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Original Research

Agent-Based Modeling as a Tool for Ecological Comanagement of Grazing Lands

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ABSTRACT

Rangeland management necessitates addressing complex and dynamic social-ecological challenges and opportunities at scales appropriate to target landscapes. We combine geospatial and climate data in an agent-based system dynamics model to simulate temporally and spatially scalable rangeland human-environment-animal-forage relationships. Modeling highly variable grazing system elements requires both adaptability and mathematical realism. Agent-based modeling makes it possible to test alternative approaches to real-world scenarios without taking risks associated with actual experimentation on working operations. Our agent-based model, Ecological Comanagement of Rangelands, or *ECo-Range*, allows managers to simulate cattle grazing scenarios by setting environmental conditions and management decisions that affect simulation outcomes. In this sense, ECo-Range is not just a product of scientific inquiry, but a tool to be used for collaborative discovery, as it illuminates relationships among environmental conditions, management decisions, and ecological and livestock outcomes for modeled landscapes. ECo-Range explores the complexities of grazing management, embracing rather than excluding variability and heterogeneity inherent in rangeland social-ecological systems. We first present ECo-Range, explaining the model's relevance to the fields of simulation modeling and rangeland management. We then present a case study on the Colorado Front Range as proof of concept to test the utility, validity, and applicability of ECo-Range as a learning tool to explore scenarios related to government-owned landscapes that necessitate comanagement approaches to cattle grazing.

Introduction

Rangelands cover about 54% of the Earth's land surface (ILRI et al. 2021), supporting human and animal life and global ecological processes. Rangelands are typically managed as natural ecosystems and include diverse grazable grassland, forestland, shrubland, and desert lands that span elevation gradients from marshes to alpine communities (Society for Range Management 1998). Rangelands are water-dependent ecosystems, where seasonality, intensity, and high interannual variability of precipitation influence land use practices (Ellis and Galvin 1994; Hobbs et al. 2008). Though rangelands provide a myriad of ecosystem services (Goodwin et al. 2023), pastoralism, or ranching, is one way in which people who live in rangeland systems have found utility in these landscapes, in this case for the provision of high-quality food sources and animal by-products (Hobbs et al. 2008).

In the western United States (and globally), cattle grazing can contribute to the maintenance of rangeland ecosystems that evolved with grazing, while producing food for expanding local and global human populations (Environment Colorado Research and Policy Center 2006; Gibson 2009; Knapp et al. 1999; Towne et al. 2005). However, agriculture and natural resource conservation objectives can be paradoxical, where some food production methods can result in massive disturbance, degradation, and even conversion of large landscapes and ecosystem processes. This paradox is complicated by a body of literature on the dynamics of cattle grazing and effects on the environment that present sometimes conflicting evidence and conclusions (Abdalla et al. 2018; Cusack et al. 2021; Daniel et al. 2002; Derner et al. 2018; Derner et al. 2006; Pietola et al. 2005; Porensky 2020; Reeder et al. 2004; Sharrow

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2007; Teague et al. 2016; Teague et al. 2011). Inconsistencies in research and anecdotal cattle management outcomes may result from a lack of systems-thinking that integrates the complexity of rangeland social-ecological dynamics (Briske et al. 2008a; Teague et al. 2013).

Cattle are a top agricultural commodity in much of the western United States (United States Department of Agriculture 2017), and evaluating their role in grassland ecosystem sustainability is crucial. However, such evaluation has historically excluded the dynamic human decision-making dimension in favor of adhering to more controlled scientific methods (Briske et al. 2008b; Teague et al. 2013; Wilmer et al. 2019). Furthermore, in a published discussion on the book, *Politics of Scale: A History of Rangeland Science,* it was emphasized that environmental challenges on rangelands are primarily driven by human behavior and social dynamics, rather than solely by ecosystem processes (Hudson 2019). These perspectives highlight the importance of incorporating human decision-making in rangeland evaluation more explicitly.

Simulating social-ecological systems

Rangeland management necessitates addressing complex and dynamic social-ecological challenges and opportunities at relevant spatial and temporal scales. We believe that system dynamics modeling is an ideal tool for such applications. System dynamics modeling was first conceptualized by Forrester (1961) in the field of industrial management. Forrester's basic premise was that we can better understand complex phenomena if we examine the behavior of a system over time and under various conditions. Forrester claimed that we can avoid conflict between short-term and long-term goals through systems modeling (Doerr 1996; Forrester 1961). The social and ecological outcomes of complex system processes are not easily predicted nor understood as they span large spatial and temporal scales (Jablonski et al. 2018; Lynn et al. 2010; Miller and Frid 2022; Schrieks et al. 2021). Therefore, modeling of these systems poses many challenges due to nonlinear feedbacks, interactions that lack independence, and spatial and temporal heterogeneity (Levin et al. 2013; Miller and Frid 2022).

Systems modeling in the broadest sense includes approaches such as symbolic modeling, simulation modeling, computational simulation, dynamical systems modeling, bioeconomic modeling, chain modeling, structurally realistic modeling, and integrated modeling (Boone and Galvin 2014; Schlüter et al. 2019). A common denominator of these diverse approaches is that they can be used to better understand the role of humans in natural systems (An et al. 2021; Boone and Galvin 2014). When we create systems models to simulate livestock grazing management, we need to consider a broad set of theoretical, practical, and ecological variables, where domestic livestock are the agents of biophysical change.

Livestock agency, however, is affected by human management decisions and interactions with environmental stochasticity. This complexity creates an ideal canvas for a unique form of modeling—agent-based modeling (ABM), where computer code rooted in mathematics is used to represent relationships derived from real-life processes. These are integrated into a virtual passage of time that moves forward in discrete steps, leading to a series of progressive and sequentially-dependent outcomes for the landscape of interest (Boone and Galvin 2014). The analytical process that ensues in ABM reflects interactions among system components such as decision-making and biophysical processes, and can deepen understanding of multiple relationships within a dynamic system (An et al. 2021; Boone and Lesorogol 2016; Miller and Frid 2022).

Extensive literature reviews have assessed ABM as a tool to explore agriculture and rangeland social-ecological or coupled human and natural systems (An 2012; Monlezun 2022; Schrieks et al. 2021). These reviews support ABM's utility for the multiscalar, interdisciplinary, and dynamic relationships between humans and nature (An 2012; Schrieks et al. 2021). ABM is particularly effective for the simulation of landscape processes in which individuals, or *agents,* interact with each other and the conditions of a constantly changing environmental matrix (Dumont and Hill 2004; Miller and Frid 2022; Schlüter et al. 2012). Relationships between variables come to life through computational flexibility and an engaging interface where the user may define scenario inputs, visualize unfolding processes, and evaluate the state of the virtual system via outputs. Parameters and thresholds may be modified with the click of a button to explore alternative conditions scenarios representing a range of potential realities. The inclusion of manipulatable elements and thresholds representing human decisions, such as the addition or subtraction of stock, pasture divisions, and watering locations may add further complexity to an ABM yet represent the realities of managed grazing systems.

ABM can model individual decision-making while incorporating heterogeneity and feedbacks, which can provide an insightful, knowledge-building approach in increasingly unpredictable environments. ABM combines data-driven realism with spatially-explicit simulation of interactions and dynamic patterns of social-ecological systems (An et al. 2021; Miller and Frid 2022; Sakamoto 2016), and may be used to inform stakeholder decision-making based on their context-specific questions.

Introducing the ECo-Range model

Our project aimed to embrace rather than exclude the social-ecological complexities of grazing systems in Western landscapes, thereby addressing complex and dynamic social-ecological challenges and opportunities at scales appropriate to target landscapes. Our model, Ecological Comanagement of Rangelands, or *ECo-Range*, combines geospatial and climate data in an agent-based system dynamics model to simulate temporally and spatially scalable rangeland human-environment-animal-forage relationships. In this article, we present ECo-Range and apply it to a local landscape on the Colorado Front Range as proof of concept to test the utility, validity, and applicability for managers of this temporally and spatially explicit application. We establish grazing management scenario options based on a case study typical of government-owned lands allotments that necessitate collaborative approaches to management between rancher producers and government agency personnel (Monlezun et al. 2024).

