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Measuring adaptive decision making in livestock grazing systems

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Adaptive management is essential for managing complex grazing systems under environmental uncertainty. However, its implementation in grazing operations is inconsistently defined and measured. This study addresses this limitation by developing and validating the Adaptive Management Index (AMI), a standardised instrument that quantifies adaptive management at the ranch level. The AMI incorporates 64 indicators identified through literature and validated through expert input to measure four key phases of adaptive management – planning, monitoring, evaluation and adjustment. A mail survey of 2 100 livestock producers in the Southern Great Plains of Texas yielded 255 useable responses. Principle component analysis and multivariate regression were used to create and validate the AMI. Findings reveal that while planning, monitoring and adjustment are moderately practised among respondents, the evaluation phase is underutilised. AMI scores were significantly associated with producers' mental models of grazing system dynamics, indicating a link between adaptive management implementation and perceptions of system interconnectivity. The AMI enables a more precise understanding of management complexity and provides a tool for assessing adaptive grazing strategies independent of grazing method. This study advances the conceptualisation and operationalisation of adaptive management in grazing systems and offers a foundational resource for researchers and producers to support learning-driven decision making that builds social-ecological resilience.

Keywords: adaptive management, grazing management, learning, mental models, rotational grazing

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Introduction

Grazing management is embedded within complex and dynamic social-ecological systems (SES) influencing rangeland ecological processes, livestock production and producer livelihoods (Hruska et al. 2017). Increasing variability in climatic and environmental conditions has increased uncertainty regarding how management decisions affect system behaviour and structure over time (Williams 2011). Consequently, the effectiveness of any grazing strategy depends on the capacity of managers to make informed decisions under conditions of uncertainty. Adaptive management has long been promoted as an essential approach for rangeland stewardship in such contexts (Holling 1978; Savory and Butterfield 1999). It emphasises iterative cycles of planning, implementation, monitoring, evaluation and adjustment of management actions, with the goal of improving decision making through learning about system structure and behaviour (Walters 1986; Allen et al. 2011; Williams 2011; Herrick et al. 2012).

Adaptive management involves proactive planning for adverse conditions, monitoring to identify decision triggers, and developing a suite of both proactive and reactive strategies available for implementation as circumtances require (Kachergis et al. 2014; Roche 2016; Haigh et al. 2021; Woodmansee et al. 2025). Such actions are frequently characterised by flexibility in response to changing climate, weather and forage conditions (Alfonso-Ortega et al. 2013; Steffens et al. 2013; Teague et al. 2013; Derner and Augustine 2016), though they must be tailored to local environmental contexts (Donaldson et al. 2025).

Beyond specific practices, adaptive management is fundamentally a learning process that relies on structured decision making and feedback mechanisms to support evaluation, learning and continuous improvement (Allen and Garmestani 2015; Wilmer et al. 2018; Fernández-Giménez et al. 2019). These cycles drive not only changes in management but also in how managers conceptualise their systems. Such shifts represent 'double-loop' learning processes, wherein mental models are revised in light of new information and experience (Sterman 1994). Mental models represent the knowledge structures or perceptions that individuals hold about how systems function, and they can be evaluated to assess both individual and social learning (Özesmi and Özesmi 2004; Sterman 2006; Gray et al. 2014; Luján Soto et al. 2021). Evidence suggests that application of adaptive management frameworks in grazing systems can reshape producers' mental models, enabling them to interpret and interact with their land in new ways (Gosnell et al. 2019; Stanley et al. 2024). Assessing such learning is therefore a critical component to understanding whether adaptive management is occurring and how it may be strengthened.

Despite this, adaptive management is often conflated with specific grazing methods. For example, adaptive multi-paddock (AMP) grazing has been defined by paddock number and specific grazing principles without explicitly considering the underlying processes of planning, monitoring, evaluating and adjusting, making practical management implications unclear (Teague et al. 2013; Mosier et al. 2021; Apfelbaum et al. 2022; Johnson et al. 2022). Research on a collaborative adaptive approach to grazing management has clearly and thoroughly incorporated planning, monitoring and feedback mechanisms in grazing management decision making (Wilmer et al. 2018). While this approach could not overcome the effects of a tenfold increase in stock density on vegetation or animal performance, it demonstrated strong potential for enhancing social learning, facilitating stakeholder engagement, and achieving production outcomes that exceeded those of non-adaptive management (Fernández-Giménez et al. 2019; Augustine et al. 2020; Derner et al. 2021). These findings highlight the need for clearer indicators and standardised approaches for evaluating adaptive management in practice to continue disentangling the effects of grazing method from the adaptive management process and enable clear management implications from research.

Conceptual frameworks for adaptive management in rangelands have been well established (Allen et al. 2017; Kachergis et al. 2022), and evaluation criteria for adaptive management phases have been proposed (Chaffin and Gosnell 2015). However, no standardised method exists to quantify the extent to which adaptive processes are implemented in grazing systems. This gap has led to inconsistent definitions and applications of adaptive management in research and practice, hindering both evaluation and adoption, and complicating efforts to disentangle the influence of grazing methods from the adaptive processes used to guide them (Allen et al. 2011; Steffens et al. 2013).

To address this gap, we developed the Adaptive Management Index (AMI), a standardised instrument designed to quantify the extent of adaptive management implementation in grazing systems. The AMI translates general adaptive management principles into grazing-specific indicators that can be measured, compared and applied across diverse management contexts, allowing adaptive processes to be evaluated independently of grazing methods. By validating the AMI against measures of learning through mental model change, we link the conceptual foundation of adaptive management as a learning process to its practical evaluation in grazing systems. In doing so, the AMI complements existing frameworks, extends previous efforts to establish evaluation criteria, and provides a mechanism for disentangling adaptive management processes from grazing methods.

