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Calibrating Agro-Hydrological Model under Grazing Activities and Its Challenges and Implications

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Abstract: Recently, the Agricultural Policy Extender (APEX) model was enhanced with a grazing module, and the modified grazing database, APEXgraze, recommends sustainable livestock farming practices. This study developed a combinatorial deterministic approach to calibrate runoff-related parameters, assuming a normal probability distribution for each parameter. Using the calibrated APEXgraze model, the impact of grazing operations on native prairie and cropland planted with winter wheat and oats in central Oklahoma was assessed. The existing performance criteria produced four solutions with very close values for calibrating runoff at the farm outlet, exhibiting equifinality. The calibrated results showed that runoff representations had coefficients of determination and Nash–Sutcliffe efficiencies >0.6 in both watersheds, irrespective of grazing operations. Because of non-unique solutions, the key parameter settings revealed different metrics yielding different response variables. Based on the least objective function value, the behavior of watersheds under different management and grazing intensities was compared. Model simulations indicated significantly reduced water yield, deep percolation, sediment yield, phosphorus and nitrogen loadings, and plant temperature stress after imposing grazing, particularly in native prairies, as compared to croplands. Differences in response variables were attributed to the intensity of tillage and grazing activities. As expected, grazing reduced forage yields in native prairies and increased crop grain yields in cropland. The use of a combinatorial deterministic approach to calibrating parameters offers several new research benefits when developing farm management models and quantifying sensitive parameters and uncertainties that recommend optimal farm management strategies under different climate and management conditions.

Keywords: agro-hydrological model; Agricultural Policy Extender (APEX); APEXgraze; normal probability distribution; equifinality; runoff; native prairie; cropland



Citation: Nelson, A.M.; Maskey, M.L.; Northup, B.K.; Moriasi, D.N. Calibrating Agro-Hydrological Model under Grazing Activities and Its Challenges and Implications. *Hydrology* **2024**, *11*, 42. <https://doi.org/10.3390/hydrology11040042>

Academic Editor: Lin Lin

Received: 23 February 2024

Revised: 13 March 2024

Accepted: 18 March 2024

Published: 22 March 2024



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1. Introduction

Grazing and haying are options for managing agricultural lands that can provide conservation benefits [1]. To achieve sustainable conservation benefits from grazing operations, it is crucial to understand the relationships among erosion, vegetation, and grazing. These relationships can help reduce runoff and the transport of pollutants from grazing lands [2,3]. The livestock industry is experiencing intensification in production activities due to an increase in the demand for livestock commodities, which, in turn, is affecting these relationships. In addition, grazing lands provide crucial habitats for wildlife and biodiversity and opportunities for soil health maintenance [4,5].

Grazing lands contain approximately 10% of carbon in soils, a key component of healthy soil and the global carbon cycle [6,7]. However, overgrazing degrades carbon storage and water and soil quality within farms or watersheds [3,8] and leads to the degradation of grassland communities, reduction in vegetative cover, degradation of topsoil,

and pollution of waterways with fecal waste [9]. Therefore, proper grazing management is an essential strategy to minimize the negative impacts and support the sustainable use of ecosystems.

Efforts to simulate hydrologic changes in watersheds from intensive agriculture involved integrating diverse information from different sources using agro-hydrological models [10–12]. Intensive forms of agriculture, including cattle management and climate change, impact the hydrological processes within watersheds [13]. Such agro-hydrological models include Watershed Analysis Risk Management Framework, WARMF [14], HYDRUS [15,16], European Hydrological System Model, MIKE-SHE [17], Soil and Water Assessment Tool, SWAT [18], Environmental Policy Integrated Climate, EPIC [19], Agricultural Policy/Environmental Extender, APEX [20], Root Zone Water Quality Model, RZWQM [21,22], and Better Assessment Science Integrating Point and Nonpoint Sources, BASINS [23]. These models are either conceptual or numerical and semi-distributed or distributed in nature, but all require parameterization. Although several advances have integrated important processes, such as biophysical processes, socio-economic components, etc., into hydrological models [24], these models inherit simplified and/or incomplete assumptions behind the physical processes that drive responses, which include a lack of adequate data, ignoring intrinsic details [25], and inclusion of relevant management practices (including grazing) applied in agricultural activities [2,3,8].