ECo-Range includes options for environmental conditions (i.e., precipitation level and seasonal precipitation pattern) and management decisions (i.e., cattle numbers, and landscape fragmentation level) that correlate to initial stock density and grazing intensity. In the Colorado case study, ECo-Range simulates a single 5-month (150-day) on-range grazing season and produces measurable outcomes including variables reflective of both livestock and environmental drivers. Outcomes include quantity of residual forage biomass, animal performance, and degree of residual vegetation heterogeneity. Residual forage biomass indicates how much above-ground biomass remains following a grazing event. Animal performance is assessed by a calculation of the mean individual cow mass across the simulated herd. Residual vegetation heterogeneity, an important indicator for wildlife habitat conservation (Toombs et al. 2010), is evaluated using an index of dispersion calculation. The utility and adaptability of ECo-Range lies in its ability to answer a multitude of stakeholder questions.

ECo-Range is a product not only of scientific inquiry but it is also informed by and designed for social learning and collaborative discovery. Grazing management is highly complex, reflecting an alchemy of social and ecological values, drivers, and perceived outcomes. ECo-Range uses a combination of geospatial data and ABM to explore these complexities, incorporating the variability and heterogeneity inherent in social-ecological systems, and particularly rangeland systems.

Methods: Agent-Based Model Protocol

Our methods follow a standard ABM description protocol: the Overview, Design Concepts, and Details (ODD) protocol (Grimm et al. 2017). The elements of Grimm's ODD protocol guide documentation, publication, and replication, although not every category applies to every ABM (Grimm et al. 2020).

Purpose

ECo-Range was developed as an investigative and educational tool for rangeland stakeholders to gain insight into human-environment-animal-forage dynamics of cattle grazing systems under various environmental and decision-making scenarios. We use the model to answer the overarching question: *How do select cattle management and land use decision scenarios affect grazing system outcomes under various environmental conditions?* ECo-Range is intended to simulate grazing system dynamics in specific ecological and geographical contexts, where the human decision-making dimension—the input of stakeholders or managers—is influential in the ecological (animal and land-based) outcomes of cattle grazing. These dynamics are demonstrated through scenario manipulations involving cattle number, division of pastures (number, size, and arrangement), water source locations, and forage availability, alongside programmable manipulations in precipitation patterns, forage consumption rates, cattle weight gain/loss, forage regrowth rates, and pasture rotation thresholds.

Entities, state variables, and scales

ECo-Range contains two entities: *agents* representing cattle and *patches* representing portions of the grazing landscape through which agents move to access resources. The following cattle and landscape parameters were calibrated and verified collaboratively with the ranch manager (NT) of the case study landscape, as well as through literature.

Agents

Each model agent represents a 250 kg *cow*, signifying a weaned calf in the Lowry Ranch case study, with a forage consumption rate of 2.5% of its body weight (Launchbaugh 2014; Rasby 2013). *Cow* is the word embedded in model code as a net term to capture the generic bovine in common language. This parameter can be modified to fit other ranch contexts, and any stage of cattle production may be modeled simply by changing this starting weight coefficient.

Two components formed the foundation of the ECo-Range landscape, which contributed geographical and data-driven realism to modeling scenarios: 1) *area of interest* and 2) the *landscape texture*.

Area of interest

As proof of concept, ECo-Range was designed to represent a context-specific grazing landscape, the Lowry Ranch in Colorado. We created our simulated landscape in NetLogo 6.2.0 (Wilensky 1999) using methods that can be replicated on other ranches, rangeland study sites, and other regions across the globe with proper parameterization to local conditions. Lowry Ranch is a property of the Colorado State Land Board acquired in three separate transactions in 1964, 1966, and 1991 (Colorado State Land Board 2020). Located on the Colorado Front Range, Lowry Ranch is characterized by a semiarid climate with mild winters, low annual precipitation, low humidity, high evaporation, and periodic droughts (Mladinich 2006; Montgomery et al. 2016; Soil Survey Staff 1999). Climate models predict that interannual variability and extreme weather conditions in this region will continue to increase throughout this century (Derner et al. 2018; Klemm et al. 2020), posing increased challenges for rangeland management.

Lowry Ranch has a long diverse history as farm and ranch land prior to the drought of the 1930s, then as an army airfield and experimental bombing range from 1938 through World War II and the Korean War, with intermittent leases for livestock grazing (Sovell 2010). It was converted back into ranch land in 1998 under the state's Stewardship Trust and managed exclusively in a continuous grazing regime until 2008 when cattle use was discontinued for the following 6 years (Sovell 2010). In 2014, with a new stewardship initiative with the Colorado Natural Heritage Program and The Nature Conservancy, Lowry transitioned to being *holistically managed*, using a rotational grazing framework that incorporates ecological-social-economic adaptive planning for its 10,463 hectares (Colorado State Land Board 2020). Although Lowry Ranch is a government-owned property whose revenue supports public education, it is not open to the public for recreation due to its focus on ecological stewardship and revenue-driven objectives (Colorado State Land Board 2020).

We defined our ABM area of interest in ECo-Range using geospatial data shared by the ranch, including ranch boundaries and various historical pasture and water location configurations (Fig. 1). We used ArcGIS Pro (Esri 2020) to create additional hypothetical pasture configurations representing different levels of fragmentation (pasture divisions) for scenario development.

Landscape texture

To simulate various rangeland scenarios in which cattle could interact with the model world, we represented forage as the *textural* aspect of the landscape. We used ArcGIS geospatial analysis tools to evaluate Normalized Difference Vegetation Indices (NDVI) (Masek et al. 2006), a graphical indicator of reflected or re-emitted radiation used to assess vegetation quantity and/or quality (Rouse et al. 1974). NDVI for the ECo-Range case study was created from 30 m resolution Landsat satellite imagery (Masek et al. 2006) of Lowry Ranch, which is primarily composed of grassland. Specifically, a graphical layer of mean NDVI from May 17 to June 17 of each year from 2010 to 2020 (except 2011 and 2015, where imagery was damaged due to faulty satellite sensors), was downloaded from Climate Engine (Huntington 2017). This date range was used to simulate vegetative conditions at initiation of the grazing season. ArcGIS Pro (Esri 2020) was used to process imagery for use in NetLogo.

Annual water-year precipitation data from the Byers station of the Colorado Climate Center and the COCoRaHS Network (Community Collaborative Rain, Hail, and Snow Network) Station ID CO-AR-314 on Lowry Ranch headquarters were used to classify *precipitation level* of each NDVI year layer as: *Below Average*, ⟨340 mm; *Average*, 340–430 mm; or *Above Average*, ⟩430 mm. These classes were based around a 29-year (1981–2010) "normal" of 406 mm as reported by the National Oceanic and Atmospheric Administration (Colorado Climate Center 2022).

Pasture boundaries were defined using fence and livestock water geospatial location data obtained from the Colorado State Land Board and formatted for NetLogo using ArcGIS Pro and Microsoft Paint 3D. This combination of input data sources resulted in a spatially explicit model interface reflecting a realistic, to-scale depiction of the Lowry Ranch grazing system (Fig. 2). Each patch in the ECo-Range landscape represents a 30×30 m pixel. NDVI was used as a proxy for biomass (forage) distribution based on a transformation yielding units $g \cdot m^{-2}$ (Boone and Galvin 2014).

