International Journal of Agriculture, Food and Innovation–MIYR
2026, Volume 1, Issue 1, pp.12~42
https://doi.org/10.53468/ijafi.2026.1.1.12

Indicator conflation in rangeland sustainability research: a PCCL framework with variable provenance and inference boundaries for Mongolia

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CITATION

Tamir Ariunsukh. Indicator conflation in rangeland sustainability research: a PCCL framework with variable provenance and inference boundaries for Mongolia. International Journal of Agriculture, Food and Innovation-MIYR, 2026, 1(1), 12~42. https://doi.org/10.53468/ijafi.2026.1.1.12

ARTICLE INFO

Received: 11 September 2026
Revised: 14 September 2026
Accepted: 28 September 2026
Available online: 30 September 2026

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Abstract: Satellite products, machine learning (ML), ecological surveys, and household panels increasingly inform pastoral policy. Yet their indicators are often treated as interchangeable: high satellite-derived productivity is read as evidence of healthy rangeland, rising soil organic carbon (SOC), or higher herder income. To address this indicator conflation, this conceptual paper proposes the Productivity, Condition, Carbon, and Livelihood (PCCL) framework for Mongolian rangelands. PCCL separates four core constructs (ecological productivity, rangeland condition, soil carbon, and household welfare and resilience) from two conversion stages (livestock production and value capture). It also draws four inference boundaries between measurement, prediction, association, and causal inference. The framework is formalised as a time-indexed causal graph. Each variable receives a provenance code (observed, remotely sensed, proxy, model-reconstructed, ML prediction, or simulated) that sets the highest inferential stage it can support. Applied to recent Mongolian studies, the taxonomy shows that these studies address different links of the PCCL chain at different inferential stages, rather than replicating a single relationship. A Monte Carlo experiment with synthetic data illustrates the consequences. The ML stage reproduced its satellite target with $R^2 = 0.90$, yet ignoring provenance attenuated the income effect of productivity by about 45%. Adding model-reconstructed SOC produced spurious SOC effects in 27% of runs. Calibration against field data restored approximately unbiased estimates. The paper reports no new empirical estimates. Its contribution is an inference and reporting architecture, six formally stated hypotheses, and applications to rangeland monitoring, results-based payments, product traceability, and climate adaptation.

Keywords: Indicator conflation; Inference boundaries; Variable provenance; Pastoral systems; Mongolian rangelands; Rangeland condition; Soil organic carbon; Value capture

1. INTRODUCTION

Pastoral rangelands are simultaneously ecological systems, forage production environments, carbon reservoirs, livestock production systems, and foundations of household welfare. This multifunctionality creates a basic analytical problem, which this paper calls *indicator conflation*: variables that describe one component of the system are routinely used as proxies for broader sustainability outcomes that they do not directly measure.

The problem has grown as satellite remote sensing and machine learning (ML) have expanded the spatial and temporal coverage of grassland monitoring. The Normalized Difference Vegetation Index (NDVI) has long been used to characterise vegetation responses across broad scales, but its ecological meaning remains context-dependent

[1]. Recent reviews document rapid growth in optical, radar, and multi-source satellite applications for grassland biomass, productivity, classification, and quality assessment [2, 3]. At the same time, satellite estimates of carbon uptake remain model-dependent and sensitive to assumptions about light-use efficiency, environmental constraints, and parameterisation [4]. These developments increase analytical power, but predictive performance alone does not resolve construct validity, ecological interpretation, spatial transferability, or causation [5].

Mongolia is a particularly informative setting because climatic variability, extensive livestock mobility, heterogeneous ecological zones, soil constraints, and pastoral livelihoods interact at multiple scales. Dryland research has long emphasised that degradation emerges from coupled climatic, ecological, and human processes rather than from a single universal driver [6]. Grazing theory predicts that vegetation responses depend on aridity, evolutionary history, and grazing regime [7], and syntheses show that grazing effects vary across ecological attributes and environmental gradients [8–10]. The Mongolian literature has produced sharply different estimates of rangeland degradation: Sainnemekh et al. [11] report values ranging from approximately 22% to 95%, reflecting differences in definitions, indicators, reference conditions, spatial coverage, and study design. Such variation means that "degradation" cannot be treated as a single, directly observed variable.

Recent causal evidence further complicates simple narratives. Using spatially disaggregated nationwide data for 1984–2024 and a quasi-experimental design, Purevjav et al. [12] estimated a modest negative effect of herd size on primary productivity at interannual frequencies, whereas weather effects were approximately an order of magnitude larger; at decadal scales, the herd-size effect disappeared and temperature effects dominated. These results do not imply that grazing pressure is ecologically irrelevant. They show that the importance of grazing depends on the outcome, the ecological zone, and the temporal scale under study.

Three recent Mongolian studies illustrate how different analytical domains are now being combined. Sodnomdavaa [13] uses ML and multi-source remote sensing to predict a gross primary productivity (GPP) proxy derived from the Moderate Resolution Imaging Spectroradiometer (MODIS). Davaatseren et al. [14] relate vegetation dynamics, field ecological information, livestock factors, and household income in Ö ndörshireet Soum. Davaatseren et al. [15] extend the analysis to livestock pressure, reconstructed SOC, household outcomes, and carbon-finance scenarios. These studies are not independent replications of one causal mechanism; they illuminate different positions in a longer ecological and economic chain.

This paper develops the PCCL framework with explicit inference boundaries. Its contribution is conceptual and methodological rather than empirical: no new field or survey data are collected, no published model is re-estimated, and no new causal coefficient is claimed. The framework contributes in four ways. First, it separates six substantively different analytical components. Second, it formalises their hypothesised relationships as a causal graph that makes confounders, mediators, and moderators explicit. Third, it introduces an operational provenance taxonomy that records whether each variable is observed, remotely sensed, a proxy, model-reconstructed, an ML prediction, or simulated. Fourth, it specifies the evidence required to move from measurement to prediction, association, and causal interpretation, and illustrates the consequences of ignoring these requirements with a small simulation using synthetic data.

The central principle is straightforward: related indicators are not necessarily equivalent indicators, and stronger computation does not automatically imply stronger inference. Section 2 sets out the scope and evidence base; Section 3 defines the six components; Section 4 formalises them as a causal graph; Section 5 develops inference boundaries, provenance coding, error propagation, and validation; Section 6 reviews identification strategies; Sections 7–9 position PCCL relative to existing frameworks, scale effects, and value intensification; Sections 10–12 derive testable hypotheses, policy applications, and transferability; Sections 13–14 discuss limitations and conclude.

2. SCOPE, EVIDENCE SELECTION, AND ANALYTICAL LOGIC

2.1 Type of Synthesis and Selection Criteria

This article is a targeted conceptual synthesis, not a systematic review or meta-analysis. The literature is used to test, qualify, and connect the proposed framework, not to estimate pooled effect sizes or to claim exhaustive coverage. Studies were selected purposively according to four criteria: (i) the study addresses at least one PCCL component or conversion stage, or the validation and identification methods needed to link them; (ii) it is a peer-reviewed article, an authoritative synthesis, or—in one methodological case—a widely cited working paper; (iii) global meta-analyses and syntheses were preferred for general relationships, and Mongolia-specific studies for contextual evidence; and (iv) for the three recent Mongolian studies, inclusion required that they jointly span remotely sensed and ML-predicted productivity, vegetation condition, SOC, livestock pressure, and household income, using variables of contrasting provenance.

The three recent Mongolian studies were therefore chosen as *illustrative cases* for applying the provenance taxonomy, not as a representative sample of Mongolian rangeland research. They share several authors and two of them focus on a single soum, so they are not statistically independent. Because selection was purposive rather than protocol-based, selection bias is possible, and no statement in this paper should be read as a claim about the prevalence of particular practices in the literature.

2.2 Four Inferential Categories

Four inferential categories are distinguished. *Measurement* concerns how a quantity is observed or constructed. *Prediction* concerns the ability of a model to reproduce or forecast a specified target. *Association* concerns conditional statistical relationships among variables. *Causal inference* concerns whether variation in an exposure can credibly be interpreted as producing variation in an outcome under a defensible identification strategy.

These categories should not be collapsed. High accuracy against a satellite-derived target does not validate the physical quantity that the target is intended to represent. A statistically significant regression coefficient does not become causal because the model is complex or includes many controls. Conversely, causal credibility depends primarily on research design and identifying assumptions rather than on predictive sophistication [16, 17].

The same discipline applies to substantive constructs. GPP, vegetation condition, SOC, livestock output, and household income describe different states or processes. PCCL therefore treats pastoral sustainability as a linked system with distinct analytical layers rather than as a single latent construct measurable by one convenient indicator.

2.3 Evidence Base

Table 1 lists the studies that carry most of the argument and indicates which PCCL component each informs. The table is illustrative rather than exhaustive.

Table 1. Selected evidence base supporting the PCCL framework and its inference boundaries (illustrative, not exhaustive).

