



Application of grazing land models in ecosystem management: Current status and next frontiers

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Abstract

Grazing land models can assess the provisioning and trade-offs among ecosystem services attributable to grazing management strategies. We reviewed 12 grazing land models used for evaluating forage and animal (meat and milk) production, soil C sequestration, greenhouse gas emission, and nitrogen leaching, under both current and projected climate conditions. Given the spatial and temporal variability that characterizes most rangelands and pastures in which animal, plant, and soil interact, none of the models currently have the capability to simulate a full suite of ecosystem services provided by grazing lands at different spatial scales and across multiple locations. A large number of model applications have focused on topics such as environmental impacts of grazing land management and sustainability of ecosystems. Additional model components are needed to address the spatial and temporal dynamics of animal foraging behavior and interactions with biophysical and ecological processes on grazing lands and their impacts on animal performance. In addition to identified knowledge gaps in simulating biophysical processes in grazing land ecosystems, our review suggests further improvements that could increase adoption of these models as decision support tools. Grazing land models need to increase user-friendliness by utilizing available big data to minimize model parameterization so that multiple models can be used to reduce simulation uncertainty. Efforts need to reduce inconsistencies among grazing land models in simulated ecosystem services and grazing management effects by carefully examining the underlying biophysical and ecological processes and their interactions in each model. Learning experiences among modelers, experimentalists, and stakeholders need to be strengthened by co-developing modeling objectives, approaches, and interpretation of simulation results.



1. Introduction

Grazing lands, including range and pasture lands, are essential for animal production (meat, milk, and fiber) systems worldwide (Dermer et al., 2017a), and sustain the world population of nearly 8 billion through the provision of high-quality dietary protein (Snow et al., 2014). They are also critical for a variety of regulating, cultural, and supporting ecosystem services desired by society (Havstad et al., 2007; Yahdjian et al., 2015). Grazing lands provide key habitats for wildlife and biodiversity (Fuhlendorf and Engle, 2001; West, 1993), as well as opportunities for maintaining and enhancing soil health (Dermer et al., 2018). Growing demand for livestock products is producing an imperative for sustainable intensification of livestock agriculture that attempts to reconcile increased production with long-term environmental stewardship (Spiegel et al., 2018).

The multiple purposes of grazing lands mean that land managers are faced with difficult decision-making processes associated with complex production and conservation problems (Boyd and Svejcar, 2009) in intertwined social-ecological systems (Lubell et al., 2013; Wilmer et al., 2018). These complex problems vary in time and space, which require process-based understanding of the problem(s), adaptive management and coordination of management and research (Boyd and Svejcar, 2009). Changing climates will affect forage supply and its quality for livestock (Augustine et al., 2018; Ghahramani and Moore, 2016) and require greater adaptive capacity, with enhanced decision-making skills, which integrates biophysical, social, and economic considerations (Derner et al., 2017b).

Grazing land managers need decision-making tools to cope with seasonal, annual, and inter-annual variability of weather, variable production, and commodity market price fluctuations (Derner et al., 2012; Kipling et al., 2016a,b; Kragt and Robertson, 2014; Moore, 2014; von Lampe et al., 2014). Grazing land models can assist managers with decision-making through evaluation of alternative management strategies under current as well as projected conditions, including from predicted climate change (Bunting et al., 2016; Fullman et al., 2017; Kalaugher et al., 2017; Moore and Ghahramani, 2014; Snow et al., 2014). Modeled output of multiple ecosystem services from alternative management scenarios can provide valuable insight into tradeoffs, but challenges remain for decision-making at spatial and temporal scales relevant to land managers (de Groot et al., 2010; Derner et al., 2012; Nelson et al., 2009). Increasing utility of models in grazing lands for decision-making and adaptive management is possible when goals associated with decision-making are matched with the complexity of the model (Derner et al., 2012).

Previous reviews of grazing land models have identified gaps related to modeling feed intake and rumen function of grazing animals, plant diversity, grazing animal-forage interactions, and animal growth (Brilli et al., 2017; Bryant and Snow, 2008; Cavalli et al., 2019; Del Prado et al., 2013; Kipling et al., 2016a, 2016b; Snow et al., 2014). However, these reviews have not addressed applications of grazing land models for multiple ecosystem services, assessing trade-offs among these services and long-term sustainability considerations. Our objective was to review grazing land models (Table 1), based on a literature search of 12 commonly-used models, for simulating the impacts of grazing management on the ecosystem services of forage production, animal production, plant diversity, soil carbon (C) sequestration,

Table 1 List of models that are currently supported by model developers and are commonly applied to grazing lands for forage and animal production, soil health, air quality, and ecosystem services.

Name	Websites	Key references
ALMANAC (Agricultural Land Management Alternative with Numerical Assessment Criteria)	https://www.ars.usda.gov/plains-area/temple-tx/grassland-soil-and-water-research-laboratory/docs/193226/	Kiniry et al. (1999, 2005, 2006, 2013)
APEX (Agricultural Policy/Environmental eXtender Model)	https://epicapex.tamu.edu/apex/	Gassman et al. (2010); Wang et al. (2014), and Zilverberg et al. (2017)
APSIM (Agricultural Production Systems Simulator)	https://www.apsim.info	Holzworth et al. (2014) and Keating et al. (2003)
DairyMod/SGS (sustainable grazing systems) pasture model	http://imj.com.au/dairymod/ http://imj.com.au/sgs/	Johnson et al. (2003, 2008, 2012, 2016)
DairyNZ-WFM (Whole Farm Model)	https://www.dairynz.co.nz/about-us/research/farm-systems-modelling/	Beukes et al. (2008, 2010a,b, 2011, 2014, 2017a,b)
DayCent (daily CENTURY model)	https://www2.nrel.colostate.edu/projects/daycent/	Parton et al. (1993, 1998) and Del Grosso et al. (2000a,b)
FASSET (Farm ASSESSment Tool)	https://www.fasset.dk/	Berntsen et al. (2003, 2005, 2006) and Hutchings et al. (2007)

GPFARM-Range (Great Plains Framework for Agricultural Resource Management)	https://www.ars.usda.gov/plains-area/fort-collins-co/center-for-agricultural-resources-research/rangeland-resources-systems-research/docs/system/gpfarm/	Andales et al. (2005, 2006), Fang et al. (2014a,b), and Qi et al. (2012, 2015)
GRAZPLAN	http://www.grazplan.csiro.au	Donnelly et al. (1997), Freer et al. (1997), and Moore et al. (1997)
IFSM (Integrated Farm System Model)	https://www.ars.usda.gov/northeast-area/up-pa/pswmru/docs/integrated-farm-system-model/	Rotz et al. (1989, 1999, 2005)
PaSim (Pasture Simulation Model)	https://www1.clermont.inra.fr/urep/modes/pasim.htm	Riedo et al. (1998), Vuichard et al. (2007a, b), Ma et al. (2015), Brilli et al. (2017), and Sándor et al. (2017, 2018a)
SAVANNA	http://www.nrel.colostate.edu/assets/nrel_files/labs/coughenour-lab/pubs/Manual_1993/modeldescription_plusfigs.pdf http://www.nrel.colostate.edu/assets/nrel_files/labs/coughenour-lab/pubs/Manual_1993/user_manual.pdf	Coughenour (1984, 1991), Ludwig et al. (2001), and Metzger et al. (2005)