Methods

We applied methodologies for scale development (Mackenzie et al. 2011; Boateng et al. 2018), survey (Dillman et al. 2014), and composite indicator construction (OECD 2008) to identify indicators of the adaptive management process. First, we used scale development methodology to conceptualise the adaptive management construct, identify indicators, and evaluate indicator content validity. Second, we used survey methodology to gather producer data on the implementation of adaptive management indicators and their perceptions of grazing system dynamics for index construction and validation. Third, we created the adaptive management index (AMI) following composite indicator construction methodology. Finally, we returned to scale development methodology to establish construct validity of the index. Each of these steps is described in detail below.

Construct conceptualisation, indicator generation, and content validation

We used scale development methodology for construct conceptualisation, indicator generation, and content validation (Mackenzie et al. 2011; Boateng et al. 2018). For construct conceptualisation, we conducted a thorough literature review to identify critical phases of the adaptive management process. From this review, we generated potential indicators of adaptive management by extracting items that reflected the application of each phase. We searched the literature for key words including adaptive management, strategic adaptive management, adaptive co-management, collaborative adaptive management, decision triggers, and adaptive monitoring. We also drew on the US Roundtable for Sustainable Beef industry sustainability framework for the cow-calf sector to guide indicator development (USRSB 2019).

When we identified indicators that were too broadly defined, we tailored them to apply specifically to grazing management. For example, although decision triggers are an important general feature of adaptive management, they must relate to specific grazing system indicators that prompt management actions. Accordingly, we modified indicators to reflect this specificity. We excluded indicators related to the implementation phase from the overall AMI becausegrazing management implementation is more appropriately captured through metrics describing the timing, intensity, frequency and duration of grazing (Stanley et al. 2024), which remains the subject of ongoing research.

Content validation evaluates how well metrics represent the construct of interest. To evaluate indicator content validity, we asked panel of ten professional grazing management experts, representing both academic researchers and practitioners with extensive experience in rangeland management, to assess the relevance of each indicator. The panel included university faculty, research scientists, extension professionals and ranching practitioners recognised for their contributions to grazing management. We provided panelists with the conceptual definition of adaptive management and asked them to rate each indicator using a four-point Likert scale, including Not Relevant, Somewhat Relevant, Relevant, and Highly Relevant. We calculated the modified kappa statistic (k^*) for each indicator, which adjusts the item-level Content Validity Index (I-CVI) score for chance agreement (Polit et al. 2007). We retained indicators with modified kappa statistic (k^*) score values greater than or equal to 0.60 (Polit et al. 2007). We used the valid indicators in a survey of livestock producers in the Southern Great Plains of Texas, USA to determine the degree of implementation of the identified adaptive management indicators in their grazing systems.

Producer survey and study area

We conducted a mail survey of livestock producers in Texas from July to November 2022 to evaluate the implementation of each adaptive management indicator, construct an overall AMI, and evaluate perceptions of grazing systems dynamics to assess the AMI's construct validity. We distributed the survey to 2 100 livestock producers with at least 247 acres (100 hectares) of land in the Texas region of the Southern Great Plains. We obtained the mailing list of potential respondents from a third-party agricultural data provider that maintains and licenses producer contact information for research and marketing purposes. We targeted producers who rely on their beef operation for a substantial amount of income. We set the acreage cutoff to ensure we sampled income-dependent operations, given that over 90% of livestock producers with annual sales of at least $50 000 operate on at least 220 acres in Texas (USDA NASS 2017). We used stratified random sampling across three land size categories (247–493 acres, 494–987 acres, and 988+ acres) to ensure similar representation across a broad range of operation sizes.

The survey reached producers in 174 of the 254 counties in Texas. East Texas was not represented due to smaller property sizes in that region, which often did not meet the eligibility cutoff used in the sampling design. Parts of West and Far West Texas were also not represented in the final sample. This absence was likely a result of the random sampling approach combined with the relatively low density of agricultural producers in those counties. As a result, the counties surveyed were concentrated primarily in the larger central region of the state, with strong representation spanning from north to south.

The surveyed counties encompass a diverse set of ecological regions, including the High Plains, Rolling Plains, Blackland Prairie, Edwards Plateau, South Texas Plains, Gulf Coast Prairie, Post Oak Savannah and Cross Timbers. These regions vary considerably in climate, vegetation and forage availability. Tall- and mid-grass prairies dominate the Blackland Prairie and Post Oak Savannah, while short-grass prairies and mixed-shrub systems characterise the High Plains, Edwards Plateau and South Texas Plains. Rainfall gradients range from more than 35 inches annually in the Gulf Coast Prairie and Blackland Prairie to less than 20 inches in the western High Plains and Edwards Plateau. Importantly, more than 95% of land in Texas is privately owned. Therefore, the adaptive management practices evaluated here occur largely within the cultural and economic context of income dependent, privately owned or leased operations.

To measure the implementation of adaptive management indicators, we asked survey respondents to rate each indicator using a five-point response scale: very unlike me, somewhat unlike me, neutral, somewhat like me, and very like me. To measure perceptions of grazing system dynamics for construct validation purposes, we used a closed cognitive mapping method for mental model elicitation. We provided survey respondents with paired comparisons of mental model elements, which included livestock-related profitability, number of animals on the land, attention to grazing management, ecosystem function, and herbaceous biomass production, and asked them if a reduction in one element would increase, decrease or not change the remaining elements (Moon et al. 2019; Biedenweg et al. 2020). We also asked survey participants about demographic and operation characteristics.

We administered the survey in two rounds of five separate mailings. The first round of mailings targeted 1 500 producers and included a pre-survey notification letter (Week 1), the survey questionnaire (Week 2), a reminder card (Week 4), a replacement questionnaire to non-respondents (Week 6), and a second replacement questionnaire (Week 11) (Dillman et al. 2014). We sent the third questionnaire to non-respondents instead of the usual final reminder card due to the unsatisfactorily low response rate of only about 10% after the fourth mailing. Additionally, we initiated another round of five mailings including a pre-survey notification letter (Week 9), the survey questionnaire (Week 11), a reminder card (Week 12), a replacement questionnaire to non-respondents (Week 16), and a final reminder/thank you card (Week 19) with an additional group of 600 producers. We received 535 responses from the 2 100 producers, representing a gross response rate of 25.5%. Of these, 239 were ineligible mostly because they reported operating on less than 247 acres of land, and 41 did not complete the questionnaire. Accordingly, we had 255 completed questionnaires that were useful data for analysis, representing a usable response rate of 12.1%. Subsequently, we sent a one-page questionnaire to 400 randomly selected non-respondents (i.e. approximately 25%) to ascertain non-response bias across selected operation and demographic characteristics (Lindner et al. 2001). Fifty-six (14%) of these non-respondents completed and returned the short questionnaire. Of those, 20 did not operate grazing systems in Texas or did not meet the minimum acreage requirement leaving 36 for the non-response bias analysis.

