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Plant parameterization and APEXgraze model calibration and validation for US land resource region H grazing lands

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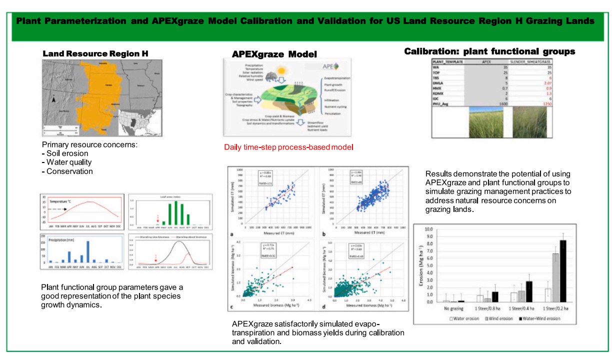
HIGHLIGHTS

- Soil erosion, water quality and conservation are primary resource concerns on grazing lands.
- APEXgraze is a promising model to assess natural resource management options on grazing lands.
- Because of the high plant species variability in grazing lands, APEXgraze was calibrated using plant functional groups.
- Plant functional group parameters gave a good representation of the plant species growth dynamics.
- The model satisfactorily simulated evapotranspiration and biomass yields during calibration and validation.

GRAPHICAL ABSTRACT



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ABSTRACT

CONTEXT: Grazing lands account for 66.7% of all agricultural land in the United States. Soil erosion, water quality and conservation have been identified as primary resource concerns on grazing lands. Biophysical models driven by daily climatic variables enable assessment of natural resource management options over time and across large landscapes, especially where on-the-ground assessments are not feasible.
OBJECTIVE: The objectives of the study were to develop plant functional groups to parameterize, calibrate and validate the APEXgraze model. The calibrated and validated model was applied to demonstrate its potential to evaluate environmental resource concerns and ecosystem services on grazing lands as impacted by increased cattle stocking densities, initially focusing on Land Resource Region (LRR) H - the Central Great Plains.
METHODS: Because of the high plant species variability in grazing lands, APEXgraze was calibrated using plant functional groups. A total of 64 plant functional groups were identified as representing plant species in the Central Great Plains. When the functional group parameters were incorporated into the APEXgraze model, along

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with the soils data, daily weather, and a zero-grazing management system, the functional group parameters gave a reasonable representation of the plant species growth dynamics, to include leaf area development and biomass yields. The calibrated and validated model was applied to demonstrate its potential application to evaluate the impacts of high cattle stocking densities on evapotranspiration, surface runoff, water stress, water and wind erosion, and soil organic carbon storage.

RESULTS AND CONCLUSIONS: Overall, model evaluation metrics indicated satisfactory performance by APEXgraze during calibration and validation against evapotranspiration (ET) data for the contiguous United States and National Resources Inventory (NRI) reconstructed field-measured biomass yields. Mean simulated ET values were reasonable, and within 10% of observed ET values. The model was able to explain 98% (R^2) of the variance in observed ET values in both calibration and validation. In addition, Nash-Sutcliffe Efficiency (NSE) was >0.50, and Willmott's d was closer to 1 (> 0.80) in both calibration and validation. Aboveground biomass calibration and validation metrics were not as strong as those for ET. Still, overall model evaluation metrics indicated satisfactory performance by APEXgraze. Simulated mean biomass yields were respectively within 16% and 11% of measured biomass yields during calibration and validation. The model was able to explain 75% (R^2) of the variance in measured biomass yields during calibration and 70% of the variance during validation. Both NSE and d were respectively >0.50, and closer to 1 (> 0.80) in both calibration and validation. APEXgraze's utility was successfully demonstrated by its potential application to evaluate the impacts of high cattle stocking densities on evapotranspiration, surface runoff, water stress, water and wind erosion, and soil organic carbon storage on grazing lands.

Significance: Following successful calibration and validation, the APEXgraze model was applied to demonstrate its potential application to evaluate environmental resource concerns and ecosystem services on grazing lands as impacted by increased stocking densities.

1. Introduction

Grazing lands account for 38% of all land and two-thirds of agricultural land in the United States, covering approximately 238 million hectares consisting of rangeland, pastureland, grazed forestland, native and naturalized pasture, hayland, and grazed cropland (Lubowski et al., 2006). Grazing lands provide multiple economic and ecosystem benefits other than feed for livestock and wildlife: food, fiber, forest products, bioenergy feedstocks, reduced soil erosion and improvements in water quality, wildlife habitat, aesthetics, carbon sequestration and climate change mitigation (Sanderson et al., 2011). While providing all these immense benefits, soil erosion, water quality and conservation have been identified as primary resource concerns that could potentially threaten the productivity and sustainability of grazing lands. Conservation practices to protect soil and water resources are a critical part of grazing management because much of the land is classified as marginal for cropland and presents great management challenges (Helms, 1997).

Sanderson et al. (2011) point out that early conservation efforts on grazing lands started during the dust bowl days of the 1930s. Despite several decades of applying conservation practices on grazing lands, significant conservation issues still remain. More recently, government agencies are increasingly being tasked by the United Sates Congress to account for money invested in conservation of natural resources (Sanderson et al., 2011). In 2003, the United States Department of Agriculture (USDA) Natural Resources Conservation Service (NRCS) entered into partnership with USDA Agricultural Research Service, USDA National Institute of Food and Agriculture, other federal agencies, and many external partners to create the Conservation Effects Assessment Project (CEAP). The goal of CEAP is to quantify the environmental effects of conservation practices and programs and develop the science base for managing the agricultural landscape for environmental quality (Mausbach and Dedrick, 2004; Duriancik et al., 2008). Conservation effects are assessed at national, regional, and watershed scales on croplands, wetlands, wildlife, and grazing lands (Briske et al., 2011; Metz and Rewa, 2019).

The grazing lands component of the CEAP National Assessment was born out of a desire to more effectively quantify the environmental benefits of conservation practices routinely applied on grazing lands. Quantification of the effectiveness of conservation practices and programs on grazing lands requires quantitative measures of their specific effects on soil, water, animals, plants, and air (Briske et al., 2011; Fox et al., 2019; Metz and Rewa, 2019). Due to the high spatial and temporal variability that characterizes most grazing lands, biophysical models driven by daily climatic variables enable assessment of natural resource management options over time and across large landscapes (watershed-, regional-, and national-scale), especially where on-the-ground assessments are not feasible. Examples of biophysical models that have been applied to simulate the impacts of management options on animal-plant-soil-water interactions and ecosystem services in grazing lands are summarily described in Zilverberg et al. (2017). A comprehensive review of grazing land models is beyond the scope of this paper. However, 12 of the most commonly-used models for simulating the impacts of grazing management on the ecosystem services of forage and animal production, plant diversity, soil carbon sequestration and nitrogen losses in both extensively managed rangelands and intensively managed grasslands are discussed in Ma et al. (2019), among which are the ALMANAC and APEX models, two sister models to APEXgraze. A number of grazing models are also described in Mohtar et al. (1997). This paper describes and discusses the plant parameterization, calibration and validation of the APEXgraze model, an offshoot from the enhanced APEX model - version 0806 (Zilverberg et al., 2017, 2018). The APEX model was enhanced to better simulate allocation of new biomass, response to water stress, competition for soil water, and regrowth of herbaceous perennials on grazing lands (Zilverberg et al., 2017). Selective grazing components were also added to better represent animal preferences for plants and grazer diet quality (Zilverberg et al., 2018). APEXgraze was specifically adapted to simulate the effects and benefits of conservation practices on grazing lands in the contiguous U.S. (CONUS).

While the goal of the CEAP grazing lands component is to quantify the environmental effects of conservation practices on grazing lands in the CONUS, because of the very diverse ecosystems represented by grazing lands, a broad regional approach that initially focuses on Land Resource Region (LRR) H (Fig. 1) was chosen.

The first objective was to develop APEXgraze plant modeling parameter datasets for plant species found within LRR H based on the concept of plant functional groups as described and demonstrated in Kiniry et al. (2013) and Williams et al. (2017). Modeling of vegetation at regional scales requires that the great diversity of plant species be captured in much fewer logical categories (or plant functional groups) based on their function and use of resources in ecosystems. According to Kiniry et al. (2013), shared features allow plant species to be simulated as a generalized functional group rather than as individual species. Furthermore, considering plants in the context of functional groups rather than individual species allows one to expand the implications beyond a single-species study. The second objective was to apply the

Fig. 1. Location of Land Resource Region H: Texas (35%), Kansas (29%), Oklahoma (16%), Nebraska (13%), New Mexico (4%), Colorado (3%). Source: USDA NRCS (2006). One location/sample point (★) in North Kansas was selected for testing the created functional groups' capabilities to accurately describe the plant species growth curve patterns through APEXgraze simulation of plant growth and biomass accumulation.

functional group parameters along with other model input data, which included daily weather, soils data, and a zero-grazing management system to parameterize, calibrate and validate the APEXgraze model. USDA-NRCS National Resources Inventory (NRI) field-measured biomass yields gathered at 5062 LRR H NRI grazing lands sampling locations and evapotranspiration (ET) data for the CONUS (Fig. 2, Reitz et al., 2017) served as the datasets for model calibration and validation. Accurate depiction of water balance with models such as APEXgraze is critical, especially in arid and semi-arid regions where precipitation and ET are the main drivers affecting plant growth and biomass yield. Finally, the third objective tested the potential application of the calibrated and validated APEXgraze model to evaluate the impacts of high cattle stocking densities on grazing lands resource concerns and ecosystem services.

2. Methods

2.1. Study location

The study location is LRR H (Fig. 1) which is in the south-central part of the Great Plains and covers approximately 57 million hectares. The northern part of the region is a nearly-level to gently rolling fluvial plain, while the southern part is more of an eroded plateau with entrenched streams. The average annual precipitation ranges from 510 to 735 mm, most of which falls during spring and fall thunderstorms. Snowfall provides only a small portion of the annual precipitation. The average annual temperature ranges from 12 to 16 °C, while freeze-free period ranges from 190 to 235 days. According to USDA NRCS (2006), soils in this region are dominantly Mollisols, but significant acreages of Alfisols, Entisols, and Inceptisols also occur. Freshwater is provided by ground and surface sources, 73% and 27%, respectively. About 91% of the water is used for irrigation. The native vegetation consists mainly of mid and tall prairie grasses, but some areas support short prairie grasses or a mixture of these and other prairie grasses. Small areas of oak-savanna occur in the southern part of the region. Approximately 99% of the land is privately owned, with beef production as the dominant enterprise. In addition, irrigated corn, alfalfa, and forage crops are grown along many of the major streams. Dryland winter wheat and other small grains are grown for either cash or feed. Overgrazing and the spread of invasive plants and noxious weeds are the major resource concerns on LRR H grazing lands. On cropland, the major resource concerns are wind and water erosion, soil organic matter maintenance and soil moisture management. Surface water quality is also a concern, with sediment, nutrients, pesticides, and salinity as the major non-point sources of surface- and ground-water pollution (USDA NRCS, 2006).