Time passage in ECo-Range takes place at two-time scales. *Ticks* represent the passage of time in 1-day increments. Each *redraw* represents animal decision-making during 1 hour of grazing, and

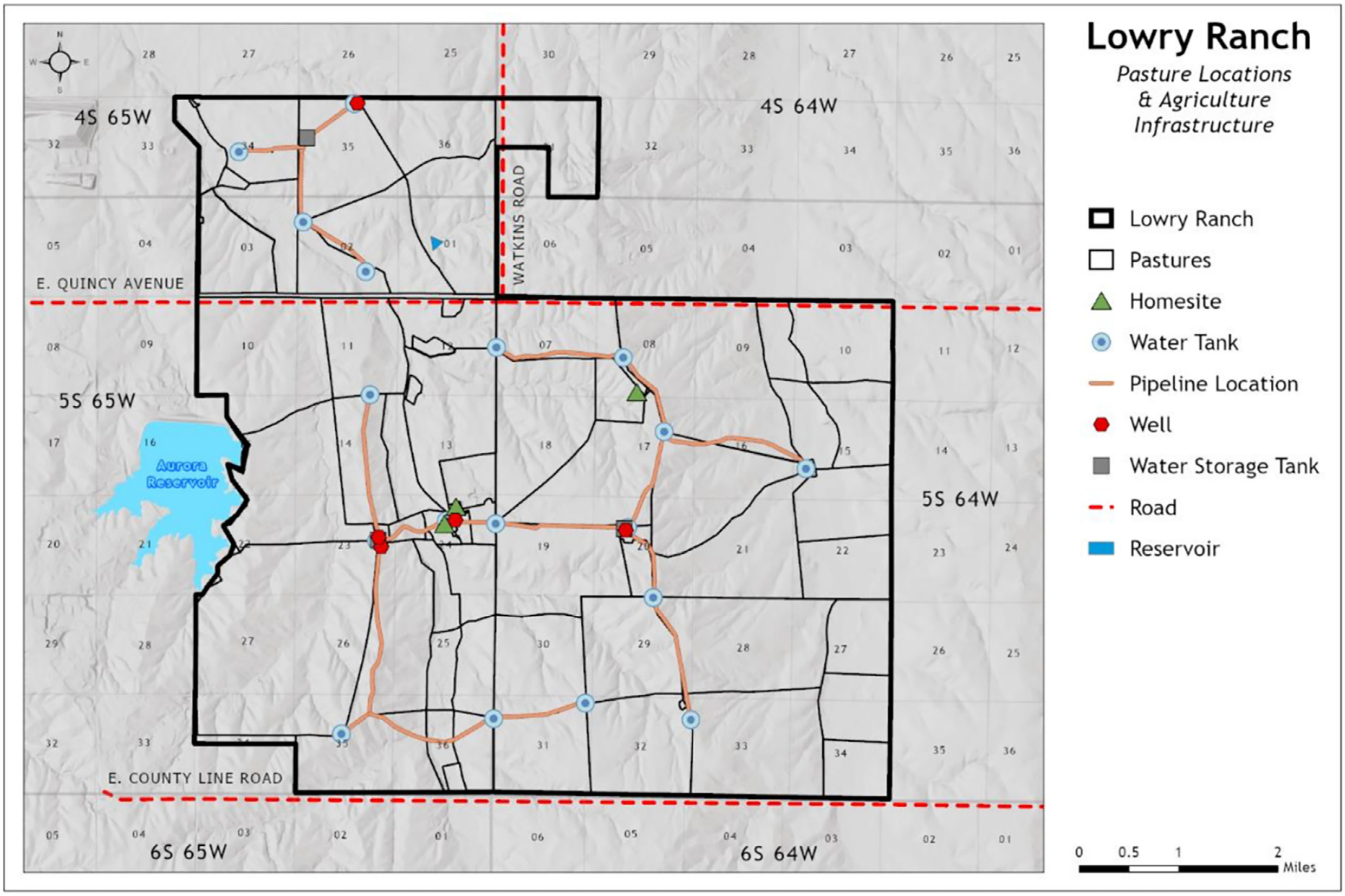

Figure 1. Map of Lowry Ranch, including agricultural infrastructure, used to define the area of interest for our ECo-Range case study. Map provided by the Colorado State Land Board.

Figure 2. Example of ECo-Range interface using Lowry Ranch, depicting a Landsat NDVI geospatial data-sourced landscape with to-scale fence and water point locations, illustrating midsimulation points of observation and observed outcomes. Created in NetLogo 6.2.0.

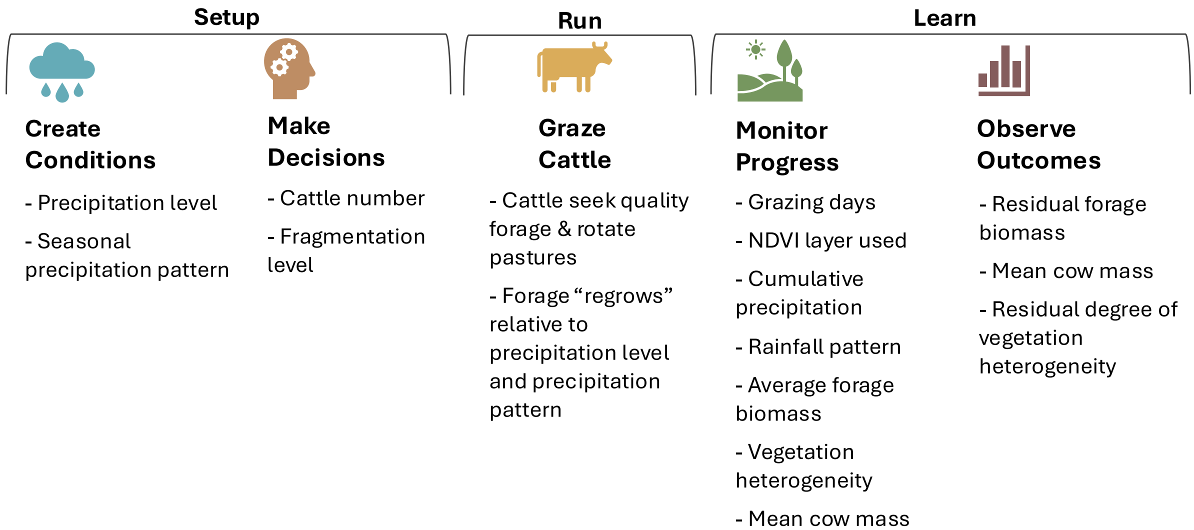

Figure 3. ECo-Range agent-based model process in five phases. Each phase incorporates subphases that are programmed and parameterized mathematically to represent an authentic social-ecological system.

10 progressive *redraws* are coded into each tick. This reflects cattle spending an average of 10 hours per day engaged in herbivory, a research-based standard (Kilgour 2012). Therefore, agents (cattle) are individually coded to interact with 10 patches per day (one patch per redraw), and the biomass of each patch is incrementally reduced to simulate that it has been grazed. This equates to each cow grazing 0.9 ha (approx. 2.2 acres) per day. Cattle are coded to gain, maintain, or lose weight at each redraw depending on patch biomass. ECo-Range assumes that cattle would rest, ruminate, travel, or access water outside of the 10-hour per day simulated grazing period. Therefore, we did not model cattle use of water locations, except to dictate the location where cattle begin grazing in a new pasture. When cattle rotate to a new pasture, they begin at a water location and commence grazing from there. All other animal husbandry activities such as gathering, confinement, or chute work is assumed to occur outside the simulated passage of time.

Process overview and scheduling

The ECo-Range modeling process incorporates five phases to simulate a grazing season: Create Conditions, Make Decisions, Graze, Monitor, and Observe Outcomes (Fig. 3).

Setup. The initial setup of ECo-Range provides landscape parameter manipulations that reflect complexities related to environmental variability and the human dimension in grazing systems. These manipulations can be made in the *Create Conditions* phase and the *Make Decisions* phase, respectively (Fig. 3). The user may select one option from each category in these phases (Fig. 4). For example, the user may manipulate the initial stocking density via the *cattle number* (100–1 500 head) setup option.

Run. The *Graze Cattle* phase represents energy moving through the rangeland system from precipitation to forage to cattle (Fig. 4).

Design concepts

The Design Concepts portion of the ECo-Range model description follows Grimm's ODD protocol, which walks through model elements that should be considered in ABM design (Grimm et al. 2020).