Pasture management practices, such as haying, for example, have advantages over overgrazing, including reduced effects on bulk density and organic carbon of soils, and improved water quality [1,3]. Mohtar et al. [26] developed a comprehensive model for grazing systems to evaluate the effects of climate and pasture management biomass accumulation, nutrient flows, and animal intake. Some other studies have examined forage shortages [27], forage production [28–32], weight gain by steers [33], and weight gain by cattle [34,35].

Hydrologic and water quality models, such as SWAT, APEX, and RZWQM, were applied to study the impacts of land use, management practices, and climate on agricultural production and soil and water resources, but few were applied to grazing systems. Zilverberg et al. [36] addressed the allocation of new biomass, response to water stress, competition for soil water, and regrowth of herbaceous perennials in the process-based hydrological model, APEX. Later, they improved this model to allow for the selective grazing of plant species and dietary-specific excretion of urine and feces [7]. Research on the effects of grazing on the quality and quantity of water generated at farm-scale watersheds is limited. A few studies focused on the effects of grazing management on surface runoff and water quality in agroforestry watersheds and grass buffers [3,37–40]; however, these studies are not well suited to grazing management applied to rangelands. While these studies mainly concentrated on seasonal grazing with uniform schedules, the impact of multiple and unique grazing patterns on water quality and quantity from cultivated land remains unclear.

The APEX model has a wide range of applications to determine agriculture-related management practices, such as nutrient management [20,41], tillage operations [42–44], conservation practices [45,46], alternative cropping, and the impact of climate change on crop yield [47,48]. APEX provides daily, monthly, and yearly predictions for water balance and crop growth in subareas that are homogeneous in climate, soil type, and management based on sets of parameters. The APEX has been used nationally to recommend best management practices due to its versatile capability to simulate conservation practices. For example, several researchers used the APEX model to investigate the impact of management practices on runoff and sediment from agricultural fields [49–52]. Kumar et al. [38] and Gautam et al. [3] also demonstrated the ability of APEX to simulate runoff and sediment losses from agroforestry lands that are grazed without using a modified version of APEX with a grazing module.

Zilverberg et al. [7,36] upgraded plant–animal interactions in the previous APEX version with an enhanced grazing database, which led to the APEXgraze model. The APEXgraze model allows for the evaluation of grazing management effects on soil degradation, wa-

ter quality, and plant communities in rangeland watersheds and environmental impacts under current and projected climate conditions [5,35,53]. This upgrade has, however, not been evaluated for capturing runoff and sediment dynamics at farm-scale watersheds, and none of the studies parametrized the “APEXgraze” under grazing systems in pastures or croplands [54,55].

There is a need to fill knowledge gaps when pasture and croplands are under grazing management using a process-based hydrological model like APEXgraze to investigate the responses of grazing operations to small (farm)-scale watershed processes while providing flexible grazing schedules of multiple herds and owners during grazing management. The objectives of this study were to (1) simplify the calibration procedure for hydrological models; (2) demonstrate the capability of the recently modified APEX model, APEXgraze, in simulating runoff, sediment, and nutrients at the farm scale under grazing operations; and (3) evaluate the impact of grazing on water quantity and quality at the outlet of the farm. While there is no existing literature on utilizing the APEXgraze model for simulating surface runoff in grazing scenarios, it is important to evaluate its effectiveness in capturing such runoff and explore the effects of different grazing management techniques on maintaining a sustainable watershed.

2. Materials and Methods

2.1. Study Area

This research was conducted at the Water Resources and Erosion (WRE) watersheds (Figure 1), located in central Oklahoma. The WRE facility is located on the USDA-ARS Oklahoma and Central Plains Agricultural Research Center located in El Reno, Canadian County (35°33′29″ N, 98°1′50″ W), and encompasses eight watersheds. Each watershed has an area of 1.6 ha (80 m wide × 200 m long), surrounded by artificial berms and natural boundaries with longitudinal slopes ranging from 2.6% to 3.6%. At the outlet of each watershed, Chickasha samplers were used to collect water samples that passed through H-flumes [56].