2.2. Plant parameterization

While the majority of plant parameters for modeling croplands were developed from measurements collected on customized field plots, broadly applying similar techniques on grazing lands would be prohibitive, both in cost and time because of the often very high diversity of

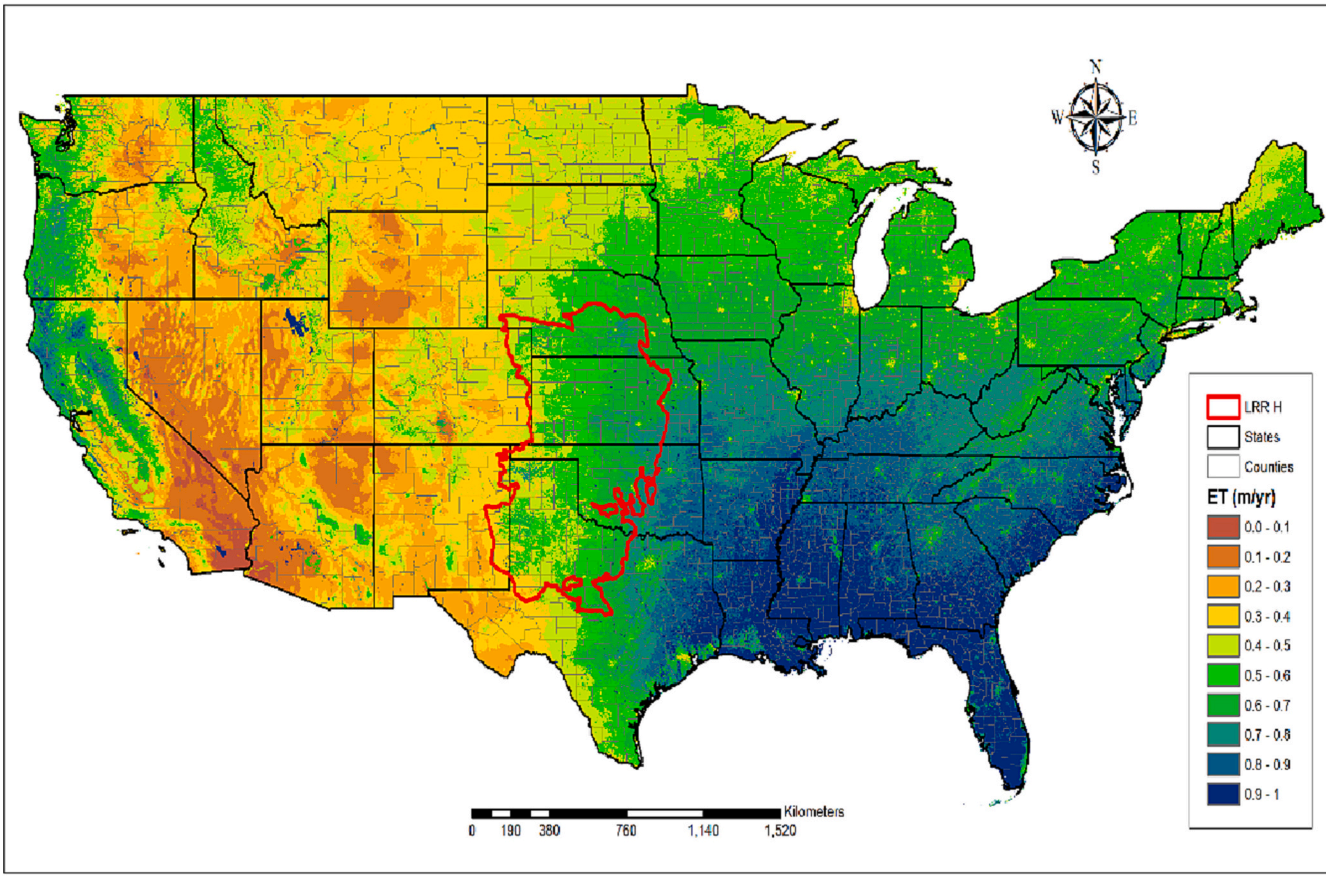

Fig. 2. National annual evapotranspiration (ET) data at hydrologic unit code 8 (HUC8) scale for the contiguous United States (CONUS) used to calibrate Land Resource Region (LRR – demarcated in purple) H NRI points. Adapted from Reitz et al. (2017). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

plant species. For example, LRR H is estimated to have approximately 1136 distinct plant species,[1] while the current APEX model's plant growth module has about 170 crops/plant species, each defined by up to 70 unique parameters. It is important to note that while the APEX plant growth module (and similarly so for APEXgraze) uses 70 parameters to simulate plant growth, a minimum set of 25 parameters (Table 1) were identified as being critical for model calibration, validation and use, and are implemented in the APEX-CUTE Auto-Calibration Tool (Wang et al., 2014). The minimum basic set of parameters can also be used to distinguish between individual plant species. These parameters were identified based on previous APEX sensitivity analysis studies (Wang et al., 2006; Yin et al., 2009), literature values, and APEX developers' and users' experiences and recommendations, as summarized by Wang et al. (2012). It is, however, critically important to remember that these parameters were originally developed for croplands and could perform differently in rangeland settings.

Taking note of the high diversity of plant species in LRR H grazing lands, a key goal of the study was to test if calibration/validation of APEXgraze could be done using a smaller representative subset of plants. Hence, plant modeling parameters for the region were developed based on the concept of plant functional groups. As mentioned earlier, plant functional groups are composed of plant species with similar responses to the environment and similar effects on ecosystem functioning. The functional groups and functional group number, their primary growing season and number, duration and habit proposed for simulation modeling of grazing lands in the CEAP grazing lands component are presented in Table 2. The approximately 1136 plant species in LRR H were placed in their appropriate functional groups and assigned parameter values of a functional group representative plant species. Three approaches were employed for grouping: 1) parameter values were assigned to functional group representative plant species based on the same or similar plant species already in the ALMANAC (Kiniry et al., 1992), EPIC/APEX (Williams et al., 2000; Gassman et al., 2010) and SWAT (Arnold et al., 2012) models,[2] 2) using data from the literature, USDA NRCS Plants and USDA NRCS NRI Grazing lands databases, and 3) expert knowledge. Choosing a parameter template for a given species from the ALMANAC, EPIC/APEX and SWAT plant databases involved selecting the best-fit for a species based on a set of matching criteria that included the plant's genus and species, functional group and primary functional group season, and crop category (variable IDC - Crop category number in APEX User's Manual), for example, annual or perennial, cool or warm season, legume or non-legume etc.

2.3. The APEXgraze model

The APEXgraze model Rel. 1811 (Osorio et al., 2018) is an offshoot from the enhanced APEX model - version 0806 (Zilverberg et al., 2017, 2018). A detailed description of the original APEX model is given in Gassman et al. (2010), while details of the enhancements are described in Zilverberg et al. (2017, 2018). Similarly to the enhanced APEX model, APEXgraze is a daily time-step process-based model, is highly flexible and dynamic, and can be applied to estimate the impacts of grazing, land management, conservation practices, and/or climate on a wide range of environmental indicators and natural resource concerns, including water quantity and quality; wind and water erosion; soil carbon

[1] USDA NRCS National Resources Inventory (NRI) CEAP-GL database.

Table 1
Minimum basic set of plant parameters for simulation modeling with ALMANAC, EPIC/APEX and SWAT plant growth modules[21] and the default, minimum, and maximum multipliers for parameter adjustments for autocalibration. The minimum and maximum values represent the permissible range within which parameters can be adjusted. Source: APEX-CUTE Tool (Wang et al., 2014).

Plant parameter definition	Symbol	Default	Minimum Value	Maximum Value
Radiation use efficiency (g MJ^{-1} m^{-2})	WA	1	0.9	1.1
Harvest index	HI	1	0.75	1.25
Optimal temperature for plant growth (°C)	TOP	1	0.8	1.2
Minimum temperature for plant growth (°C)	TBS	1	0.8	1.2
Maximum leaf area index (LAI)	DMLA	1	0.75	1.25
Fraction of growing season when LAI declines	DLAI	1	0.75	1.25
First point on optimal LAI curve	DLAP1	1	0.5	1.5
Second point on optimal LAI curve	DLAP2	1	0.5	1.5
Leaf area decline rate	RLAD	1	0.9	1.1
Maximum plant height (m)	HMX	1	0.9	1.1
Fraction of root weight at emergence	RWPC1	1	0.5	1.5
Fraction of root weight at maturity	RWPC2	1	0.5	1.5
Nutrient uptake parameter (N) at early in the season	BN1	1	0.9	1.1
Nutrient uptake parameter (N) at mid-season	BN2	1	0.9	1.1
Nutrient uptake parameter (N) at maturity	BN3	1	0.9	1.1
Nutrient uptake parameter (P) at early in the season	BP1	1	0.9	1.1
Nutrient uptake parameter (P) at mid-season	BP2	1	0.9	1.1
Nutrient uptake parameter (P) at maturity	BP3	1	0.9	1.1
Lignin fraction in plant at 0.5 maturity	BLG1	1	0.9	1.1
Lignin fraction in plant at full maturity	BLG2	1	0.9	1.1
Light extinction coefficient	EXTC	1	0.9	1.1
Threshold vapor pressure deficit (VPD) (KPA)	VPTH	1	0.9	1.1
Vapor pressure deficit (VPD) value (KPA)	VPD2	1	0.9	1.1
First point on frost damage curve	FRST1	1	0.5	1.5
Second point on frost damage curve	FRST2	1	0.5	1.5

sequestration; pesticide fate and movement; nitrogen (N) and phosphorus (P) nutrient cycling and losses. Like its sister model ALMANAC (Kiniry et al., 1992), the APEXgraze plant growth module is capable of simulating multiple plant species growing together and competing for light, water, and nutrients. Light competition is a function of the leaf area index (LAI) and plant height. Water and nutrient competition are functions of plant demand and root depth and distribution. APEXgraze comes with a standalone APEXeditor: A Spreadsheet-Based Tool for editing apex model input and output files (Osorio Leyton, 2019).

As pointed out earlier, another objective of the study was to calibrate and validate APEXgraze against biomass yield data gathered at LRR H NRI grazing lands sample points/locations, and ET data for the CONUS (Fig. 2, Reitz et al., 2017). The model comes with a calibration and validation tool with a graphical user interface that facilitates easy model calibration and validation (Stone Environmental Inc., 2021). In addition, the tool has an embedded locations-sampling algorithm that allows for the selection of the same or different unbiased random ensembles of NRI sample points to simulate during calibration and validation. Both the calibration and validation tool, and the locations-sampling algorithm are implemented in an enhanced APEX-CUTE 5.1 tool (Stone Environmental Inc., 2021). APEX-CUTE allows for manual adjustment of parameters and their ranges iteratively between autocalibration simulations, and also incorporates sensitivity and uncertainty analysis of parameters.

Since calibrating and fine-tuning functional group plant parameters was one of the main goals of the study, the calibration tool was hard-coded to ensure that each functional group representative plant species was represented in the calibration sample at least once or twice, if possible. As expected, some plant species were difficult to sample because they are rare in landscapes.

2.4. APEXgraze parameterization, calibration, and validation

APEXgraze parameterization, calibration, and validation were conducted using data and information gathered at 5062 LRR H NRI grazing lands sampling locations/points, in particular, soils data and biomass yields. The NRI sample points allow the NRI rangeland on-site data to be linked to broader estimates of surface area and land cover use provided in the NRI (USDA, 2015). Other key model parameterization input datasets included: daily weather data, developed functional group plant parameters, and a zero-grazing management practice.

Compiled daily weather data for the CONUS (precipitation and minimum/maximum temperature) from 1950 to 2018 were obtained from White et al. (2007). These weather data, derived from weather monitoring stations applicable to United States Geological Survey 12-digit watersheds are available at https://nlet.brc.tamus.edu/Home/Swat in APEX and SWAT formats. For both calibration and validation, the model applied the daily weather from the nearest weather station to the NRI sampling location/point.

Soils at each NRI sample point were identified from the NRI data collected on-site. Soil properties parameter data were obtained from a customized soils database for CEAP Grassland modeling (Osorio-Leyton, 2021; pers. comm.). The soil attribute tables were created using an intelligent system to match (Soil Matching Tool) raw pedon data in the National Cooperative Soil Survey database to map units from the 2018 Soil Survey Geographic database (https://www.nrcs.usda.gov/wps/portal/-nrcs/main/soils/survey/). This process uses linear empirical equations and machine learning algorithms to impute missing values and update the physical and chemical properties of the soils. The final soil attribute tables provide the most suitable soil information for processed-based modeling.

Timing of grazing lands seasonal life cycle events is critical not only on ecosystem productivity but also in designing effective grazing management and conservation practices. Developed functional group plant parameters were adjusted and refined by testing the accuracy of the parameters to adequately describe the representative plant species growth curve pattern through APEXgraze simulation of plant growth and dry matter accumulation during the growing season at a location/NRI point in North Kansas. This location was chosen because the grass species composition at this location typically represents mid and tall prairie grasses found in LRR H, in addition to some areas with short prairie grasses.