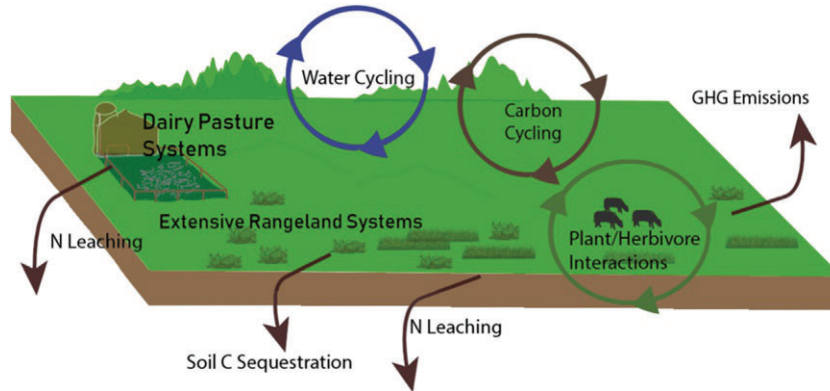


Fig. 1 Ecosystem impacts commonly simulated in grazing land models.

and nitrogen (N) losses (Fig. 1) in both extensively managed rangelands and intensively managed grasslands. We first review the grazing land models for applications to increase understanding of the ecosystem for: (1) plant-animal interactions, (2) animal-animal interactions, (3) forage production, (4) animal production, and (5) natural resources and production tradeoffs. Second, we review the models for application to short- and long-term decision-making. Third, we conclude with a next frontier for grazing land models to improve their utility for land managers.



2. Model applications for systems understanding

Among the 12 mechanistic models in Table 1 and 2, DayCent and ALMANAC have no animal component, and APEX's cow-calf production is yet to be tested. APSIM is combined with GRAZPLAN for animal simulation. For vegetative production, APSIM, DairyNZ WFM, DayCent, and PaSim simulate the vegetation cover (or sward) as a single-plant community (although a percentage of legumes can be set to simulate symbiotic nitrogen fixation). Most models have daily time step and run at field scale. However, SAVANNA uses a weekly time step, and APEX and SAVANNA have GIS (Geographic Information System) capability to be used at watershed or regional scales. The 12 models differ in complexity of simulated biophysical processes, but also share some components. For example, the soil C and N module of the CENTURY model is used in DayCent, PaSim, IFSM, SAVANNA, and APEX. APEX and ALMANNAC are branches of the EPIC (Environmental Policy Integrated Climate) model. Components of the SPUR model (Simulation of Production and Utilization of Rangelands), an early grazing

Table 2 Characteristics of grazing land management models in terms of forage and animal production, soil health, air quality, and ecosystem services.

Name	Spatial and temporal scales	Vegetation diversity	Animal diversity	Soil health/air quality	Provisioning services	Crop-livestock systems capability
ALMANAC	Field scale, daily time step	Multiple grass species or functional groups	Not simulated	Soil C	Vegetation growth	Separated
APEX	Spatially explicit, GIS capability, daily time step	Up to 10 grass species or functional types	Cow-calf production	Soil C, N leaching and in runoff, soil erosion, GHG emission	Vegetation, animal weight gain, milk production	Separated
APSIM	Field scale, daily time step	Single pasture species or functional group	Not simulated	Soil C and N, N leaching, GHG emission	Vegetation growth	Separated
DairyMod/SGS	Farm scale, Daily time step	Up to 5 plant species	Milking dairy cow (DairyMod) and sheep and beef (SGS)	Soil C, N leaching, GHG emission	Milk production, animal weight gain	None
DairyNZ-WFM	Farm scale, Daily time step	Single pasture species plus climate-driven crop models e.g. maize, Lucerne, oats, chicory, brassica. Pasture-crop rotations modeled	Individual dairy animal is simulated.	GHG emission, N leaching ^a	Vegetation, animal weight gain and milk production, plus economic performance of the farm	None
DayCent	Field scale, daily time step	Single plant species	Not simulated	GHG emission, N leaching, soil C and N	Biomass production	Separated

Continued

Table 2 Characteristics of grazing land management models in terms of forage and animal production, soil health, air quality, and ecosystem services.—cont'd

Name	Spatial and temporal scales	Vegetation diversity	Animal diversity	Soil health/air quality	Provisioning services	Crop-livestock systems capability
FASSET	Field scale, daily time step	Up to 4 plant species	Cattle can be simulated individually or in groups. Pigs are housed year around	GHG emission, N leaching, animal dung and urine, soil C storage	Forage and animal weight gain, milk production	Integrated
GPFARM-Range	Farm scale, daily time step	Multiple grass species or functional types	cow-calf production	Soil C, soil erosion, nutrient in runoff	Forage production and animal weight gain	Integrated
GRAZPLAN	Farm scale, daily time step	Multiple forage species or functional types	Cow-calf, sheep, stocker, livestock finishing, multiple enterprise	Soil C and N, soil erosion, GHG emission, N leaching ^a	Forage production, animal weight gain, wool production, milk production	Integrated
IFSM	Farm scale, daily time step	Multiple grass species and functional types of grass, legume, and forb	Dairy, cow-calf, stocker, finish cattle	GHG emission, ammonia emission, soil N, N leaching	Forage and cattle production	Integrated
PaSim	Field scale, daily	Mixed sward as a single vegetation type	Cow, heifer, sheep, goat	Soil C, GHG emission	Vegetation, animal weight gain and milk production	None
SAVANNA	Spatially explicit, GIS capability, weekly time step	Multiple grass species or functional types, bushes, and trees	Cattle, deer, wolf, and sheep	Soil C and N	Animal weight gain, forage production	None

^aWhen combined with APSIM.

land model (Hanson et al., 1988), have been used in GPFARM, IFSM, and GRAZPLAN. As such, this review is limited to applications of grazing land models at field scales, with emphasis on individual model' ability to understand systems behavior and responses to management and weather/climatic variability.

2.1 Plant-animal interactions

Plant-animal interactions are complex and impact soils, nutrient cycling, plant community structure and composition, and resulting vegetation heterogeneity (Coughenour, 1991; Derner et al., 2009; Milchunas and Lauenroth, 1993; Sándor et al., 2018a). Therefore, it is a challenge for grazing land models to be highly process-based to account for the complexity of interactions, but still be applicable to land managers for decision-making relevance regarding spatial variability (Clark et al., 2000; Eckard et al., 2014; Hutchings et al., 2007; Tietjen and Jeltsch, 2007).

Plant-animal interactions influence the dynamics of grazing lands at a range of different spatial scales. At small (patch) scales, animal grazing increases the heterogeneity of grazing lands due to selective grazing and waste deposition (Sándor et al., 2018a; Zilverberg et al., 2018). These are particularly challenging dynamics to simulate (Eckard et al., 2014), not least because of the need to model land areas with different grazing or excretion histories separately (e.g., Snow et al., 2017).