Soils in the study site are dominated by Bethany and Kirkland silt loams, with smaller areas of Milan loams, Aydelotte silt loams, and Renfrow silt loams [57]. This region has a semi-arid to subhumid climate characterized by long, hot, and dry summers and short, temperate, and dry winters [55]. The average annual precipitation in the study area for the 1976–1999 period was 875 mm, with approximately 40% occurring in the spring (March–May). Readers may refer to Vogel et al. [58,59] for management practices and soil properties in WRE watersheds and Nelson et al. [55] for methods of collection and analysis of historical data.

Nelson et al. [54] reported all management activities applied from 1977 to 2000. These management systems are common to grazing management and cropping patterns that are applied across the Southern Great Plains. Such information includes planting, fertilizer and pesticide applications, timing and length of grazing periods and tillage operations like plowing, mulching, disking, and harvesting. The aim was to implement this dataset and calibrate the APEX model based on measured surface runoff and sediment from this same time period [55].

This study examined the impact of grazing on runoff and soil erosion. As an exploratory work to illustrate the effort to study how management impacts both surface runoff and sediment in runoff, this work considered two watersheds, one in native prairie (WRE1) and one in cropland, where winter wheat was grown (replaced by spring oats during one season; WRE8).

WRE1 consisted of tallgrass prairie that was managed by grazing during most years and with hay harvest during a smaller subset of years. In comparison, WRE8 was a field that received tillage and was used to grow winter wheat in continuous rotation, separated by periods of summer fallow [55]. Records showed WRE8 was double cropped with wheat and oats in the sixth year. The key information regarding management activities in these

watersheds is summarized in Table 1, as extracted from Nelson et al. [54] and organized in Tables S1–S4 for planting, fertilizer and pesticide application, and grazing schedules.