Adjusted key parameters included the maximum leaf area index (DMLA), the critical leaf area development curve (LADC) parameters (DLAP1 and DLAP2, DLAI and RLAD), and radiation use efficiency (WA) for biomass yield (Table 1). Parameters were adjusted by iteratively running APEXgraze until an acceptable goodness-of-fit match of the growth curve of each species was achieved. For purposes of this study, only results for five functional groups will be presented for demonstration. Wherever possible, simulated plant growth curves were compared to plant phenology reports and information in the literature, particularly at: https://plants.sc.egov.usda.gov/home and https://www.inaturalist.org/.

Table 2
Plant Functional Groups (FG) used in Modeling CEAP-Grazing Lands (GL), including the FG Season, Duration and Habitat.

Functional Group (FG)	FG Number	FG Season	FG Season Number	Duration	Habit
Tallgrass	101	Spring Tallgrass	1	Perennial	Grass
Tallgrass	101	Summer Tallgrass	3	Perennial	Grass
Midgrass	105	Spring Midgrass	5	Perennial	Grass
Midgrass	105	Summer Midgrass	7	Perennial	Grass
Shortgrass	109	Spring Shortgrass	9	Perennial	Grass
Shortgrass	109	Summer Shortgrass	11	Perennial	Grass
Suffrutescent Grass	113	Spring Suffrutescent Grass	13	Perennial	Grass
Suffrutescent Grass	113	Summer Suffrutescent Grass	15	Perennial	Grass
Stoloniferous Grass	117	Spring Stoloniferous Grass	17	Perennial	Grass
Stoloniferous Grass	117	Summer Stoloniferous Grass	19	Perennial	Grass
Rhizomatous Grass	121	Spring Rhizomatous Grass	21	Perennial	Grass
Rhizomatous Grass	121	Summer Rhizomatous Grass	23	Perennial	Grass
Perennial Grasslike	125	Spring Perennial Grasslike	25	Perennial	Grass
Perennial Grasslike	125	Summer Perennial Grasslike	27	Perennial	Grass
Annual Grasslike	129	Spring Annual Grasslike	29	Annual	Grass
Annual Grasslike	129	Summer Annual Grasslike	31	Annual	Grass
Annual Grass	133	Spring Annual Grass	33	Annual	Grass
Annual Grass	133	Summer Annual Grass	35	Annual	Grass
Lichen	137	Lichen	37	Perennial	Cryptogam
Moss, Liverwort, Hornwort	138	Moss, Liverwort, Hornwort	38	Perennial	Cryptogam
Clubmoss	139	Clubmoss	39	Perennial	Forb
Fern	140	Fern	40	Perennial	Cryptogam
Monocot Forb	142	Monocot Forb	42	Perennial	Forb/Herb
Herbaceous Vine	144	Herbaceous Vine	44	Perennial	Forb
Woody Vine	146	Woody Vine	46	Perennial	Shrub
Perennial Forb	148	Spring Perennial Forb	48	Perennial	Forb
Perennial Forb	148	Summer Perennial Forb	50	Perennial	Forb
Annual Forb	152	Spring Annual Forb	52	Annual	Forb
Annual Forb	152	Summer Annual Forb	54	Annual	Forb
Monocot Shrub	156	Monocot Shrub	56	Perennial	Shrub
Deciduous Subshrub	158	Deciduous Subshrub	58	Perennial	Shrub
Evergreen Subshrub	160	Evergreen Subshrub	60	Perennial	Shrub
Deciduous Shrub	162	Deciduous Shrub	62	Perennial	Shrub
Evergreen Shrub	164	Evergreen Shrub	64	Perennial	Shrub
Deciduous Rhizomatous Shrub	166	Deciduous Rhizomatous Shrub	66	Perennial	Shrub
Cacti	168	Cacti	68	Perennial	Shrub
Monocot Tree	170	Monocot Tree	70	Perennial	Tree
Deciduous Tree	172	Deciduous Tree	72	Perennial	Tree
Evergreen Tree	174	Evergreen Tree	74	Perennial	Tree
Evergreen Coniferous Tree	176	Evergreen Coniferous Tree	76	Perennial	Tree
Deciduous Coniferous Tree	178	Deciduous Coniferous Tree	78	Perennial	Tree
Evergreen Rhizomatous Tree	180	Evergreen Rhizomatous Tree	80	Perennial	Tree
Deciduous Rhizomatous Tree	182	Deciduous Rhizomatous Tree	82	Perennial	Tree

Adapted from USDA NRCS National Resources Inventory (NRI) CEAP-GL database.

The zero-grazing management practice was used for calibrating and validating the NRI grazing lands biomass yields. Since there are no records of historical management at the NRI points, for modeling purposes, it was assumed the modeled NRI points were historically not subjected to any grazing, manure/urine deposits, burning etc.

For any sample point, harvested biomass was reconstructed to represent the biomass yield of each plant species at a given location at a single point in time (NRI Grazing Land On-Site Data Collection handbook, 2021). The reconstructed biomass yield represents the total normal annual air-dry production and is made up of only those plants that contributed 90% of the biomass. It is probably important to note here that the reconstructed weights represent the plant not being grazed, which fits our reason for using the zero-grazing management practice in the simulations. Also, it should be emphasized that the ability of the "reconstructer" is very important for the reconstruction of weights. The reconstructer has to use expert knowledge to estimate the percent of current growth that is ungrazed, the percent of the growth curve completed and the percent of normal production, which creates some uncertainty in these values if the reconstructer does a poor job of estimating.

After noticing the presence of some extreme biomass values in the datasets of some functional groups, a data quality inspection of the reconstructed yields was conducted to assess normality and discern any potential 'outlier values' in the dataset using the Tukey's fences technique and a multiplier constant of 1.5 (Tukey, 1977). Removal of the outliers reduced the total number of locations available for calibration/validation from 5062 to 4637.

2.5. Model calibration and validation set-up

The developed functional group plant parameters (PLANTABLE.DAT file in APEXgraze) along with the customized daily weather, soils data, and the zero-grazing management system were input into APEXgraze and applied to calibrate and validate APEXgraze against field-measured biomass yields gathered at 4637 (after removal of outliers) LRR H NRI grazing lands sampling locations and corresponding ET data (Reitz et al., 2017). For purposes of calibration and validation and noting that the native vegetation is dominated by prairie grasses, simulations were

[2] The ALMANAC (Kiniry et al., 1992), EPIC/APEX (Williams et al., 1984; Gassman et al. ., 2010) and SWAT (Arnold et al., 2012) models share the same plant growth module. However, the plant table input datasets contain similar and also different plant species.

conducted over a 15-yr time series (2000–2014). The first five years (2000–2004) of the simulation were used to initialize model parameterization input data, in particular, soil conditions, and also to allow good establishment for perennials. The last 10 years (2005–2014) cover the period through which the NRI survey was conducted and hence were used for the calibration and validation. APEXgraze automatic N and P fertilizer application options were applied to a level that did not impose any major nutrient stress. Nutrient stresses are anticipated when modeling rangelands because APEXgraze, like most other models does not account for the contribution of leguminous forbs and other plants to nutrient cycling of such key nutrients as N, nor do the models also account for atmospheric N deposition. Model simulations were initiated on January 01, while green-up occurred when the base temperature of the plant species was reached. The average functional group potential heat units reported in the NRCS NRI grazing lands database were used to set-up the length of the growing season to maturity. Biomass sample harvests occurred on September 30, September being the month when the majority of the NRI biomass samples were harvested.

In APEX, and similarly so in APEXgraze, herbaceous plant population input values (PPLP1 and PPLP2 in the APEX Manual) can be stated in terms of number of plants m^{-2} or basal area, the percentage of the soil surface that is covered by the base of a plant (Zilverberg et al., 2017). Due to uncertainty in the accuracy of the available basal area data, the plant population was calculated based on the fraction of biomass contributed by each plant species to the total biomass of a given location/sample point (actually the total biomass for the species that make up 90% of the biomass) based on the plant population S-curves. The calculated plant population was then used to accordingly modify the management file in APEXgraze. A demonstration of how the population algorithm works is presented in the Appendix.

APEXgraze was calibrated and validated by comparing the model-predicted yearly average aboveground standing biomass [Standing live biomass (STL) + Standing dead biomass (STD)] (partitioned by functional group) on September 30 to the NRI reconstructed biomass yield, also assumed to have been harvested on the same date. For calibration, 70 locations were selected using the sampling algorithm and were subject to the constraint that 'All functional group representative plants had to be present at least once, if possible'. For validation, 210 locations were selected with the same constraint. With a varying number of plant species present at any given location (in some cases, up to six), the selected calibration and validation locations had a total of 323 and 856 plant species/biomass samples, respectively. For ET, there were a total of 70 and 210 locations for calibration and validation, respectively.

APEX-CUTE allows manual adjustment of parameters and their ranges iteratively between autocalibration simulations. Initial results of APEXgraze autocalibration with the default functional group parameter values were judged unacceptable. Therefore, a subset of the minimum basic plant parameters was selected for both manual and auto adjustment. This subset was comprised of the most influential parameters to plant growth and production, and included the radiation use efficiency, maximum leaf area index (initially manually adjusted), fraction of growing season when LAI declines, and maximum crop/plant height and root depth (auto adjusted). All the other parameters were kept as their default values. The manual and autocalibration default functional group parameter values were adjusted within the suggested permissible ranges (Table 1). Parameters were adjusted by iteratively running APEXgraze until an acceptable goodness-of-fit match of the simulated and reconstructed aboveground biomass yields was achieved.

2.6. Potential applications of the APEXgraze model

Following successful calibration and validation, the APEXgraze model was applied to demonstrate its potential application to evaluate environmental resource concerns and ecosystem services on grazing lands as impacted by increased stocking densities. Model simulations were conducted at the same location in North Kansas (Fig. 1) that was used to test the utility of functional group plant parameters and the APEXgraze model to adequately describe plant species plant growth and dry matter accumulation during the growing season. Evaluated resource concerns and ecosystem services at the location included average annual precipitation, ET, surface runoff, water stress, water and wind erosion, and soil organic carbon storage. The dominant and simulated functional groups and their respective representative plant species at the location were Tallgrass (big bluestem - *Andropogon gerardii*), Midgrass (little bluestem - *Schizachyrium scoparium*), Rhizomatous grass (western wheatgrass - *Pascopyrum smithii*), Annual grass (field brome - *Bromus arvensis*) and Perennial forb (common plantain - *Plantago major*).

Model simulations set-up was similar to what is described in section 2.5. In this study we estimate actual ET by the Hargreaves equation (Hargreaves and Samani, 1985), while runoff is estimated by the SCS Curve Number (CN) method (USDA SCS, 1972). The water stress factor is computed by considering supply and demand and is measured by the number of days the plant suffers stress. To simulate rainfall/runoff erosion, we used the Universal Soil Loss Equation (USLE) (Wischmeier and Smith, 1978), while for wind erosion, the model uses the Wind Erosion Continuous Simulation (WECS, Williams et al., 2008) equation. APEXgraze uses the Century model (Parton et al., 1987, 1993, 1994) modified by Izaurralde et al. (2006) to estimate soil organic carbon storage.

We simulated the impacts of three high stocking densities with yearling steers, ranging from heavy (Reeves et al., 2014) to medium and extreme stocking density: i) 1 steer 0.8 ha^{-1}, ii) 1 steer 0.4 ha^{-1}, and iii) 1 steer 0.2 ha^{-1} and compared the impacts to a no grazing – zero steers ha^{-1} treatment. The stocking rate of 1 steer 0.8 ha^{-1} is the recommended stocking density per month for a loamy ecological site in central North Dakota (Sedivec and Printz, 2012). Grazing was initiated on May 1 and terminated on Oct. 1. APEXgraze simulations were conducted over a 45-yr time series (1976–2020). The first fifteen years (1976–1990) of the simulation were used as a spin-up period to initialize model parameterization input variables. The last 30 years (1991–2020) data were analyzed to generate 30-yr average annual values of the variables used to assess impacts on the aforementioned resource concerns and ecosystem services.

3. Model performance evaluation statistics

The calibration and validation performance of APEXgraze where the predicted ET and aboveground biomass yields were compared with observed/measured ET and reconstructed biomass yields was based on several goodness-of-fit metrics including the means, R^2 (coefficient of determination, using regression through the origin), NSE (Nash-Sutcliffe Efficiency) (Nash and Sutcliffe, 1970), and the index of agreement (*d*) (Legates and McCabe, 1999; Willmott, 1981). Data analyses were conducted using SAS version 9.4 for Windows (SAS, 2018).