At the field scale, animal trampling effects can cascade to vegetation, soil compaction, soil hydrology, and soil aeration, especially under high stocking rates (Adiku et al., 2010). However, under light and moderate grazing, effects on soil physical properties were limited to shallow (<10 cm) depths, short-lived and minimal (<10% of reduction in vegetation) based on literature, experiments, and APSIM simulation (Bell et al., 2011). Under high grazing levels or wet conditions, compaction effects on root growth and infiltration can affect long-term productivity of rangelands (Bell et al., 2011). Under wet conditions, animal trampling can also break soil aggregates and reduce soil aeration and infiltration, and such effects may last for weeks to years (Beukes et al., 2013; Drewry, 2006). In DairyNZ WFM, Laurenson et al. (2016) assumed a percentage loss in pasture regrowth potential following grazing for 90 days when soil water content was greater than a critical soil water content above which the soil would be compacted. Beukes et al. (2013) and Laurenson et al. (2016), using the DairyNZ WFM, found that no grazing under wet soil conditions was less profitable compared with 6–10 h grazing per day because of increased plant senescence and the costs of feeding.

At the farm scale, grazing land models are being used to understand the role of diverse feeds and forages in managing for livestock productivity. A significant example is the use of modeling to understand the value of crop forage in integrated crop-livestock systems (Bell and Moore, 2012). Using APSIM and GRAZPLAN, Moore (2009) compared winter wheat with spring wheat, for dual-purpose cereals at several locations in Australia. The benefit of adopting dual-purpose winter wheat depended on location and rainfall. Light grazing of wheat crops in a cool-temperate environment increased wheat yield, especially in dry years, due to a delay in phenology and conservation of soil water for transpiration during the grain filling stage. However, grazing at a high intensity reduced yield in wet years (Harrison et al., 2012a,b). In addition to grazing crops, grazing crop stubble may be beneficial, but it would not fully replace supplemental feed, based on a GRAZPLAN simulation study in Australia (Thomas et al., 2010).

At the landscape scale, modeling analyses can provide insight into the resilience of human-managed ecosystems under grazing and other management strategies regarding the capacity of these grazing lands to absorb disturbance and perturbation (Kalaugher et al., 2013). For example, Ludwig et al. (2001) used the SAVANNA model to compare grassland and woodland savanna resilience to grazing in Australia. They found the grassland was more resilient to grazing than the woodland savanna. In another study in northern Australia also using SAVANNA, Liedloff et al. (2001) simulated the trade-off between fire and grazing and found that both simulation and experimental observation showed intensive fire controlled woody species, especially shrubs. However, fire also damaged both perennial and annual grasses. High grazing intensity reduced perennial grasses in both the woodland savanna and grassland in long-term simulations. Moderate grazing on the woodland savanna produced higher annual grass biomass than either heavy or no grazing treatments.

2.2 Animal-animal interactions

In all 12 models (Tables 1 and 2), animal-animal interactions are limited to competition for forage and the provision of milk by mothers to their offspring. DairyNZ WFM, FASSET, and GRAZPLAN track the growth of individual animals, but not their grazing patterns in rangelands or pasturelands (Table 2). A promising, but computationally expensive approach to representing the behavior of grazing animals and their social interactions, is the use of agent-based techniques, in which each animal is simulated as a mobile agent (Fust and Schlecht, 2018; Jablonski et al., 2018).

SAVANNA is one of the few models used to study interactions among different types of animals, and in which animals are distributed and aggregated based on diet selectivity and grazing patterns mediated through competition for forage (Weisberg et al., 2002). For example, simulations with the SAVANNA model suggest an optimal population of 3.7–4.7 elk km⁻² in North Park, Colorado, by considering interaction among elk, cattle, and deer (Weisberg et al., 2002). At high elk density, there was more intra-competition among elk than inter-competition between elk and cattle, which caused elk intake rate to decrease during winter. Plumb et al. (2009) also used the SAVANNA model and estimated an ecological carrying capacity of 2500–4500 bison in Yellowstone National Park, which would be reduced when there was pressure from the elk population. SAVANNA was also used to model animal grazing patterns using artificial water provisioning (Fullman et al., 2017; Hilbers et al., 2015; Plumb et al., 2009), fencing (Boone and Hobbs, 2004), and land cultivation (Boone et al., 2002, 2006). Predicted Climate change would intensify competition between animal populations, especially under more extreme climate change scenarios (e.g., A1B and A2), due to shortage of herbaceous vegetation and abundance of woody species (Bunting et al., 2016; Fullman et al., 2017).

2.3 Forage production

The ability to simulate forage production and its seasonal dynamics is a requirement for all grazing land models. In semi-arid rangelands, forage growth is more affected by rainfall than by temperature (Kelly et al., 2000; Parton et al., 1993; Zilverberg et al., 2017). However, grazing land models have difficulty simulating seasonal dynamics of forage production due to high intra-annual distribution and variability of precipitation. For example, Andales et al. (2006) found that the GPFARM-range model could not simulate the quick recovery of vegetation after a severe drought year and that simulated variability among years was less than observed in terms of forage production. Zilverberg et al. (2017) noted that the APEX model needed improvement to accelerate forage growth for late season precipitation. Similarly, Lee et al. (2012) found that spatial and temporal variation simulated by the DayCent model was less than actual measured forage production of a key species. Zilverberg et al. (2017) found the APEX model adequately simulated total plant biomass, but simulated forage production of individual species was problematic. The inability to simulate seasonal variation could also overestimate ranchers' profit by 10–20% (Vogeler et al., 2016).

Correct phenology simulation is essential for grazing land production (Corson et al., 2007a; Cullen et al., 2008; Riedo et al., 1998), especially when grasses have a short growth cycle (e.g., 4–6 weeks) and can have multiple growth cycles in a year when water is available (Kiniry et al., 2017; Moore et al., 2015). Lee et al. (2012) found that DayCent simulated higher forage biomass for systems with 2–3 harvests compared to a single cutting per year, due to reduced growth-stage development. PaSim simulated initiation of growth in autumn 25 days earlier, and maximum growth rate 20 days earlier than the measured dates in Italy (Pulina et al., 2018). Correct responses of phenology or growth stages to photoperiods, temperature, defoliation, and water stresses need to be included in grazing land models (Smith et al., 2017).

Competition among plant species in grazing lands is not well simulated either. Most studies have focused on aboveground light interception and evaporative demand (Confalonieri, 2014). Kim et al. (2016) used the ALMANAC model to simulate 10 grass species in rainout shelters and found strong interaction between soil type and species in terms of plant height and basal diameter. Simulations required different potential leaf area index when grasses were grown independently or competitively, which could be due to the inability of the model to simulate plant responses to soil nutrient and water status. Under low irrigation, the model over-estimated effects of water stress when species were simulated independently; whereas, the model performed better when all species grew competitively together, since the model was calibrated under competitive growth.

Forage quality is generally measured by N (or crude protein) concentration in biomass, digestibility, and metabolizable energy content. However, most models have difficulty simulating dynamics of plant N uptake. For example, Riedo et al. (1998) found PaSim underestimated N concentration in harvested biomass. Corson et al. (2007a,b) found that IFSM-SPUR simulated more N uptake in the spring, which depleted soil N in the summer months. Nitrogen uptake is also affected by soil clay content (Lee et al., 2012), soil C mineralization (Berntsen et al., 2005; Meyer et al., 2015), and competition among species (Vogeler et al., 2017a). Variability of dung and urine distribution influences plant N uptake (Hutchings et al., 2007).