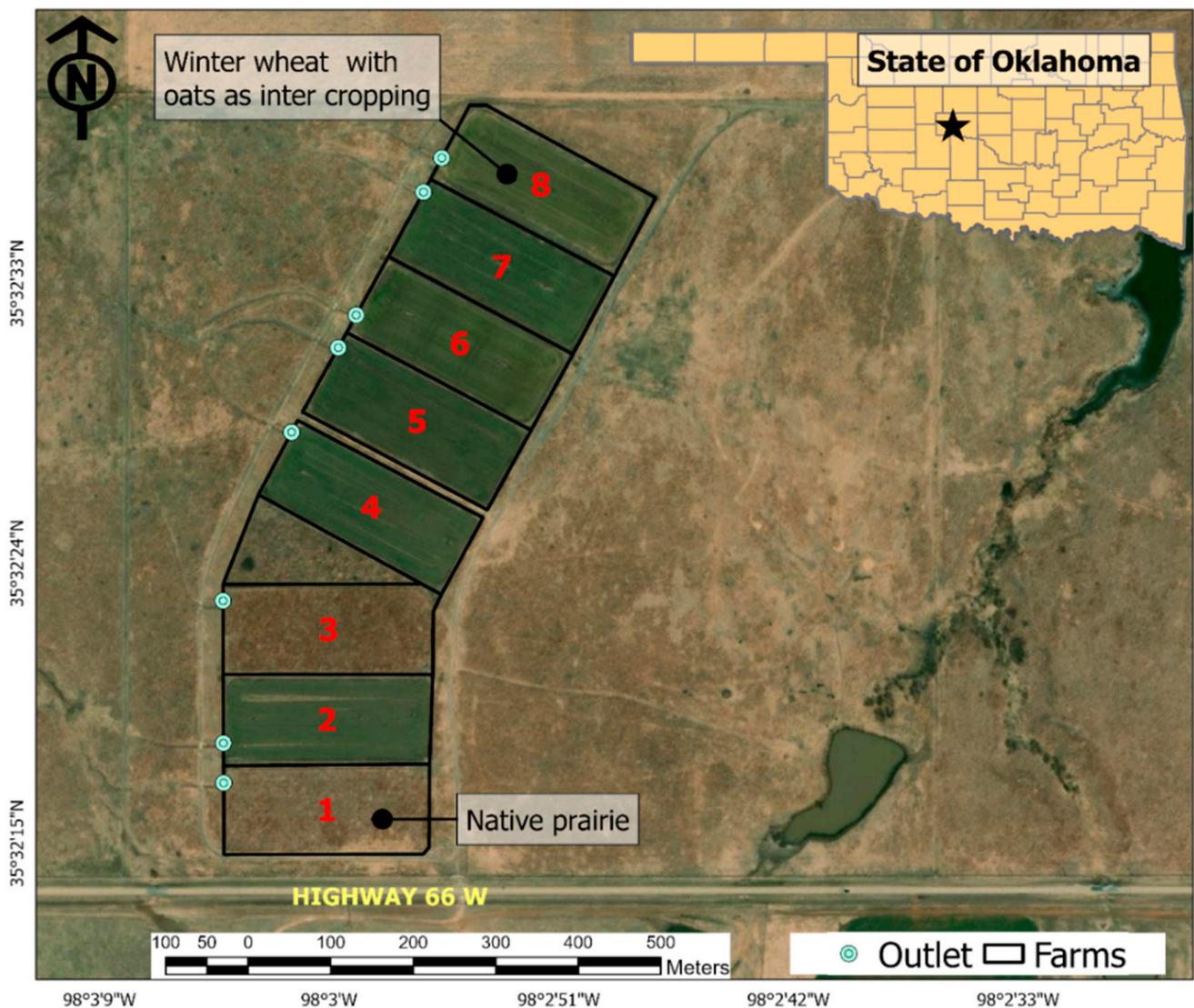


Figure 1. Location of study site within Water Resources and Erosion (WRE) watersheds in El Reno, OK. Circles are the outlets with installed H-flume for runoff measurement.

Table 1. Key information about farm management activities in the two watersheds (1977–2000).

Activities	WRE1	WRE8
Planting schedules	Once at the very beginning *	22 times (once a year)
Crops	Native prairie	Wheat and oats
Total plant population	3000 plants/m ²	7289 plants/m ² of wheat and 714 plants/m ² of oats (1983)
Number of fertilizer species	4	8
Total fertilizer applied	706 kg/ha	4811 kg/ha
Number of times fertilizers applied	2	29
Number of pesticide species	3	14
Total pesticides applied	3 kg/ha	41 kg/ha
Number of times pesticides applied	2	12
Number of classes of cattle that grazed	3	5
Total number of grazed animals	153	100
Total number of days grazed	620	480

* Planting date was considered at the very beginning for modeling purposes; it was a pre-established prairie.

More activities related to management were conducted on WRE8 than on WRE1 over 23 years (Table 1) in terms of plant population and applications of fertilizers and pesticides to support winter wheat and oats. The frequency of grazing operations was higher in WRE1, where native prairie provides forage for cattle. It is important to note that while calves, mature cattle, and stockers were grazed for longer periods in WRE1, calves, bulls, yearlings, heifers, and stockers were pastured for shorter periods in WRE8, where grazing could be applied to wheat during November through April [60]. The native pasture in WRE1 is a minimally disturbed watershed, with only grazing and the cutting and bailing of hay being applied until grasses were burned in March 1999. Alternatively, WRE8 was a more disturbed site due to tillage operations, which included plowing (moldboard and stubble mulch), disking (tandem, single, and double), harrowing (spring tooth and spike tooth), shredding crop residues, sweeping, cultivating, and harvesting crops (see [54]).

2.2. Agricultural Policy Environmental Extender (APEX) Model

To expand the APEX model's applicability to rangeland and pastureland, Zilverberg et al. [36] improved the plant growth module of APEX Version 0806 to better simulate dynamics in grazing lands. Later, Zilverberg et al. [7] incorporated the diet selection of graze to address the management of nutrients that affect forage quality. They disseminated the revised APEX model as "APEXgraze," with subsequent improvements to the spreadsheet interface [61]. Cheng et al. [31] evaluated the improved APEX to investigate the responses of forage productivity from different types of grazing management to soil, topography, plant populations, and weather of US rangelands. These advancements were applied to study the weight gain of cattle and intake of dry matter under different grazing management [34].