4. Results

4.1. Plant functional group parameterization

A total of 64 functional groups that included the functional group season (spring or summer active growth season) for grasses and forbs were created from plant species occurring in LRR H (Table 3). The created functional group parameters were refined and tested for their capability to accurately describe the plant species growth curve patterns through APEXgraze simulation of plant growth and biomass accumulation including the time of establishment/green-up and maximum production etc. as impacted by various site-specific ecological conditions, such as soil type and climate (Fig. 3). Timing of grazing lands seasonal life cycle events is critical on ecosystem productivity and in designing effective grazing management and conservation practices. Accurate simulation of these seasonal life cycle events is challenging, but crucial. A 10-year study to predict the performance of cattle at the Central Plains

Table 3
Land resource region (LRR) H plant species were assigned to 64 functional groups (FGs) that included the FG season (spring or summer active growth season), Duration and Habitat. The Plantable number and APEXgraze plant symbol are also included in the table.

Functional Group (FG)	FG number	FG season	FG Season Number	Duration	Habit	Plantable number	APEXgraze Symbol
Tallgrass	101	Spring Tallgrass	1	Perennial	Grass	1	TRDA
Tallgrass	101	Summer Tallgrass	3	Perennial	Grass	2	ANGE
Midgrass	105	Summer Midgrass	7	Perennial	Grass	4	SCSC
Shortgrass	109	Spring Shortgrass	9	Perennial	Grass	6	HOJU
Shortgrass	109	Summer Shortgrass	11	Perennial	Grass	7	BOGR
Suffrutescent Grass	113	Summer Suffrutescent Grass	15	Perennial	Grass	8	MUPO
Stoloniferous Grass	117	Summer Stoloniferous Grass	19	Perennial	Grass	9	BODA
Rhizomatous Grass	121	Spring Rhizomatous Grass	21	Perennial	Grass	10	PASM
Rhizomatous Grass	121	Summer Rhizomatous Grass	23	Perennial	Grass	11	PAOB
Perennial Grasslike	125	Spring Perennial Grasslike	25	Perennial	Grass	12	CARE
Perennial Grasslike	125	Summer Perennial Grasslike	27	Perennial	Grass	13	CYPE
Annual Grass	133	Spring Annual Grass	33	Annual	Grass	14	HOPU
Annual Grass	133	Summer Annual Grass	35	Annual	Grass	15	PACA
Monocot Forb	142	Monocot Forb	42	Perennial	Forb	16	COER
Herbaceous Vine	144	Herbaceous Vine	44	Perennial	Forb	17	SMIL
Perennial Forb	148	Spring Perennial Forb	48	Perennial	Forb	18	SPCO
Perennial Forb	148	Summer Perennial Forb	50	Perennial	Forb	19	AMPS
Annual Forb	152	Spring Annual Forb	52	Annual	Forb	20	PLPA
Annual Forb	152	Summer Annual Forb	54	Annual	Forb	21	AMDR
Woody Vine	146	Woody Vine	46	Perennial	Shrub	22	VITI
Monocot Shrub	156	Monocot Shrub	56	Perennial	Shrub	23	YUCC
Evergreen Subshrub	160	Evergreen Subshrub	60	Perennial	Shrub	25	GUSA
Evergreen Shrub	164	Evergreen Shrub	64	Perennial	Shrub	26	ARFI
Cacti	168	Cacti	68	Perennial	Shrub	27	OPUN
Evergreen Tree	174	Evergreen Tree	74	Perennial	Tree	29	DIVI
Midgrass(I)	106	Spring Midgrass(I)	6	Perennial	Grass	30	AGCR
Midgrass(I)	106	Summer Midgrass(I)	8	Perennial	Grass	31	BOIS
Shortgrass(I)	110	Spring Shortgrass(I)	10	Perennial	Grass	32	LOPE
Rhizomatous Grass(I)	122	Summer Rhizomatous Grass(I)	24	Perennial	Grass	33	SOHA
Perennial Grasslike(I)	126	Spring Perennial Grasslike(I)	26	Perennial	Grass	34	CAGR
Annual Grass(I)	134	Spring Annual Grass(I)	34	Annual	Grass	35	BRAR
Annual Grass(I)	134	Summer Annual Grass(I)	36	Annual	Grass	36	SEVI
Monocot Forb(I)	143	Monocot Forb(I)	43	Perennial	Forb	37	ALAS
Perennial Forb(I)	149	Spring Perennial Forb(I)	49	Perennial	Forb	38	PLMA
Perennial Forb(I)	149	Summer Perennial Forb(I)	51	Perennial	Forb	39	LECU
Annual Forb(I)	153	Summer Annual Forb(I)	55	Annual	Forb	40	MELU
Evergreen Subshrub(I)	161	Evergreen Subshrub(I)	61	Perennial	Shrub	41	KRAR
Deciduous Shrub(I)	163	Deciduous Shrub(I)	63	Perennial	Shrub	42	TAGA
Annual Forb(I)	153	Spring Annual Forb(I)	53	Annual	Forb	44	SAKA
Deciduous Tree(I)	173	Deciduous Tree(I)	73	Perennial	Tree	45	PRJU
Evergreen Tree(I)	175	Evergreen Tree(I)	75	Perennial	Tree	46	GUAR
Tallgrass(I)	102	Spring Tallgrass(I)	2	Perennial	Grass	47	TRD3
Rhizomatous Grass(I)	122	Spring Rhizomatous Grass(I)	22	Perennial	Grass	48	BRIN
Clubmoss	139	Clubmoss	39	Perennial	Forb	50	EQHY
Fern	140	Fern	40	Perennial	Cryptogam	51	BOLU
Deciduous Shrub	162	Deciduous Shrub	62	Perennial	Shrub	52	SYOR
Evergreen Shrub(I)	165	Evergreen Shrub(I)	65	Perennial	Shrub	53	ARF2
Evergreen Coniferous Tree	176	Evergreen Coniferous Tree	76	Perennial	Tree	55	JUNP
Deciduous Coniferous Tree	178	Deciduous Coniferous Tree	78	Perennial	Tree	56	LAOC
Deciduous Tree(I)	173	Deciduous Tree(I)	73	Perennial	Tree	57	ULPA
Deciduous Subshrub	58	Deciduous Subshrub	58	Perennial	Shrub	58	ABIN
Deciduous Tree	172	Deciduous Tree	72	Perennial	Tree	59	JUNI
Herbaceous Vine	144	Herbaceous Vine	44	Perennial	Forb	60	VICI
Rhizomatous Grass	121	Spring Rhizomatous Grass	21	Perennial	Grass	62	POAR
Annual Forb(I)	153	Summer Annual Forb(I)	55	Annual	Forb	63	KUST
Rhizomatous Grass(I)	122	Spring Rhizomatous Grass(I)	22	Perennial	Grass	64	POCO
Clubmoss	139	Clubmoss	39	Perennial	Subshrub	65	DIO2
Midgrass	105	Spring Midgrass	5	Perennial	Grass	66	LEDU
Stoloniferous Grass	117	Spring Stoloniferous Grass	17	Perennial	Grass	67	AGST
Woody Vine(I)	147	Woody Vine (I)	47	Perennial	Shrub	68	VITS
Herbaceous Vine	144	Herbaceous Vine	44	Perennial	Forb	69	CONV
Perennial Forb(I)	149	Summer Perennial Forb(I)	51	Perennial	Forb	70	LOTU
Lichen	137	Lichen	37	Perennial	Cryptogam	71	THME
Evergreen Shrub	164	Evergreen Shrub	64	Perennial	Shrub	72	BAPT

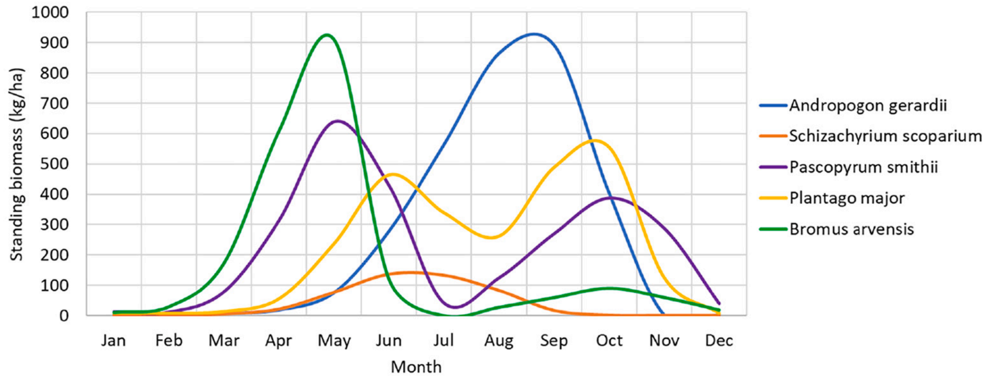

Fig. 3. APEXgraze simulated growth curve patterns of five widely common grazing lands functional group representative plant species: Tallgrass (big bluestem - *Andropogon gerardii*), Midgrass (little bluestem - *Schizachyrium scoparium*), Rhizomatous grass (western wheatgrass - *Pascopyrum smithii*), Annual grass (field brome - *Bromus arvensis*) and Perennial forb (common plantain - *Plantago major*) at a location in North Kansas. Standing biomass is an average of 10-year simulation values.

Experimental Range, a Long-Term Agroecosystem Research (LTAR) network location in Eastern Colorado noted that weight gain was affected by the timing of forage green-up and senescence (browning down) (Kearney et al., 2021).

For purposes of this study and demonstration, Fig. 3 shows APEXgraze simulated growth curve patterns of the five functional group representative plant species: Tallgrass (big bluestem), Midgrass (little bluestem), Rhizomatous grass (western wheatgrass), Annual grass (field brome) and Perennial forb (common plantain), at the location in North Kansas (Fig. 1). Big bluestem and little bluestem, as the representative plant species for the Tallgrass and Midgrass functional group groups (Table 3) are warm season grasses that green-up in March or early April. Big bluestem matures in late August or early September, while little bluestem will continue to grow until the first killing frost. Western wheatgrass greens-up in March or early April and matures in August. Reasonable fall regrowth is possible if soil moisture is available (bimodal growth). Field brome is a winter annual with spring growth starting earlier than most other annual grasses. It produces dense, low leafy growth in the fall. Lastly, common plantain is a perennial forb whose active growth period is between March/April and October/November depending on availability of soil moisture.