The average age of survey respondents was 68 years (SD = 10.9), which is about 10 years above the average age of farm and ranch producers in the US (USDA NASS 2017). Of the respondents, 87.4% were male. On average, they had owned and operated grazing systems for 36.3 years (SD = 15.6), were third-generation ranchers (SD = 1.7), and had about 15 years (SD = 2.5) of formal education. The largest segment of grazing land that respondents had operated was, on average, 2 733.3 acres (SD = 6 216.9), and current management practices had been in place for 28.5 years (SD = 20.5). Survey respondents averaged around $301 000 in annual gross sales in a typical year (SD = $995.5) and the beef cattle enterprise made up 36.2% of their total household income (SD = 28.0). Ninety-five percent of the respondents had cow–calf operations, 17.2% had stocker operations, and 3.9% had grass-finishing operations, indicating that some operate more than one enterprise. Overall, 71% of respondents' largest tract of grazing land consisted of native rangeland and 35.8% contained improved pasture, indicating that some operations have a mix of both native rangeland and introduced pasture.

In general, there were no statistically significant differences between the respondents' and non-respondents' response data, except that the non-respondents indicated that, on average, a higher proportion of their total household income was derived from their beef cattle enterprise ($p = 0.001$). Due to this difference, the results cannot be extrapolated to the survey population without caveats. Nevertheless, this does not prevent the use of the survey data to develop an AMI. It

simply suggests that its utility must be evaluated against a more diverse sample of managers in future research.

Adaptive management index construction

We conceptualised adaptive management as a composite index that aggregates multiple indicators representing distinct phases of the process (Bedford and Speklé 2018; El Gibari et al. 2019). Composite indices distil the complexity of dynamic phenomena into a single measure that is easier to interpret than evaluating multiple indicators individually, which is useful for capturing adaptive management complexity in livestock operations (El Gibari et al. 2019).

We constructed the AMI using survey responses related to adaptive management indicators following procedures for multivariate analysis, normalisation, indicator weighting, and aggregation outlined in OECD (2008). First, we used the Missing Completely at Random (MCAR) test to determine the extent and pattern of missing data (Little 1988). Missing data were determined to be missing completely at random (p = 0.333). Next, we evaluated the data to identify careless responses, which can inflate correlations directly impacting principal component analysis results and therefore construct validity (Ward and Meade 2023). We identified careless responses using the Individual Response Variability (IRV) Index, which is calculated as the standard deviation of responses for an individual (Dunn et al. 2018). The IRV assumes that respondent views and responses regarding constructs being measured will vary, while inattentive respondents will have more identical responses indicating insufficient response effort (Dunn et al. 2018). The cutoff score for removing careless responses was set at IRV = 0 to capture the lowest IRV values in the sample (Dunn et al. 2018). We eliminated 17 respondents with an IRV of zero and two additional respondents with extreme outliers in key operational characteristics.

We applied principal component analysis (PCA) to assess the proportion of variance explained by the adaptive management indicators. We selected PCA over other multivariate methods since we were primarily interested in identifying which indicators to retain. We used Bartlett's Test of Sphericity and the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy to determine the appropriateness of applying PCA to this data set (OECD 2008; Hair et al. 2022). We retained components with eigenvalues greater than one and considered component loadings greater than or equal to 0.30 to be meaningful for structure interpretation (OECD 2008; Hair et al. 2022).

Since the extracted components did not align clearly with specific phases of the adaptive management process, we aggregated indicators by phase rather than by component and applied equal weights to avoid introducing bias (Greco et al. 2019). We evaluated arithmetic and geometric mean aggregation methods to determine the most appropriate approach for index construction. However, with equal weights assigned to each indicator, arithmetic and geometric aggregation methods produced similar, highly correlated AMI values (r = 0.99). Due to ease of calculation, we used arithmetic mean aggregation.

We hierarchically aggregated phase-level indicators into the AMI. First, we aggregated indicators into indices for each phase and then aggregated phases into the overall AMI. To avoid bias of the AMI towards rotational grazing systems, we excluded indicators relevant only to rotational grazing systems when scoring continuously grazed systems (Table 1). This resulted in fewer indicators being present in some phases for continuously grazed systems.

Adaptive management index validation

Construct validity measures the extent to which an instrument relates to other constructs in ways that are consistent with theory (Raykov and Marcoulides 2010). We evaluated the construct validity of the AMI using producer perceptions represented as mental models of grazing system dynamics. We elicited these mental models through a survey-based, closed cognitive mapping exercise in which producers evaluated the directional influence between paired comparisons of five key grazing system elements: livestock-related profitability, animal numbers on land, attention to grazing management, ecosystem function, and herbaceous biomass production. The research team selected these elements from the grazing management literature and theory as critical contributors to grazing system dynamics (Özesmi and Özesmi 2004; Moon et al. 2019; Biedenweg et al. 2020). The purpose of this exercise was to assess how producers perceived the interconnectedness of key grazing system elements as a way of characterising their mental models.

We transformed survey responses into adjacency matrices and calculated outdegree, indegree and centrality for each element (Özesmi and Özesmi 2004). Outdegree represents the number of elements influenced by a given element, indegree reflects the number of elements influencing it, and centrality, calculated as the sum of outdegree and indegree, indicates an element's overall connectedness or importance in the system. We then compared centrality values against AMI scores to evaluate whether greater adaptive management implementation was associated with more integrated representations of grazing system dynamics. If higher AMI scores aligned with higher centrality of key elements, this would indicate a relationship between adaptive management implementation and more complex or dynamic understandings of grazing systems, which may reflect processes of learning. This relationship would support the construct validity of the AMI by demonstrating that it is aligned with a core theoretical outcome of adaptive management: learning that results in refined perceptions of complex system dynamics.