Literature-indicated recent enhancements in model performance appeared useful in describing decisions related to grazing management, but modeling runoff from grazed lands was not evaluated [5,31,34,62]. To study the impact of grazing operations on surface runoff from farm-scale watersheds, APEXgraze requires two additional databases. One database includes herd information related to owners to indicate animal species and the number of cattle and herds for each owner. The second database includes information on grazing characteristics related to each herd, such as forage thresholds, grazing limit, intake, the body weight of animals, amount of milk that female cattle produce during lactation, and time of parturition and removal of cattle from the herd [63]. In particular, the APEXgraze model enabled the evaluation of the effect of grazing on runoff, sediment, and nutrients and changes in watershed responses from grassland and cropland under grazing activities.

2.3. Modeling Framework

2.3.1. Preliminary Model Setup

In this study, the individual APEX model for each watershed (Figure 1), starting with building basic parameter files for the APEX model, was developed using the Nutrient Tracking Tool (NTT) interface (Figure 2). A variety of interfaces, such as WinAPEX [64], ArcAPEX [65], APEXEditor [61], and NTT [66–68], exist to set up the APEX model. The NTT interface allows users to simulate complex management scenarios via the APEX model with the required databases embedded in this interface [69,70]. NTT is a web-based interface that uses APEX 0806, which is the basis of APEXgraze. The NTT model populates land use and soil data, including basic management practices and weather data required for the APEX model. Except for land use and soil information from NTT, the remaining input files, which are basic parameters to the APEX model, suited to the APEXgraze model, including data on crops, fertilizers, pesticides, and management, were modified using APEXgrazeEditor, an Excel-based tool for editing APEX input files suitable for APEXgraze. Information on crop characteristics (Table S5), fertilizers (Table S6), pesticides (Table S7), and management, including tillage and grazing schedules (Table S8), were corrected in this spreadsheet. The grazing information from both watersheds was removed for ungrazed scenarios. The management schedule for native prairie (WRE1) used conventional

operations, such as cutting, baling, and burning, while cropland (WR8) had more management information [54,55]. The prepared grazer file was similar to the one developed by Zilverberg et al. [36]. After updating and maintaining consistency in the APEX input files, four models were organized for the two watersheds, each without grazing and with grazing.

