing rather than assumed from static residence. It identified four recurrent mismatches—pixel-to-pasture, residence-to-grazing-area, temporal aggregation, and administrative-boundary mismatch—and proposed mobility-weighted exposure as a general organizing device. The framework does not replace established distinctions among productivity, condition, carbon, livestock production, value capture, and welfare; it complements them by specifying how ecological information should be spatially assigned before those relationships are estimated.

For future Mongolian research, the most valuable advance may therefore be relatively simple: record where livestock actually graze, when they are there, and how those locations map to environmental observations. Once exposure is aligned with pastoral behavior, remote sensing, field ecology, household panels, econometrics, and machine learning can be combined with substantially stronger inferential discipline.

References

- Ahlborn, J., von Wehrden, H., Lang, B., Römermann, C., Oyunbileg, M., Oyuntsetseg, B., & Wesche, K. (2020). Climate–grazing interactions in Mongolian rangelands: Effects of grazing change along a large-scale environmental gradient. *Journal of Arid Environments*, 173, 104043. <https://doi.org/10.1016/j.jaridenv.2019.104043>
- Ariunsukh, T. (2026). Beyond single indicators of rangeland sustainability: A productivity, condition, carbon, and livelihood framework with explicit inference boundaries for Mongolia [Preprint]. Preprints.org. <https://doi.org/10.20944/preprints202609.0968.v1>
- Davaatseren, E., Sodnomdavaa, T., Enkhbayar, E., Bayarsaikhan, S., & Mandakh, U. (2026). Rangeland degradation, vegetation dynamics, and household income in a Mongolian pastoral system: Panel evidence from Öndörshireet Soum. *Land*, 15(6), 954. <https://doi.org/10.3390/land15060954>
- Gotway, C. A., & Young, L. J. (2002). Combining incompatible spatial data. *Journal of the American Statistical Association*, 97(458), 632–648. <https://doi.org/10.1198/016214502760047140>
- Gotway, C. A., & Young, L. J. (2007). A geostatistical approach to linking geographically aggregated data from different sources. *Journal of Computational and Graphical Statistics*, 16(1), 115–135. <https://doi.org/10.1198/106186007X179257>
- Khishigbayar, J., Fernández-Giménez, M. E., Angerer, J. P., Reid, R. S., Chantsallkham, J., Baasandorj, Y., & Zumberelmaa, D. (2015). Mongolian rangelands at a tipping point? Biomass and cover are stable but composition shifts and richness declines after 20 years of grazing and increasing temperatures. *Journal of Arid Environments*, 115, 100–112. <https://doi.org/10.1016/j.jaridenv.2015.01.007>
- Kyriakidis, P. C. (2004). A geostatistical framework for area-to-point spatial interpolation. *Geographical Analysis*, 36(3), 259–289. <https://doi.org/10.1111/j.1538-4632.2004.tb01135.x>
- Lundberg, S. M., & Lee, S.-I. (2017). A unified approach to interpreting model predictions. *Advances in Neural Information Processing Systems*, 30, 4765–4774.
- Michler, L. M., Kaczensky, P., Ploechl, J. F., Batsukh, D., Baumgartner, S. A., Battogtokh, B., & Treydte, A. C. (2022). Moving toward the greener side: Environmental aspects guiding pastoral mobility and impacting vegetation in the Dzungarian Gobi, Mongolia. *Rangeland Ecology & Management*, 83, 149–160. <https://doi.org/10.1016/j.rama.2022.03.006>
- Michler, L. M., Kaczensky, P., Oyunsaikhan, G., Bartzke, G. S., Devineau, O., & Treydte, A. C. (2023). To move or not to move—factors influencing small-scale herder and livestock movements in the Dzungarian Gobi, Mongolia. *Regional Environmental Change*, 23, 131. <https://doi.org/10.1007/s10113-023-02126-y>

- Openshaw, S. (1984). Ecological fallacies and the analysis of areal census data. *Environment and Planning A*, 16(1), 17–31. <https://doi.org/10.1068/a160017>
- Purevjav, A.-O., Avirmed, T., Wilcox, S. W., & Barrett, C. B. (2025). Climate rather than overgrazing explains most rangeland primary productivity change in Mongolia. *Science*, 389(6766), 1229–1233. <https://doi.org/10.1126/science.adn0005>
- Reich, B. J., Yang, S., Guan, Y., Giffin, A. B., Miller, M. J., & Rappold, A. G. (2021). A review of spatial causal inference methods for environmental and epidemiological applications. *International Statistical Review*, 89(3), 605–634. <https://doi.org/10.1111/insr.12452>
- Roberts, D. R., Bahn, V., Ciuti, S., Boyce, M. S., Elith, J., Guillera-Arroita, G., Hauenstein, S., Lahoz-Monfort, J. J., Schröder, B., Thuiller, W., Warton, D. I., Wintle, B. A., Hartig, F., & Dormann, C. F. (2017). Cross-validation strategies for data with temporal, spatial, hierarchical, or phylogenetic structure. *Ecography*, 40(8), 913–929. <https://doi.org/10.1111/ecog.02881>
- Sainnemekh, S., Barrio, I. C., Densambuu, B., Bestelmeyer, B., & Aradóttir, Á. L. (2022). Rangeland degradation in Mongolia: A systematic review of the evidence. *Journal of Arid Environments*, 196, 104654. <https://doi.org/10.1016/j.jaridenv.2021.104654>
- Sodnomdavaa, T. (2026). Assessing proxy-based grassland gross primary productivity using machine learning approaches and multi-source remote sensing. *Sustainability*, 18(4), 1944. <https://doi.org/10.3390/su18041944>
- Waller, L. A., & Gotway, C. A. (2004). *Applied spatial statistics for public health data*. John Wiley & Sons. <https://doi.org/10.1002/0471662682>
- Zeger, S. L., Thomas, D., Dominici, F., Samet, J. M., Schwartz, J., Dockery, D., & Cohen, A. (2000). Exposure measurement error in time-series studies of air pollution: Concepts and consequences. *Environmental Health Perspectives*, 108(5), 419–426. <https://doi.org/10.1289/ehp.00108419>
- Zhang, J., & Goodchild, M. F. (2002). *Uncertainty in geographical information*. Taylor & Francis.