The APEXgraze simulated growth curves corroborate well with information presented elsewhere in the literature, particularly at: https://plants.sc.egov.usda.gov/home and https://www.inaturalist.org/, demonstrating that grazing lands plants can be classified into a manageable number of functional groups that can be used for modeling. The characterization of vegetation cover as being composed of a mixture of a few functional groups was a major step forward for dynamic

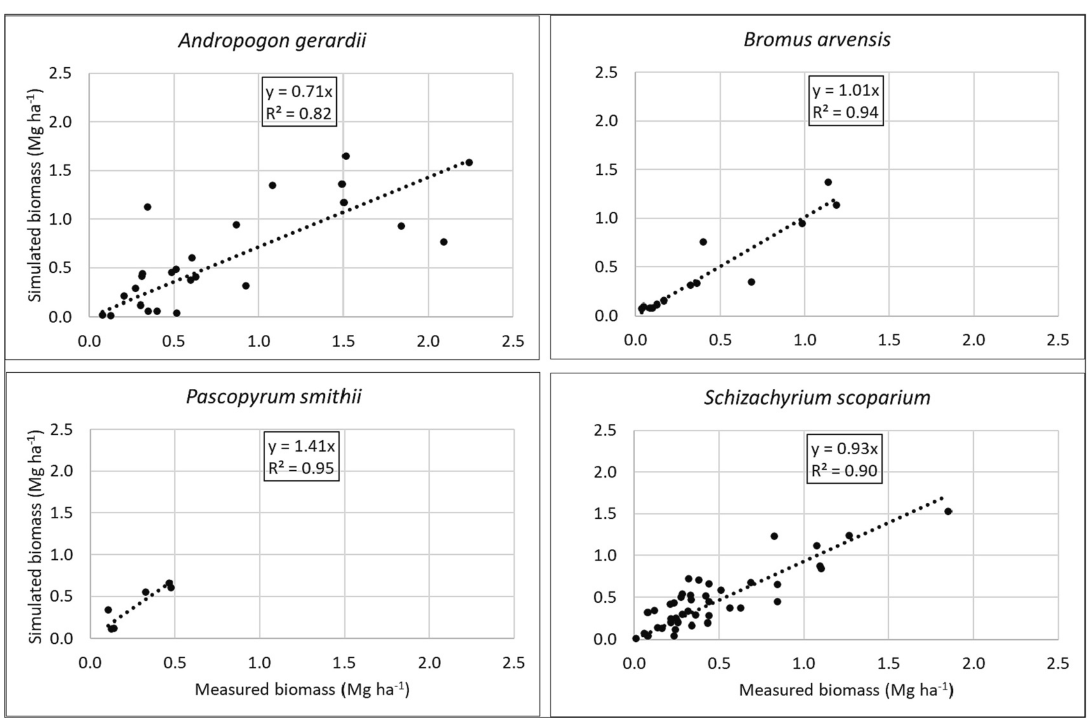

Fig. 4. Testing APEXgraze and functional group parameters' capability to simulate National Resources Inventory reconstructed aboveground biomass yields among five grazing lands plant species: big bluestem (*Andropogon gerardii*), field brome (*Bromus arvensis)* western wheatgrass (*Pascopyrum smithii*),) and little bluestem (*Schizachyrium scoparium*) at a location in North Kansas. Note: The perennial forb, common plantain (*Plantago major*) appeared in one location only. Each data point is a different site/location.

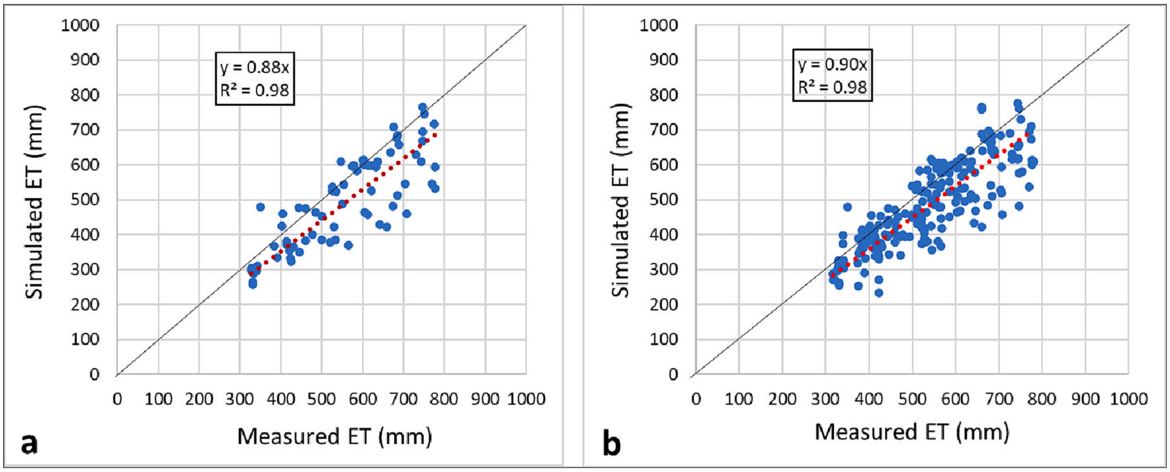

Fig. 5. APEXgraze calibration (a) and validation (b) against national annual average evapotranspiration (ET) data at Hydrologic Unit Code 8 (HUC8) scale for the contiguous United States (CONUS) (Data source for measured ET: Reitz et al., 2017).

process-based modeling (Prentice and Cowling, 2013; Kiniry et al., 2013; Williams et al., 2017).

APEXgraze's capability to simulate NRI reconstructed aboveground biomass yields for big bluestem, field brome, western wheatgrass and little bluestem are shown in Fig. 4. The perennial forb, common plantain is not represented because it appeared in only one location. Little bluestem, big bluestem, field brome, and western wheatgrass respectively appeared in 43, 25, 13 and 6 out of the 70 calibration locations. Overall, there was a good agreement between simulated and NRI reconstructed aboveground biomass yields among the FG functional group representative species, with R^2 values >80%.

4.2. Plant functional group calibration and validation

Following removal of the outliers there were 4637 NRI locations available for the sampling algorithm to randomly choose for calibration and validation. Seventy locations populated with a total of 323 plants were used for calibration, while 210 locations populated with 856 plants were used for validation. During calibration, functional group parameters were adjusted by iteratively running APEXgraze until there was a reasonable match between simulated and observed/measured ET and aboveground biomass. The ET and biomass were calibrated in concert. No functional group parameters were adjusted during validation.

4.2.1. Simulated versus actual evapotranspiration across locations

Calibration and validation of APEXgraze simulated average annual ET against ET data for the CONUS (Reitz et al., 2017) is shown in Fig. 5 with the corresponding model performance metrics in Table 4. Overall, calibration and validation metrics indicate satisfactory performance by APEXgraze in simulating ET using functional group parameters in LRR H. Mean simulated ET values were reasonable, and within 10% of observed ET values. The model was able to explain 98% (R^2) of the variance in observed ET values in both calibration and validation. R^2 values typically >0.5 are considered acceptable (Santhi, 2001; Van Liew et al., 2003). Additionally, model simulation can be judged as satisfactory if NSE > 0.50 (Moriasi et al., 2007), and Willmott's d is closer to 1 (Willmott, 1981).

4.2.2. Simulated versus reconstructed aboveground biomass yields across locations and functional groups

Aboveground biomass calibration and validation metrics were not as strong as those for ET, with the calibration metrics being slightly better than the validation metrics (Fig. 6). However, overall model performance was still satisfactory in simulating biomass yields using functional group parameters in LRR H (Table 4). Similar to mean simulated ET values, simulated mean biomass yields were reasonable, and were respectively within 16% and 11% of reconstructed biomass yields during calibration and validation. The model was able to explain 75% (R^2) of the variance in measured biomass yields during calibration and 70% of the variance during validation. Both NSE and Willmott's d were respectively >0.50, and closer to 1.

4.3. Potential applications of the APEXgraze model

The fully calibrated and validated APEXgraze model was applied to evaluate the impact of high stocking density on environmental resource concerns and ecosystem services on grazing lands at the location in North Kansas (Fig. 1). Evaluated resource concerns and ecosystem services at the location included average annual precipitation, ET, surface runoff, water stress, water and wind erosion, and soil organic carbon storage.

4.3.1. Site precipitation, evapotranspiration, surface runoff, and water stress

Rainfall is highly variable over time (Fig. 7), while ET accounts for at least 98% of the precipitation (Table 5; Fig. 7). Since 98% of the annual precipitation leaves the watershed as ET, there is usually very little to no surface runoff except that generated from extreme precipitation events (Fig. 7).The 30-year average surface runoff with no grazing was only 3.21 ± 2.3 mm, ranging from 0 to 25 mm. Rainfall characteristics are key drivers in runoff generation mechanisms (Sen et al., 2010; Fang et al., 2022). In semi-arid regions runoff may be generated under high intensity rainfall even in short duration and small rainfall depth events (Smith et al., 2010). The plant species under no grazing suffered on average, a total of 30 ± 7 water stress days, ranging from 9 to 90 days. While water stress days seemed to numerically decrease with increasing stocking density (Table 5), stocking density had little apparent effect on ET and surface runoff.

4.3.2. Water and wind erosion

Total sediment losses are composed of losses by water and wind erosion (Fig. 8). Overstocking can result in loss of plant cover and hence exposing the soil to erosion. Overall, there is some correlation between the increase in sediment losses, for both water and wind erosion with increasing stocking density: heavy (1 steer 0.8 ha^{-1}), ii) medium (1 steer 0.4 ha^{-1}), and iii) extreme (1 steer 0.2 ha^{-1}). Due to the aridity of the location, water erosion is a relatively minor constraint or concern, with model-simulated average annual rates of water erosion at the extreme

Table 4
APEXgraze model performance metrics during calibration and validation against estimated annual average evapotranspiration (ET) and reconstructed NRI annual average aboveground biomass yields.

Performance Metric	Calibration	Validation	Performance Metric	Calibration	Validation
Measured ET (mm)	555	535	Measured biomass (Mg ha^{-1})	0.415	0.445
Simulated (T (mm)	493	485	Simulated biomass (Mg ha^{-1})	0.347	0.397
R^2	98	0.98	R^2	0.75	0.70
NSE	0.51	0.52	NSE	0.56	0.50
d	0.85	0.87	d	0.85	0.83

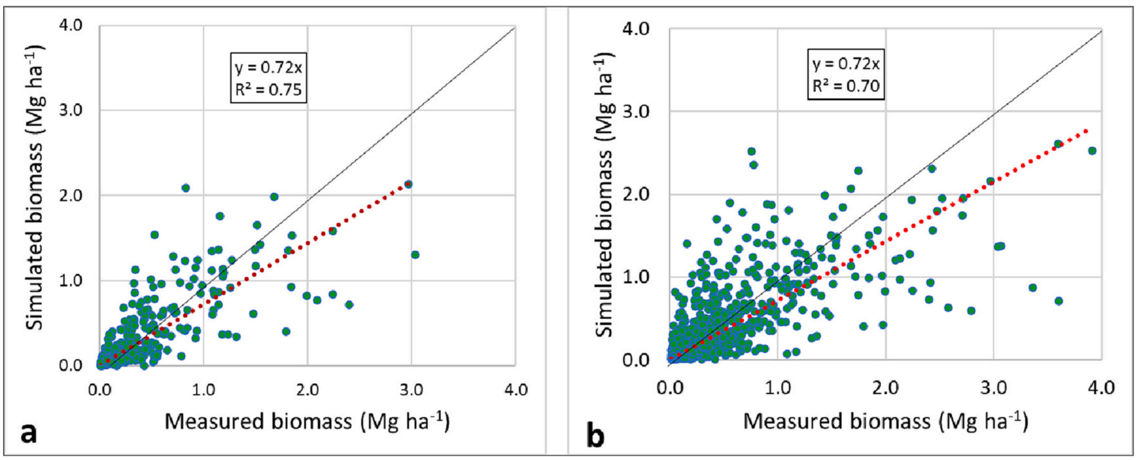

Fig. 6. (a) APEXgraze calibration and (b) validation against National Resources Inventory reconstructed aboveground biomass yields. The biomass yields are reconstructed estimates that represent the biomass yield of each plant species at a given location at a single point in time.

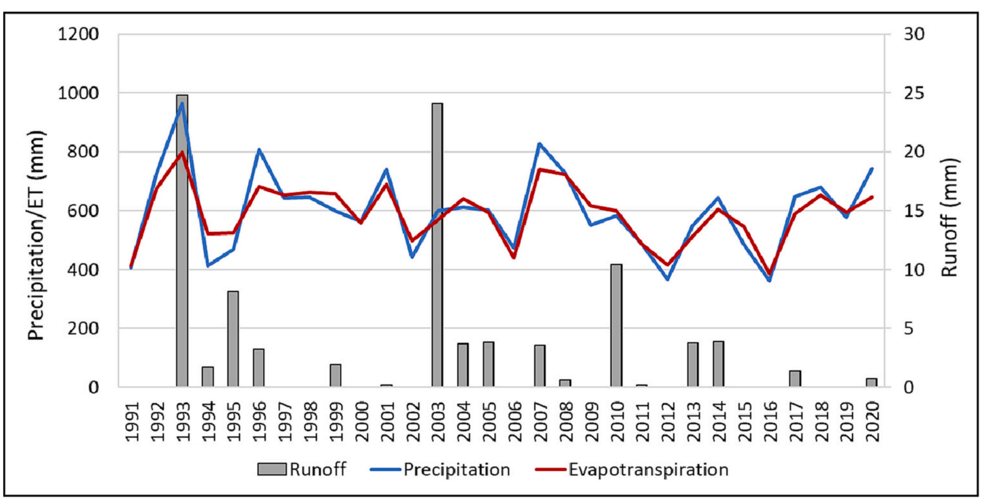

Fig. 7. Annual precipitation, evapotranspiration (ET) and surface runoff at a semi-arid grazing lands location in North Kansas.