Basic principles

Cattle grazing is a dynamic process that takes place on heterogeneous landscapes. Forage availability and quality are driven by environmental factors and cattle use of that forage, which is co-driven by management decisions involving stocking rate, fencing, and water availability. The sustainability of managed grazing systems depends on human decision-making and adaptation to evolving temporal and spatial conditions, which create feedback loops with ecological outcomes.

Emergence

Potential emergent patterns include relationships between any independent and dependent variables in the model, including, for example, cattle number and residual forage biomass, precipitation level and final average cow mass, landscape fragmentation level and residual vegetation heterogeneity, and residual forage biomass and final average cow mass.

Adaptation

During simulation, agents (cattle) respond to dynamic and stochastic environmental variables. They are encoded to locate the next closest patch of highest biomass at each redraw in a constantly fluctuating and evolving landscape. There is no encoded learning or prediction associated with the model.

Sensing

Cattle are encoded to sense three variables during any given timestep: pasture boundaries, water location, and available biomass, based on the NDVI-informed biomass values associated with each patch.

Interaction

Cattle interact indirectly with each other as they move from patch to patch. They are encoded to avoid patches occupied by another cow.

Stochasticity

A moderate level of stochasticity is used to represent spatial variability in forage biomass and growth rates across the landscape. Available biomass and growth rate variables are dynamic throughout model simulation in response to encoded coefficients, scales, and thresholds. Cattle are encoded to interact with this dynamism. User manipulation of the environmental parameters of

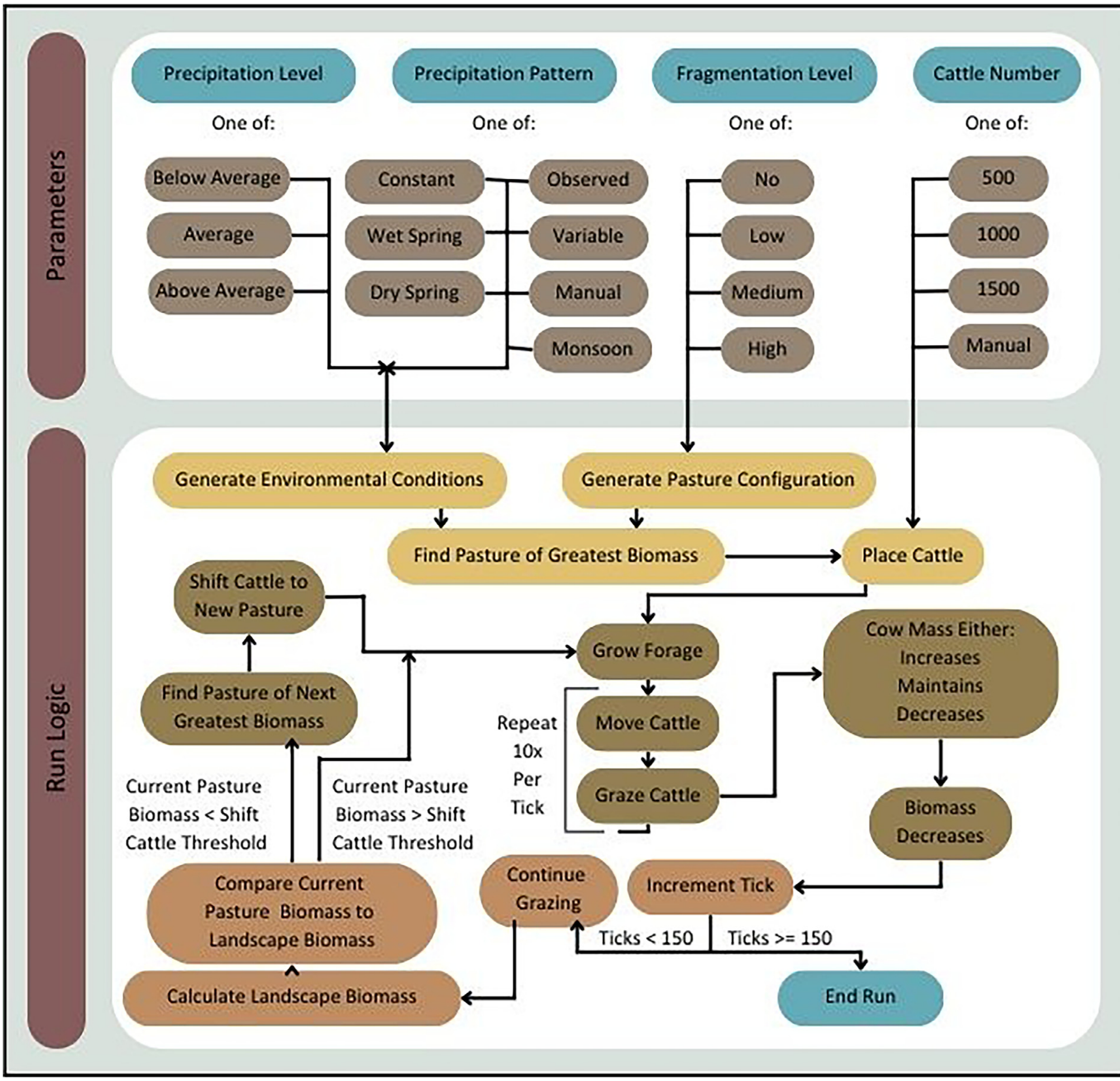

Figure 4. Flow chart describing initialization, *Parameters*, and simulation, *Run Logic*, phases, and subphases of ECo-Range model of grazing systems.

precipitation level and precipitation pattern affects both vegetation heterogeneity and growth rates during simulation. These relationships are conceptually reflective of real rangeland systems. The order in which cattle select a new patch to graze in each time step is randomized to avoid favoring a given individual.

Observation

The *Monitor Progress* phase uses interface monitors and plots to allow the user to track quantitative data in real-time as the simulation evolves (Fig. 3). Five types of data are plotted continuously in the ECo-Range model interface: *mean forage biomass* (across entire landscape), *mean cow mass* (individual), degree of *vegetation heterogeneity* (based on an index of dispersion calculation, the ratio of the standard deviation to the mean), a *precipitation tracker*, and a composite plot of these four variables (Fig. 2). Four numerical monitors are also included: the *NDVI layer used* in the current scenario, the number of *grazing days* in the current simulation, *mean cow mass* and the *cumulative precipitation* since the start of simulation (Fig. 3). Additionally, data are printed to report explicit timestep conditions, including total landscape mean biomass, current pasture mean biomass, and the current 50% threshold needed to trigger a pasture rotation.

The *Observe Outcome* phase evaluates three model outcomes: residual forage biomass, mean cow mass, and residual degree of vegetation heterogeneity (Fig. 3). These dependent variables of interest reflect both ecological and animal performance objectives. From an ecological perspective, greater residual forage biomass and vegetation heterogeneity lead to better outcomes for wildlife habitat and plant-soil nutrient cycling. This brings benefits for the dormant season and the next spring season's growth, contributing to ecological sustainability. From a cattle performance perspective, greater cattle weight gains lead to better outcomes for cattle health and ranch profitability, thereby supporting economic sustainability. The Netlogo BehaviorSpace tool is used to synthesize and report outcome data. For our protocol, these data were further organized in Microsoft Excel and prepared for statistical analysis. R Studio Version 1.3.1093 and the *tidyverse* and *ggplot2* packages were used to produce data summaries and conduct 4-way analysis of variance (ANOVA) with interaction effects (R Core Team 2019).

Initialization

Landscape initialization begins when the model user sets the initial values for four parameters: 1) initial cattle number, 2) annual precipitation level (i.e., below average, average or above average), 3) precipitation pattern (distribution pattern of rainfall over time), 4) landscape fragmentation level (based on number, size, and arrangement of paddocks without a change in total area), and then clicks the *setup* button (Fig. 4). The user first selects a *cattle number* contributing to a specific stock density scenario. When the user selects a *precipitation level,* the model is programmed to randomly select an available NDVI layer associated with that class of precipitation.