2.4 Animal production

Unlike croplands where crop yield is the final product, grazing land models need to simulate both the primary (forage biomass) and secondary

production (animal weight gains) correctly. When there is simulation error in plant biomass but reasonable simulation of animal gain, the model is compensating for plant biomass error by adjusting animal parameters (Stout et al., 1990). Grazing land models also have difficulty simulating animal weight gain after animals were switched to pasture from hay due to lack of responses to rumen microorganisms and palatability (Stout et al., 1990). In addition, models may consider genetic variation and genetic-management interactions when simulating animal weight gain and milk production (Washburn and Mullen, 2014). For example, using the IFSM model, Rojas-Downing et al. (2017) found higher milk productivity in confinement systems, followed by the seasonal pasture grazing systems and the annual pasture grazing system. Soder and Rotz (2003) used the DAFOSYM, a precursor of IFSM, to study the economic and environmental impact of grazing on dairy farms, and found that grazing animals produced less milk compared to animals receiving harvested feed, but grazing reduced economic risk.

Stocking rate is one of the key decisions facing land managers. For example, Beukes et al. (2008) used the DairyNZ WFM to study the efficiency of feed utilization and milk production under five annual stocking rates (between 2.2 and 4.3 cows ha⁻¹ Yr⁻¹). Results showed acceptable prediction of pasture production, animal intake, body weight, and milk production, but it over-predicted milk solids by 31%, which was consistent across years and herds. The over-prediction of milk solids indicated that the model was too efficient in converting nutrients to milk, which could be caused by the model's insufficient response to nutrition, insufficient accounting of energy expenditure, and failure to account for low forage quality in the summer. Increasing lignin content of forage did decrease milk solids, but also decreased body weight.

Analyses of stocking rate effects can employ metrics other than the production of forage and meat or milk. In a study using SAVANNA, Christensen et al. (2003) simulated the impacts of 14 different stocking rates on vegetation resilience and recovery in Inner Mongolia, China. They found a grazing intensity of 0.49 (biomass in grazed area/biomass in ungrazed area) resulted in maximum system resilience. A grazing intensity above 0.49 (i.e., 39 animal units year⁻¹ km²) was predicted to cause an increase in shrub primary production and root biomass as well as permanent damage even without further grazing.

2.5 Natural resources and production tradeoffs

2.5.1 Soil C sequestration

Soil C sequestration could offset 20–35% of global greenhouse gas (GHG) emissions, and maximizing acreage and soil C storage of grazing lands is the

most effective management strategy (Minasny et al., 2017). Carbon sequestration in grazing lands is influenced by primary production, grazing intensity, root dynamics, and soil organic C (SOC) decomposition (Kirschbaum et al., 2015, 2017). Depending on sampling method and other management, conflicting results for soil C sequestration may be obtained (Kirschbaum et al., 2017; Mudge et al., 2011). When C flux was measured in an open field, it was also important to filter out CO₂ fluxes from grazing animals near the eddy-covariance measurement towers (Kirschbaum et al., 2015).

The CENTURY model was the first designed to simulate plant biomass, soil C and soil N in the North America Great Plains (Parton et al., 1987) and was then incorporated into several other grazing land models (e.g., IFSM, APEX, SAVANNA, PaSim) for better simulation of soil C and N processes. Parton et al. (1987) established that precipitation, soil texture, temperature, and plant lignin content were the controlling factors for aboveground biomass production and soil organic matter (SOM) in the Great Plains. They also noted that steady states of SOM were affected by soil texture as well as grazing intensity. Reducing grazing intensity would effectively restore degraded grasslands, especially under predicted climate change conditions (Chang et al., 2015). In a recent study with GPFARM-Range, Qi et al. (2012) found that grazing had little effect on soil total C and N over 14 years in the semi-arid Great Plains. Long-term data and frequent samplings are needed for better evaluation of soil C and N, as well as root growth.

Converting croplands to grasslands generally increases SOC storage. Using the APSIM-Pasture model, Liu et al. (2016) simulated $>0.3 \text{ T C ha}^{-1} \text{ year}^{-1}$ increase in SOC with zero or low stocking rate in eastern Australia. Even a four-year pasture rotation would significantly reduce SOC decline in croplands. However, grazing would slow C sequestration in soils due to greater removal of forage. Haney et al. (2010) showed higher SOC and higher water extractable C under grass than under corn production, but they also noticed differences in soil C sequestration among different grass species. Simulated total soil C sequestration is higher when spatial heterogeneity is included (Hutchings et al., 2007).

Simulated soil C storage change varies greatly among models. For example, Veltman et al. (2017) found that soil C change ranged from -0.70 (APEX) to $0.64 \text{ T C ha}^{-1} \text{ year}^{-1}$ (DNDC) for a 9-year period; whereas, IFSM and DayCent predicted negligible soil C changes. Such a high discrepancy among models could be due to inconsistent allocation of initial soil C across different pools in the models (Veltman et al., 2017).

2.5.2 Greenhouse gas (GHG) emission

Enteric methane (CH_4) emissions from ruminants, nitrous oxide (N_2O) emissions from the soil, and changes in the soil C stock are generally the major terms in the GHG balance of grazing lands. Simultaneous, long-term field measurements of all three of these fluxes are mostly conducted (Valbuena-Parralejo et al., 2019) over relatively small areas, but GHG budgets need to be evaluated at the farm or ranch scale (Del Prado et al., 2013). Modeling analyses are therefore essential to evaluating GHG balances and mitigation options. Most of the development effort in recent years has improved the modeling of N_2O fluxes, despite the far greater importance of enteric CH_4 to the global GHG balance (Herrero et al., 2013).

DayCent is the most common model used to simulate GHG emission in grazing lands worldwide. However, the goodness of its predictions may vary greatly due to uncertainty in input parameters. The inherent small-scale variability in N_2O fluxes, and hence the large uncertainty at the field scale predicted by models, suggests that N_2O emissions predictions are difficult to conduct at larger scales. For example, in a New Zealand study, Stehfest and Muller (2004) found that DayCent overestimated annual N_2O fluxes by >300% on a urine-affected pasture due to overestimation of both the fraction of N_2O formation during nitrification and soil water content. In general, DayCent simulates N_2O emissions better for croplands than for grazing lands (Fitton et al., 2014; Ryals et al., 2015), and simulates much lower GHG emissions than that estimated by the IPCC method (Nichols et al., 2018).

FASSET is another model used for GHG emissions in grazing lands, especially for intensively managed grasslands. Hutchings et al. (2007) simulated GHG emissions under fertilized pastureland and found that heterogeneity due to uneven distribution of dung and urine caused differences in simulation results, depending on fertilizer rate. FASSET simulated less GHG emissions when dung and urine were evenly distributed compared to a patchy distribution. The localization of dung and urine saturated the soil with N, which exceeded the N uptake capacity and inhibited soil microbial activities for nitrification. In addition, FASSET simulated greater GHG emissions with high clay soils, grazing (compared to cutting), and high temperature conditions (Chatskikh et al., 2005). Soil compaction generally increased N_2O emissions, but this was not considered in the model (Hutchings et al., 2007).