Table 5
Impact of high stocking density on evapotranspiration (ET), surface runoff and water stress days at a semi-arid grazing lands location in North Kansas.

Stocking density	Precipitation (mm)		Potential ET (mm)		ET(mm)		Runoff (mm)		Water stress (days)	
(ha per steer)	Mean	Range	Mean	Range	Mean	Range	Mean	Range	Mean	Range
No grazing	598 ± 51	362–966	1798 ± 35	1560–2070	590 ± 36	387–797	3.2 ± 2.3	0–25	30 ± 7	5–90
0.8	598 ± 51	362–966	1798 ± 35	1560–2070	591 ± 38	378–819	3.2 ± 2.2	0–24	33 ± 8	7–93
0.4	598 ± 51	362–966	1798 ± 35	1560–2070	591 ± 37	387–810	3.4 ± 2.4	0–28	30 ± 7	9–87
0.2	598 ± 51	362–966	1798 ± 35	1560–2070	580 ± 32	444–787	3.3 ± 2.3	0–27	19 ± 4	10–46

±Mean confidence limit at $p \leq 0.05$.

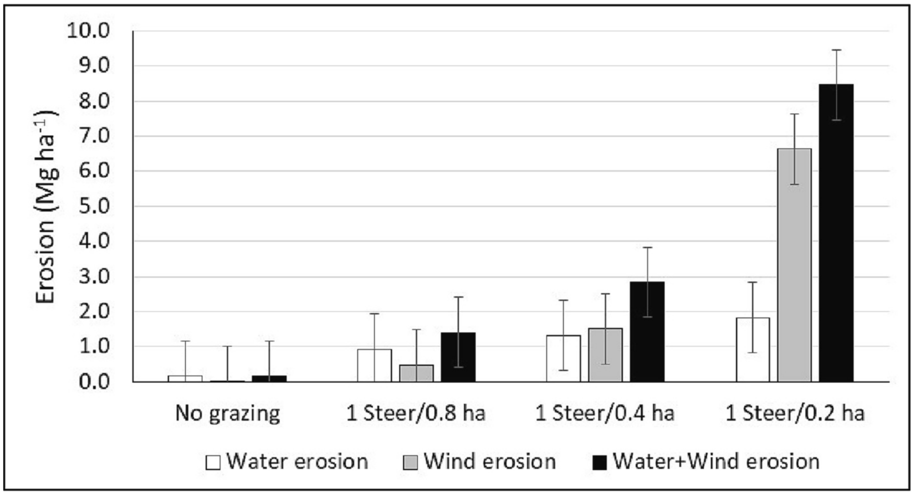

Fig. 8. Impacts of stocking density on water and wind erosion at a semi-arid grazing lands location in North Kansas. Error bars are mean confidence intervals at $p \leq 0.05$.

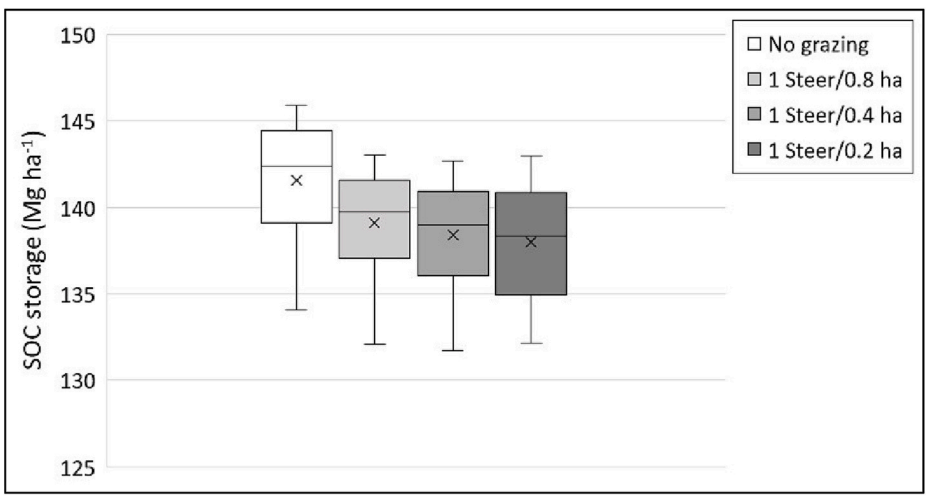

Fig. 9. Impacts of stocking density on soil organic carbon storage at a semi-arid grazing lands location in North Kansas.

stocking density being only 1.83 Mg ha^{-1} y^{-1}, compared to an average of 6.63 Mg ha^{-1} y^{-1} for wind erosion.

4.3.3. Soil organic carbon storage

The high stocking densities of heavy (1 steer 0.8 ha^{-1}), ii) medium (1 steer 0.4 ha^{-1}), and iii) extreme (1 steer 0.2 ha^{-1}) decreased soil organic carbon relative to the No grazing treatment by 2.4, 3.2 and 3.5 Mg ha^{-1}, respectively (Fig. 9). Our findings are supported by the results of a recent meta- analysis of 83 studies of extensive grazing, covering 164 sites across different countries and climatic zones, that showed that high stocking densities result in a decrease in soil organic carbon storage, although the impact on soil organic carbon is climate-dependent (Abdalla et al., 2018).

Besides stocking density, results can however, also be influenced by other interacting factors that include the type of grazers and botanical composition of the grazing lands. At this location in North Kansas, five different plant species were simulated: big bluestem, little bluestem, western wheatgrass, field brome and common plantain. High stocking density decreases water availability, which in turn decreases plant community composition, aboveground biomass, leaf area and light interception and thereby, net primary production (Manley et al., 1995; Pineiro et al., 2010).

5. Discussion

5.1. Plant functional group parameterization, calibration and validation

Due to the high plant species variability that is often found in grazing lands, modeling the effects and benefits of conservation practices on grazing lands would be much more efficient if the grazing lands plants were simulated as functional groups rather than as individual plant species. When incorporated into the APEXgraze model, the suite of developed plant functional groups that represent LRR H grazing lands plant species (Table 3), the functional group parameters gave a good representation of the functional group plant species growth dynamics as shown in Fig. 3. As pointed out earlier, The APEXgraze simulated growth curves validate well with information presented elsewhere in the literature, particularly at: https://plants.sc.egov.usda.gov/home and https://www.inaturalist.org/, demonstrating that grazing lands plants can be classified into a manageable number of functional groups that can be used for modeling. The characterization of vegetation cover as being composed of a mixture of a few functional groups was a major step forward for dynamic process-based modeling (Prentice and Cowling, 2013; Kiniry et al., 2013; Williams et al., 2017). According to Prentice and Cowling (2013), the fundamental idea behind plant functional groups is that there are inevitable trade-offs between different plant traits, such that not all combinations of traits are possible; therefore, plants can be classified into a manageable number of plant functional groups. When correctly parameterized, calibrated and validated, grazing land models like APEXgraze can enhance the ability to assess natural resource management options over large landscapes (region and watershed-scale). Overall, model performance evaluation metrics indicated satisfactory model performance during both calibration and validation against ET data and NRI reconstructed biomass yields.

It is however important to caution that discontinuous biomass measurements contain rather large uncertainties, mainly due to the spatial heterogeneity of grassland covers (Snow et al., 2014), which makes model evaluation difficult (Vuichard et al., 2007; Gomára et al., 2020). Our reconstructed biomass yields had about 8.4% outlier values that were discounted before evaluations could be conducted.

5.2. *Potential applications of the APEXgraze model*

As mentioned earlier, biophysical models driven by daily climatic variables enable assessment of natural resource management options over time and across large landscapes, especially where on-the-ground assessments are not feasible. Model outputs can help assess ecosystem impacts and services associated with shifts in both management practices and species composition. According to (Euliss et al., 2010), a process-based model could be implemented to help guide site monitoring and adaptive management approaches. In this way, it could be a valuable tool for conservation practice planning.

5.3. *Site precipitation, water stress, evapotranspiration and surface runoff*

The ratio of total annual precipitation to potential ET of 0.33 (i.e., the Aridity Index) (Table 5) classifies the Kansas location as semi-arid (UNESCO, 1979). In arid and semi-arid regions precipitation and ET are the main drivers of plant growth and biomass yield. Managers and producers struggle with high interannual change in biomass yield or aboveground annual net primary productivity, which according to Reeves et al. (2021), often varies 40% between years due to fluctuating precipitation and drought. From Fig. 7, it is very clear that rainfall is highly variable over time, while ET accounts for at least 98% of the precipitation. Since 98% of the annual precipitation leaves the watershed as ET, there is usually very little to no surface runoff except that generated from extreme precipitation events (Table 5; Fig. 7). Aboveground annual net primary productivity directly influences production of livestock as a critical determinant of stocking density. Based on a body of economic and decision-making research in the western United States, Ritten et al. (2010) and Torrell et al. (2010) emphasize the importance of flexible stocking rates, which are strongly influenced by the aboveground annual net primary productivity. In the current study, increasing stocking density (Table 5), numerically decreased the number of water stress days, while there was little apparent effect on ET and surface runoff.

5.4. *Water and wind erosion*

It has been long recognized that overgrazing as a result of high stocking density contributes to the deterioration of soil stability and porosity, and increases erosion and soil compaction (Fleischner, 1994). Our APEXgraze-simulated results on the impacts of high stocking densities on water and wind erosion agree with other findings reported elsewhere in the literature. Lai and Kumar (2020) conducted a global meta-analysis of 287 papers published between 2007 and 2019 on livestock grazing impacts on soil properties and reported similar findings. The combined water and wind sediment losses of 8.46 Mg ha^{-1} y^{-1} at the extreme stocking density (1 steer 0.2 ha^{-1}) fails to meet the USDA NRCS (2010) acceptable planning criteria threshold of <4.5 Mg ha^{-1} y^{-1} of soil loss. This erosion control threshold represents field-level losses that are feasible to attain using traditional soil conservation treatments. Although not fully discussed here, it is important to note that erosion can also result in considerable soil organic carbon and nutrient losses in sediment. APEXgraze can be applied to greatly aid ranchers in optimizing stocking rate decisions for conservation planning aimed at reducing soil erosion.

5.5. *Soil organic carbon storage*

APEXgraze simulated effects of high stocking densities on soil organic carbon storage suggested that high stocking densities can lead to soil organic carbon losses. Similar observations were made by Cui et al. (2005) and Rounsevell et al. (1999), stocking density can modify soil structure, function and capacity to store soil organic carbon, whose reduction could lead to reduced soil fertility and consequently, land degradation. To protect grazing land soil health, Abdalla et al. (2018) recommend that stocking density and management practices should be optimized according to climate region and plant species type. APEXgraze can be applied to grazing lands to understand the impacts of stocking density on soil organic carbon accumulation and storage and to provide the most effective soil organic carbon management options. Improved rangeland management has the biophysical potential to sequester 1.3–2 Gt CO^2 eq yr^{-1} (Smith et al., 2007). Assuming a CO_2 price of US$20–50 per ton for carbon sequestration (Viglizzo et al., 2019)., this stresses the great interest of grazing lands for carbon sequestration.

6. Concluding remarks and way forward

APEXgraze is a highly flexible and dynamic model that comes with a calibration and validation tool and a graphical user interface that streamlines model calibration and validation. In addition, the tool has an embedded locations-sampling algorithm that allows for the selection of the same or different unbiased random ensembles of NRI sample points to simulate during calibration and validation. Both the calibration and validation tool, and the locations-sampling algorithm are implemented in an enhanced APEX-CUTE. The advantage of APEX-CUTE is it allows manual adjustment of APEX parameters and their ranges iteratively between autocalibration simulations. Following successful calibration and validation with LRR H grazing lands plant species functional groups, the APEXgraze model was applied to demonstrate its potential application to evaluate environmental resource concerns and ecosystem services on grazing lands as impacted by increased stocking densities. Evaluated resource concerns and ecosystem services at an arid and semi-arid location in north Kansas included average annual precipitation, ET, surface runoff, water stress, water and wind erosion, and soil organic carbon storage. A fuller understanding of the impacts of high stocking density on cattle production and grazing lands will not only minimize producers' enterprise risk, but it will also allow for sustained cattle production. This will become increasingly important to meet the demand for an estimated increase of 200 million tonnes of animal protein per year by 2050 (FAO, 2012).