The landscape initializes with one of nine NDVI layers associated with *precipitation level*. Based on total rainfall data documented for 10 years, model years were assigned to the following precipitation classes. Total rainfall amounts for years 2012, 2017, 2018, and 2020 form the selection pool for the *below-average rainfall* class. Years 2016 and 2019 form the selection pool for the *average rainfall* class. Years 2010, 2013, and 2014 are allocated to the *above-average* class selection pool. Maximum biomass production is encoded for each landscape patch based on a transformation applied to the NDVI. This yields appropriate forage units ($g \cdot m^{-2}$) which are portrayed in the texture of the NDVI image as varying shades of green (Boone and Galvin 2014). Cattle are coded to begin the simulation at the water source in the pasture with highest mean biomass on the landscape.

The *precipitation pattern* options allow the user to create a scenario that reflects local or regional weather patterns or other hypothetical scenarios of interest (Fig. 4). A series of 15 sequential precipitation sliders, each representing a dekad (10-day) of time, can be set to a range of precipitation quantities over the 150-day simulated grazing period (Fig. 2). Daily rainfall quantities are drawn from a normal distribution based on the slider value as the mean. Average daily rainfall values were derived from climate data as described in the previous section. Alternatively, the user may select one of six preset precipitation patterns, including *constant* (unchanging, used as control scenario), *variable* (random throughout season), *observed* (manually entered to represent a specific scenario of interest), *dry spring* (increasing moisture gradient following low spring moisture), *wet spring* (moisture concentration in spring)*, or monsoon* (moisture concentration in midsummer with moderate spring and late summer moisture).

Next, a fencing and water location map, based on the *fragmentation level* selection, overlays the NDVI base layer. Fragmentation levels were collaboratively designed with the Lowry Ranch manager (NT) to represent four realistic pasture division arrangements for the landscape designated as *no*, *low*, *medium*, and *high* fragmentation (Fig. 5). Fragmentation levels (land area per fenced pasture) combined with cattle number correlate to a modeled stocking density or grazing intensity. Lowry Ranch's *no*, *low*, *medium*, and *high* fragmentation levels reflect a range of scenarios from the least intensive system of an open, nonfenced ranch to an intensive rotational grazing system with numerous small pastures (Fig. 5). Pasture sizes range from one large pasture (approximately 10,400 ha) in the no-fragmented scenario to approximately 50 pastures, each approximately 208 ha, in the high-fragmentation scenario.

Input data and function

Cattle are coded to *move* from patch to patch with each hour, moving to a nearby patch that optimizes the highest available biomass. Thirty-percent of total initial biomass per 30×30 m patch is made available to cattle as forage. This value is sometimes referred to as "consumption rate" (Wockner 2009) or "harvest efficiency" (Bidwell 2017), where the balance of initial biomass is lost to other impacts such as trampling, presence of unpalatable species, decomposition, and use by wildlife that are not explicitly represented in the model. An ECo-Range user may modify the 30% forage availability coefficient to adapt to various research inquiries. For example, it may be reduced to 15% for conservation of wildlife habitat, or it may be increased to 60% if the user wanted to model a higher-impact grazing approach.

Cattle move 10 times over 10 hours per day, simulating the amount of time per day cattle engage in grazing behavior (Kilgour 2012), and remain in the same pasture until the available forage reaches a coded threshold. When a cow first encounters a patch, the biomass of that patch decreases by 0.625 kg, based on a standard daily intake of 2.5% body weight intake rate for a 250 kg animal. At the same time, cattle gain mass, maintain mass, or lose mass based on the current pasture's biomass relative to the overall initial ranch biomass (Fig. 5). This function takes into account changes in biomass over the grazing season relative to its initial state, representing an evolving landscape of forage availability and quality as the growing season matures (Kilcher 1981). For example, if the current pasture's biomass is above 90% of the initial ranch biomass, then the cattle will gain weight at a desired rate of 0.30% of body mass per day (Byrne 2020; Filley 2013). If the current pasture's biomass is below 52.5% of the initial ranch biomass, cattle will lose weight at a rate of 0.33% of total body mass per day (Parish and Rhinehart 2009; Rhinehart 2020). There are two additional weight-gain intervals between the high and low extremes which are used to represent fluidity in animal-forage quality dynamics. Weight gain-loss thresholds can be modified in the code to reflect local knowledge of animal feed efficiency of the modeled herd based on breed and genetics.

Forage is coded to *grow* incrementally with each tick based on average daily rainfall estimates derived from the selected precipitation level. Forage growth is coded using a base equation derived from a study on similarly arid grasslands in the African Serengeti (Fryxell et al. 2005), and coefficients were modified to reflect biophysical patterns (Boone and Galvin 2014; Fryxell et al. 2005) observed on Lowry Ranch.

When mean biomass of the current pasture diminishes to 50% of the mean total landscape biomass, cattle are encoded to *shift* (rotate) to a new pasture of highest biomass and continue grazing. We modeled this threshold based on the "take half, leave half" rule-of-thumb approach to grazing management (Bidwell 2017; Sayre 2017). However, the 50% threshold can be modified based on the modeled landscape and grazing system in question, as it is designed to prevent the virtual livestock from overgrazing the modeled landscape. ECo-Range is programmed to stop at 150 ticks at the conclusion of the 5-month grazing season of 150 grazing days. On Lowry Ranch this represents a May to September grazing season. The length of a grazing season or number of grazing seasons represented in a single simulation may be modified in the code to match any landscape or research question of interest. At this point, the ECo-Range simulation is ready to be executed.

Methods: simulation

For the Lowry Ranch case study, we asked the research question: *Which modeled environmental variables (1. precipitation pattern, and 2. precipitation level) and management variables (3. fragmentation level, and 4. cattle number), when set at varying values in the ECo-Range model, result in significantly different outcomes for (a) mean forage biomass, (b) mean cow mass, and (c) vegetation heterogeneity in the context of the Lowry Ranch landscape?* We hypothesized that, when varied, all environmental and management variables would result in significantly different outcomes for all three response variables the model is designed to measure.

We tested the aptitude and functionality of our ABM as a rangeland management tool and application of social-ecological systems theory using a factorial simulation protocol that facilitated evaluation of results. We used a total of 72 unique initial condition parameter combinations for the simulation (*precipitation level* × *precipitation pattern* × *cattle number* × *fragmentation*