Both IFSM and DairyNZ have the capability to simulate whole farm level GHG emissions. For example, using IFSM, Rotz et al. (2009) found

that grazing animals produced less net emissions of GHG compared to confined animals due to less manure storage but increased N leaching due to urine deposited by grazing animals. Although GHG emissions per cow were higher for a confinement dairy than for a grazing-based dairy, confinement dairy farms had greater milk production per cow. As a result, the C footprint was similar between the two dairy production systems (Belflower et al., 2012). Under future climate, methane emissions from manure storage and application may increase by 18–54% and 26–120%, respectively (Thivierge et al., 2017), as will enteric methane emissions (Del Prado et al., 2013). Based on IFSM simulation results, Powell and Rotz (2015) concluded that reducing dietary crude protein could decrease N₂O emissions by 15–43% without affecting milk production, which agreed with Gregorini et al. (2016) who used the DairyNZ WFM. GHG emissions were also highest when manure was deposited on wet soil. For example, Van der Weerden et al. (2017) combined DairyNZ WFM and APSIM to study optimum grazing duration when soil water content exceeded a certain threshold (i.e., >85% field capacity). They found that 13 h day⁻¹ grazing was the most cost-effective management as GHG emissions were reduced by 9% without significant increases in silage-feeding requirement. However, the duration-controlled grazing was not profitable unless an off-paddock facility already existed (Laurenson et al., 2017). Otherwise, applying a nitrification inhibitor may be more economical despite lower efficiency in mitigating GHG emission and N leaching (Romera et al., 2017).

Considerable differences remain among models in their simulations of GHG balances (Veltman et al., 2017). Moore et al. (2014) reviewed six models for GHG emissions (FullCAM, DayCent, DNDC, APSIM, WNMM, and AgMod) and found that although the models had similar underlying structures, the representation of each individual sub-process is diverse and complex. They also differ in model initialization, software implementation, distribution, and software quality assurance. Uncertainty in the prediction of GHG emissions among the models makes model-based decision-making difficult (Del Prado et al., 2013; Moore et al., 2014). For example, Veltman et al. (2017) found that simulated GHG emissions could vary by 3- to 50-fold among IFSM, Manure-DNDC, and DayCent. In addition, Manure-DNDC simulated a methane sink whereas IFSM and DayCent simulated a methane source for the same dairy farm.

2.5.3 N leaching

Nitrogen leaching from urine and feces accounts for 70–90% of N leaching in grazing lands (Vogeler and Cichota, 2016), but it is more of a concern in

intensively managed pasturelands than in extensively managed rangelands due to fertilizer application. Extensive studies have evaluated N leaching from urine patches, including overlapping patches and uncertainty in soil properties (Cichota et al., 2013; Vogeler et al., 2017b). For example, Cichota et al. (2013), using the APSIM model, studied N leaching from grazing systems in New Zealand and found that when urine was deposited on the same location twice within 20 days, N in the two urine events should be accumulated and treated as a single urine patch. However, when the delay between the two urine events was >180 days, independent patch simulation is sufficient for N leaching. In addition, soil heterogeneity greatly affected simulated uncertainty of N leaching. Therefore, it is critical to have correct input of soil physical properties when models are used for evaluating environmental impacts on grazing land (Vogeler et al., 2017b).

Grazing land models can guide strategies to mitigate N leaching without affecting ranchers' profit. For example, Beukes et al. (2012) and Vogeler et al. (2013) applied DairyNZ WFM (linked with APSIM) to develop mitigation strategies of: (1) using cows with a lower replacement rate and higher genetic capacity for longer lactation, (2) limiting N intake, (3) stand-off pasture on a loafing pad, (4) reducing fertilizer rate, and (5) using a nitrification inhibitor. The mitigation strategies not only increased milk production by 8% (wet year) and 17% (dry year), but also decreased N leaching by 20–55% (Vogeler et al., 2013). Grazing diverse pastures could also reduce urine N excretions by 17–23% due to lower crude protein content based on a study with DairyNZ WFW in New Zealand (Beukes et al., 2014). Nitrogen leaching could be reduced by 11–19% due to both less N intake and large urine volumes from cows grazing diverse pasture, but the decrease in forage yield compared to a standard pasture could affect farmers economically. Further studies on rooting system of a diverse pasture are needed because deeper-rooted species can extract more soil N from deeper soil layers, further reducing N leaching.



3. Model application for prediction and decision support

In addition to systems understanding, mechanistic models have the capability to predict systems behavior under different conditions through the integrated biophysical processes embedded in the models. Given the empirical nature of the models, each must be calibrated to some extent under certain assumptions before transferring to different soil, climate,

and management conditions. To develop a model application for prediction and decision support purposes, users need to: (1) select a model or models based on objectives and decision support criteria; (2) determine the confidence intervals for model acceptance; (3) calibrate the model(s) with available experimental data; (4) extrapolate simulated results to other soils and management conditions (short-term) and climate (long-term); and (5) evaluate the short- and long-term predictions given the uncertainty in model inputs and structure.

3.1 Model parameterization

Model selection is not an easy task for users (Thomas et al., 2013), but model parameterization is even more difficult. In practice, most grazing land models are parameterized by trial-and-error. Even for crop models, nearly half of the users found best parameter values by trial-and-error within an average of three iterations (Seidel et al., 2018). Optimization algorithms have also been used in some cases, such as Monte-Carlo and Bayesian approaches (Gottschalk et al., 2007; Sándor et al., 2016a; Touhami and Bellocchi, 2015). Even among those who claim to divide the data between calibration and validation, iteration is used to select parameters suitable for both datasets (Seidel et al., 2018). Based on 211 returned surveys from model users, Seidel et al. (2018) concluded that model calibration has been a major obstacle in model application, such as what parameters to calibrate, which data to use for calibration or validation, and how to estimate parameter uncertainty.

In general, model parameters could be more robust when multiple treatments or multiple site-years of data are used for calibration (Di Vittorio et al., 2010; Fensterseifer et al., 2017; Ma et al., 2015), especially when model calibrations are completed under one set of conditions (Descheemaeker et al., 2014a; Vuichard et al., 2007a). For example, in calibrating PaSim, Ma et al. (2015) found that the parameters obtained by optimizing net ecosystem exchange, gross primary production, ecosystem respiration, and evapotranspiration across 12 experimental sites in Europe provided the best results compared to parameters obtained from selected sites. Touhami and Bellocchi (2015) found that Bayesian calibration reduced parameter and simulation uncertainty of PaSim, though it may not be effective because of the complexity of the model. Simulation error in one process may affect results of associated processes. Therefore, a poorly represented process in a model could potentially propagate throughout the whole system and make the users suspect other processes are incorrect (Sándor et al., 2016a).

Interactions among model parameters were also an issue in model calibration (Ma et al., 2015). When a model is not adequately calibrated with a dataset, users should look for better modules to improve certain processes, rather than using unrealistic model parameters to match experimental observations (Foy et al., 1999).

For some model inputs, such as weather data and soil properties, there is considerable temporal and spatial variability in measurements. Sensitivity analysis has been frequently used to identify which parameters to calibrate (Touhami et al., 2013). Since all experiments are conducted at specific sites and the models are more-or-less empirical in describing some processes, there is an interaction between calibrated parameters and sites (Behrman et al., 2014). As a result, recalibration of a model for different sites is needed, given the correlation among soil and plant parameters and uncertainty in model parameterization (Behrman et al., 2014; Foy et al., 1999; Teague and Foy, 2002, 2004). A database of model parameters might be needed for different locations. Another issue for grazing lands is model initialization for grass establishment and soil C pools with a spin-up run (Calanca et al., 2007; Chang et al., 2013; Kiniry et al., 2002; Parton et al., 1993).