Study	Domain	PCCL component(s)	Contribution to PCCL	Primary evidential role
Pettorelli et al. [1]	Remote sensing, NDVI	Productivity; condition	NDVI supports broad-scale ecological monitoring but remains an indirect vegetation indicator.	Measurement, construct validity
Bangira et al. [2]; Pinna et al. [3]	Grassland remote sensing and ML	Productivity	Productivity studies use multiple proxies (biomass, leaf area, chlorophyll) that are related but distinct.	Measurement

Study	Domain	PCCL component(s)	Contribution to PCCL	Primary evidential role
Prentice et al. [4]	Satellite GPP	Productivity	GPP estimates depend on model structure, parameters, and physiological assumptions.	Measurement, model validity
Purevjav et al. [12]	Mongolia: climate versus herd size	Productivity; grazing pressure	Weather can dominate herd-size effects on productivity; temporal scale changes interpretation.	Causal, scale dependence
Sainnemekh et al. [11]	Mongolia: degradation review	Condition	Degradation estimates diverge because definitions, indicators, references, and scales differ.	Construct heterogeneity
Bestelmeyer et al. [18]; Herrick et al. [19]	Rangeland states and reference conditions	Condition	State-and-transition models and site-specific references formalise nonlinearity and alternative states.	Conceptual ecology
Eldridge et al. [9]; Maestre et al. [10]	Grazing impacts	Condition; productivity	Grazing effects differ across ecosystem attributes, climate, soils, and biodiversity.	Context dependence
Piñeiro et al. [20]; McSherry & Ritchie [21]	Grazing and SOC	Soil carbon	SOC responds to grazing through several pathways and varies with precipitation, texture, and intensity.	Mechanism, heterogeneity
Ren et al. [22]	Global grazing and carbon	Soil carbon	Historical grazing altered carbon stocks, with strong dependence on intensity and context.	Global synthesis
Fernández-Giménez et al. [23]	Mongolia: adaptive capacity	Welfare and resilience	Mobility, information, storage, and social capital can reduce dzud vulnerability.	Livelihood mechanism
Kakinuma et al. [24]	Mongolia: post-dzud inequality	Welfare and resilience	Herd recovery did not imply recovery of household equality after the 2009–2010 dzud.	Livelihood outcome
Dashbal et al. [25]	Mongolia: resilience-based management	Condition; value capture	Monitoring, governance, incentives, traceability, and marketing can be institutionally linked.	Governance, value capture
Roberts et al. [26]; Ploton et al. [27]	Structured cross-validation	All predicted variables	Ignoring spatial and temporal dependence underestimates prediction error.	Prediction validation
Meyer et al. [28]; Yates et al. [29]	Target-oriented validation	All predicted variables	Validation design should follow the prediction target and dependence structure.	Prediction validation
Proctor et al. [30]; Alix-García & Millimet [31]	Remotely sensed variables in econometrics	All RS/ML variables	Using satellite-derived variables in regressions can bias parameters unless measurement error is modelled.	Measurement error, inference

3. THE PRODUCTIVITY, CONDITION, CARBON, AND LIVELIHOOD FRAMEWORK

PCCL organises six analytical components (Figure 1). Four are *core constructs*—ecological productivity (P), rangeland condition (C), soil carbon (C), and household welfare and resilience (L)—which give the framework its name. Two are *conversion stages*—livestock production and value capture—that describe how ecological resources may become household value. The three ecological constructs are analytically distinct but mutually connected and

jointly shaped by climate, ecological potential, grazing, and disturbance; the framework imposes no causal ordering among them. Sections 3.1–3.6 define each component, and Table 2 in Section 3.7 synthesises their indicators, moderators, and interpretive limits.

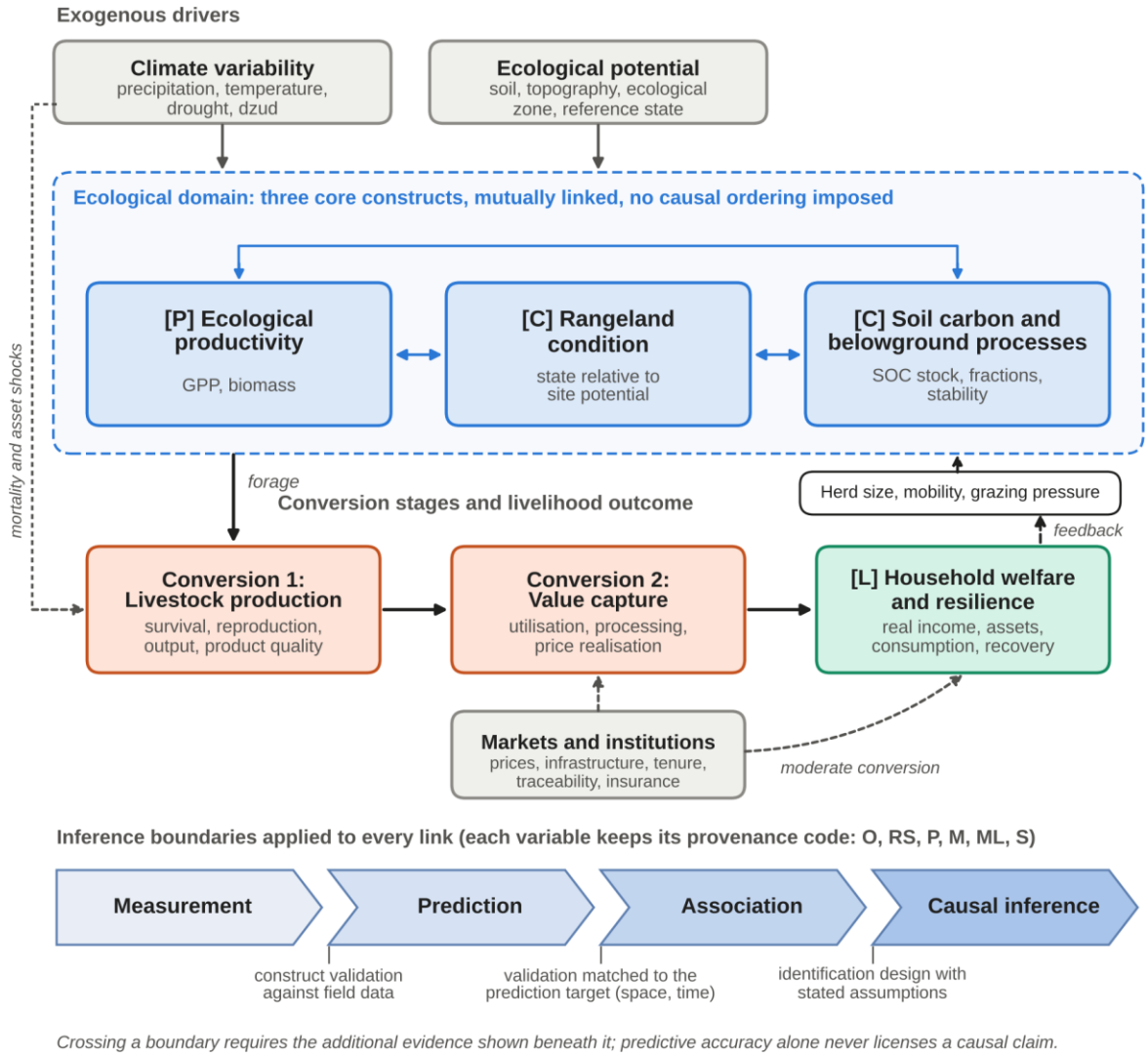


Figure 1. The PCCL framework. Three ecological constructs (blue) are mutually linked without an imposed causal ordering; two conversion stages (orange) translate ecological production into household welfare (green); climate, ecological potential, and markets and institutions act as exogenous drivers or moderators; and household decisions feed back to grazing pressure. The band at the bottom shows the four inference stages and the additional evidence required to cross each boundary. The figure is conceptual and does not represent estimated coefficients.

3.1 Ecological Productivity

The first component concerns primary ecosystem production. GPP is the gross carbon fixed through photosynthesis before autotrophic respiration and is therefore primarily a carbon-flux concept. NDVI and related vegetation indices provide valuable information on vegetation dynamics, but they are indirect spectral measures rather than direct observations of photosynthetic carbon uptake [1]. Satellite GPP products extend monitoring across large areas, yet their estimates depend on sensor information, model structure, environmental constraints, parameterisation, and physiological assumptions [4]. Biomass, leaf area, chlorophyll, and other productivity proxies capture related but distinct attributes [2, 3].

This establishes the first inference boundary: agreement with a remotely sensed GPP target is not equivalent to independent field validation of true GPP. Sodnomdavaa [13] is best interpreted within this boundary. Its contribution is the predictive characterisation of a MODIS GPP proxy from Sentinel-2, climatic, phenological, and geographical predictors, evaluated with random, spatially grouped, and leave-one-year-out validation. As the study itself notes, the target is a model-based proxy rather than a direct observation of carbon fluxes, so its results concern relative spatial and interannual patterns and should not be reinterpreted as ground-truth measurement of photosynthesis.

Climate also exerts a strong influence on this component. The evidence of Purevjav et al. [12] shows why a decline in productivity cannot automatically be attributed to grazing-induced degradation, and why a temporary increase in productivity cannot automatically be interpreted as ecological recovery.

3.2 Rangeland Condition

Rangeland condition is broader than contemporaneous productivity. It concerns ecosystem state relative to an ecologically defensible reference or potential. State-and-transition approaches were developed precisely because rangelands can occupy alternative states and respond nonlinearly to disturbance and management [18]. Grazing responses depend on moisture and evolutionary history [7], and empirical syntheses show that grazing can alter biomass and multiple components of ecosystem structure and function in ways that vary across environmental settings [8–10]. Condition indicators therefore include vegetation cover, functional composition, species structure, bare ground, erosion, soil stability, hydrological function, and state-and-transition information rather than a single greenness metric.

A favourable rainfall year may increase annual vegetation growth on a site whose longer-term structure or resilience remains impaired. Conversely, drought can sharply reduce annual productivity without implying persistent anthropogenic degradation. Using $\not\equiv$ to denote "is not an equivalent measure of", the distinction can be written as

$$P_t \not\equiv C_t \qquad (1)$$

where P_t is ecological productivity and C_t is rangeland condition in period t.

Reference conditions are therefore critical. Herrick et al. [19] emphasise that land health assessment should account for ecological potential specific to soil and climate rather than rely mechanically on a universal historical benchmark. This principle is directly relevant to Mongolia, where degradation estimates vary greatly across studies and ecological zones [11].

Formal monitoring can also be strengthened by local knowledge. Mongolian pastoralists have long used detailed ecological knowledge to guide pasture use and interpret rangeland change [32]. Jamsranjav et al. [33] found that some herder assessments of rangeland condition corresponded with field-measured vegetation indicators across Mongolian ecological zones, and Gantuya et al. [34] documented a rich set of locally perceived indicators of ecological change across habitat types. Such evidence supports multi-indicator monitoring rather than reliance on a single remote sensing metric.

Davaatseren et al. [14] provide site-specific evidence linking peak-season Sentinel-2 NDVI, field geobotanical and soil surveys, and household income in a five-wave panel from Өndörshireet Soum. Within PCCL, the study informs the connection between condition and livelihood; the authors frame their panel estimates as associations, and these local associations should not be generalised mechanically to national causal effects.

3.3 Soil Carbon and Belowground Processes

The third ecological component concerns SOC and related belowground processes. SOC is affected by plant inputs, roots, decomposition, soil moisture, temperature, texture, erosion, nutrient cycling, and livestock disturbance. These processes operate over time scales that differ from seasonal greenness or annual GPP. SOC can contribute to ecological resilience, but an SOC stock is not by itself a complete measure of resilience [35].