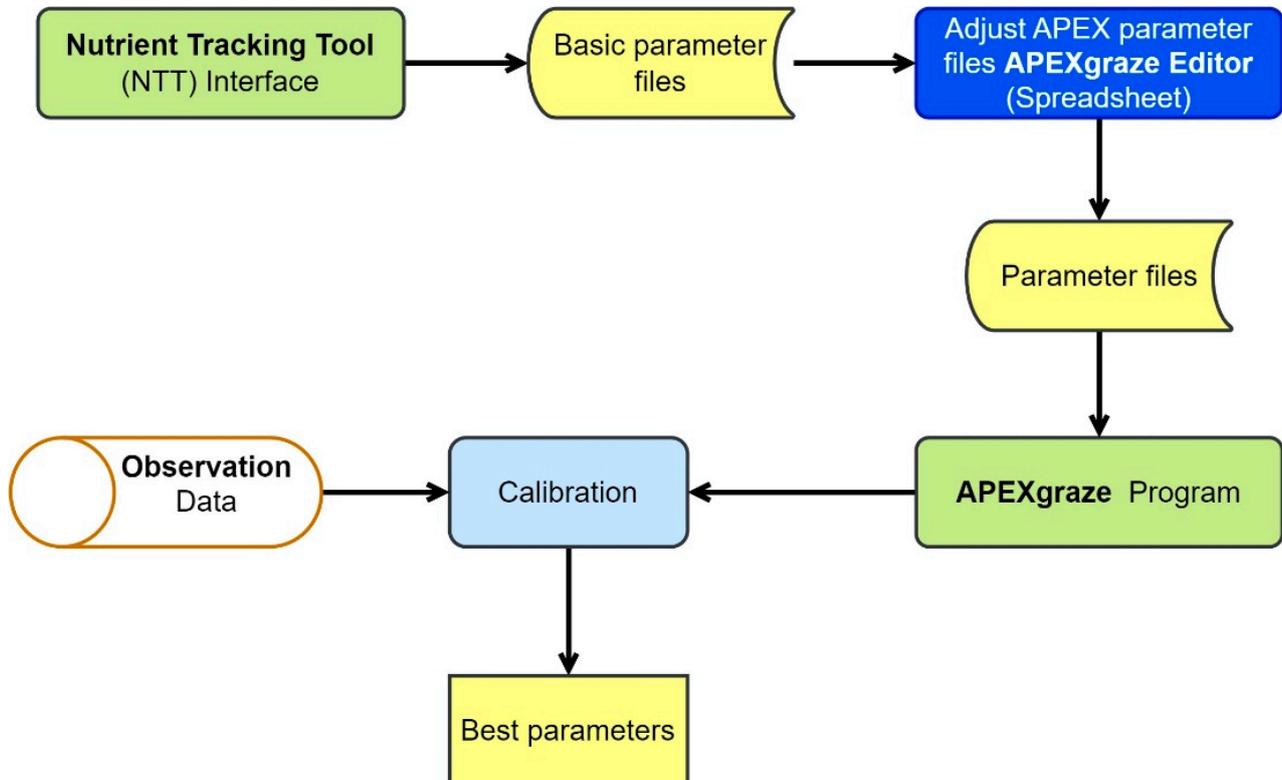


Figure 2. Generalized research protocol with basic workflow diagram. While “Basic parameter files” are the APEX-related input files generated from the NTT, “Parameter files” refer to the updated files using APEXgraze Editor before simulation.

2.3.2. Parameter Selection

Once the control and parameter files were extracted from the NTT interface and updated, the start date of the simulation and the number of years were set in the control file based on the available measurements. The simulation began on 1 January 1979, for 22 years for WRE1, and on 1 January 1978, for 23 years for WRE8, so each simulation ended in 2030.

Then, the model was parameterized using an updated parameter file (Figure 2) that includes 100 process-specific parameters plus the default 70 S-curve [63]. Twenty key parameters (Table 2) related to hydrology and sediment were selected from prior works [50,69,71]. The upper and lower bounds of these parameters, published in the APEXgraze user manual [63], are listed in Table 2, as are the initial parameters obtained from WRE1 through NTT. Among them, additional parameters for transport capacity and the threshold capacity of transport in Revised Universal Soil Loss Equation 2, RUSLE2 [72,73], were considered, since the equation is suitable for highly disturbed lands, such as pastures, rangelands, and grazing lands [74,75].

Table 2. Range of key parameters related to surface runoff (hydrology) and sediment, including initial values from the NTT interface, as defined in the user manuals [63,76].

PARAM (n)	Parameter's Definition	Lower	Upper	Initial
PARAM [2]	Root growth–soil strength	1	2	2
PARAM [4]	Water storage N leaching	0	1	0.9
PARAM [7]	N fixation	0	1	0.9
PARAM [8]	Soluble phosphorus runoff coefficient	10	20	20
PARAM [14]	Nitrate leaching ratio	0.1	1	0.6
PARAM [15]	Runoff CN residue adjustment parameter	0	0.3	0.05
PARAM [17]	Soil evaporation–plant cover factor	0	0.5	0.2
PARAM [20]	Runoff curve number initial abstraction	0.05	0.4	0.2
PARAM [23]	Hargreaves PET equation coefficient	0.0023	0.0032	0.0032
PARAM [34]	Hargreaves PET equation exponent	0.5	0.6	0.48
PARAM [42]	SCS curve number index coefficient	0.3	2.5	0.8
PARAM [50]	Rainfall interception coefficient	0.05	0.3	0.1
PARAM [69]	Coefficient adjusting microbial activity in the topsoil layer	0.1	1	1
PARAM [70]	Microbial decay rate coefficient	0.5	1.5	1
PARAM [72]	Volatilization/nitrification partitioning coefficient	0.05	0.5	0.5
PARAM [18]	Sediment routing exponent	1	2	1.5
PARAM [19]	Sediment routing coefficient	0.0001	0.05	0
PARAM [45]	Sediment routing travel time coefficient	0.5	10	5
PARAM [65]	RUSLE2 transport capacity parameter	0.001	0.1	0.001
PARAM [66]	RUSLE2 threshold transport capacity coefficient	1	10	1