We used hierarchical multiple regression to assess whether the AMI predicted the centrality of key grazing system elements in producers' mental models. This approach allows for the stepwise evaluation of how much additional variance in element centrality can be explained by the AMI beyond that which is explained by demographic and operational characteristics. The first model included demographic and operational characteristics to determine whether these factors significantly predicted the centrality of grazing system elements. Operation and demographic variables included age, gender, education level, generations of ranching heritage, length of experience operating grazing systems, length of time that current management practices have been in place, size of the largest tract of grazing land, average gross sales of beef cattle, and percent of total household income from beef cattle. The second model added the AMI

Table 1: Adaptive management phase indicator descriptions and modified kappa (*k**) results

Code	Indicator description	*k**
	PLANNING PHASE	
	Extent to which producers have LONG-TERM goals for maintaining/enhancing:	
PI 1	Profitability of their ranch as a whole	0.90
PI 2	Health/condition of their grazing land	1.00
PI 3	Personal well-being	0.90
	Extent to which producers have SHORT-TERM goals for maintaining/enhancing:	
PI 4	Profitability of their ranch as a whole	0.79
PI 5	Health/condition of their grazing land	0.90
PI 6	Personal well-being	0.79
	Extent to which producers use grazing management practices for maintaining/enhancing:	
PI 7	Profitability of their ranch as a whole	0.79
PI 8	Health/condition of their grazing land	0.90
PI 9	Personal well-being*	*0.34*
	Extent to which producers conduct the following activities prior to the start of each grazing season:	
PI 10	Assess current forage resource conditions	0.90
PI 11	Compare current forage resource conditions to potential optimum conditions	0.90
PI 12	Determine amount of rest needed to move forage resources towards optimum conditions**	0.90
PI 13	Set stocking rates, and grazing timing/duration to optimise forage resource conditions**	0.66
	Extent to which producers make specific and measurable predictions of how grazing management decisions will impact:	
PI 14	Profitability of their ranch as a whole	0.90
PI 15	Health/condition of their grazing land	1.00
PI 16	Personal well-being	0.79
	Extent to which producers determine levels of precipitation or forage condition to 'trigger' adjustments during the grazing season:	
PI 17	Number of animals on their land	1.00
PI 18	Number of herds their animals are separated into*	*0.50*
PI 19	Grazing days per paddock before animals are moved**	0.90
PI 20	Rest days per paddock before being grazed again**	0.79
PI 21	Which paddocks to remove from grazing rotation (defer) and for how long**	0.79
PI 22	Size of paddocks*	*0.34*
PI 23	Timing of grazing in each paddock**	0.79
	MONITORING PHASE	
	Extent to which producers regularly measure or observe the following:	
MI 1	Abundance or diversity of native plant species	0.90
MI 2	Abundance or diversity of invasive plant species	0.90
MI 3	Abundance or diversity of animal species of interest (i.e. game, pollinators, etc.)	0.66
MI 4	Diversity of bird species*	*0.50*
MI 5	Amount of bare ground	0.90
MI 6	Amount of standing forage biomass	1.00
MI 7	Degree and/or pattern of forage use	0.80
MI 8	Soil carbon*	*0.34*
MI 9	Soil aggregate stability*	*0.34*
MI 10	Soil compaction*	*0.50*
MI 11	Soil water retention	0.80
MI 12	Water quality*	*0.50*
MI 13	Extent and condition of riparian systems	0.66
MI 14	Precipitation levels	0.90
MI 15	Animal body condition scores	1.00
MI 16	Their connection to the community*	*0.50*
MI 17	Their life satisfaction	0.90
	Extent to which producers keep detailed records of the following:	
MI 18	Livestock-related income	1.00
MI 19	Non-livestock related income	1.00
MI 20	Veterinary costs	1.00
MI 21	Fencing installation/maintenance costs	1.00
MI 22	Water installation/maintenance costs	1.00
MI 23	Feed and supplement costs	1.00
MI 24	Labour hours	0.80
MI 25	Number of grazing season days cattle must be fed hay or any other forage substitute	0.80
MI 26	Number of animals on the land	0.90
MI 27	Number of herds*	*0.50*

* = indicators removed from further analysis due to having scores $k < 0.60$

** = indicators that were excluded from aggregation for continuous grazing operations

Table 1 is continued on next page

Table 1: *(cont.)*

Code	Indicator description	*k**
	Extent to which producers keep detailed records of the following:	
MI 28	Number, size and location of paddocks**	0.66
MI 29	Grazing days per paddock before animals are moved**	0.90
MI 30	Rest days per paddock before being grazed again**	0.90
MI 31	Timing of grazing in each paddock**	0.90
MI 32	Which paddocks were deferred and for how long**	1.00
	EVALUATION PHASE	
	Extent to which producers evaluate the following after each grazing season:	
EI 1	Trends in the monitored data over time	0.80
EI 2	Whether the monitoring approach was adequate, cost effective and feasible	0.80
EI 3	Whether the intended grazing plan was fully executed	0.66
EI 4	Whether the selected management actions achieved the desired outcomes	0.90
EI 5	Whether the selected indicators for management actions achieved desired outcomes	0.89
EI 6	Whether the predicted outcomes were correct	0.60
EI 7	Whether the outcomes were acceptable	1.00
EI 8	Whether outcomes were result of management or result of environmental effects*	*0.41*
EI 9	Whether the overall goals are being met	1.00
	ADJUSTMENT PHASE	
	Extent to which producers consider whether, when and how to adjust the following after each grazing season:	
AI 1	Number of animals on their land	0.90
AI 2	Number of herds animals are separated into*	*0.50*
AI 3	Number and size of paddocks*	*0.34*
AI 4	Amount of time animals spend grazing in each paddock before being moved**	0.80
AI 5	Amount of time paddocks rest before being grazed again**	0.66
AI 6	Which paddocks get temporarily removed from grazing rotation and for how long*	*0.34*
AI 7	Timing of grazing in each paddock**	0.80
AI 8	Indicator(s) to determine how many animals should be on your land	0.76
AI 9	Indicator(s) to determine how many herds animals should be in*	*0.41*
AI 10	Indicator(s) to determine how long animals graze each paddock before moving**	0.66
AI 11	Indicator(s) to determine how long paddocks should rest before being re-grazed**	0.90
AI 12	Indicator(s) to determine which paddocks should be temporarily removed from the grazing rotation and for how long**	0.80
AI 13	Indicator(s) to determine size and number of paddocks to use*	*0.50*
AI 14	Indicator(s) to determine the timing of grazing events in each paddock**	0.80
AI 15	What, how and/or when to monitor	0.90
AI 16	The overall goals of their operation	1.00