Vegetation indicators may contain information relevant to soil carbon dynamics, but they are not direct measurements of soil carbon stocks. Two nonequivalences are central:

$$\mathrm{GPP}_t \not\equiv \mathrm{SOC}_t \qquad (2)$$

$$\mathrm{NDVI}_t \not\equiv \mathrm{SOC}_t \qquad (3)$$

The effect of grazing on SOC is heterogeneous. Mechanistic reviews identify several pathways through which grazing can alter soil carbon, including changes in plant production, nutrient cycling, decomposition, and soil physical conditions [20]. McSherry and Ritchie [21] showed that grazing effects vary with precipitation, soil texture, vegetation characteristics, and intensity, and broader syntheses report that grassland management can either increase or reduce soil carbon stocks depending on practice and context [36]. Zhou et al. [37] found that grazing intensity significantly altered belowground carbon and nitrogen cycling, Hao et al. [38] reported SOC losses under heavy grazing in Chinese grasslands, and Ren et al. [22], synthesising 1,473 observations globally, found substantial historical carbon losses associated with grazing but strong variation with grazing intensity and environmental context. In a Mongolian grassland, Pan et al. [39] show that grazing and topography interact to alter SOC pool distribution and stability.

The grazing effect should therefore be treated as conditional on intensity, climate, soil, vegetation, topography, seasonality, spatial concentration, and management. A universal claim that more livestock always causes lower SOC is not supported by the available evidence.

Davaatseren et al. [15] provide a Mongolian application connecting livestock pressure, vegetation, SOC, household income, and carbon-finance scenarios. Their annual SOC values for 2002–2023 are reconstructed with a RothC-style trajectory linked to an NDVI backcast and anchored to a 2024 field baseline. These trajectories remain model-derived quantities, not independently observed annual SOC measurements, and PCCL requires that this provenance remain visible throughout interpretation (Section 5).

3.4 Livestock Production (Conversion Stage 1)

Ecological production does not translate automatically into household welfare. The first conversion stage is the biological conversion of forage into animal output. It depends on herd composition, survival and mortality, reproduction, animal health, product quality, mobility, and labour. Indicators include herd size and composition, offspring survival, adult mortality, milk, meat, and fibre output per animal, and product quality. Herd size describes an asset stock; it is neither a measure of production efficiency nor of welfare.

Livestock systems exposed to climatic variability face risks not only through forage production but also through animal mortality, disease, and mobility constraints [40, 41]. In Mongolia, vulnerability to dzud—severe winter conditions that cause mass livestock mortality—emerges from interacting physical, biological, socioeconomic, and institutional factors [42]. Livestock production is therefore a conversion stage with its own exposure to climate shocks, not a passive reflection of rangeland productivity:

$$P_t \not\equiv L_t \not\equiv Y_t \qquad (4)$$

where L_t denotes livestock production and Y_t household welfare.

3.5 Value Capture (Conversion Stage 2)

The second conversion stage concerns the share of potential livestock output value that households actually retain. It depends on product utilisation (including secondary products such as hides, wool, and offal), processing, prices, transport, market access, transaction costs, bargaining power, and institutions. Two households with identical herds and identical output can retain very different value if one sells unprocessed products at the farm gate while the other has access to processing, traceability, or better-priced markets.

Davaatseren et al. [14] report that greater underutilisation of secondary livestock products, measured through a processing audit, is associated with lower household income, and that the income gain associated with larger herds

weakens where waste ratios are high. These relationships are consistent with the PCCL mechanism but remain associational unless supported by a causal design. Value capture is developed further in Section 9, which proposes indicators and tests.

3.6 Household Welfare and Resilience

The livelihood construct concerns real income, assets, consumption, food security, risk exposure, and the capacity to absorb and recover from shocks. Community-based rangeland management can strengthen adaptive capacity through mobility, information exchange, storage, and social capital [23]. Longer-term analyses show that ecological and cultural tipping processes can be linked [43] and that the 2009–2010 winter disaster was followed by a persistent increase in inequality among sampled herder households even after aggregate livestock numbers recovered [24]. Survey evidence from five aimags after the 2023–2024 dzud likewise documents widespread livestock losses among herding households [44]. Consequently, herd recovery is not equivalent to livelihood recovery, and household income alone captures only one dimension of welfare.

3.7 Synthesis of the Six Components

Table 2 summarises the six components. Climate, soil, topography, ecological potential, extreme events, livestock pressure, market conditions, and institutions modify the relationships among them. The framework does not assume that productivity causes rangeland condition or that condition mechanically causes soil carbon change; these relationships can operate in both directions and remain conditional on context.

Table 2. Conceptual architecture of the PCCL framework. The architecture is conceptual rather than deterministic: it organises constructs and interpretive limits and does not imply estimated causal coefficients.

Component	Role	Core construct	Illustrative indicators	Main moderators	Interpretive boundary
Ecological productivity	Core construct (P)	Photosynthetic production and biomass generation	GPP, aboveground biomass, vegetation growth	Climate, phenology, soil water, ecological potential	Does not by itself establish rangeland condition, SOC, or welfare
Rangeland condition	Core construct (C)	Ecological state relative to site potential or reference	Vegetation cover, composition, bare ground, erosion, state indicators	Climate history, grazing regime, disturbance, site potential	Annual greenness does not by itself identify degradation or its cause
Soil carbon and belowground processes	Core construct (C)	Soil carbon status and related belowground processes	Field SOC, carbon fractions, soil stability, reconstructed SOC (flagged M)	Plant inputs, decomposition, moisture, texture, grazing, topography	SOC alone does not establish overall ecological resilience or recovery
Livestock production	Conversion stage 1	Biological conversion of forage into animal output	Herd composition, survival, reproduction, output, product quality	Forage access, animal health, mobility, extreme events, management	Herd size alone does not measure livelihood welfare or sustainability
Value capture	Conversion stage 2	Conversion of livestock output into retained economic value	Product utilisation, processing, price realisation, market access, transaction costs	Infrastructure, institutions, traceability, bargaining power	Higher output does not guarantee higher retained household value

Component	Role	Core construct	Illustrative indicators	Main moderators	Interpretive boundary
Household welfare and resilience	Core construct (L)	Economic outcomes and capacity to absorb shocks	Real income, assets, consumption, risk exposure, recovery	Markets, institutions, social capital, climate shocks, diversification	Economic recovery does not necessarily imply ecological recovery

4. METHODOLOGICAL FRAMEWORK: CAUSAL RELATIONSHIPS AND INFERENCE BOUNDARIES

4.1 Structural Representation of the PCCL Causal Graph

A verbal framework leaves unclear which variables are confounders, mediators, or moderators, and therefore which identification assumptions a given empirical claim requires. This section formalises PCCL as a directed acyclic graph (DAG). The DAG is a set of hypotheses, not a finding: each arrow encodes an assumed direct effect, and each missing arrow encodes a testable restriction [16, 17].

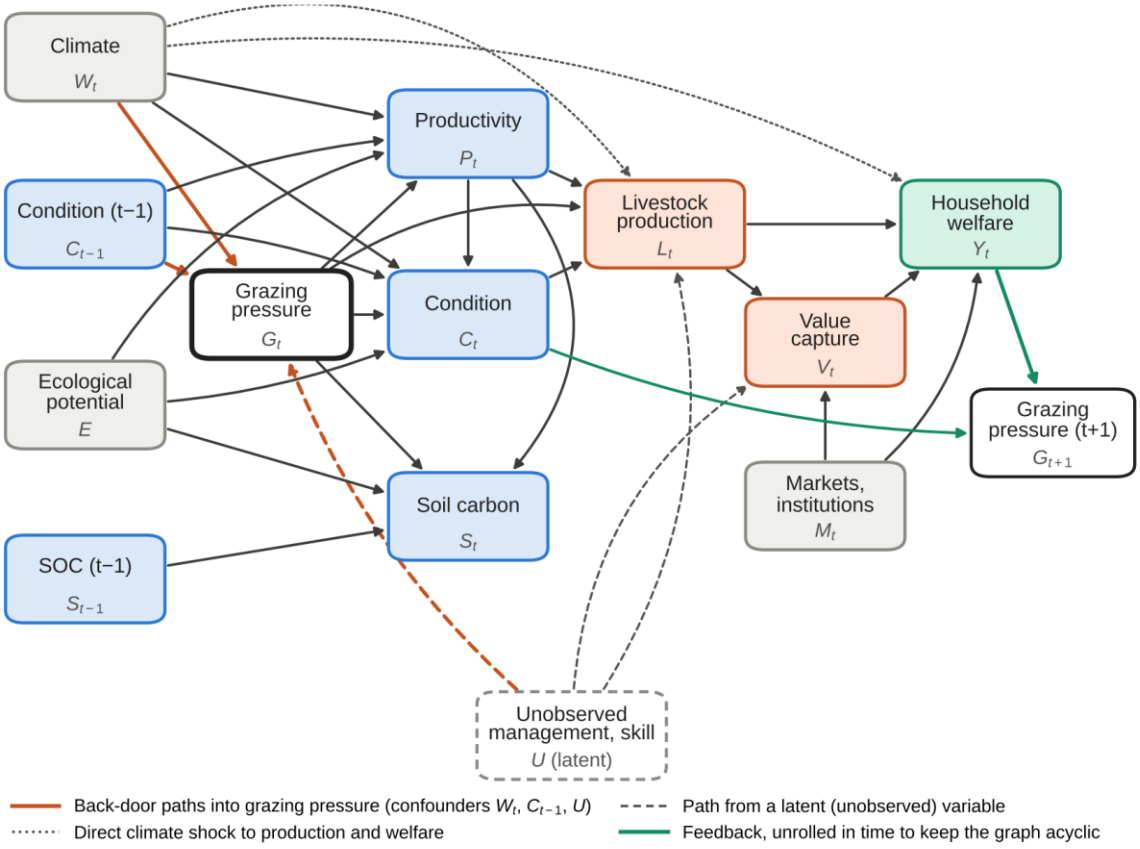


Figure 2. A time-indexed directed acyclic graph (DAG) for PCCL. Orange arrows mark back-door paths into grazing pressure that confound grazing–ecology relationships. Dashed arrows originate in a latent variable (unobserved management and skill); dotted arrows mark direct climate shocks to production and welfare; green arrows show feedback to the next period, which is unrolled in time so that the graph remains acyclic. Markets and institutions enter as a parent of value capture and welfare; their moderating role is expressed in the functional form of Equation (10) rather than as a separate arrow.