3.2 Short-term prediction for alternative management

After a model is calibrated, it can be used as a tool to evaluate provision of multiple ecosystem services under various management practices. For example, Andales et al. (2006) found that GPFARM-range could be used as a tactical tool since forage production was adequately predicted based on soil water content on May 1 and forecasted weather after May 1. Fang et al. (2014a) improved the GPFARM-range model for forage intake, forage quality, and forage use efficiency to study stocking rate effects on forage and steer production at the High Plains Grasslands Research Station in Wyoming from 1982 to 2012. Sensitivity analyses showed that the responses of steer weight gain and peak biomass to stocking rate depend on rainfall (wet or dry year) with optimum stocking rate of 0.88 steers $\text{ha}^{-1} \text{yr}^{-1}$ for dry and normal seasons and up to 1.10 steers $\text{ha}^{-1} \text{yr}^{-1}$ for wet years. When considering cost, the economically feasible stocking rate was 0.33 steers $\text{ha}^{-1} \text{yr}^{-1}$ for dry years to 0.44 steers $\text{ha}^{-1} \text{yr}^{-1}$ for wet years. A similar decision tool was developed by Fang et al. (2014b) for different soils and stocking rates. A set of regression equations were proposed to predict peak biomass and steer weight gain under various stocking rates, soil and weather conditions.

In addition to stocking rate, the grazing window is also important, as ranchers try to narrow grazing gaps to reduce purchased feed. For example, using the GRAZPLAN model and 60 years of weather data, [Descheemaeker et al. \(2014a\)](#) found that, on highly productive soils, introducing summer-growing perennials would have high grazing potential, ranging from 31 to 156 and 67 to 193 days under light and heavy grazing conditions, respectively, during the summer-autumn feed gaps. The potential grazing days would be under 67 days for low productivity soils.

Grazing land models can also be used to evaluate system resilience under alternative management. For example, in an East Africa study, [Metzger et al. \(2005\)](#) used the SAVANNA model to study two rangelands, one with only wet season grazing and the other with both wet and dry season grazing. They found that both rangelands were resilient to grazing in terms of species diversity. However, the abundance of forbs, shrubs, and bare land were positively correlated to grazing intensity during dry seasons when forage had lower quality and animals gathered close to water sources rather than searching for high quality forage.

Ranchers or farmers are unlikely to use a complex model in their daily decision-making ([Kalaugher et al., 2013](#); [Romera et al., 2013](#)). One way around this barrier is to restrict the model to a small part of its parameter space by means of a user interface, thus simplifying the effort required to provide inputs. The GrassCheck system, based on the model of [Barrett et al. \(2005\)](#), is currently being used to extend results from Northern Ireland to the rest of the United Kingdom; AskBill ([Kahn et al., 2017](#)), which is based on a simplified version of Ecomod, is a newer example. An alternative approach is to build a more flexible simulation tool that is used by advisors to make probabilistic forecasts of system dynamics (e.g., GrassGro; [Salmon and Donnelly, 2008](#)). Implementation of model-based decisions also depends on the type of livestock production systems and social factors. For example, based on the SAVANNA model, [Boone et al. \(2004\)](#) found that the decision of destocking herds based on forecasted drought was adopted by 44% of the commercial farmers, but only 3% of communal farmers, even though a wrong decision on destocking would promote more and better forage for the remaining herds.

3.3 Long-term prediction and adaptation to climate change

Long-term simulations of grazing land models are essential to understand and forecast the direct and indirect effects of climate change on vegetation

and whole system productivity (Kipling et al., 2016b). One common application of grazing land models is to explore the impacts of climate change and adaptation options for crop-livestock farms. Simulation results show that year-to-year variability poses significant risk for ranchers' revenues and that alleviation of dry-season feed gaps is critical for climate adaptation, especially under high stocking density (Descheemaeker et al., 2018). For example, using a combined APSIM-GRAZPLAN model in the AusFarm platform, Ghahramani and Moore (2016) evaluated the sustainability of current crop-livestock farming systems in Western Australia under climate change conditions projected for year 2030. They predicted a decline in above ground net primary production (ANPP) and ground cover, especially for crops. CO₂ fertilization was offset by higher temperatures and evapotranspiration demand, especially in drier areas. GHG emissions were predicted to decline, but soil erosion would increase due to less ground cover. They also predicted that no current management systems would be as profitable as now in 2030, especially in drier regions, unless a higher percentage of land was allocated to livestock production. In addition, livestock production was less affected by climate change than cropping systems due to prevailing low stocking rates, which suggests that ranchers may increase livestock production for adaptation to climate change (Ghahramani and Moore, 2016; Rodriguez et al., 2014).

Other adaptation strategies evaluated by grazing land models are high irrigation, high fertilization, new vegetation species, improved animal genetic traits, and flexible stocking rates. In general, irrigation and fertilization could mitigate climate change (Ghahramani and Moore, 2013; Graux et al., 2013; Kalaugher et al., 2017; Rodriguez et al., 2014). Using GRAZPLAN, Moore and Ghahramani (2014) evaluated the effects of livestock genetic improvement on mitigating climate change effects. They found that breeding for greater fleece growth in sheep enterprises and for larger body size in cow and steer enterprises were the most effective genetic adaptations. Higher conception rates and improved tolerance to heat stress had less adaptation benefit.

Simulated mitigation and adaptation strategies varied with management systems and projected weather conditions. For example, due to the current low stocking rate in Australia, Ghahramani and Moore (2016) recommended increasing stocking rates as climate changes, whereas Kalaugher et al. (2017) proposed decreasing stocking rates in New Zealand for 2030–2050 given the current high stocking rates. Using GRAZPLAN in southern Australia, Ghahramani and Moore (2013) simulated effective mitigation practices by increasing soil fertility and adding a legume (Lucerne) to the feed-base. However, these adaptations would not be effective after 2030, except under

high rainfall regions. In addition, as climate change may increase the uncertainty of vegetation production, ranchers need to adjust accordingly. For instance, the uncertainty of summer forage production would increase in France because summer drought would become more frequent (Graux et al., 2013). However, spring and winter forage production were expected to increase. Such a projection may orient changes in feeding practices, such as offering more summer feeding. Most recently, Sándor et al. (2018b) used grassland models to develop mitigation strategies for GHG emissions at five grassland sites worldwide and claimed that a multi-model approach improved understanding of GHG flux dynamics in pasturelands.



4. Multi-location and multi-model comparison

Model predictions vary considerably across locations due to differences in plant-animal-environment interactions. Likewise, simulation results obtained from multiple models for the same dataset vary greatly due to differing approaches and underlying model assumptions. One of the most extensive comparison across locations using a single model was conducted with PaSim in Europe. Gottschalk et al. (2007) studied the uncertainty of PaSim in simulating net ecosystem exchange at four sites in France, Switzerland, Ireland, and Scotland. Uncertainty in model input was estimated using Latin hypercube sampling from probability density functions of each parameter, including radiation, temperature, precipitation, atmospheric CO₂ concentration, soil properties (bulk density, clay fraction, pH, SOC), and N management practices. There was no consistent order in sensitivity among the input variables in net ecosystem exchange prediction across sites because model performance depended on both measurement and simulation uncertainties. In general, uncertainty was greater under drier climate conditions. Calanca et al. (2007) used PaSim to analyze gross primary production, ecosystem respiration, and net ecosystem exchange for five sites in Hungary, Scotland, Ireland, France, and Switzerland. There was much variation when outputs were estimated on a daily basis, but the model performed better on a yearly basis. NPP was closely related to precipitation. The model overestimated N₂O fluxes by two- to sevenfold, underestimated peak emissions of N₂O, and poorly predicted the timing of the peaks. Later, Ma et al. (2015) extended PaSim to 12 observational sites across Europe and found that gross primary production was better simulated than ecosystem respiration. Across years and locations, the model simulated average years better than dry years with extreme events. Recent improvements in plant

acclimation to temperature may help PaSim photosynthesis and respiration modules respond better to temperature extremes (Sándor et al., 2018a).