* = indicators removed from further analysis due to having scores $k < 0.60$
** = indicators that were excluded from aggregation for continuous grazing operations

as a predictor variable to evaluate whether AMI values explain additional variance in element centrality beyond what can be attributed to demographic or operational characteristics. By comparing the models, this hierarchical approach isolates the unique contribution of adaptive management implementation to element centrality beyond what can be attributed to sociodemographic factors alone.

Results

Identifying constructs, generating indicators, and validating index content

The five phases of adaptive management derived from the literature were planning, implementation, monitoring, evaluation and adjustment. Eighty indicators of the application of four of these adaptive management phases were also identified: 23 indicators for planning, 32 indicators for monitoring, 9 indicators for evaluating, and 16 indicators for adjusting (Table 1). Key planning indicators focus on goal setting, inventorying forage resources, predicting management outcomes, and setting decision triggers for adjusting management actions. Key monitoring indicators focus on measurement or observation of aboveground biodiversity, forage, soil, water and weather conditions, and personal wellbeing, as well as financial and grazing management record keeping. Key evaluation indicators focus on assessment of monitored data, management plan and outcomes achieved. Key adjustment indicators focused on the modification of management actions, decision triggers, monitoring approach, and overall goals. Content validation conducted by the panel of grazing management professionals determined that 16 of the identified indicators had a modified kappa statistic below 0.60, indicating they are not sufficiently representative of the respective adaptive management phase (Table 1). Ultimately, 64 indicators (80%) were included in the producer survey: 20 for planning, 25 for monitoring, 8 for evaluation, and 11 for adjustment (Table 1).

Constructing the adaptive management index

The KMO measure of sampling adequacy was 0.902 and Bartlett's Test of Sphericity was highly significant (14 503; $p < 0.001$), indicating sufficient correlation between the indicators for conducting principal components analysis. The 64 indicators converged into ten components (Table 2;

detailed indicator contribution to these components are presented in supplemental Table S1). The ten components explained almost 80% of the variance across the 236 respondents included in the analysis. Component 1 explains 26.6% of the variance among managers studied and consists of indicators related to the planning, monitoring, and adjustment of grazing management actions (PI 19–23, MI 29–32, AI 4–7, AI 10–14), which are specifically applicable to rotationally grazed systems. Component 2 explains 12.0% of the variance and consists of indicators related to monitoring the amount of substitutional feeding required (MI 25) and evaluating monitored data and the effectiveness of management actions (EI 1–7, 9). Component 3 explains 8.6% of the variance and consists of indicators related to financial and operational record keeping (MI 18–23, 26). Component 4 explains 8.4% of the variance and consists of indicators related to ecological and animal well-being monitoring (MI 1–3, 5–7, 11, 13–15). Component 5 explains 6.3% of the variance and consists of indicators related to planning for the impact of management actions on economic, ecological, and social conditions (PI 11, 14–16), and monitoring labor requirements (MI 24). Component 6 explains 4.7% of the variance and consists of indicators related to establishing short-term economic and ecological goals for the operation (PI 4–5). Component 7 explains 4.1% of the variance and consists of indicators related to planning for and monitoring social well-being (PI 3, 6, MI 17). Component 8 explains 3.1% of the variance and consists of indicators related to adjusting stocking rate (AI 1, 8). Component 9 explains 3.1% of the variance and consists of indicators related to establishing long-term economic and ecological goals for the operation (PI 1–2). Finally, component 10 explains 2.3% of the variance and consists of indicators related to using grazing management as a tool to achieve ecological and economic goals for the operation (PI 7, 8).

PCA was used as a data reduction technique to identify the most informative indicators of adaptive management. All indicators loaded onto components with eigenvalues greater than or equal to one (Table 2). Therefore, all 64 indicators were retained for further analysis. These indicators were subsequently organised into the Adaptive Management Index (AMI) according to the four core phases of the adaptive management cycle. Indicators associated with each phase were averaged to generate composite scores representing the degree of implementation for that specific phase. For example, all indicators classified under Planning were combined to compute the Planning phase subscore, with the same approach applied to Monitoring, Evaluation, and Adjustment. The assignment of indicators to their respective adaptive management phases is detailed in Table 1. The values for each phase were then averaged to calculate the overall Adaptive Management Index score for each respondent.

Average values for each of the four phases of adaptive management and the AMI are presented in Figure 1. Planning phase values for grazing managers in the study ranged from 1.70 to 5.00 (M = 4.14, SD = 0.71), monitoring phase values ranged from 1.78 to 5.0 (M = 4.10, SD = 0.68), evaluation phase values ranged from 1.00 to 5.00 (M = 3.46, SD = 1.10), and adjustment phase values ranged from 1.00 to 5.00 (M = 3.97, SD = 0.87). The cumulative AMI values ranged from 1.00 to 5.00 (M = 3.85, SD = 0.80). A repeated measures ANOVA revealed a statistically significant difference in mean scores across the four adaptive management phases – Planning, Monitoring, Evaluation, and Adjustment ($p < 0.001$). Post-hoc pairwise comparisons using Bonferroni-adjusted paired *t*-tests indicated that Evaluation scores were significantly lower than all other phases ($p < 0.001$), suggesting that producers implement Evaluation practices less frequently than other components of adaptive management. The relatively low number of indicators in the Evaluation phase ($n = 8$) may have contributed to this result, since responses to one or two items would carry proportionally greater weight than in phases with more indicators. Adjustment scores were also significantly different from Planning and Monitoring ($p = 0.0035$ and $p = 0.0318$, respectively), while no significant difference was observed between Planning and Monitoring. These results suggest that while producers tend to engage similarly in planning and monitoring activities, evaluation and adjustment remain less developed, with evaluation emerging as the most limiting phase of adaptive management implementation.