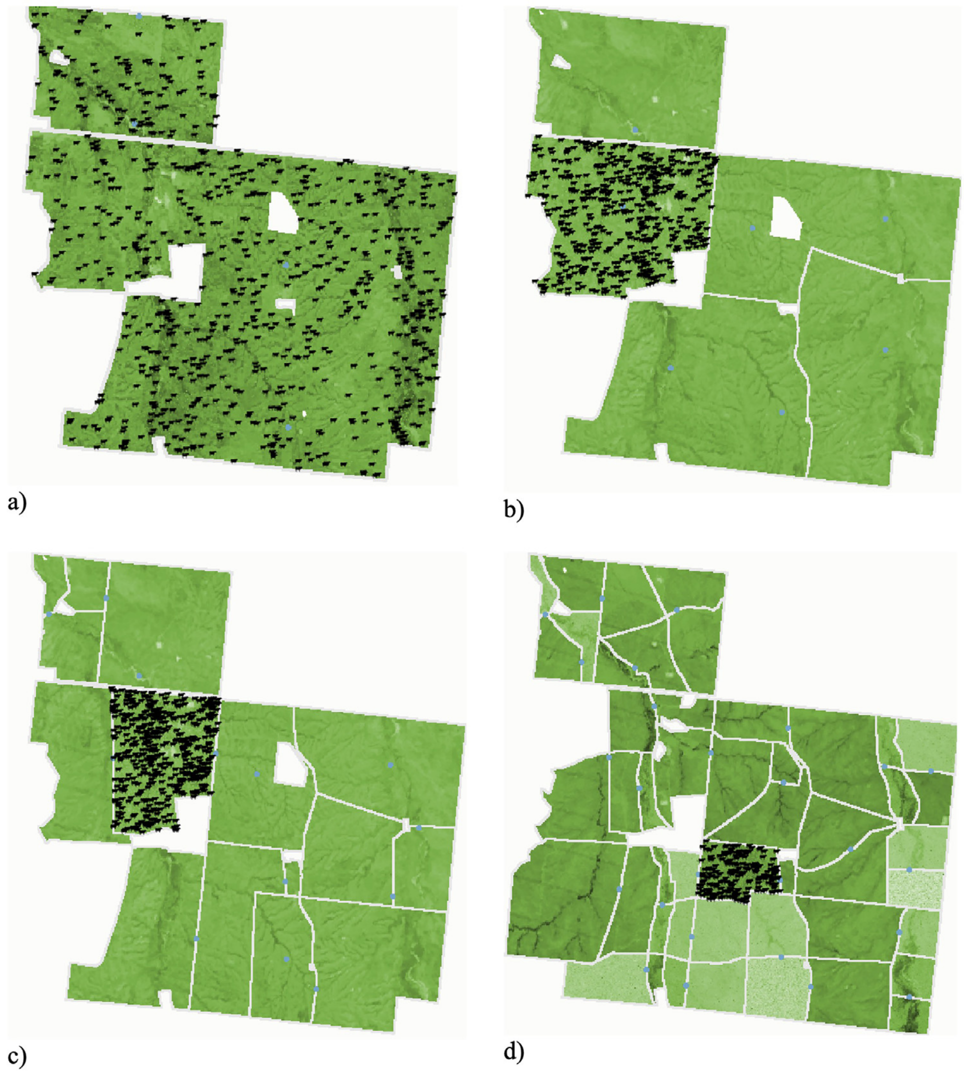

Figure 5. Four scenarios for landscape fragmentation level used in ECo-Range agent-based model grazing system. Each level represents a different degree of fragmentation on the Lowry Ranch landscape. a) no fragmentation, b) low fragmentation, c) medium fragmentation, d) high fragmentation.

level). This represented a subset of possible conditions available for each parameter in the ECo-Range model. Each parameter combination was replicated five times for a total of 360 simulations (Fig. 6). Condition subsets were selected collaboratively with the Lowry Ranch manager (NT) to best represent diverse yet realistic scenarios on the ranch.

Results: Simulation Outcomes

Of our 72 modeled scenario combinations, 36 were conducted under *wet spring* conditions and 36 were conducted under *monsoon* conditions. These patterns were chosen because they approximate actual field seasons on Lowry Ranch, a wet spring of 2021 and monsoon pattern of 2022. Results were summarized for both precipitation patterns to provide the spectrum of interannual variability common in our case study region. We illustrate several pathways for how scenario outcomes might be evaluated (e.g., summary statistics, ANOVA), but do not exhaust all potential options. We encourage model users to explore results in ways that will provide the most benefit for stakeholder learning, collaborative discovery and management, and knowledge-building.

We performed a 4-Way ANOVA, with a significance level $\alpha = 0.01$, for each of the three continuous outcomes and direct effects of the four categorical scenario conditions (Tables 1 and 3). We also tested interaction effects among independent variables (Table 2). To reduce risks of spurious significance reports from multiple comparisons, we used a more restrictive significance level than is typical. In summary, for mean forage biomass and mean cow mass, all four environmental conditions (precipitation level and pattern) and management conditions (cattle number and land fragmentation level) had a significant direct effect ($P < 0.01$). These variable-to-outcome relationships also resulted in high *F*-values, signifying that the variance between scenario conditions was greater than the variance within each scenario condition. For the vegetation heterogeneity outcome, only fragmentation level had a significant direct effect ($P < 0.01$).

Forage Biomass: We observed a negative relationship between cattle number and final forage biomass ($P < 0.01$), and a positive relationship between land fragmentation level and final forage biomass ($P < 0.01$) (Table 1). Scenarios of low cattle number and high land fragmentation resulted in highest forage biomass outcomes (Table 3). Conversely, high cattle number and low land fragmentation scenarios resulted in lowest forage biomass outcomes. These results are congruent with our knowledge of forage utilization, where higher cattle stocking densities will remove greater amounts of biomass if other environmental conditions are held

Table 1
Results of 4-way analysis of variance (ANOVA) for direct effects of scenario conditions on grazing system outcome variables in ECo-Range agent-based model simulation.

Outcome variables	Scenario conditions		*F*-value	*P* value
Mean forage biomass	Environmental	Precipitation pattern	429.27	<0.01
(lbs/patch)		Precipitation level	3 282.78	<0.01
	Management	Fragmentation level	37.83	<0.01
		Cattle number	2 061.53	<0.01
Mean cow mass	Environmental	Precipitation pattern	288.23	<0.01
(kg)		Precipitation level	65.85	<0.01
	Management	Fragmentation level	29.81	<0.01
		Cattle number	192.20	<0.01
Vegetation heterogeneity	Environmental	Precipitation pattern	4.30	0.05
(Index of dispersion)		Precipitation level	3.21	0.06
	Management	Fragmentation level	30.74	<0.01
		Cattle number	0.24	0.63

Table 2
Results of 4-way analysis of variance (ANOVA) for interaction effects of independent variables in ECo-Range agent-based model simulation.

Outcome variables	Interaction effects	*F*-value	*P* value
Mean forage biomass	Precipitation pattern × cattle number	36.83	<0.01
(lbs/patch)	Precipitation level × fragmentation level	4.34	<0.01
	Fragmentation level × cattle number	4.99	<0.01
Mean cow mass	Precipitation pattern × fragmentation level	12.56	<0.01
(kg)	Precipitation pattern × cattle number	8.23	<0.01
	Precipitation level × fragmentation level	4.67	<0.01
	Precipitation level × cattle number	31.18	<0.01
	Fragmentation level × cattle number	12.50	<0.01
Vegetation heterogeneity	Precipitation pattern × precipitation level	6.68	<0.01
(Index of dispersion)	Precipitation pattern × cattle number	19.60	<0.01
	Fragmentation level × cattle number	4.37	0.01

Of 33 tested interaction effects, only 11 significant interactions, $\alpha = 0.01$, are reported.

Table 3
ECo-Range agent-based model example protocol summary of results.

Precipitation Level	Management Decisions		Forage Biomass *Mean Biomass (kg/patch)*	Cattle Performance *Mean Cow Mass (kg)*	Vegetation Heterogeneity *(Index of Dispersion)*
Below Average	Cattle Number	500	42.5	364	5.35
		1000	29.6	348	4.04
		1500	20.8	323	4.91
	Landscape Fragmentation Level	No	28.9	347	1.96
		Low	31.7	334	5.30
		Medium	29.2	339	6.43
		High	34.0	360.	5.38
Average	Cattle Number	500	68.6	367	3.94
		1000	56.5	363	3.85
		1500	45.4	350	3.86
	Landscape Fragmentation Level	No	54.0	368	1.90
		Low	56.8	353	5.22
		Medium	57.1	356	4.16
		High	59.3	363	4.27
Above Average	Cattle Number	500	80.8	368	4.25
		1000	68.5	364	4.52
		1500	59.4	357	4.25
	Landscape Fragmentation Level	No	64.9	372	2.13
		Low	69.1	358	5.74
		Medium	71.8	358	4.81
		High	72.4	364	4.69

Outcomes measured and evaluated included: residual forage biomass, cattle performance, and residual vegetation heterogeneity. Highlighted cells in the last three columns indicate the management decision variable producing the best outcome for a given precipitation level scenario.