At present, model comparison is limited to whole models, not underlying biophysical processes or modules. As a result, differences among model applications cannot be attributed to individual processes. The use of multiple models and model ensembles is recommended (Sándor et al., 2018b). For example, Sándor et al. (2016a) compared two models (PaSim and Biome-BGC MuSo) using five eddy covariance sites in Germany, France, Italy, and Switzerland. Model performance was marginal to acceptable for weekly aggregated results in terms of evapotranspiration, soil water content, soil temperature, and C and water fluxes. Overall, simulation of net ecosystem exchange showed less accuracy with Biome-BGC than with PaSim. However, C use efficiency was either overestimated by PaSim or underestimated by BBGC MuSo at all locations and at all temporal scales.

In a follow-up study, Sándor et al. (2017) applied nine models at nine sites across Europe and Israel for simulations of soil temperature, soil water, and aboveground biomass. All models simulated soil temperature well, but soil water content and plant biomass were not always well simulated. In general, there were greater variability among models than within models. Poor biomass simulation was attributed to poor representation of phenology, lack of differentiation among plant functional types, over simplification of biophysical processes, and incorrect responses to the environment. Ehrhardt et al. (2018) compared 12 models (or model versions) for ANPP simulation with data from France, New Zealand, UK and USA and found that the ensemble results of ANPP were improved with more data used for model calibration, but less for N₂O emissions. None of the models was able to simulate both ANPP and N₂O emissions satisfactorily at all sites. The authors attributed the discrepancy among model simulation results to differences in model structure, inability to simulate spatial variability, methods of model calibration, and users' experiences.



5. Next frontiers

5.1 Identified knowledge gaps

We identified several knowledge gaps that could improve the simulation of ecosystem processes (Table 3). First, improvements on forage production simulation are needed (Ehrhardt et al., 2018). Simulations of root dynamics, root carbon storage for regrowth, and rooting depth need to be improved due to the importance of roots in water and nutrient uptake

Table 3 Current status and future needs of grazing land models to address ecosystem services.

Applications	System understanding		Decision support		Climate change projection	
	Current status	Needs	Current status	Needs	Current status	Needs
Ecosystem services						
Forage production	Total biomass is simulated well on a seasonal basis, but very few studies have root biomass reported. In general, short-term data are used for model evaluation. Shrubs are simulated less satisfactorily than grass species. Vegetation recovery after drought is not simulated well	The temporal and spatial aspects are not well represented in the models, neither are individual species and functional groups. Better simulation of plant phenology is needed. Forage quality needs to be better simulated along with soil N dynamics and N uptake	Vegetation growth in response to initial soil water content and forecasted weather is used as decision criteria. Short-term prediction (e.g., 28 days) of biomass can be used as surrogates to reduce field monitoring needs of managers	Better responses of vegetation growth, and phenology to water and nitrogen stresses need to be simulated. Potential grazing window of a grazing land needs to be better quantified based on forage productivity	CO ₂ fertilization can offset high temperature effects on forage production. Forage quality may decline under projected climate change. Irrigation, N fertilizer, and deep-rooted species can mitigate climate change effects	Better responses to temperature stresses, atmospheric CO ₂ , and possible diseases on forage production. New or invasive species need to be evaluated. Extreme events (e.g., high temperature, drought, water logging) need to be better simulated. Changes in vegetation compositions from herbaceous to woody species need to be quantified

Animal production (weight gain and milk solids)	When animal feeds and forage (quality and quantity) are simulated correctly, animal production is reasonable. Individual animal grazing behavior is not simulated in response to stocking intensity and vegetation status	Differences in animal genetics need to be parameterized. The quantity and quality of forage available for animal grazing in rangelands needs to be better simulated. Animal-vegetation and animal-animal interactions need better quantification	Various stocking rates are proposed under different grazing land ecosystems and weather conditions. Grazing temporal window is also simulated reasonably well. Decision on stocking and destocking can be made based on forage prediction	Better simulation of selective grazing of animals under various stocking rate and vegetation status is needed. Adaptive grazing needs to be further investigated. Vegetation regrowth after fire and grazing need to be further studied	Reducing stocking rate may be an option to mitigate climate change, along with improved livestock genetics. Allocation of farmlands between crops and forages may vary under climate change	Animal responses to heat stress and disease epidemics. Differences in animal productivity and grazing should be further addressed. Economic analysis needs to be added for each mitigation strategies
Soil C sequestration and storage	All the models simulated soil C sequestration in grazing lands, but high stocking rate may reduce the trend. Considerable differences in simulated soil C among grazing land models	A better understanding of root growth and decomposition of dead plant residue	Soil C sequestration has not been used for decision support but it is simulated for various management practices. Converting croplands to grasslands increases soil C	Soil C should be included in decision support as part of soil health and sustainability, along with other production goals	Soil C may not be affected by climate change because high biomass production is offset by high mineralization rate	Effects of soil temperature, soil water content, and soil texture on soil C mineralization should be further studied

Continued

Table 3 Current status and future needs of grazing land models to address ecosystem services.—cont'd

Applications	System understanding		Decision support		Climate change projection	
	Current status	Needs	Current status	Needs	Current status	Needs
Ecosystem services GHG emission and mitigation	Wide variability in GHG simulation among grazing land models. Urine and feces are the main causes of GHG emission in grazing lands, but enteric methane emission is the main source from confined animals	Better quantification of the spatial and temporal variability of GHG measurement and modeling in grazing lands. Better simulation of soil C and N dynamics under various soil and climate conditions	GHG may be mitigated by increasing grazing time of animals. Reducing dietary crude protein may decrease GHG emission from animals by lowering N fertilizer rate.	Better simulation of enteric GHG emission from animals based on dietary intake is needed. Better inventory of total GHG emission at whole farm level should be provided for decision support. Better estimation of GHG from manure storage	GHG emission may increase or decrease under climate change scenarios, depending on management practices and mitigation strategies. Low forage quality may increase enteric methane emission	IPCC type emission factors need to be updated for various management and animal genetics. Regional assessment of GHG on grazing land is needed. GHG emission efficiency from nitrification and denitrification processes should be re-calibrated