Table 2: Results of factor analysis using principal component analysis extraction method with a varimax rotation. The adaptive management indicators resulted in 10 factors that explain 79.13% of the variance in the data

Component	Eigenvalue	% of Variance	Cumulative %
1	17.02	26.59	26.59
2	7.70	12.03	38.62
3	5.52	8.63	47.25
4	5.40	8.44	55.69
5	4.00	6.25	61.94
6	2.98	4.66	66.60
7	2.61	4.08	70.68
8	2.00	3.12	73.80
9	1.95	3.05	76.85
10	1.46	2.28	79.13

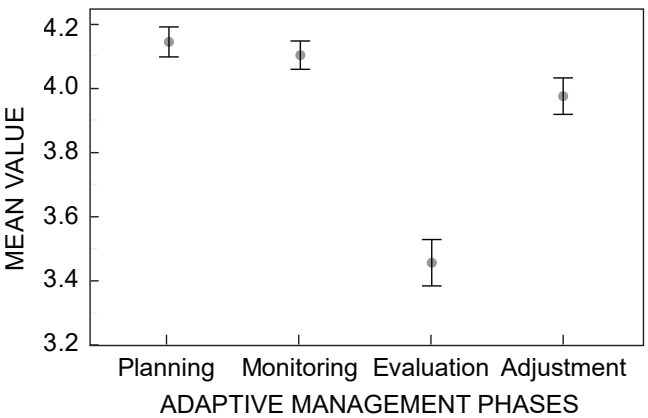

Figure 1: Average values and associated error bars for each of the four adaptive management phases. The evaluation phase values are significantly lower than the other three phases ($p < 0.001$)

Validating index construct

To assess the construct validity of the AMI, we used hierarchical multiple regression to examine the relationship between AMI values and grazing system element centrality

Table 3: Hierarchical multiple regression output for predicting the centrality of the five grazing system elements in respondents' mental models of grazing systems. Model 1 contains only demographic and operation characteristics as predictor variables. Model 2 contains demographic and operation characteristics and the adaptive management index

Variables	Livestock-related profitability		Animal numbers on land		Attention to grazing management		Ecosystem function		Herbaceous biomass production	
	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
Age (years)	0.094	0.095	0.114	0.120	0.002	0.006	0.046	0.061	0.031	0.041
Gender (0 = female; 1 = male)	0.059	−0.006	0.037	−0.035	0.034	−0.026	−0.046	−0.123	0.002	−0.075
Education (years)	−0.039	−0.046	0.044	0.039	0.050	0.050	0.107	0.109	0.109	0.109
Ranching heritage (generations)	−0.036	−0.106	0.006	−0.074	0.022	−0.045	0.108	0.020	0.031	−0.059
Size (acres)	0.145	0.120	0.012	−0.018	0.063	0.041	0.148	0.110	0.183*	0.141
Gross livestock sales ($1 000)	−0.021	−0.038	0.049	0.027	0.091	0.073	0.105	0.075	0.021	−0.006
Income from beef (%)	0.147	0.145	0.108	0.107	0.145	0.144	0.107	0.118	0.096	0.104
Ownership (years)	−0.002	0.018	−0.028	−0.003	0.023	0.044	−0.051	−0.034	−0.144	−0.125
Current management (years)	−0.165	−0.151	−0.085	−0.070	−0.183	−0.169	−0.110	−0.100	−0.056	−0.043
Adaptive management index (AMI)		0.237**		0.265**		0.229**		0.326***		0.329***
R^2	0.074	0.121*	0.033	0.092	0.080	0.124*	0.107*	0.198***	0.076	0.169**
Δ r^2		0.047		0.059		0.044		0.091		0.093
Adjusted r^2	0.017	0.060	−0.025	0.031	0.024	0.065	0.052	0.143	0.019	0.112

Note: The listed values for the dependent variable in each column represent the standardized regression coefficient. * = p <0.05, ** = p < 0.01, *** = p < 0.001

derived from the survey-based closed cognitive mapping exercise. Centrality scores represent producer perceptions of interconnectedness or overall importance of five key elements within grazing systems: livestock-related profitability, animal numbers on land, attention to grazing management, ecosystem function, and herbaceous biomass production. Table 3 presents the results of two-step regression models with grazing system elements shown as dependent variables.

For livestock-related profitability, Model 1 explained 7.4% of the variance in centrality ratings but was statistically not significant. Inclusion of AMI in Model 2 improved the model (ΔR^2 = 0.047) with AMI emerging as a significant predictor of this element's centrality (p < 0.01). A similar pattern was observed for animal numbers on land. Whereas, Model 1 explained a non-significant portion of the variance (R^2 = 0.033), Model 2 accounted for 9.2% of the variance. The AMI was a significant predictor of this element's centrality (p < 0.01), indicating that AMI values and the importance of stocking rates in producers' mental models are positively associated. For attention to grazing management, inclusion of AMI in Model 2 improved the model (ΔR^2 = 0.044), with AMI again serving as a significant predictor (p < 0.01). For ecosystem function, Model 1 was statistically significant (p < 0.05), and adding AMI further improved model fit (ΔR^2 = 0.091) and AMI was a strong and significant predictor (p < 0.001). Finally, for herbaceous biomass production, Model 1 explained 7.6% of the variance with size of grazing operations emerging as a statistically significant predictor (p < 0.05). The inclusion of AMI improved the model (ΔR^2 = 0.093), with AMI again demonstrating a strong positive association with this element centrality (p < 0.001).