Mutual dependence among the ecological constructs and feedback from household decisions to grazing would create cycles in a static graph. PCCL avoids this by indexing variables in time, so that, for example, past condition C_{t-1} affects current productivity and herding decisions, and current welfare Y_t affects next-period grazing pressure G_{t+1}

(Figure 2). With climate W_t, time-invariant ecological potential E, latent management and skill U, and markets and institutions M_t, the graph corresponds to the nonparametric structural system

$$P_t = f_P(W_t, E, G_t, C_{t-1}, \varepsilon_{P,t}) \quad (5)$$

$$C_t = f_C(W_t, E, G_t, P_t, C_{t-1}, \varepsilon_{C,t}) \quad (6)$$

$$S_t = f_S(E, G_t, P_t, S_{t-1}, \varepsilon_{S,t}) \quad (7)$$

$$L_t = f_L(P_t, C_t, G_t, W_t, U, \varepsilon_{L,t}) \quad (8)$$

$$G_t = f_G(W_t, C_{t-1}, Y_{t-1}, U, \varepsilon_{G,t}) \quad (9)$$

$$V_t = f_V(L_t, M_t, U, \varepsilon_{V,t}), \qquad Y_t = f_Y(L_t, V_t, M_t, W_t, \varepsilon_{Y,t}) \quad (10)$$

where S_t is SOC, G_t is grazing pressure, V_t is retained value, and the ε terms are mutually independent disturbances. No functional form is imposed; the system can be specialised to linear structural equations, threshold models, or state-and-transition dynamics as data permit.

4.2 Confounders, Mediators, and Moderators

The graph makes three roles explicit. *Confounders* are common causes of an exposure and an outcome. For the effect of grazing pressure on productivity or condition, climate (W_t), past condition (C_{t-1}), and unobserved management (U) are confounders, because herders adjust stocking and movement in response to forage and weather while the same factors affect vegetation directly. *Mediators* lie on causal paths: the effect of rangeland condition on welfare is hypothesised to run through livestock production and value capture ($C_t \to L_t \to V_t \to Y_t$). *Moderators* change the strength of a relationship: markets and institutions do not alter forage production, but they shape how much of a given livestock output is retained as household value. In a nonparametric DAG, moderation is represented by M_t entering f_V jointly with L_t.

The graph also identifies *bad controls* [45]. When estimating the total effect of condition on welfare, conditioning on livestock production blocks the mediated path and therefore estimates only a residual direct effect. Livestock production is also a collider on the path $P_t \to L_t \leftarrow U$, so conditioning on it can induce spurious association between productivity and unobserved management.

Three implications follow. First, the effect of grazing on productivity is identified by covariate adjustment only if W_t, C_{t-1}, and U are measured or their influence is removed by design. Because U is latent, credible estimates require designs such as unit fixed effects (if U is time-invariant) or exogenous variation in grazing location, as exploited by Purevjav et al. [12]. Second, the effect of condition on welfare is confounded by direct climate shocks ($W_t \to Y_t$) and by grazing ($G_t \to C_t$, $G_t \to L_t$); adjustment for W_t and G_t is necessary but not sufficient if U affects both. Third, the graph implies testable conditional independencies. In particular, because SOC has no direct path to welfare in the absence of carbon payments,

$$Y_t \perp S_t \mid L_t, V_t, M_t, W_t \quad (11)$$

where $\perp$ denotes conditional independence. A rejection of Equation (11) would indicate either a missing pathway (for example, payments linked to carbon that create a direct $S_t \to V_t$ channel) or measurement artefacts of the kind examined in Section 5.5. A results-based carbon payment scheme would add exactly such an arrow, which is why PCCL treats carbon finance as a policy-contingent pathway rather than a natural feature of the system (Section 11.2).

4.3 Variable Provenance and Classification

4.3.1 Four Analytical Stages

Explicit inference boundaries form the methodological core of PCCL. The four analytical stages are ordered by the evidence each requires (Figure 1, bottom band):

① *Measurement*: how a quantity is observed or constructed, and how well it represents the intended construct.

② *Prediction*: how well a model reproduces or forecasts a specified target, evaluated with validation matched to the intended use.

③ *Association*: conditional statistical relationships among variables.

④ *Causal inference*: effects identified by a design whose assumptions are stated and defensible.

Crossing from one stage to the next requires additional evidence: construct validation against field data (measurement to prediction of the construct rather than the proxy), validation matched to the prediction target (prediction to association), and an identification design (association to causation). Better predictive performance alone does not justify causal interpretation, and a model-derived variable does not become an observed variable when it is used in a subsequent econometric model. The distinction is especially important for spatial and spatiotemporal data, where random partitions can yield optimistic error estimates because nearby observations are not independent [26, 28, 29, 46].

4.3.2 Operationalising the Provenance Taxonomy

Every variable in a PCCL analysis is assigned a provenance code (Table 3). The code describes how *this* analysis obtained the variable and sets a default *inferential ceiling*: the highest stage that the variable can support without further evidence.

Table 3. PCCL provenance codes, minimum reporting requirements, and default inferential ceilings.

Code	Definition	Examples in Mongolian rangeland research	Minimum reporting	Default inferential ceiling
O	Directly observed with a documented protocol (field, laboratory, survey, census)	Field SOC by dry combustion; quadrat biomass; household survey income; census herd counts	Sampling design, protocol, measurement error or quality control	Any stage, subject to design
RS	Remotely sensed quantity derived from a sensor signal with standard processing	Sentinel-2 or Landsat NDVI; MODIS reflectance	Sensor, product version, compositing, masking, spatial and temporal resolution	Measurement of a spectral property; links to a construct require validation
P	Proxy: an observed or remotely sensed variable standing in for an unmeasured construct	NDVI as a condition proxy; sheep units as grazing pressure; income as welfare	Construct mapping and the evidence supporting it	Association with the proxy; claims about the construct require validated mapping
M	Model-reconstructed quantity, including reanalysis and process-model output	MODIS GPP (light-use-efficiency model); RothC-style SOC trajectories; ERA5-Land climate	Model, parameters, inputs and their codes, calibration and validation	Inherits its inputs; cannot provide independent evidence about relations with its own inputs
ML	Machine-learning prediction of a specified target	ML reconstruction of MODIS GPP from Sentinel-2; ML-predicted SOC	Target and its code, features, validation design, area of applicability	Prediction of the target, not of the construct; ceiling equals the target's code

Code	Definition	Examples in Mongolian rangeland research	Minimum reporting	Default inferential ceiling
S	Simulated or scenario output	Carbon-finance net present value scenarios; climate projections	Assumptions, parameter ranges, sensitivity analysis	Conditional "if–then" statements only; no empirical association or causal claim

Six rules make the taxonomy operational in multi-stage workflows.

Rule 1 (point of use). A code describes how a variable was obtained in the analysis at hand. Census herd counts are O-coded; when converted to sheep units with species coefficients and used to represent grazing pressure, the resulting variable is P-coded.

Rule 2 (compound codes). Chains are written explicitly, with the outermost operation first: ML[M[RS]] denotes an ML prediction of a model-derived target computed from remotely sensed inputs (for example, ML predictions of MODIS GPP), and M[RS] denotes a model reconstruction driven by remotely sensed inputs.

Rule 3 (weakest-link inheritance). A derived variable cannot hold a higher evidential status than its weakest input unless it is independently validated against O-coded data. Such an upgrade must be reported with the validation sample, design, and statistics.

Rule 4 (reuse across studies). When a variable produced in one study is reused in another—for example, published reconstructed SOC—it retains its original code, and its uncertainty must be imported (through published error estimates, ensembles, or multiple imputation) rather than treated as exact.

Rule 5 (shared-input check). When two variables in a downstream model share an input—for example, NDVI used both as a regressor and as a driver of reconstructed SOC—the shared input must be reported, and associations between the two variables must not be presented as independent evidence.

Rule 6 (reporting). A provenance table listing each variable, the construct it represents, its code chain, source, validation, and uncertainty treatment should accompany any integrated PCCL analysis, together with the inferential stage claimed for each result. Journals publishing integrated ecological–economic analyses could adopt this table as a minimum reporting standard.

4.3.3 Applying the Taxonomy to Recent Mongolian Studies

Table 4 applies the taxonomy to the four Mongolian studies that most directly inform PCCL. The purpose is not to evaluate their quality—all four discuss their own limitations—but to show that they occupy different positions in the PCCL chain and support different inferential stages.

Table 4. Application of the provenance taxonomy to recent Mongolian studies. Codes follow Table 3; "highest stage" refers to the strongest inferential stage supported by the design for the principal result.

Study	Key variables and provenance codes	PCCL components	Design and validation	Highest stage supported
Sodnomdavaa [13]	MODIS GPP target: M[RS]; predictions: ML[M[RS]]; Sentinel-2 bands and indices: RS; climate predictors: M where taken from gridded or reanalysis products	Productivity	Gradient boosting and other learners; random, spatially grouped, and leave-one-year-out validation; no field validation of absolute GPP	Prediction of a model-derived target

Study	Key variables and provenance codes	PCCL components	Design and validation	Highest stage supported
Davaatseren et al. [14]	Peak-season Sentinel-2 NDVI: RS, used as P for condition; field SOC (120 plots): O; household income and herd size (114-household panel): O; by-product waste ratio (processing audit): O; precipitation anomaly (ERA5-Land): M	Condition; soil carbon; livestock production; value capture; welfare	Two-way fixed-effects panel (five waves, 2018–2024); instrumental-variable model using lagged NDVI as robustness check	Association (authors' framing)
Davaatseren et al. [15]	Livestock pressure in sheep units: P (from O census); pasture-user-group disaggregation: M; NDVI with pre-Sentinel backcast: RS and M; annual SOC 2002–2023: M[RS], anchored to O field baseline; ML predictions of reconstructed SOC: ML[M[RS]]; income: O; carbon-finance outcomes: S	Grazing pressure; soil carbon; welfare; value capture (scenario)	Fixed-effects panels at two scales; ML holdout and leave-one-year-out checks; Monte Carlo and bootstrap uncertainty; 20-year scenario model	Association for income relations; prediction (internal consistency) for ML; conditional statements for scenarios
Purevjav et al. [12]	Satellite-derived primary productivity: RS; herd size from livestock census: O; weather: M (gridded)	Productivity; grazing pressure	Quasi-experimental design exploiting seasonal variation in grazing locations; nationwide, 1984–2024	Causal, conditional on design assumptions and temporal scale

Two observations follow. First, the four studies answer different questions at different inferential stages, so they should not be counted as convergent replications. Second, the most interpretively sensitive variables are compound codes such as ML[M[RS]] and M[RS]. For example, when an ML model is trained to predict reconstructed SOC whose annual values are themselves driven by an NDVI backcast, high out-of-sample R^2 reflects internal consistency between model components rather than validation against observed SOC—a point that Davaatseren et al. [15] themselves acknowledge. Similarly, the leave-one-year-out results reported by Sodnomdavaa [13], which are markedly weaker for one year (2018) than for others, illustrate why temporal transfer must be evaluated separately from spatial interpolation.