2.3.3. Calibration Protocol

The sets of key parameters were optimized through calibration by adjusting key parameter values within their appropriate ranges until the model output and the observed data were reasonably comparable. Obtaining optimized parameters was iterative and required several simulations to arrive at the optimal parameters. Several algorithms have been implemented to optimize sets of APEX parameters and identify sensitive parameters [77,78]. Wang et al. [77] proposed a procedure for calibrating and performing a sensitivity analysis of APEX models by using Morris, SOBOL, and Fourier Amplitude Tests (FAST) of sensitivity methods without accounting for Kolmogorov–Smirnov analyses of the cumulative distribution of observations. Kolmogorov–Smirnov analyses also have well-known limitations like center-oriented distribution and need more parameters that come from simulation only. These methods are inappropriate for nonlinear models and exhibit the problem of dimensionality. Talebizadeh et al. [78] developed a framework based on model behavior and the features of Monte Carlo simulation, which requires knowledge of parameter distribution.

The limitations of existing methods of parameterization led to the development of an alternative philosophy that avoids probability distributions in parameter range. These distributions are largely based on the literature and a limited amount of data. This approach relies on current data with available bounds of data (parameters) instead of relying on previously documented distributions that are based on limited numbers of data points. Maintaining the parameterization with the most available bounds of data minimizes the risk of underestimating the overall system's effectiveness.

While the parameters to be calibrated are hard to measure precisely, the limited understanding of the probability distribution of the data led to an assumption of a normal distribution for each parameter relying on lower and upper bounds from the literature and user manuals [63,64,77,79]. Note that since the bounds are not enough to compute mean and variance, the proposed route simply assumes these bounds as left and right tails of the normal distribution. By making this assumption, the calibration process can be simplified as this assumption not only maximizes the precision of the calibrated parameters but also adequately expands the parameter space.

This simplified calibration framework used a five-step procedure, as shown in Figure 3. The process involves (1) generating parameter space, (2) iteration, (3) evaluating performance, (4) filtering, and (5) selecting the optimal set of full parameters encompassing key ones. As a first step, generating parameter space simply involves discretizing each parameter within its lower and upper bounds (Table 2). The discretized parameters for arbitrarily N sets are formulated as follows:

$$\theta_{i,m} = \theta_{n,m} + \frac{\delta_m}{N} \times i, \quad i \in (1, N) \tag{1}$$

where $\theta_{i,m}$ is the i^{th} discretized parameter, m so that $\theta_{i,m} \in (\theta_{n,m}, \theta_{x,m})$; $\delta_m = \theta_{x,m} - \theta_{n,m}$, θ_n and θ_x are lower and upper range of m parameters so that $m \in M$, and M is set indices of 20 selected parameters (Table 2), i.e.,

$$M = [2, 4, 7, 8, 14, 15, 17, 18, 19, 20, 23, 34, 42, 45, 50, 69, 65, 66, 70, 72] \tag{2}$$