<p>N leaching and remediation</p>	<p>N leaching in pasturelands is adequately simulated in response to fertilizer management. However, it is not well simulated on rangelands due to spatial variability</p>	<p>Better simulation of hot spots where urine and feces are deposited. Better simulation of soil N dynamics under various soil and climate conditions</p>	<p>N leaching may be mitigated by breeding efficient cows, feeding low protein forages, standing-off animals on loafing pad when soil is wet, reducing fertilizer, using a nitrification inhibitor and establishing swards with multiple plant species of different rooting depths</p>	<p>Better representation of animal waste deposit in grazing lands and N dynamics in manure storage piles. Better simulation of plant N uptake is needed. Better estimation of N leaching from manure and urine in confinement dairy operations</p>	<p>N leaching may increase due to high N fertilizer application under climate change conditions to improve forage quality</p>	<p>Farm level and regional assessment of N leaching potential under climate change conditions. Better simulation of soil hydrology and soil N cycling should improve predictability of N leaching under climate change conditions</p>
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(Descheemaeker et al., 2014b; Qi et al., 2012; Robertson et al., 2015; White and Snow, 2012; Zilverberg et al., 2017). Considerable errors may exist with field measurement of root biomass and in differentiating live and dead root biomass (Milchunas, 2009). Grass phenology is simulated less satisfactorily than for crops and needs to be improved, especially when grass nutritive characteristics are growth stage related (Pembleton et al., 2013). To better simulate forage quality or crude protein content, season-specific critical N curves and translocation of N within pasture canopy needs to be improved (Pembleton et al., 2013; Vogeler and Cichota, 2016). Nitrogen fixation in grazing lands can be important and should be investigated further, especially under changing climate conditions (Li et al., 2014). Plant diversity or invasion under climate change or alternative management is also generally poorly simulated (Li et al., 2014). A related issue is the poor understanding and simulation of soil N supply from decomposition of SOM (Robertson et al., 2015). Plant responses to extreme events are also a major concern of farmers and ranchers, but are not well simulated in current models (Kalaugher et al., 2017; Li et al., 2015; Robertson et al., 2015). Recent collaborations between experimentalists and modelers on improving plant responses (e.g., root/shoot ratio, leaf expansion, photosynthesis, phenology, species composition) to the intensity and duration of high temperature and extreme droughts have shown promise (Gellesch et al., 2017; Sándor et al., 2018a; Wang et al., 2018; Webber et al., 2017).

Second, the ability to simulate spatial and temporal variability in pasture production and animal grazing is essential for model application in grazing land management. Spatial heterogeneity due to soil topography, soil texture, and grazing intensity affects simulation of N leaching (Cichota et al., 2013; Hutchings et al., 2007), biomass production (Guo et al., 2016, 2018; Lee et al., 2012; Sándor et al., 2018a), plant diversity (Confalonieri, 2014; Guo et al., 2016, 2018; Moulin et al., 2018; Movedi et al., 2019; van Oijen et al., 2018), GHG emissions (Del Prado et al., 2013), and economic return (Vogeler et al., 2016). However, the effects of soil heterogeneity on plant production depend on rainfall regime and spatial scale, and is manifest more under arid and semi-arid conditions (Guo et al., 2018). Most management scenarios in grazing lands involve changes in how livestock are moved in space and time by managers in response to spatiotemporal variability in forage resources and plant regrowth. One potentially significant innovation is a linking between agent-based models that simulate individual animal behavior in a spatiotemporal rangeland and process-based grazing land models that simulate forage dynamics to capture the grazing efficiency

and design of realistic adaptive management practices (Fust and Schlecht, 2018). As stated by Fust and Schlecht (2018), “modeling approaches to combine vegetation characteristics with animal behavior and movement and metabolic productivity in a spatially-explicit manner to incorporate important dryland aspects such as spatial heterogeneity are missing so far.” As climate change may cause even greater temporal and spatial variability of grazing lands, agent-based grazing land models are critical to the next frontier of grazing land management.

Third, evaluation of models with well-designed experimental data is essential for identifying knowledge gaps and the best process-based modules (Derner et al., 2012). The uncertainty of model input parameters, such as soil properties, needs to be addressed and included in modeling results (Hutchings et al., 2007; Vogeler et al., 2017b). Experiments that quantify spatial heterogeneity in soil properties and associated variation in plant community composition, biomass production, and phenology, along with measures of livestock movement in space and time will be essential for parameterizing spatial models. Integration of real-time monitoring data on crops and soils into modeling should be explored and utilized for timely decision-making (Edirisinghe et al., 2012; Robertson et al., 2015). Models must also be flexible in design (i.e., modularization) for ease of incorporating new experimental knowledge and management experience and skills. New approaches for integrating spatial and temporal experimental or monitoring data, social and economic metrics, and manager’s knowledge and perspectives are needed to bring grazing land modeling to the next level (Derner et al., 2012, 2018; Peters et al., 2018). Artificial intelligence self-learning and self-training of system models with big data (including remotely sensed data) should be a goal for developing the next generation of decision support tools (Getz et al., 2018).

5.2 Improving model adoption

Since each grazing land is unique, grazing land models may need to be calibrated for specific landscapes with available weather, soil, and plant data. As simulation errors of biophysical models are common, expert opinion of local producers may be an added dimension in decision-making (An, 2012; Kalaugher et al., 2013; Wilmer et al., 2018). The two main goals of developing models are to understand biological and environmental interactions among system processes and to use simulation results as metrics for decision-making (Holzworth et al., 2014; Kipling et al., 2016a).

Co-learning experiences between scientists and farmers or ranchers can create useful decision tools (Holzworth et al., 2014; Miller et al., 2017; Rodriguez et al., 2014; Wilmer et al., 2018), which helps develop tailored options related to individual farms and minimize risk (Descheemaeker et al., 2016). Complex and mechanistic models are useful to improve our understanding of grazing land ecosystems, but the ultimate goal of modeling may also be to meet the demands of policymakers and stakeholders, who are more interested in large scale and novel changes, rather than scientific findings of many mechanistic models (Kipling et al., 2016a). Simulated processes unsupported by data may lead to over-parameterization across locations (Getz et al., 2018).

Normalization of data and models will help modelers reach a higher plateau with globally available tools and computation abilities (Ginaldi et al., 2016; Porter et al., 2014), such as the Google Earth Engine for sharing data (Holzworth et al., 2014). When a model improvement is needed, a large test dataset should be used to evaluate the changes under a wide range of soil, climate, plant, and management conditions (Holzworth et al., 2014). Smart farming requires farm-specific models that can reflect near real-time events and use real-time data (O'Grady and O'Hare, 2017). Although empirical models are site specific, they may be practical as they need no calibration on the user's end and provide the same accuracy as mechanistic models in some cases, especially when there is uncertainty in input parameters (Araujo et al., 2012).



6. Conclusion

Based on a literature search of 12 models to simulate dynamics of grazing lands, most applications are at the field scale, with a few on the farm or ranch level. The models evaluate alternative management practices on vegetation and animal production as well as environmental impacts under current and projected climate conditions. Several knowledge gaps are identified to improve forage and animal simulation, including plant phenology, root growth, forage quality, and animal grazing efficiency. In addition, our review suggests three areas of improvements to increase model adoption as decision support tools. One, grazing land models need to be user-friendly by utilizing available big data. This would minimize model parameterization so that multiple models can be applied, reducing simulation uncertainty. Two, efforts are needed to reduce the inconsistency among grazing land models in simulated ecosystem services and grazing management effects by carefully

examining the underlying biophysical processes and their interactions in each model. Three, co-learning experiences among modelers, experimentalists, and stakeholders need to be strengthened by co-developing modeling objectives, approaches, and interpretation of simulation results.

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