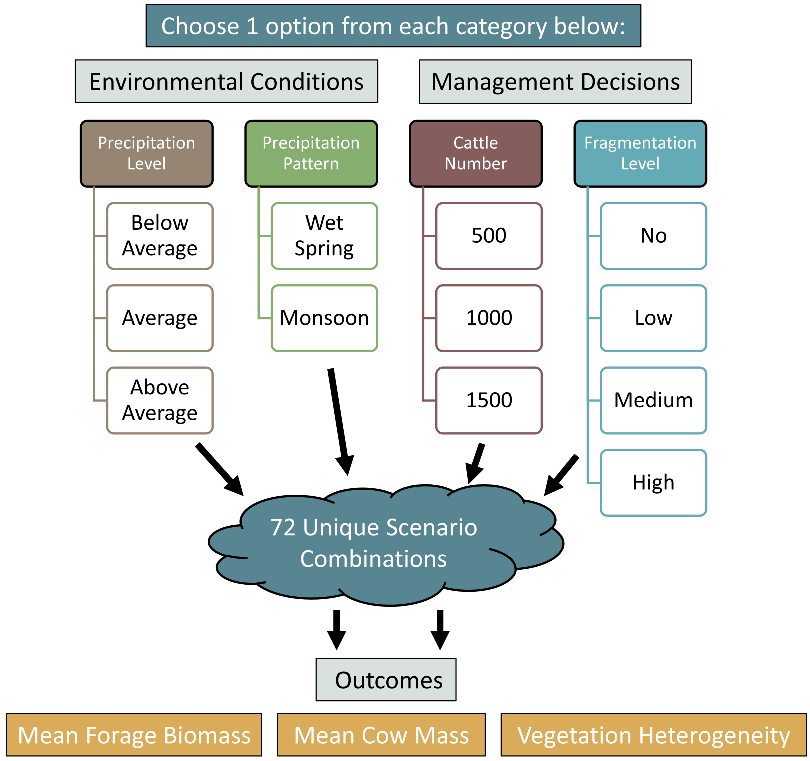

Figure 6. The Lowry Ranch simulation protocol includes locally realistic parameter options that combine to create 72 unique scenarios to evaluate our three measurable outcomes of mean forage biomass, vegetation heterogeneity, and mean cow mass.

constant. We also saw that precipitation level had a direct effect on final forage biomass ($P < 0.01$), where below-average precipitation level scenarios produced the lowest biomass values and above-average precipitation level scenarios produced the highest biomass values ($P < 0.01$). There were also significant interaction effects between precipitation pattern × cattle number, precipitation level × fragmentation level, and fragmentation level × cattle number, meaning that relative outcomes were a result of codependence among these independent variables (Table 2).

Cow Mass: Modeled cattle performance outcomes were negatively correlated with cattle number ($P < 0.01$), with the lowest cattle number scenarios resulting in greatest mean cow mass at the end of a simulated growing season (Tables 1 and 3). The influence of land fragmentation on modeled cattle performance was significant ($P < 0.01$) and dependent on annual precipitation level and pattern, demonstrating an interaction effect between these independent variables (Table 2). Under scenarios of below-average precipitation, high landscape fragmentation level resulted in the greatest mean cow mass ($P < 0.01$), while under scenarios of average and above-average precipitation, high and no landscape fragmentation levels produced the greatest outcome ($P < 0.01$) (Tables 1 and 3). Interestingly, low and medium fragmentation scenarios, the midlevels, produced the lowest mean cow mass ($P < 0.01$). Significant interaction effects also emerged between cattle number and each of the other three independent variables: precipitation pattern, precipitation level, and fragmentation level (Table 2). Therefore, the significant direct effect of cattle number on final mean cow mass was likely dependent on these other variables.

To determine whether ECo-Range will be useful in other contexts, we needed to be confident that model inputs and outcomes reasonably reflected reality. Therefore, we calibrated and validated cow mass model behavior collaboratively with the Lowry Ranch manager (NT). Our results illustrated that cattle performance in ECo-Range is comparable to the real system, with 368 kg in body mass at the end of 150 days as the objective in a favorable season. Although there is debate in the literature regarding continuous versus rotational grazing systems (Augustine et al. 2020; Briske et al. 2008a; Teague et al. 2013), anecdotal observations from Lowry Ranch indicate that cattle have performed better in a more intensive rotational grazing system. ECo-Range may be used to test such observations prior to implementing an experimental study on the range. We also noted a larger than expected range of values for mean cow mass across scenarios, a difference of approximately 100 kg from the lowest to highest values. This degree of spread in the data was unpredicted yet offers insight on an important issue for ranch management. It informs us that environmental conditions and management decisions may have broad and variable effects on cattle performance, implications of which can directly impact ranch profitability and economic sustainability.

Vegetation heterogeneity: Land fragmentation level had the only significant direct effect on vegetation heterogeneity outcomes ($P < 0.01$) (Table 1). The no-fragmentation scenario was associated with the lowest vegetation heterogeneity compared to all other fragmentation levels within each precipitation level (Table 3). The low and medium fragmentation levels resulted in the highest vegetation heterogeneity outcomes. Differences in cattle number did not lead to statistically different outcomes for vegetation heterogeneity ($P = 0.63$) (Table 1). However, there was a significant interaction effect between fragmentation level × cattle number, meaning that fragmentation level significance may be dependent on cattle number (Table 2). We conclude that low, medium, and high fragmentation levels, across modeled cattle number scenarios, resulted in greater vegetation heterogeneity than no fragmentation, where cattle had continuous access to the full ranch landscape.

Vegetation heterogeneity, variability in structure and composition of plant communities, is an important management outcome when considering the coexistence of cattle and wildlife species, such as birds (Davis et al. 2020; Derner et al. 2009; Toombs et al. 2010). Grasslands supporting greater vegetation heterogeneity and plant community diversity may provide spatial and temporal niches for greater numbers of animal species (Toombs et al. 2010). Other research on the effects of grazing intensity on bird habitat concluded that higher grazing intensities that result in structural uniformity are associated with a decrease in bird abundance and richness (Barzan et al. 2021; Kantrud 1981; Willcox et al. 2010). This is likely due to a reduction in vegetation structure and function needed to provide diverse bird habitat (McFarland 2010). The implication for cattle management is more nuanced than stocking rate or grazing intensity within a given year. In fact, it is the interannual flexibility of recovery period, frequency, and season of use in a differential management approach that can result in maximum biodiversity and heterogeneity (McFarland 2010). For more than 10 years Lowry Ranch has collaborated with Rocky Mountain Bird Observatory to monitor bird species presence, and there has not been a correlation between increased fragmentation and a decline in bird species presence.

In our modeled scenarios, precipitation pattern ($P = 0.05$) and level ($P = 0.06$) were not statistically significant drivers of vegetation heterogeneity, yet relationships among variables were observed (Tables 1 and 3). When our Lowry Ranch scenario's precipitation level was set to below average, the lowest cattle number setting produced the highest final forage biomass, mean cow mass, and vegetation heterogeneity (Table 3). Positive outcomes in this precipitation scenario were found with high and medium fragmentation levels but not with low fragmentation or no-fragmentation levels. Beneficial outcomes for an average precipitation level scenario were also related to lower cattle numbers. In the above-average precipitation scenario, the lowest cattle number setting was still associated with the highest forage biomass and mean cattle mass outcomes. However, the moderate cattle number setting was linked to the greatest vegetation heterogeneity.

Discussion: Model Evaluation and Next Steps

ECo-Range provides opportunities to test and learn about relationships among environmental conditions, management decisions, and ecological and livestock outcomes for rangelands. Model results support observations that have been made related to real-world synergies and tradeoffs. For example, while higher cattle numbers and higher fragmentation levels may correlate with better cattle performance, these conditions can be less favorable for vegetation heterogeneity and species that depend on that heterogeneity.

Modeling the social-ecological dynamics of highly variable and heterogeneous systems requires both adaptability and mathematical realism. ECo-Range tests real-world ecological plus management conditions scenarios without assuming the risks associated with actual experimentation on working operations. ECo-Range as a management planning and learning tool may be capable of answering a multitude of place-based stakeholder questions, such as: *Can increasing the number of pastures in my rotational grazing schedule result in better cattle weight gain? Could decreasing my stocking rate increase vegetation heterogeneity, providing habitat for wildlife? If we get a wet spring, could decreasing my number of pasture divisions improve the amount of residual biomass at the end of the grazing season?* Managers can parameterize the model based on the landscape of interest, and customize questions based on the operation's management objectives, within the scope of data available to the ECo-Range model.