4.4 Measurement Error and Uncertainty Propagation

The provenance codes become analytical tools when combined with standard measurement-error results [47]. Suppose a construct X (for example, true productivity) affects an outcome Y with slope β, but the analyst uses $X^* = X + u$, where u is classical error independent of X and of the outcome disturbance. The least-squares slope then converges to

$$\text{plim}\hat{\beta} = \lambda\beta, \qquad \lambda = \frac{\sigma_X^2}{\sigma_X^2 + \sigma_u^2} \qquad (12)$$

where λ is the reliability of X^*. When covariates Z are included, the relevant reliability is the conditional reliability $\lambda_{X|Z} = \sigma_{X|Z}^2/(\sigma_{X|Z}^2 + \sigma_u^2)$, which is smaller than λ whenever Z explains part of X. This is why controlling for climate, which explains much of the variation in productivity, aggravates attenuation of a remotely sensed productivity regressor.

Analytical chains compound the problem. If each stage $k = 1, \ldots, K$ adds independent error, so that $X^{(k)} = X^{(k-1)} + u_k$, the reliability of the final variable is the product of stage reliabilities:

$$\lambda_{\text{chain}} = \prod_{k=1}^{K} \lambda_k , \qquad \lambda_k = \frac{\text{Var}\left(X^{(k-1)}\right)}{\text{Var}(X^{(k)})} \qquad (13)$$

ML predictions require separate treatment. If an ML model is trained to predict a remotely sensed target X^{RS} with reliability λ_{RS} relative to the construct, and its features carry information about X only through X^{RS}, then in the linear-Gaussian case

$$\text{corr}^2\left(\hat{X}^{ML}, X\right) = R^2_{ML} \cdot \lambda_{RS}, \qquad \text{plim}\hat{\beta}_{ML} = \lambda_{RS}\,\beta \qquad (14)$$

where R^2_{ML} is the coefficient of determination against the target. A high R^2_{ML} shows that the model reproduces its target, including the target's error; it does not remove the attenuation inherited from the target. This is the formal content of the first inference boundary (Section 3.1).

Two further distortions matter in integrated studies. First, when an estimated variable is used as a regressor, conventional standard errors ignore first-stage estimation error and are too small [48]; the whole chain must be bootstrapped or corrected analytically. Second, measurement error in remotely sensed variables is often nonclassical—correlated with the true value or with covariates—so that bias can take either sign [30, 31]. Finally, *derived-variable leakage* arises when a model-reconstructed variable $S^M = aN + bW + \eta$ is built from a vegetation input N that carries information about X. If X^* is attenuated, S^M absorbs part of the effect of X, and

$$\text{plim}\hat{\beta}_S = \beta\,\frac{\text{Cov}(X, S^M \mid X^*, W)}{\text{Var}(S^M \mid X^*, W)} \neq 0 \qquad (15)$$

even when the true effect of SOC is zero. Rule 5 in Section 5.2 is designed to expose this case.

4.5 A Monte Carlo Illustration

To show how these mechanisms operate together, a small Monte Carlo experiment was run with synthetic data (design details in Appendix A). Climate drives true productivity; true SOC partly depends on productivity; household income depends on productivity (true effect $\beta_P = 0.30$ in standard-deviation units) and climate, but *not* on SOC ($\beta_S = 0$). Analysts observe productivity as a field measurement (O), a remotely sensed target with reliability $\lambda_{RS} = 0.70$ (RS), or an ML prediction of that target with $R^2_{ML} = 0.90$ (ML[RS]); and SOC as a field measurement (O) or as a reconstruction driven by an independent vegetation index and climate (M[RS]). Each scenario was replicated 2,000 times with 400 units per replication.

Table 5. Monte Carlo results: estimated income effects under alternative provenance of productivity and SOC (synthetic data; 2,000 replications, n = 400). True values: $\beta_P = 0.30$, $\beta_S = 0$.

Scenario	**Productivity (code)**	**SOC (code)**	**Mean $\hat{\beta}_P$**	**Relative bias**	**95% CI coverage for β_P**	**Share of runs rejecting $\beta_S = 0$**
A. Field data	O	O	0.276	−8.0%	93.6%	5.2%
B. Remote sensing	RS	O	0.174	−42.2%	29.4%	9.0%
C. ML prediction of RS target	ML[RS]	O	0.167	−44.5%	27.8%	10.9%
D. Integrated chain	ML[RS]	M[RS]	0.147	−51.0%	20.5%	26.9%
E. Provenance-aware	ML[RS], calibrated to O subsample	Not used (M-coded; effect not identified)	0.307	+2.3%	95.4% (bootstrap); 93.0% (naive)	—

Note. Coverage is the share of replications whose 95% confidence interval contains the true value. In scenario E, the ML prediction is calibrated against field productivity in a validation subsample of 100 units (regression calibration), and standard errors are obtained by bootstrapping both the validation and main samples (199 resamples); "naive" uses conventional standard errors that ignore the calibration stage. The ML stage achieved $R^2 = 0.90$ against its remotely sensed target but only $R^2 = 0.63$ against true productivity; reconstructed SOC shared 8% of its variance with true SOC.

The results illustrate each inference boundary (Table 5; Figure 3). Although the ML stage reproduced its satellite target with $R^2 = 0.90$, the downstream income effect was attenuated by about 45% (scenario C), close to the attenuation obtained with the satellite variable itself (scenario B) and consistent with Equation (14). Adding model-reconstructed SOC worsened the attenuation and produced a "significant" SOC–income association in 26.9% of replications, more than five times the nominal 5% rate, although SOC has no effect on income in the data-generating process (scenario D). Figure 3B shows that this false-positive rate increases with the weight of the vegetation input in the SOC reconstruction, whereas field-measured SOC does not exhibit this dependence. Even field-measured SOC shows mildly inflated rejection rates (about 9–14%) when productivity is attenuated, because true SOC co-varies with true productivity; with field-measured productivity (scenario A), the rejection rate is nominal. Calibrating the ML prediction against a modest field subsample and bootstrapping the full chain restored an approximately unbiased estimate with nominal coverage (scenario E), whereas conventional standard errors that ignore the calibration stage under-covered slightly, as Pagan [48] predicts.

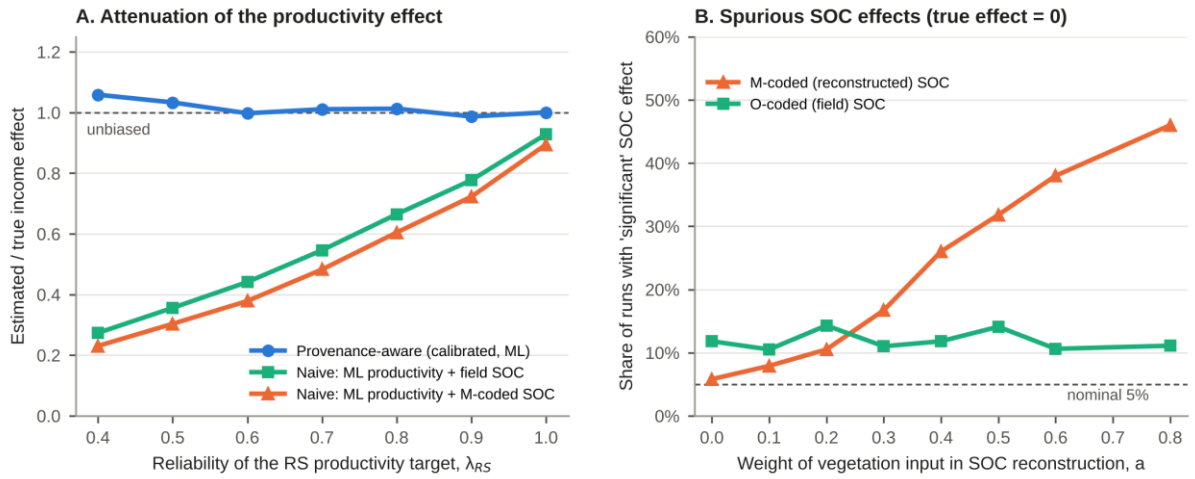


Figure 3. Monte Carlo illustration with synthetic data. (A) Ratio of the estimated to the true income effect of productivity as a function of the reliability of the remotely sensed productivity target, for naive estimators using ML predictions (with field or model-reconstructed SOC as a covariate) and for the provenance-aware estimator calibrated against field data. (B) Share of replications in which the SOC coefficient is "significant" at the 5% level although its true value is zero, as a function of the weight of the vegetation input in the SOC reconstruction. Each point is based on 1,000 replications.

The simulation is deliberately stylised—linear, Gaussian, and with classical errors—so it understates the complexity of real analyses. Its purpose is to show that provenance codes have predictable quantitative consequences and that these consequences can be corrected only with O-coded validation data and full-chain uncertainty propagation.

4.6 Validation Protocols Matched to Inference Goals

The choice of validation strategy must match the intended inference. Table 6 maps common strategies to the type of error they estimate and to PCCL applications.

Table 6. Validation strategies mapped to inference goals and PCCL components.