Across all five grazing system elements identified above, the addition of AMI significantly improved model fit. These results indicate that individuals with higher AMI scores perceive greater interconnectedness and importance of these elements in their mental models of grazing system dynamics. This finding supports the construct validity of the AMI by linking it to mental model complexity, an indicator of learning in adaptive management.

Discussion

Clarifying adaptive management implementation

Adaptive management frameworks have been applied across many natural resource contexts – from species and freshwater conservation to ecosystem restoration and rangeland management (Kingsford et al. 2011; Roux and Foxcroft 2011; Runge 2011; LoSchiavo et al. 2013; Thomann et al. 2020; Derner et al. 2022). Despite variation in terminology (e.g. strategic adaptive management, adaptive co-management), all frameworks share five foundational phases: planning, implementation, monitoring, evaluation, and adjustment (Armitage et al. 2009; Innes and Booher 2010; Fabricius and Cundill 2014; Fernández-Giménez et al. 2019). Critically, these phases are iterative to support learning and improved decision making under uncertainty.

In livestock grazing systems, adaptive management is often conflated with specific grazing methods, particularly rotational or multi-paddock systems. However, adaptive management is a process, not a grazing method, and can be implemented regardless of grazing system structure. Managers of

continuous systems can plan, monitor, evaluate and adjust actions just like those using rotational strategies. Conversely, while rotational grazing has more capacity to be flexible, it is not inherently adaptive. Rotational grazing systems may be implemented prescriptively without applying adaptive processes. By decoupling adaptive management implementation from grazing method, the AMI offers a more precise lens through which to assess the drivers of ecological and economic outcomes in grazing systems. This enables more targeted research and extension programmes focused on improving decision-making processes rather than prescribing specific grazing practices.

This study reinforces that adaptive management should be evaluated based on the degree to which its core phases are implemented, not by the grazing method employed. It also builds on previous work that established criteria for broadly evaluating adaptive management phases by developing explicit metrics for measuring each phase of adaptive management for livestock grazing systems (Chaffin and Gosnell 2015).

Key findings on AMI and its components

This study addressed a long-standing gap in adaptive management research by offering a tool for quantifying the implementation of adaptive management at the ranch level – a previously unmeasured but critical factor in grazing system outcomes. Drawing on 64 validated indicators, the AMI quantifies the planning, monitoring, evaluation and adjustment phases of adaptive management as practised by livestock producers. While the complete set of 64 indicators was necessary to establish a robust foundation for measuring adaptive management, we recognise that this number may limit the practicality of the AMI for routine application. Future research should test this practicality and refine the index as needed by identifying a streamlined subset of indicators that retain diagnostic power while improving usability for producers, extension professionals and agencies.

Among the adaptive management phases, evaluation scored the lowest. This is notable because evaluation allows managers to compare predicted with actual outcomes using monitored data, which is vital for promoting iterative reflective learning about when and how to adjust management in the face of uncertainty (Roux and Foxcroft 2011; Williams and Brown 2018). The lower evaluation scores highlight a critical gap in the feedback loop between monitoring, learning and management (Nie and Schultz 2012; Fernández-Giménez et al. 2019). Without strong evaluation practices, the transition from action to learning is weakened, constraining decision-making improvement and long-term resilience.

This pattern may reflect the relative difficulty of evaluation practices compared to planning or monitoring, as evaluation often requires synthesising diverse types of information and comparing outcomes to expectations, which can be resource- or time-intensive. The relatively small number of evaluation indicators may have contributed to this result. Nonetheless, the findings are consistent with previous research highlighting producer challenges in interpreting and applying monitoring data (Smith et al. 2023), suggesting that evaluation remains an area of concern warranting greater attention. Strengthening support for producer evaluation skills and tools could therefore be an important focus for outreach programmes seeking to advance adaptive management.

Incorporating predetermined decision triggers into the planning phase may help facilitate the connection between monitoring and adjustment and, thereby, lead to more effective implementation of adaptive management. Decision triggers are management thresholds identified by predetermined levels of resource status that signal when it is necessary to adjust management actions to avoid undesirable outcomes (Cook et al. 2016; Foster et al. 2019). Decision triggers may enhance producers' ability to interpret monitoring data and act in a timely, goal-oriented manner, thereby closing the feedback loop that links observation to action.

Importantly, the AMI maintains comparability across grazing method by excluding rotational-specific indicators for continuously grazed systems. This ensures that AMI scores reflect adaptive decision-making processes rather than structural features of grazing systems. Finally, indicators related to evaluation and adjustment explained more variation among producers than those related to planning or monitoring, indicating that the subsequent phases of the adaptive management cycle may differentiate more experienced or engaged managers.

Linking AMI to learning and mental models

A major contribution of this study is the empirical link between adaptive management implementation and mental model structure. Higher AMI values were significantly positively associated with increased centrality of five key grazing system elements in producers' mental models of grazing systems – profitability, animal numbers, grazing management, ecosystem function, and biomass production. This positive association suggests that producers who more fully implement adaptive management have a more integrated and interconnected understanding of grazing system dynamics. This aligns with theoretical claims that adaptive management fosters double-loop learning by shifting not only management actions but also underlying assumptions and perceptions of system connectivity (Sterman 1994; Fernández-Giménez et al. 2008).

These findings are corroborated by Stanley et al. (2024) who examined how holistic management (HM) influences ranchers' mental models in California. Their qualitative analysis revealed that the HM decision-making framework facilitated learning, leading to shifts in how ranchers perceived their land and made management decisions (Stanley et al. 2024). This study provides quantitative evidence of a similar learning dynamic: higher AMI values were associated with more integrated mental models of grazing system dynamics. Together, these studies offer converging evidence that adaptive management is a learning process that reshapes how producers perceive and understand grazing systems. This highlights the value of the AMI as a tool that enables a more complete understanding of how producers learn, adapt and make decisions in complex grazing environments.