While further testing will be needed, the results presented here are a demonstration of the feasibility of using functional groups to parameterize and calibrate/validate biophysical models to simulate alternative grazing management practices to address natural resource concerns on grazing lands. APEXgraze could be applied to help guide land managers implement adaptive management options. So, in this way, it could be a valuable tool for conservation practice planning.

Software and data availability

The Agricultural Policy / Environmental eXtender (APEX) model is an open- source software developed by a team of soil, water, plant, and environmental researchers at the Blackland Research & Extension Center and USDA Grassland, Soil, and Water Laboratory in Temple, Texas. The core team spans three agencies: Texas A&M AgriLife Research, USDA Agricultural Research Service, and USDA Natural Resources Conservation Service. The software and supporting tools, including APEX-CUTE, can be downloaded for free at: https://epicapex.tamu.edu/software/. APEXgraze is an offshoot from APEX and was developed by Texas A&M AgriLife Research, in collaboration with USDA Natural Resources Conservation Service. The Figshare workspace dedicated to APEXgraze is available at https://figshare.com/s/1fe0ea5beb92698db09e

Authorship contribution statement

Manyowa N. Meki: Conceptualization, Methodology, Writing - original draft. Javier Osorio-Leyton: Data curation, Software programming, Writing - reviewing & editing. Evelyn M. Steglich: Writing - reviewing & editing. Jim R. Kiniry: Provision of plant parameters, Writing - reviewing & editing. Marco Propato, Mike Winchell, Hendrik Rathjens: Software programming, Writing - reviewing & editing. Jay P. Angerer: Supervision, Writing - reviewing & editing. Lee M. Norfleet – USDA NRCS CEAP GL: Sponsor, Writing - reviewing & editing.

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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 paper.

Data availability

Data will be made available on request.

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Appendix A. Determining the plant population for each point/species combination based on the fraction of biomass for each plant species to the total biomass for that point

The plant population for each point/species combination was based on the fraction of biomass for each plant species to the total biomass for that point (actually the total biomass for the species that make up 90% of the biomass) based on the plant population S-curves (Fig. A). The attached spreadsheet in Fig. A takes the PPLP1 and PPLP2 values as inputs and develops the S-Curve for those values. Also displayed in this spreadsheet are the plant population values that correspond to a percent of the maximum LAI which were used as a surrogate for the fraction of total biomass. The plant populations will be calculated for each point/species combination as follows:

1. Calculate the fraction of biomass of each point/species combination to the total biomass for the modeled species at a particular point.
2. Using the PPLP1 and PPLP2 values from the PLANTTABLE (in APEXgraze) for the species, calculate x and y according to the spreadsheet formulas.
   a. If PPLP1 > PPLP2 (in the case of trees), switch the values so that PPLP1 < PPLP2. This switch is only for the calculation of the plant population.
3. Determine the plant population (x) that corresponds most closely to the fraction of biomass for the species (Y) as calculated in step 1.

Table A
Below is an example calculation.

Point:	200408075020502R1							
Plant #	APEXgraze PLANT NAME	Functional Group	Reconstructed weight (Mg ha^{-1})	fraction of total biomass	PPLP1	PPLP2	Estimated Plant population (plants/m^2)	Note: when PPLP1 > PPLP2, let PPLP2 = PPLP1 in calculations and PPLP1 = PPLP2 in calculations
3	DIOL	Midgrass	0.753872	0.289642411	52.1	93.9	64	
19	AMPS	Perennial Forb	0.64904	0.249365291	42.1	91.9	72	
7	BOGR	Shortgrass	0.319872	0.122896854	72.1	96.9	73	
44	SAKA	Annual Forb (I)	0.291984	0.112182108	45.1	92.9	46	
4	SCSC	Midgrass	0.214816	0.082533672	38.1	90.9	36	

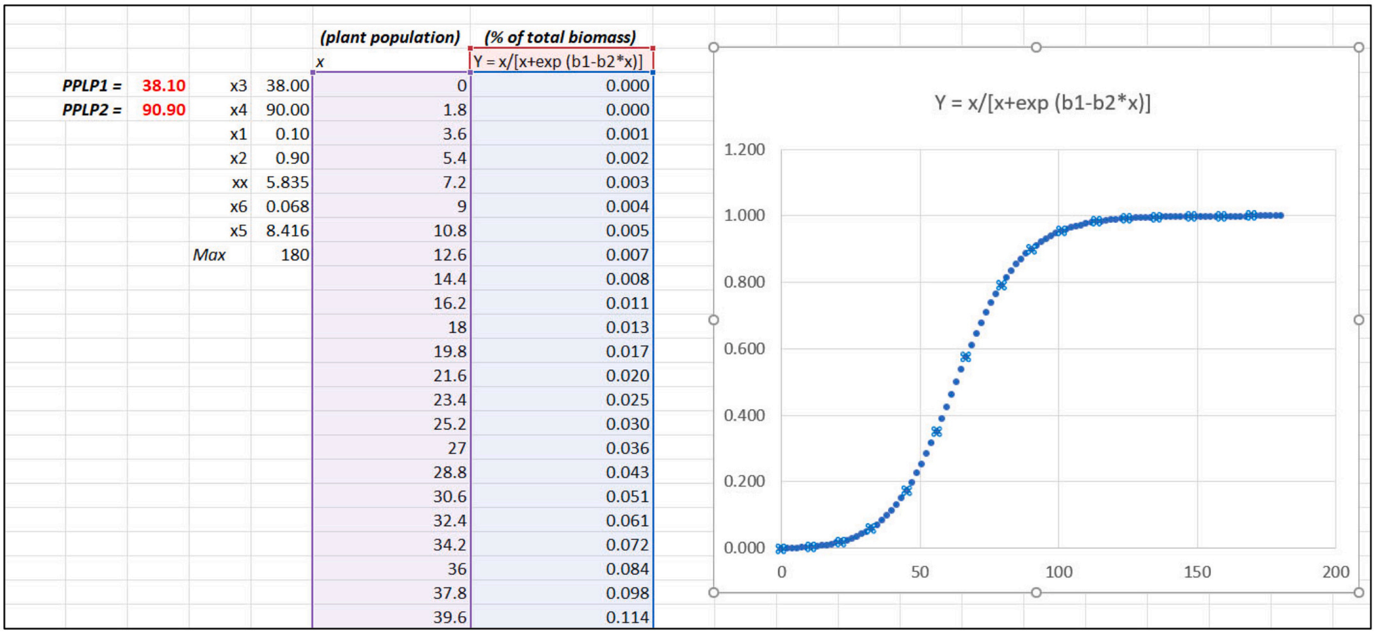

Fig. A. The plant population for each point/species combination was based on the fraction of biomass for each plant species to the total biomass for that point (actually the total biomass for the species that make up 90% of the biomass).

References

Abdalla, M., Hastings, A., Chadwick, D.R., Jones, D.L., Evans, C.D., Jones, M.B., Rees, R. M., 2018. Critical Creview of the impacts of grazing intensity on soil organic carbon storage and other soil quality indicators in extensively managed grasslands. Agric. Ecosyst. Environ. 253, 2–81.

Arnold, G.J., Moriasi, D.N., Gassman, P.W., Abbaspour, K.C., White, M.J., Srinivasan, R., Santhi, C., Harmel, R.D., van Griensven, A., Van Liew, M.W., Kannan, N., Jha, M.K., 2012. Swat: model use, calibration, and validation. Trans. ASABE 55 (4), 1491–1508.

Briske, D.D., Sayre, N.F., Huntsinger, L., Fernandez-Gimenez, M., Budd, B., Derner, J.D., 2011. Origin, persistence, and resolution of the rotational grazing debate: integrating human dimensions into rangeland research. Rangel. Ecol. Manag. 64, 325–334.

Cui, X.Y., Wang, Y.F., Niu, H.S., et al., 2005. Effect of long-term grazing on soil organic carbon content in semiarid steppes in Inner Mongolia. Ecol. Res. 20, 519–527.

Duriancik, L., Bucks, D., Dobrowolski, J.P., Drewes, T., Eckles, S.D., Jolley, L., Kellogg, R. L., Lund, D., Makuch, J.R., O'Neill, M.P., Rewa, C.A., Walbridge, M.R., Parry, R., Weltz, M.A., 2008. The first five years of the conservation effects assessment project. J. Soil Water Conserv. 63, 185A–197A.

Euliss Jr., N.H., Smith, L.M., Liu, S., Feng, M., Mushet, D.M., Auch, R.F., Loveland, T.R., 2010. The need for simultaneous evaluation of ecosystem services and land use change. Environ. Sci. Technol. 44, 7761–7763.

Fang, J., Yi, P., Stockinger, M., Xiong, L., Shen, J., 2022. Investigation of factors controlling the runoff generation mechanism using isotope tracing in large-scale nested basins. J. Hydrol. 615 (A) https://doi.org/10.1016/j.jhydrol.2022.128728.

FAO, 2012. World agriculture towards 2030/2050: the 2012 revision. In: Alexandratos, N., Bruinsma, J., (Eds.), ESA Working paper No. 12-03. Prepared by. FAO., Rome. Italy (accessed 10.14.22).

Fleischner, T.L., 1994. Ecological costs of livestock grazing in western North America. Conserv. Biol. 8 (3), 629–644.

Fox, W., Angerer, J., Tolleson, D., 2019. Conservation effects assessment project–grazing lands: an introduction to the special issue. RANGELANDS 41, 199–204.

Gassman, P.W., Williams, J.R., Wang, X., Saleh, A., Osei, E., Hauck, L.M., Izaurralde, R. C., Flowers, J.D., 2010. The agricultural policy environmental extender (APEX) model: an emerging tool for landscape and watershed environmental analyses. Trans. ASABE 53 (3), 711–740.

Gomára, I., Bellocchi, G., Martin, R., Rodriguez-Fonseca, B., Ruíz-Ramos, M., 2020. Influence of climate variability on the potential forage production of a mown permanent grassland in the French massif central. Agric. For. Meteorol. 280, 107768 https://doi.org/10.1016/j.agrformet.2019.107768.

Hargreaves, G.H., Samani, Z.A., 1985. Reference crop evapotranspiration from temperature. Appl. Eng. Agric. 1, 96–99.

Helms, D., 1997. Land capability classification: the U.S. experience. Adv. Geol. Ecol. 39, 159–175.

Izaurralde, R.C., Williams, J.R., McGill, W.B., Rosenberg, N.J., Jakas, M.C.Q., 2006. Simulating soil C dynamics with EPIC: model description and testing against long-term data. Ecol. Model. 192, 362–384.

Kearney, P.S., Porensky, L.M., Augustine, D.J., Derner, J.D., Gao, F., 2021. Predicting spatial-temporal patterns of diet quality and large herbivore performance using satellite time series. Ecol. Appl. https://doi.org/10.1002/eap.2503.

Kiniry, J.R., Williams, J.R., Gassman, P.W., Debaeke, P., 1992. A general, process-oriented model for two competing plant species. Trans. ASAE 35, 801–810.

Kiniry, J.R., Johnson, M.V.V., Venuto, B.C., Burson, B.L., 2013. Novel application of ALMANAC: modelling a functional group, exotic warm-season perennial grasses. Am. J. Exp. Agricult. 3 (3), 631–665.

Lai, L., Kumar, S., 2020. A global meta-analysis of livestock grazing impacts on soil properties. PLoS One 15 (8), e0236638. https://doi.org/10.1371/journal.pone.0236638.

Legates, D.R., McCabe, G.J., 1999. Evaluating the use of "goodness-of-fit" measures in hydrologic and hydroclimatic model validation. Water Resour. Res. 35 (1), 233–241.