Strategy	**Error it estimates**	**Appropriate inference goal**	**PCCL example**	**Caveats**
Random k-fold cross-validation	Interpolation error within the sampled domain	Gap-filling within a dense, representative sample	Filling gaps in a productivity proxy within a well-sampled soum	Optimistic under spatial or temporal dependence [26, 27]
Spatial block or leave-location-out cross-validation	Transfer error to unsampled locations	Mapping to new soums or ecological zones	National GPP or SOC maps from regional training data	Block size should reflect dependence range and prediction distance [46]; report the area of applicability [49]
Temporal holdout, leave-period-out, or forward validation	Forecast error and temporal non-stationarity	Predicting future seasons, dzud years, or post-intervention periods	Forecasting forage availability for early warning	Requires sufficient periods; extreme years may behave differently [28]
Nested cross-validation	Performance after hyperparameter tuning and feature selection	Any ML pipeline with tuning	ML models of GPP or SOC with many predictors	Inner and outer splits must respect the same dependence structure [29]
Independent probability-sample validation	Design-based map accuracy	Area-level estimates and monitoring statistics	Estimating the area of degraded land or mean SOC change	Requires probability sampling of validation sites [50]
Validation against an independent O-coded target	Construct validity	Whether predictions measure the construct rather than the proxy	Field biomass or flux data against ML GPP; field SOC against reconstructed SOC	Requires co-located field data; small samples need explicit uncertainty

Three practical rules follow. Random cross-validation should not be used to support claims about transfer to new locations or periods. Spatial and temporal validation estimate different errors and should be reported separately. And no form of cross-validation against a proxy target substitutes for validation against an O-coded measurement of the construct.

4.7 Causal Identification Strategies

4.7.1 Design-Based Strategies

Where causal questions are asked, identification must come from design rather than from algorithmic complexity. Table 7 summarises strategies that are feasible for specific PCCL relationships in Mongolia, together with their assumptions and main threats.

Table 7. Identification strategies for PCCL relationships in Mongolian rangelands.

Strategy	Example PCCL relationship	Possible source of variation	Key assumptions	Main threats
Difference-in-differences and event study	Effect of community-based rangeland management or pasture-use agreements on condition and income	Staggered adoption across soums or pasture-user groups	Parallel trends; no anticipation; heterogeneity-robust estimators under staggered timing [51, 52]	Selective programme placement; spillovers through mobility
Synthetic control	Effect of a soum-level marketing, processing, or traceability scheme on value capture	One or a few treated units with long pre-treatment series	Good pre-treatment fit; no interference with donor units [53]	Few comparable donors; coincident climate shocks
Instrumental variables	Effect of market access on value capture; effect of grazing pressure on vegetation	Exogenous shifts in road access or market prices; administrative allocation of seasonal pastures	Relevance; exclusion; monotonicity	Exclusion is often implausible—weather and lagged vegetation usually affect outcomes directly
Regression discontinuity, including geographic discontinuity	Effect of eligibility rules (e.g., index-insurance triggers or programme thresholds) or administrative boundaries with different management	Thresholds in an assignment variable; soum or protected-area borders	Continuity at the cutoff; no precise sorting [54, 55]	Herd movement across boundaries; compound treatments at borders
Natural experiments from shocks	Effect of dzud on herd dynamics, welfare, and inequality	Spatial variation in dzud severity	Exposure as good as random conditional on covariates	Exposure correlated with pre-existing vulnerability [24, 56]
Panel designs exploiting within-unit variation	Effect of herd size on productivity at different temporal scales	Seasonal variation in grazing locations	Strict exogeneity conditional on fixed effects	Dynamic feedback from forage to herding decisions [12]
Field experiments and exclosures	Effect of grazing intensity on condition and SOC; effect of processing support on value capture	Randomised exclosures, grazing trials, or interventions	Randomisation; no interference	Plot scale versus landscape scale; slow SOC response times

Existing Mongolian evidence shows that such designs are feasible. Groppo and Kraehnert [56] used spatial variation in the severity of the 2009–2010 dzud to estimate effects on child growth, and Bertram-Huemmer and Kraehnert [57] found evidence that index-based livestock insurance payouts supported household recovery after the same event. Each design identifies an effect for a particular population, period, and scale; PCCL requires that this scope accompany the estimate.

4.7.2 Heterogeneous Effects and the Role of Machine Learning

Effects in PCCL are expected to vary across ecological zones, climate states, and institutional settings, as shown for herd-size effects by Purevjav et al. [12]. ML is useful for estimating such heterogeneity *within* a credible design, for example through causal forests [58] or double/debiased ML for high-dimensional nuisance functions [59]. In these

methods, ML improves estimation, but identification still rests on the design. Causal discovery algorithms that infer graph structure from data serve a different purpose: they can generate candidate hypotheses, but their conclusions depend on strong assumptions, such as the absence of unmeasured confounders, that are rarely plausible in pastoral systems [16]. Mediation analyses that test the pathways in Figure 2 require additional sequential-ignorability assumptions and should be accompanied by sensitivity analysis [60]; a structural equation or mediation model does not become causal merely because it contains directional paths.

5. DISCUSSION, RESEARCH PROPOSITIONS, AND POLICY IMPLICATION

5.1.1 Mongolian Rangeland Frameworks

PCCL is not the first conceptual representation of Mongolia's pastoral social-ecological system. Kakinuma et al. [61] synthesise interactions between climate exposure, ecosystem change, pastoral mobility, and vulnerability. Earlier scholarship emphasised herders' ecological knowledge and the institutional problem of maintaining flexible access to spatially variable pasture resources [32, 62]. Fernández-Giménez et al. [43] explored linked ecological and cultural tipping points, and Dashbal et al. [25] describe a resilience-based national management system that connects science-based rangeland assessment, government monitoring, participatory management, governance incentives, and traceability and marketing of livestock products.

PCCL complements these approaches by adding three elements: it organises indicators by measurement domain; it imposes inference boundaries across observed, remotely sensed, modelled, predictive, associational, and causal evidence; and it separates ecological production from the economic efficiency with which that production becomes household value.

5.1.2 General Social-Ecological and Causal Frameworks

PCCL also relates to four general frameworks (Table 8). It is designed to be nested within them rather than to replace them.

Table 8. Positioning PCCL relative to established frameworks.

Framework	Primary purpose	Correspondence with PCCL	What PCCL adds
Drivers–Pressures–State–Impact–Response (DPSIR) [63, 64]	Organising environmental indicators along a policy-oriented causal chain	Climate and markets as drivers; grazing as pressure; P, C, and S as state; L as impact; policy as response	DPSIR presumes the causal chain; PCCL requires that each link be classified by inferential stage and that indicators carry provenance codes
Ecosystem services cascade [65]	Linking biophysical structure and function to services, benefits, and values	Productivity and condition as structure and function; livestock production as service; value capture as benefit and value	Treats the service-to-value step as an explicit, measurable efficiency (value capture) and attaches inference boundaries to each step
Social-ecological systems (SES) framework [66]	Diagnosing the sustainability of common-pool resource systems through nested variables	Resource system and units as ecological constructs; governance system and actors as moderators (M, U); interactions and outcomes as conversion stages and welfare	Provides a measurement and inference layer for the SES "interactions → outcomes" tier

Framework	Primary purpose	Correspondence with PCCL	What PCCL adds
Ladder of causation [16, 67]	Distinguishing association, intervention, and counterfactual reasoning	PCCL's association and causal stages correspond to the first and higher rungs	Adds measurement and prediction stages beneath association, and provenance codes that determine whether a variable can enter a causal claim at all

The common thread is that existing frameworks specify *what* should be connected, whereas PCCL specifies *how strongly* a given empirical connection can be interpreted, given the provenance of its variables and the design that produced it.

5.2 Scale Effects, Feedbacks, and Apparent Contradictions

Many apparent contradictions in rangeland research may reflect differences in scale, outcome, and design rather than genuinely incompatible findings. Dryland dynamics depend strongly on scale [6], and grazing effects vary with moisture regime, intensity, and the ecological attribute being measured [7, 9, 10]. A satellite pixel, grazing unit, soum, aimag, ecological zone, and national panel represent substantively different spatial units, and seasonal, annual, and decadal analyses capture different processes.

Mongolia offers a clear example. Using satellite data for 2002–2012, Hilker et al. [68] attributed most of the observed decline in vegetation to increased livestock numbers, whereas Purevjav et al. [12], using a longer record and a quasi-experimental design, found that climate explains most productivity change and that herd-size effects detected at interannual frequency vanish at the decadal scale. From a PCCL perspective, these studies differ in period, outcome definition, provenance of the productivity variable, temporal scale, and identification strategy. Their conclusions are therefore not directly comparable, and reconciling them requires aligning these dimensions rather than choosing a winner.

SOC adds further heterogeneity: the interaction between grazing and topography reported by Pan et al. [39] shows why slope position and carbon fractions can alter interpretation even within one grassland system. Feedbacks add another layer. Herders adjust herd size and mobility in response to forage, prices, and past losses (Figure 2), so cross-sectional associations between herd size and vegetation mix the effect of grazing on vegetation with the effect of vegetation on grazing decisions.

PCCL therefore treats relationships as conditional rather than universal. Effect magnitudes, and in some cases directions, can vary with spatial unit, temporal scale, ecological context, climatic and biophysical conditions, and management. The framework assigns no universal functional forms or parameters to these relationships.

5.3 From Herd Intensification to Value Intensification

The economic part of PCCL introduces *value intensification*: increasing the household value retained from a given ecological and livestock resource base, rather than relying primarily on additional animal numbers. Household income can increase through herd size, but also through animal productivity, reduced mortality, product quality, processing, market access, recovery of secondary products, better prices, lower transaction costs, and better risk management. Research on climate and rural livelihoods shows that smallholder and livestock systems respond through multiple interacting production and adaptation channels [40, 41], and Mongolian evidence emphasises mobility, community institutions, information access, and adaptive capacity [23, 61]. Dashbal et al. [25] show that Mongolia's resilience-based management system already links ecological monitoring with governance and the potential use of monitoring information in traceability and marketing. PCCL extends this logic by making value capture an explicit analytical stage between livestock output and welfare.