Learning and adaptation are widely recognised as cornerstones of social-ecological resilience (Adger 2000; Biggs et al. 2012; Keck and Sakdapolrak 2013; Cundill et al. 2015; Pauley et al. 2019). Consequently, embedding adaptive management processes in grazing systems is expected to strengthen their capacity to maintain ecological function in the face of increasing climatic disturbances, such as drought. The CARM experiment illustrates this potential. By deliberately integrating diverse knowledge and experience throughout

the planning, monitoring, evaluation and adjustment phases, CARM fostered social learning that directly informed collective decisions and management adjustments (Wilmer et al. 2018). To facilitate learning and adaptation in regions dominated by privately owned ranches where a formal multistakeholder approach is impractical, peer-to-peer networks and communities of practice can play an analogous role. Exchanging experiences and data within such groups may accelerate the single-, double- and triple-loop learning cycles that underpin adaptive management and, ultimately, enhance system resilience (Reed et al. 2010; Cundill and Rodela 2012; Cundill et al. 2015; Gosnell et al. 2019).

Practical applications and implications for advancing grazing management

This study contributes to the adaptive management literature in several important ways. First, it identifies specific indicators of adaptive management implementation that are linked to producer learning about the dynamic complexity of livestock grazing systems. Second, it introduces a structured and repeatable approach for quantifying the extent of implementation across the adaptive management processes. This allows researchers to disentangle the effect of grazing methods from adaptive management processes on ecological and economic outcomes, thereby improving understanding of how different management strategies shape system behaviour. More broadly, this work addresses critical knowledge gaps by offering clearly defined and communicable indicators of adaptive management implementation that can guide future research and outreach. Applying the AMI to characterise contrasting management strategies will also strengthen the ability of research to generate actionable management implications and translate findings into on-the-ground practice.

In theory, adaptive management processes facilitate social-ecological system resilience in the face of disturbances such as drought. For producers, the AMI may help guide the incorporation of specific elements related to planning, monitoring, evaluation and adjustment processes into their operations thereby strengthening their capacity to economically and ecologically persist through drought. In practice, the ability of producers to stay in business under uncertain and variable conditions is often enhanced by the adaptive capacity that stems from resilience-building strategies such as proactively planning for drought contingencies, monitoring resources and engaging in continuous learning to improve decision making. By supporting producers in identifying gaps in these processes and highlighting opportunities for improvement, the AMI can serve as a practical framework to strengthen the strategies that ultimately allow producers to remain viable through ecological and economic challenges.

For extension programmes, AMI indicators can guide outreach and training efforts by targeting the skills and processes that facilitate learning and continuous improvement in management. At the institutional level, agencies and industry-led sustainability initiatives could use AMI indicators to support producers in developing and implementing adaptive grazing management plans, which are increasingly promoted as a pathway toward sustainable livestock production (USRSB 2019). Incorporating AMI indicators into such plans would provide producers with a detailed framework for planning, monitoring, evaluation and adjustment, while also contributing to global efforts to improve the sustainability and resilience of grazing systems.

Assumptions, limitations and future research

The design and interpretation of this study rest on several assumptions and simplifications of management in rangelands. First, the AMI was constructed with a focus on livestock production, which narrows the range of objective and management actions considered and does not fully capture the strategies of producers who manage multiple enterprises, such as wildlife. Second, the survey indicators necessarily simplified the diversity of information sources that producers may use when planning, monitoring, evaluating and adjusting management decisions. The indicators emphasised the actions taken, rather than the underlying data or information sources that informed those decisions. Third, the survey targeted a single decision maker per ranch, under the assumption that this individual was most responsible for management choices.

Several limitations of the research presented here warrant attention to guide future research. First, relying on responses from a single decision maker per ranch constrains the analysis by excluding the broader range of perspectives that often shape management when decisions involve households or multiple stakeholders. Future refinement of the AMI could incorporate these additional perspectives to provide a more comprehensive understanding of adaptive management at the ranch level. Second, excluding producers with less than 247 acres reduced the usable sample size and limited generalisability to smaller-scale operations. The intention was to gather data on livestock producers who earned a substantial proportion of their household income from their livestock operation. However, 62% of livestock producers operate on less than 220 acres (USDA NASS 2017). Obtaining data from producers with smaller properties could increase the useable sample size and, therefore, enable the further development of the AMI, especially with respect to the increasing number of producers who own smaller properties. Third, self-reported perceptions of implementation may not fully align with actual practice. Although this may limit the power of the AMI to rigorously quantify the implementation of each indicator, in the absence of a comprehensive measure of adaptive management implementation, the AMI is a robust alternative. Future research should test the AMI directly against measures of forage production, livestock performance and ecosystem health. Fourth, the compensatory aggregation method used may mask deficiencies in specific phases. Future versions of the AMI may benefit from partial or non-compensatory aggregation techniques. Finally, due to identified non-response bias, with respect to proportion of total household income derived from beef cattle, extrapolating the results of this study to a larger population should be done with caution because landowners with less income from cattle may not be well represented by the AMI presented here. Future research should test the AMI across broader geographic regions, incorporate longitudinal assessments to evaluate learning over time, and explore the role of peer learning structures in promoting adaptive management.

Conclusion

This study addressed the long-standing challenge of defining and quantifying adaptive management in grazing systems by introducing the Adaptive Management Index (AMI). By translating general adaptive management principles into 64 grazing-specific indicators, the AMI offers a standardised and repeatable tool for evaluating implementation across diverse operations. The AMI has important implications for both research and practice. For researchers, it provides a framework to disentangle adaptive processes from grazing methods, thereby enabling more rigorous assessment of the drivers of ecological and economic outcomes and supporting actionable research findings. For practitioners and extension programmes, the AMI can be used to identify strengths and gaps in adaptive management implementation and guide continuous improvement over time. Agencies may also use AMI indicators to design programmes that better support adaptive capacity in ranching communities. Future research should test the AMI against ecological, production and resilience outcomes across broader geographic regions and through longitudinal designs to assess learning over time. Such applications will refine the index, enhance its relevance for producers managing under uncertainty, and strengthen its value as a tool for advancing adaptive management in grazing systems. By providing a standardised approach to measure adaptive management implementation, the AMI enables more effective evaluation of the processes within grazing strategies that are foundational to building resilience.

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