Lubowski, R.N., Vesterby, M., Bucholtz, S., Baez, A., Roberts, M.J., 2006. Major Uses of Land in the U.S. Economic Information Bulletin 14. USDA-ERS, Washington, DC.

Ma, L., Dernera, J.D., Harmel, R.D., Tatarkoa, J., Moorec, A.D., Rotzd, C.L., Augustinea, D.J., Boonee, R.B., Coughenoure, M.B., Beukesf, P.C., Van Wijkg, M.T., Bellocchih, G., Culleni, B.R., Wilmera, H., 2019. Application of grazing land models in ecosystem management: current status and next frontiers. Adv. Agron. 158, 173–215. https://doi.org/10.1016/bs.agron.2019.07.003.

Manley, J.T., Schuman, G.E., Reeder, J.D., Hart, R.H., 1995. Rangeland soil carbon and nitrogen responses to grazing. J. Soil Water Conserv. 50, 294–298.

Mausbach, J.M., Dedrick, A.R., 2004. The length we go measuring environmental benefits of conservation practices. J. Soil Water Conserv. 59 (5), 96A–103A.

Metz, L.J., Rewa, C.A., 2019. Conservation effects assessment project: assessing conservation practice effects on grazing lands. RANGELANDS 41, 227–232.

Mohtar, R.H., Buckmaster, D.R., Fales, S.L., 1997. A grazing simulation model: *GRASIM* a: model development. Trans. ASAE 40 (5), 1483–1493.

Moriasi, N.D., Arnold, J.G., Van Liew, M.W., Bingner, R.L., Harmel, R.D., Veith, T.L., 2007. Model evaluation guidelines for systematic quantification of accuracy in watershed simulations. Trans. ASABE 50 (3), 885–900. https://doi.org/10.13031/2013.23153.

Nash, J.E., Sutcliffe, J.V., 1970. River flow forecasting through conceptual models: part 1. A discussion of principles. J. Hydrol. 10 (3), 282–290.

NRI Grazing Land On-Site Data Collection handbook, 2021. https://grazingland.cssm.iastate.edu/site-data-collection-handbook-instructions (accessed November, 2021).

Osorio Leyton, J.M., 2019. APEXeditor: A spreadsheet-based tool for editing APEX model input and output files. J. Softw. Eng. Appl. 12, 432–446. https://doi.org/10.4236/jsea.2019.1210027.

Osorio, L.J., Zilverberg, C., Steglich, E., Williams, J., 2018. Agricultural Polycy/environmental eXtender model – user manual. APEXgraze Rel.1811. In: Texas A&M AgriLife research. Blackland Research & Extension Center, Temple, TX 76502, USA, p. 222.

Osorio-Leyton, Javier. 2021. Texas A&M University, AgriLife Research, Blackland Research & Extension Center 720 East Blackland Rd. | Temple, TX 76502–9622 josorio@tamu.edu | http://blackland.tamu.edu. Personal communication.

Parton, W.J., Schimel, D.S., Cole, C.V., Ojima, D.S., 1987. Analysis of factors controlling soil organic matter levels in Great Plains grasslands. Soil Sci. Soc. Am. J. 51, 1173–1179.

Parton, W.J., Scurlock, J.M.O., Ojima, D.S., Gilmanov, T.G., et al., 1993. Observations and modelling of biomass and soil organic matter dynamics for the grassland biome worldwide. Glob. Biogeochem. Cycles 7, 785–809.

Parton, W.J., Ojima, D.S., Cole, C.V., Schimel, D.S., 1994. A general model for soil organic matter dynamics: Sensitivity to litter chemistry, texture and management. In: Quantitative Modeling of Soil Forming Processes, SSSA Spec. Public. No. 39, Madison, WI, pp. 147–167.

Pineiro, G., Paruelo, J.M., Oesterheld, M., Jobbagy, E.G., 2010. Pathways of grazing effects on soil organic carbon and nitrogen. Rangel. Ecol. Manag. 63, 109–119.

Prentice, I.C., Cowling, S.A., 2013. Dynamic global vegetation models. In: Levin, S.A. (Ed.), Dynamic Global Vegetation Models, Encyclopedia of Biodiversity (second edition), 2013. Academic Press, pp. 670–689. https://doi.org/10.1016/B978-0-12-384719-5.00412-3.

Reeves, L.J., Derner, J.D., Sanderson, M.A., Hendrickson, J.R., Kronberg, S.L., Petersen, M.K., Vermeire, L.T., 2014. Seasonal weather influences on yearling beef steer productionin C3-dominated Northern Great Plains rangeland. Agric. Ecosyst. Environ. 183, 110–117. https://doi.org/10.1016/j.agee.2013.10.030.

Reitz, M., Sanford, W.E., Senay, G.B., Cazenas, J., 2017. Annual estimates of recharge, quick-flow runoff, and evapotranspiration for the contiguous u.s. using empirical regression equations. J. Am. Water Res. Association (JAWRA) 53 (4), 961–983. https://doi.org/10.1111/1752-1688.12546.

Ritten, J., Marshall Frasier, W., Bastian, C.T., Gray, S.T., 2010. Optimal rangeland stocking decisions under stochastic and climate-impacted weather. Am. J. Agric. Econ. 92, 1242–1255.

Rounsevell, M., Evans, S.P., Bullock, P., 1999. Climate change and agricultural soils impacts and adaptation. Clim. Chang. 43, 683–709.

Sanderson, M.A., Jolley, L., Dobrowolski, P., 2011. Pasture and hayland in the USA: Land resources, conservation practices, and ecosystem services. In: Nelson, C.J. (Ed.), Environmental Outcomes of Conservation Practices Applied to Pasture and Hayland of the U.S. USDA-NRCS.

Santhi, C., Arnold, G., Williams, J.R., Dugas, W.A., Srinivasan, R., Hauck, L.M., 2001. Validation of the SWAT model on a large river basin with point and nonpoint sources. J. Am. Water Res. Assoc. 37 (5), 1169–1188.

SAS, 2018. SAS Version 9.4 of the SAS System for Windows. SAS Institute Inc., Cary, NC.

Sedivec, K.K., Printz, J.L., 2012. Ecological sites of North Dakota. In: North Dakota StateUniversity Extension. Publication R-1556, Fargo, ND, p. 28.

Sen, S., Srivastava, P., Dane, J.H., Yoo, K.H., Shaw, J.N., 2010. Spatial–temporal variability and hydrologic connectivity of runoff generation areas in a North Alabama pasture—implications for phosphorus transport. Hydrol. Process 24, 342–356.doi. https://doi.org/10.1002/hyp.7502.

Smith, P., Martino, D., Cai, Z., Gwary, D., Janzen, H.H., Kumar, P., et al., 2007. Greenhouse gas mitigation in agriculture. Philos. Trans. R. Soc. B 363, 789–813. https://doi.org/10.1098/rstb.2007.2184.

Snow, V., Rotz, C.A., Moore, A.D., Martin-Clouaire, R., Johnson, I.R., Hutchings, N.J., Eckard, R.J., 2014. The challenges—and some solutions—to process-based modelling of grazed agricultural systems. Environ. Model. Softw. 62, 420–436. https://doi.org/10.1016/j.envsoft.2014.03.009.

Stone Environmental Inc, 2021. Project Cooperators. Montpelier, VT 05602 USA.

Torrell, L.A., Murugan, S., Ramirez, O.A., 2010. Economics of flexible versus conservativestocking strategies to manage climate variability risk. Rangel.Ecol. Manag. 63, 415–425.

Tukey, J.W., 1977. Exploratory data analysis. Addison-Wesley. ISBN 978-0-201-07616-5 OCLC 3058187.

UNESCO, 1979. Map of the world distribution of arid regions: Map at scale 1:25,000,000 with explanatory note. MAB Technical Notes 7. UNESCO, Paris, France (accessed 7. 21.22).

USDA, 2015. https://www.nrcs.usda.gov/Internet/FSE_DOCUMENTS/nrcseprd1389457.pdf.

USDA NRCS, 2006. Land Resource Regions and Major Land Resource Areas of the United States, the Caribbean, and the Pacific Basin. U.S. Department of Agriculture Handbook 296.

USDA NRCS, 2010. Conservation effects assessment project (CEAP). In: Assessment of the Effects of Conservation Practices on Cultivated Cropland in the Upper Mississippi River basin. http://www.nrcs.usda.Gov/technical/nri/ceap/.

USDA SCS (Soil Conservation Service), 1972. National Engineering Handbook, Hydrology Section 4. Chapters 4-1O.

Van Liew, M.W., Arnold, J.G., Garbrecht, J.D., 2003. Hydrologic simulation on agricultural watersheds: choosing between two models. Trans. ASAE 46 (6), 1539–1551.

Viglizzo, E.F., Ricard, M.F., Taboada, M.A., Vázquez-Amábile, G., 2019. Reassessing the role of grazing lands in carbon-balance estimations: meta-analysis and review. Sci. Total Environ. 661, 531–542. https://doi.org/10.1016/j.scitotenv.2019.01.130.

Vuichard, N., Soussana, J.-F., Ciais, P., Viovy, N., Ammann, C., Calanca, P., Clifton-Brown, J., Fuhrer, J., Jones, M., Martin, C., 2007. Estimating the greenhouse gas fluxes of European grasslands with a process-based model: 1. Model evaluation from in situ measurements. Glob. Biogeochem. Cycles 21, GB1004. https://doi.org/10.1029/2005GB002611.

Wang, X., Potter, S., Williams, J.R., Atwood, J.D., Pitts, T., 2006. Sensitivity analysis of APEX for national assessment. Trans. ASABE 49 (3), 679–688. https://doi.org/10.13031/2013.20487.

Wang, X., Williams, J.R., Gassman, P.W., Baffaut, C., Izaurralde, R.C., Jeong, J., Kiniry, J. R., 2012. EPIC and APEX: model use, calibration, and validation. Trans. ASABE 55 (4), 1447–1462. https://doi.org/10.13031/2013.42253.

Wang, X., Yen, H., Liu, Q., Liu, J., 2014. An auto-calibration tool for the agricultural policy environmental extender (APEX) model. Trans. ASABE 57 (4), 1087–1098. https://doi.org/10.13031/trans.57.10601.

White, M.J., Gambone, M., Haney, E., Arnold, J., Gao, J., 2007. Development of a station based climate database for SWAT and APEX assessments in the US. Water 9 (437), 1–9. https://doi.org/10.3390/w9060437.

Williams, J.R., Arnold, J.G., Srinivasan, R., 2000. The APEX Model; BRC Report no. 00-06; Texas agricultural Experiment Station, Texas Agricultural Extension Service. Texas A&M University, Temple, TX, USA, p. 2000.

Williams, J.W., Izaurralde, R.C., Steglich, E.M., 2008. Agricultural policy/environmental eXtender model. In: Theoretical Documentation. Version 0604. BREC report # 2008-17.

Williams, A.S., Kiniry, J.R., Mushet, D., Smith, L.M., McMurry, S., Attebury, K., Lang, M., McCarty, G.W., Shaffer, J.A., Effland, W.R., Johnson, M.-V.V., 2017. Model parameters for representative wetland plant functional groups. Ecosphere 8 (10), e01958. https://doi.org/10.1002/ecs2.1958.

Willmott, C.J., 1981. On the validation of models. Phys. Geogr. 2, 184–194.

Wischmeier, W.H., Smith, D.D., 1978. Predicting Rainfall erosion Losses, a Guide to Conservation Planning. U.S. Dept. Agric., Agric.. Handbook No 537.

Yin, L., Wang, X., Pan, J., Gassman, P.W., 2009. Evaluation of APEX for daily runoff and sediment yield from three plots in the upland Huaihe River watershed, China. Trans. ASABE 52 (6), 1833–1845. https://doi.org/10.13031/2013.29212.

Zilverberg, C.J., Williams, J., Jones, C., Harmoney, K., Angerer, J., Metz, L.J., Fox, W., 2017. Process-based simulation of prairie growth. Ecol. Model. 351, 24–35.

Zilverberg, C.J., Angerer, J., Williams, J., Metz, L.J., Harmoney, K., 2018. Sensitivity of diet choices and environmental outcomes to a selective grazing algorithm. Ecol. Model. 390, 10–22.