5.3.1 Measuring Value Capture Efficiency

Four indicators make the value-capture stage measurable. For household i in year t with output quantities q_{ikt} of products k (meat, milk, cashmere, wool, hides, and other by-products), the *value capture ratio* compares retained value with the gross potential value of output at reference prices p_{kt}^{ref} (for example, prices in the nearest processing market):

$$\text{VCR}_{it} = \frac{R_{it}}{\sum_k q_{ikt}\ p_{kt}^{\text{ref}}} \qquad (16)$$

where R_{it} is the value retained by the household (sales net of transaction costs plus the imputed value of own consumption). Its components can be measured separately: the *utilisation rate* $U_{it} = \sum_k q_{ikt}^{\text{used}} / \sum_k q_{ikt}$ (the complement of the waste ratio used by Davaatseren et al. [14]), and the *price realisation ratio* for product k,

$$\text{PRR}_{ikt} = \frac{p_{ikt}^{\text{farm}}}{p_{kt}^{\text{ref}}} \qquad (17)$$

Finally, *value intensity* expresses retained value per unit of grazing pressure, using sheep units (SU) or sheep-unit grazing days:

$$\text{VI}_{it} = \frac{R_{it}}{\text{SU}_{it}} \qquad (18)$$

Each indicator should carry provenance codes: retained value and quantities are usually O-coded survey variables, reference prices may be P-coded, and sheep units are P-coded conversions of O-coded counts.

5.3.2 Testing Whether Value Intensification Reduces Grazing Pressure

The hypothesis is not that value intensification automatically reduces grazing pressure; higher profitability could also create incentives for herd accumulation. Income growth can be decomposed as

$$\Delta \ln R_{it} = \Delta \ln \text{SU}_{it} + \Delta \ln \text{VI}_{it} \qquad (19)$$

which separates growth from herd expansion and from value intensification. The test of interest is whether interventions that raise VCR or VI—such as processing cooperatives, by-product collection, traceability, or market-access improvements—are followed by smaller increases in grazing pressure per unit of income gain than herd-based income growth. Operationally, herd size and grazing pressure should be treated as *outcomes* of value-capture interventions in difference-in-differences or event-study designs (Section 6), so that a "rebound" in herd size can be detected rather than assumed away.

5.3.3 Boundary Conditions

The defensible proposition is narrow: under specific conditions, additional household value may be generated with a smaller marginal increase in ecological pressure than under an income strategy based mainly on herd expansion. These conditions are expected to include (i) high baseline product loss or by-product underutilisation; (ii) feasible access to processing and markets with price pass-through to herders; (iii) the availability of alternatives to livestock as a store of wealth and insurance, such as savings or index insurance; and (iv) pasture-access rules that limit open-ended herd expansion. Where livestock remain the main savings and insurance vehicle, higher profitability may instead accelerate herd accumulation. The proposition therefore requires empirical testing, formalised as P5 in Section 10.

5.4 Testable Propositions and Future Research Agenda

The PCCL synthesis generates six propositions. Table 9 states each as a formal statistical hypothesis.

P1. Decoupling of productivity and condition. Short-term changes in remotely sensed productivity will not map directly onto ecological condition, particularly where precipitation and temperature dominate interannual variation.

P2. Climate-conditional grazing effects. The marginal relationship between livestock pressure and vegetation outcomes will differ across ecological zones, climate states, and temporal scales.

P3. Temporal decoupling between vegetation and carbon. Short-term changes in GPP or vegetation indices will explain only part of SOC variation because belowground carbon processes operate through slower and structurally different mechanisms.

P4. Mediation between ecological and economic outcomes. Relationships between rangeland condition and household income will be mediated by livestock productivity, mortality, product utilisation, prices, processing, and market access rather than operate as direct, deterministic pathways.

P5. Value intensification. Where livestock products or by-products are underutilised, improved value capture may increase household income with less incremental ecological pressure than equivalent income growth achieved predominantly through herd expansion.

P6. Provenance constraint. Uncertainty will accumulate and transferability will decline as analytical chains contain more intermediate proxy, model-reconstructed, or predicted variables, unless each transformation is independently validated.

Table 9. Formal statistical hypotheses for propositions P1–P6. Subscripts i, z, and t index units, ecological zones, and periods; Δ denotes a short-term (e.g., annual) change; variables are standardised where comparisons require it.

Proposition	Null hypothesis (H_0)	Alternative (H_1)	Suggested test and design
P1	$\delta = 0$ in $(\Delta P_{it} - \Delta C_{it}) = \delta \Delta W_{it} + u_{it}$: the gap between productivity and condition changes is unrelated to weather	$\delta \neq 0$	Panel of co-located RS productivity and field condition assessments; also report $\rho(\Delta P_{it}, \Delta C_{it})$ with a confidence interval, corrected for measurement error
P2	$\beta_z = \beta$ for all zones z, and $\beta^{(\tau)} = \beta$ for all temporal aggregation scales τ	At least one β_z or $\beta^{(\tau)}$ differs	Zone-interacted panel models within a design that addresses confounding by W_t, C_{t-1}, and U; joint Wald test; estimates at annual and multi-year scales
P3	$E[\Delta S_{it} \mid \Delta P_{it}, X_i^{\text{slow}}] = E[\Delta S_{it} \mid \Delta P_{it}]$, i.e., incremental R^2 of slow variables X^{slow} (texture, topography, grazing history, S_{t-k}) is zero	Incremental $R^2 > 0$	Repeated O-coded SOC sampling; nested models compared with spatially blocked cross-validation
P4	Natural indirect effect of C on Y through (L, V) is zero: NIE $= 0$	NIE $\neq 0$; complementary full-mediation test, analogous to Equation (11): $Y_t \perp C_t \mid L_t, V_t, M_t, W_t, G_t$	Causal mediation analysis with sensitivity analysis [60]

Proposition	**Null hypothesis (H_0)**	**Alternative (H_1)**	**Suggested test and design**
P5	$\pi_V \geq \pi_H$, where $\pi_V = \Delta G/\Delta R$ under value-capture interventions and $\pi_H = \Delta G/\Delta R$ under herd-based income growth	$\pi_V < \pi_H$ (one-sided)	Difference-in-differences with grazing pressure as an outcome, in settings with high baseline product loss
P6	$E[\hat{\beta}^{(k)}] = E[\hat{\beta}^{(0)}]$ and transfer error is invariant to the number k of unvalidated intermediate (P, M, ML) stages	$\lvert E[\hat{\beta}^{(k)}] - \beta \rvert$ and transfer error increase with k	Re-estimation of the same model with O-coded and derived versions of variables where both exist; simulation as in Section 5.5

A future empirical PCCL application should ideally use spatially explicit panel data that combine field ecology, satellite indicators, climate information, livestock production, value-capture indicators, and household outcomes while preserving provenance. Spatially blocked validation should be preferred when claims concern geographic transferability, and validation that holds out later periods when claims concern forecasting (Table 6). Where causal questions are asked, the designs in Table 7 should be used only where their identifying assumptions are substantively defensible. The most useful empirical extension would test the mechanisms linking ecological condition to livelihood outcomes: whether condition influences livestock productivity, and through it marketable output and income; and whether condition influences ecological resilience, and through it sensitivity to shocks and livelihood stability. Table 10 summarises minimum requirements by component.

Table 10. Recommended empirical approaches and minimum reporting requirements for future PCCL applications.

PCCL component	**Preferred empirical approach**	**Minimum reporting requirement**	**Illustrative sources**
Productivity	GPP or biomass calibrated against field measurements and combined with satellite products	Separate O, RS, P, and ML targets; report uncertainty and validation design	Pettorelli et al. [1]; Prentice et al. [4]
Rangeland condition	Ecological assessment against reference conditions informed by state-and-transition logic	Define ecological potential or reference; do not equate annual greenness with condition	Bestelmeyer et al. [18]; Herrick et al. [19]
Grazing effects	Analysis by ecological zone and grazing intensity within a credible design	Model climate, soil, and grazing-intensity interactions; report spatial and temporal scale	Milchunas et al. [7]; Yan et al. [8]; Eldridge et al. [9]
Soil carbon	Repeated field SOC where feasible; clearly labelled reconstructed SOC where necessary	Retain provenance and uncertainty; vegetation indices are not direct SOC measurements	Piñeiro et al. [20]; McSherry & Ritchie [21]; Ren et al. [22]
Spatial prediction	Spatial blocking or leave-location-out validation	Estimate transfer error to genuinely new locations; report area of applicability	Roberts et al. [26]; Valavi et al. [46]; Meyer & Pebesma [49]
Temporal prediction	Forward or leave-period-out validation	Distinguish interpolation from forecasting; test temporal non-stationarity	Meyer et al. [28]; Yates et al. [29]
Livestock production	Panel data on survival, reproduction, and output per animal	Separate herd stock from production efficiency; record dzud exposure	Thornton et al. [41]; Fernández-Giménez et al. [42]
Value capture	Household or enterprise data on utilisation, processing, and prices	Report VCR, utilisation, price realisation, and value intensity with provenance codes	Davaatseren et al. [14]; Dashbal et al. [25]

PCCL component	Preferred empirical approach	Minimum reporting requirement	Illustrative sources
Livelihood mechanism	Panel data linking livestock performance, prices, processing, and household outcomes	Separate ecological exposure from production efficiency and value capture	Fernández-Giménez et al. [23]; Kakinuma et al. [24]
Causal inference	Quasi-experimental or experimental identification where credible	State identifying assumptions; predictive performance is not causal identification	Purevjav et al. [12]; Table 7
Integrated policy	Multi-indicator monitoring that combines institutions and local knowledge	Keep ecological, economic, and governance indicators separate but connected	Jamsranjav et al. [33]; Dashbal et al. [25]

5.5 Policy Implications for Mongolia

The principal policy implication is that no single indicator should be used as a universal measure of pastoral sustainability. Because strong climatic variability affects ecological and economic layers simultaneously, policies that attribute low productivity mechanically to overgrazing risk misdiagnosing climate-driven variation. The opposite error is equally important: evidence that climate dominates national productivity change at some scales does not imply that local grazing pressure, soil deterioration, spatial concentration of livestock, or poor management are irrelevant. PCCL therefore shifts the policy question from "How many animals are sustainable?" to a more complete formulation: under given climate and ecological conditions, how efficiently can ecosystem production be converted into resilient livelihood value without eroding the ecological production base? Four applications illustrate what this means in practice (Table 11).