When we view grazing systems as social-ecological systems, we are better able to understand the many linkages between human decision-making and outcomes manifested in different parts of the system. Further, feedback between human decision-making and rangeland ecosystems ultimately affects the economic viability of ranching as a livelihood. Therefore, the ability to test multiple hypothetical scenarios in a virtual environment may prevent negative or costly risks and outcomes.

In evaluating the efficacy of our model, we reflect on 1) our initial scope and intention, 2) stakeholder participation in model development and calibration, 3) model limitations, and 4) user experience and model adoptability.

Scope and intention

The management of grazing systems involves theoretical, practical, and ecological variables, where domestic livestock are the agents of biophysical change. Livestock agency, however, depends on human decision-making and interaction with environmental stochasticity. While our model case study was situated in a specific geographical and social context, we incorporated flexibility and adaptability in the model's coding language so that the model can be applied to any grazing lands across the globe by adapting the mathematical coefficients in the coding language to local conditions. This case study tested the simulation of one growing season. However, ECo-Range may also be used to explore diverse temporal contexts, for example in multiyear studies to understand management decisions over a longer period of time, as in the case of a multiyear drought.

Stakeholder participation

Our overall model concept was stakeholder-driven, rooted in the challenges, concerns, and inquiries of real-time, real-scale rangeland cattle management. We developed the model as a knowledge-building tool, where stakeholders can engage in collaborative discovery and social learning by asking questions, posing scenarios, setting goals, using local knowledge, calibrating coefficients, and interpreting results. In this way, stakeholders are promoted from research *subject* to research *partner*, further strengthening the value, relevance, and reach of the science (Reid et al. 2016; Reid et al. 2021; Wilmer et al. 2019). For example, throughout model development and calibration phases, we consulted with stakeholders, especially the Lowry Ranch manager (NT), who used his local knowledge and contextual experience to guide scenario-building and verification of mathematical coefficients to accurately represent the system. The rancher stakeholder with on-site expertise is an invaluable partner in model development and optimization.

Model limitations

Representing the complexities of social-ecological systems is likely one of the biggest challenges in simulation modeling. However, there is sufficient consensus in the scientific community that simulation modeling can be productive in natural resource studies as long as the boundaries and principles of good modeling practice are respected (Jakeman et al. 2006). The authors of *Models in Ecosystem Science* playfully adapt the point from H.L. Mencken, "For every problem there is a model that is simple, clean, and wrong" (Canham et al. 2003). In other words, models need to be complex-enough yet simple-enough to make results clear and realistic, and interpretation compelling (Haraway 2016).

There are four primary areas of complexity in our ABM that we relinquished, which could have resulted in limitations. First, ECo-Range focuses on precipitation as the only driver of forage growth. Due to their complexities, other environmental variables were not incorporated but with sufficient mathematical evidence could be added to improve model realism, nuance, and validity. The possibilities are endless and may include: hours per day of sunlight versus cloudiness, solar irradiance, daily temperature patterns, elevation, latitude gradients, soil type or texture, soil water holding capacity, soil organic matter or nutrient availability, and plant species composition by functional group or other.

Secondly, our modeling of animal weight gain in ECo-Range is based on a comparison of the available biomass in a currently grazed pasture with that of the initial landscape at simulation commencement. This models how the available biomass decreases in a pasture being grazed, while the rest of the landscape continues to grow vegetatively. The more divergent these two values, the lesser the rate an animal gains mass. In other words, as available forage decreases, less mass is gained per hour of grazing. An improvement would be a more realistic and perhaps granular modeling of the change in body mass based on a calculation of metabolizable energy gained from the forage an animal consumes compared to the basal metabolism, travel energy spent, thermal energy spent, and/or other relevant variables.

Third is our use of unmanipulated NDVI imagery. NDVI is unable to differentiate vegetation that would be considered forage for cattle grazing and other vegetation that would not be considered forage for cattle, such as unpalatable species or tree cover (Ayhan and Kwan 2020). Therefore, in ECo-Range all vegetation is treated as "forage," which suits Lowry Ranch since it is predominantly grassland, but which would create some bias in the model world for or shrubland or tree-covered areas, like riparian zones. It is important for model users to assess if tree-cover is minor or significant in their context. A next step toward improving this limitation of NDVI would be to use land cover geospatial data to "mask out" tree cover from the forage biomass calculation in the model interface. Other databases may also provide an improved proxy for available forage biomass, such as the Rangelands Analysis Platform (RAP) (Allred et al. 2021).

Lastly, cattle grazing behavior in our model is relatively simplistic, as cattle seek out the closest patch of highest forage biomass. Land slope, aspect, or proximity to water or shade are variables that may affect grazing behavior in reality but are not incorporated in ECo-Range. The model does not reflect cow-to-cow interactions nor herd dynamics such as the influence of "leaders" or "followers" which may lead to clustered distributions on the landscape (Jablonski et al. 2018). For example, the model does not allow two cows to occupy the same 30×30 m patch at the same time. The model also does not represent different grazing behaviors among groups of cattle, like mature cow versus yearling grazing behavior, which can have diverse impacts on landscape variables. A next step toward improving this model component would be to incorporate more realistic cattle or herbivore behavior coding, such as that developed by Jablonski et al. (2018).

User experience and adoptability

One of the benefits of our ABM development in NetLogo is its friendly, attractive, and easily manipulable user interface. In our model, agents are shaped like cattle, water points are blue, and the landscape is illustrated on a green color scale representing a grassy environment. Monitors and plots are intuitively arranged and color-coded so that model outcomes can be easily tracked throughout a simulation. During simulation, the modeled world updates graphically so that the user can observe agent-environment interactions through simulated time. These visual features create an aesthetically interesting and interactive user experience.

While a trained modeler would be needed to parameterize ECo-Range to different geographical and social-ecological contexts, once the basic components, such as geospatial layers, are in place, the Netlogo software is accessible and adoptable, even with limited technological experience. First, Netlogo software is cost-free and does not consume excessive amounts of computer memory. Second, the user may adjust model setup options representing environmental conditions and management decisions and run the model for hypothetical scenarios without coding expertise or technical assistance. Thirdly, if the user wants more flexibility, the modeler can flag areas of the code that contain coefficients the user may want to modify or adapt to particular inquiries.

In conclusion, we believe our novel use of ABM contributes to a growing body of knowledge regarding the power and utility of social-ecological systems modeling. Not only does our model provide a virtual representation of real, context-specific system dynamics, it is a learning tool. We designed an intuitive and user-friendly interface, where linear or multifaceted questions may be explored through creation of unique user-driven scenarios and outcome observations. Today's global challenges on rangelands often encompass seemingly paradoxical endeavors, such as agriculture and conservation. Land management objectives are complicated by these already highly complex and dynamic systems. It is our hope that modeling exercises like ECo-Range can deepen our understanding of how to sustainably manage these social-ecological systems, where humans learn to craft thriving futures in relationship with the natural world.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this article.

CRediT authorship contribution statement

Anna Clare Monlezun: Writing – review & editing, Writing – original draft, Visualization, Validation, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Randall B. Boone:** Writing – review & editing, Visualization, Validation, Supervision, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Gianna Wagner:** Writing – review & editing, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation. **Nick Trainor:** Writing – review & editing, Visualization, Validation, Investigation, Conceptualization. **Stacy J. Lynn:** Writing – review & editing, Visualization, Validation, Supervision, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization.

Declaration of Generative AI and AI-Assisted Technologies in the Writing Process

During the preparation of this work, the author(s) declare nonuse of any AI or AI-assisted technologies in the writing process.

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Supplementary materials

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