5.5.1 National Rangeland Monitoring

National monitoring should maintain separate indicator layers for each PCCL component, each tagged with its provenance code. Satellite productivity is well suited to detecting anomalies and targeting field visits, but degradation should be diagnosed against site-specific reference conditions using condition indicators and state-and-transition information [18, 19, 25]. A practical step is to report climate-adjusted productivity anomalies—the part of productivity variation not explained by weather—as a screening tool, while recognising that such residuals remain associational and do not by themselves attribute change to grazing. Herder-based indicators can complement formal monitoring where they correspond with field measurements [33].

5.5.2 Results-Based Payments and Soil Carbon Finance

Results-based payments for ecosystem services, including soil carbon credits, are a direct application of PCCL's inference boundaries. Payments should be conditioned on O-coded or independently validated measurements of change, not on vegetation indices or model reconstructions alone, because SOC change is slow, spatially variable, and costly to detect [35, 69, 70]. M-coded reconstructions and S-coded scenarios, such as those in Davaatseren et al. [15], are appropriate for ex-ante feasibility screening but not for crediting. Additionality, leakage, and permanence are causal questions that require counterfactual designs rather than trend extrapolation; the broader evidence on payments for environmental services shows that effectiveness depends on conditionality and targeting [71]. In PCCL terms, a carbon payment adds a policy-contingent pathway from SOC to value capture (Section 4.3), and that pathway is only as credible as the SOC measurement that triggers it.

5.5.3 Livestock Product Traceability and Marketing

Traceability and marketing programmes act on the value-capture stage. Their success should be measured with value-capture indicators—utilisation rates, price realisation, and value intensity (Equations 16–18)—rather than with total

income or herd size. Where programmes make sustainability claims (for example, "sustainably grazed" cashmere), those claims should rest on condition indicators assessed against reference states, not on productivity alone, because favourable rainfall years can raise greenness without improving rangeland condition. Linking monitoring to traceability, as envisaged in Mongolia's resilience-based management system [25], is consistent with PCCL provided that each link is labelled with its inferential stage.

5.5.4 Climate Adaptation and Dzud Risk Management

Climate adaptation requires distinguishing forecasting from attribution. Early-warning systems for dzud are prediction tasks and should be validated with temporal holdouts that include extreme years (Table 6). Index-based livestock insurance relies on an index that is a P-coded proxy for household losses, so basis risk—the mismatch between index and actual loss—is a provenance problem that should be monitored explicitly. Evidence from Mongolia and Kenya indicates that index insurance can support recovery after climatic disasters [57, 72]. Recovery should be evaluated with welfare and asset outcomes rather than herd numbers alone, given that inequality persisted after aggregate herd recovery following the 2009–2010 dzud [24] and that the 2023–2024 dzud again caused widespread losses [44].

Table 11. Policy applications of PCCL: components, indicators, and inferential requirements.

Policy application	PCCL components	Appropriate indicators (code)	Inferential stage required	Misuse to avoid
National rangeland monitoring	Productivity; condition; SOC	Field condition against reference (O); RS anomalies for screening (RS, M)	Measurement and prediction	Declaring degradation from a greenness decline alone
Results-based payments and carbon finance	SOC; value capture	Repeated field SOC (O); validated models for interpolation (M, with validation)	Causal (additionality) and validated measurement	Crediting from NDVI or unvalidated reconstructed SOC
Traceability and marketing	Value capture; condition	VCR, utilisation, price realisation (O); condition for sustainability claims (O)	Association for monitoring; causal for programme evaluation	Using total income or herd size as the programme success metric
Climate adaptation and dzud risk	Livestock production; welfare	Forecast forage and mortality risk (ML, M); welfare and asset outcomes (O)	Prediction (early warning); causal (programme effects)	Treating herd recovery as livelihood recovery; ignoring basis risk

This framing supports integrated monitoring in which ecological condition, climate exposure, livestock performance, market conversion, and household resilience are evaluated together while retaining their analytical distinctions. It is consistent with Mongolia's progression from herder ecological knowledge and flexible pastoral institutions [32, 62] towards participatory monitoring, approaches that strengthen adaptive capacity, and resilience-based management [23, 25, 33].

5.6 Transferability Beyond Mongolia

The analytical architecture of PCCL—six components, a causal graph, provenance codes, and inference boundaries—is not specific to Mongolia and could be applied to other dryland pastoral systems, such as those of the Sahel, Central Asia, East Africa, or Patagonia. Global evidence that grazing effects on ecosystem services depend on climate, soil, and biodiversity [10] implies that the framework's structure can transfer while its parameters cannot. Four elements would need adaptation. First, ecological reference states and site potential must be defined locally [19]. Second, the dominant climate hazard differs—drought rather than dzud in many systems—which changes the climate-to-production pathway and the design of early warning and insurance [72]. Third, institutional settings differ, from communal and customary tenure to private ranching, which changes the moderators of value capture and the

feasibility of identification strategies. Fourth, data availability differs: the strength of the provenance codes that a study can achieve depends on the existence of field monitoring networks, livestock censuses, and household panels. PCCL's provenance table provides a common reporting format that would make results comparable across these contexts even when their parameters differ.

6.CONCLUSION AND LIMITATIONS

This perspective has deliberate limitations. It is not a systematic review and does not claim exhaustive coverage. No pooled effect sizes are calculated, and no new empirical model is estimated. The relationships in PCCL and in Figure 2 are theoretically and empirically motivated hypotheses, not estimated causal effects, and the evidence base was selected purposively, so selection bias is possible. The three recent Mongolian studies share authors and partly the same study area; they should not be pooled or counted as independent replications.

Several econometric and ecological complexities are made explicit by PCCL but not solved by it. *Endogeneity and simultaneity* are pervasive: herders adjust herd size and mobility in response to forage, so grazing pressure is both a cause and a consequence of vegetation. *Omitted-variable bias* arises from latent management, skill, and local institutions. *Spatial and temporal dependence* inflates apparent precision when ignored. *Non-stationarity* means that relationships estimated in one period—for instance, before or after major institutional change or under different climate regimes—may not hold in another. *Regime shifts and thresholds*, which state-and-transition models emphasise, imply that linear models can be misleading near tipping points. *Non-linearities* in grazing responses mean that average effects can conceal opposite effects at low and high intensity. Measurement error is often nonclassical, so the direction of bias is not always predictable.

The Monte Carlo illustration in Section 5.5 is linear, Gaussian, and stylised, and it is intended to demonstrate mechanisms rather than to quantify the bias in any particular study. Household income also captures only one dimension of livelihood outcomes; future research should incorporate consumption, wealth, inequality, food security, mobility, risk exposure, and resilience where data permit. Finally, PCCL is an analytical architecture rather than a universal parameterisation: its components may transfer to other dryland pastoral systems, but relationships and boundary conditions must be estimated anew in each ecological and institutional context.

Pastoral sustainability is a linked system, but it is not a single outcome that can be measured equally well by GPP, NDVI, SOC, herd size, or household income. The PCCL framework separates six components—ecological productivity, rangeland condition, soil carbon, livestock production, value capture, and household welfare—and its inference boundaries distinguish measurement, prediction, association, and causal identification. The causal graph clarifies which variables confound, mediate, or moderate each relationship; the provenance taxonomy records what each variable is; and the simulation shows that ignoring provenance can halve an estimated effect or manufacture a spurious one.

The contribution of PCCL is therefore not another estimate of degradation, productivity, carbon, or income, but a disciplined structure for deciding what each indicator measures, how layers can be connected, where uncertainty enters, and how far the evidence permits inference to travel. The most valuable next steps are empirical: co-located panels that combine field ecology, satellite indicators, livestock and value-capture data, and household outcomes; validation designs matched to the inference goal; and tests of the six hypotheses stated in Table 9, in Mongolia and in comparable dryland pastoral systems.

Data availability: No new empirical data were collected or analysed. All empirical claims refer to published studies cited in the reference list. The synthetic data used in the Monte Carlo illustration (Section 5.5; Appendix A) are generated by the script provided as Supplementary Material S1.

Code availability: The Python script that reproduces Table 5 and Figure 3 (pccl_simulation.py; random seed 20261101) is provided as Supplementary Material S1.

Ethics statement: Not applicable; this article does not report new research involving human participants, animals, or identifiable personal data.

Funding: This research received no external funding.

Conflict of interest: The author declares no conflict of interest.

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APPENDIX A. MONTE CARLO DESIGN

Data-generating process. In each replication, $n = 400$ units are drawn. All variables are standardised. Climate is $W \sim N(0,1)$. True productivity is $P = 0.6W + 0.8e_P$, so that $\mathrm{Var}(P) = 1$. True SOC is $S = 0.4P + \sqrt{0.84}\, e_S$. Household income is $Y = \beta_P P + \beta_S S + 0.20W + e_Y$ with $\beta_P = 0.30$ and $\beta_S = 0$. All disturbances e are independent standard normal.

Observed variables. Field productivity and field SOC (O) are the true values plus classical error with reliability 0.95. The remotely sensed productivity target (RS) is $P^{RS} = P + u$, with $\mathrm{Var}(u)$ chosen to give reliability λ_{RS} (baseline 0.70). The ML stage (ML[RS]) is trained on an independent sample of 1,000 units to predict P^{RS} from a feature $F = P^{RS} + v$, with $\mathrm{Var}(v)$ chosen so that $R^2_{ML} = 0.90$ against the target; a linear learner is used as a transparent stand-in for any well-calibrated ML regressor. The reconstructed SOC (M[RS]) is $S^M = aN + 0.2W + \eta$, where $N = P + n$ is an independent vegetation index with reliability 0.75, $\mathrm{Var}(\eta) = 0.2$, and $a = 0.4$ at baseline; by construction, S^M contains no soil-specific information.

Estimators. Scenarios A–D regress Y on the productivity variable, the SOC variable, and W by ordinary least squares with conventional standard errors. Scenario E draws a validation subsample of 100 units with field productivity, regresses field productivity on the ML prediction and W (regression calibration), substitutes the calibrated prediction into the income regression, and omits S^M because its effect is not identified from M-coded information. Its standard error is obtained by bootstrapping the main and validation samples jointly (199 resamples).

Replications and sensitivity analyses. Table 5 is based on 2,000 replications. Figure 3A varies λ_{RS} from 0.4 to 1.0, and Figure 3B varies a from 0 to 0.8, each with 1,000 replications per grid point and without bootstrapping. The script (Supplementary Material S1) reproduces all results with the stated random seed.

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