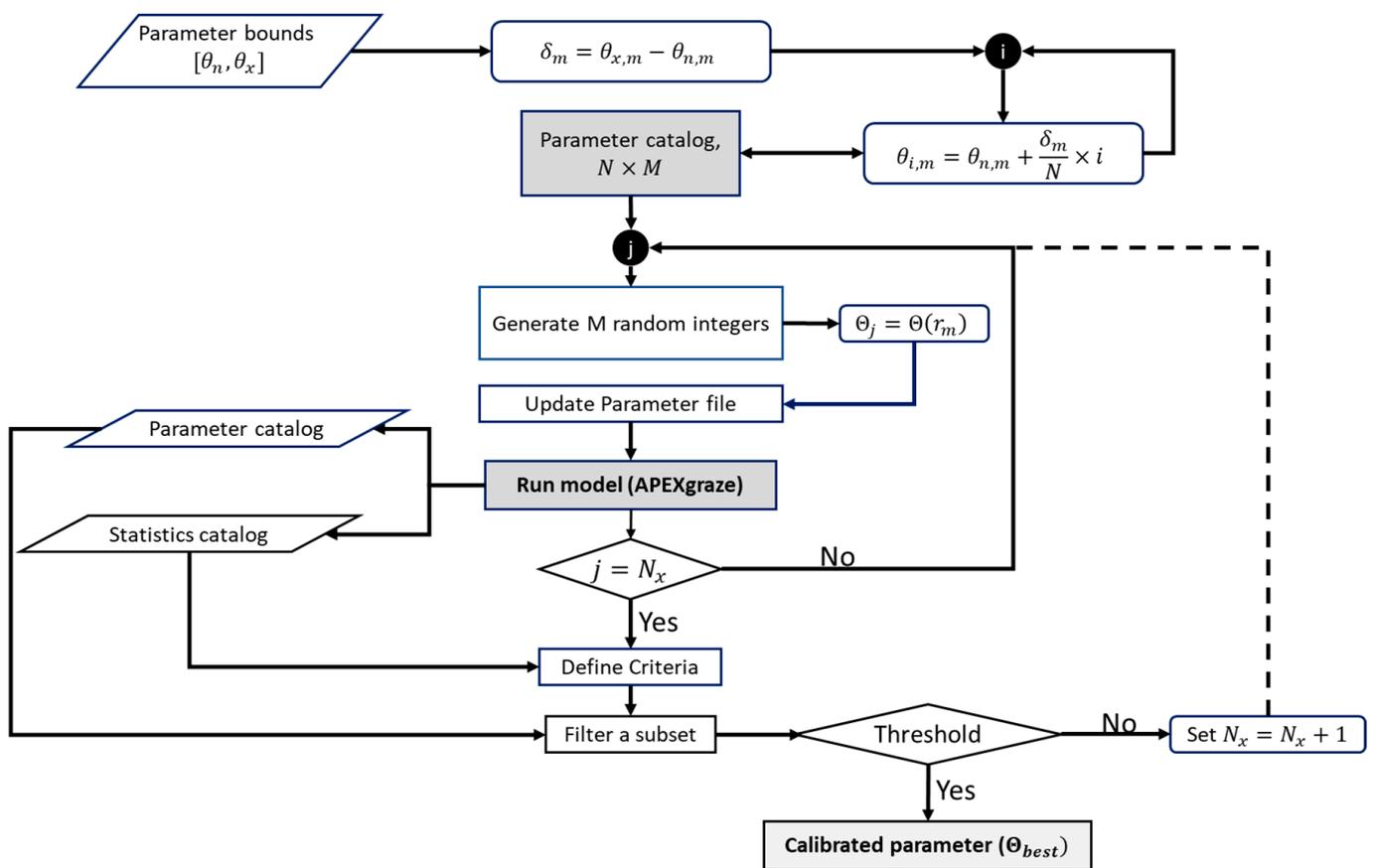


Figure 3. Calibration protocol for hydrological models.

Iteration of Equation (1) allows for the generation of the parameter space of $N \times M$ matrix. For this, $N = 1000$, which serves as a preliminary catalog of parameters.

Within this catalog, each parameter combination was chosen by setting each iteration as a random set rather than selecting sequentially. Before picking the parameters, M random integers were generated within 1 to N to represent the index of m parameter among N values as:

$$\Theta_j = \{\theta[r_1]_1, \theta[r_2]_2 \dots \theta[r_m]_m\} \tag{3}$$

where r_1, r_2, \dots, r_m are random integers for m^{th} parameters that reflects the index of each combination so that $r \in N$; and j is each iteration out of the maximum iterations, say, N_x . The process is combinatory based on fundamentals of combinatorics and probability

theory—established by French mathematician Blaise Pascal [80]—and replaces permutation event space with the generation of sets of integer numbers in each iteration. Still, optimizing the M parameters set leads to a high degree of dimensionality, i.e., N^M . Thus, a deterministic approach was proposed, in which the number of iterations becomes an additional parameter to avoid high dimensionality while picking the parameter sets.

Following the generation of a parameter set through combinatorial selection, each iteration invokes an executable APEXgraze file and stores response variables. A set of performance metrics (see Section 2.3.4) was evaluated for each iteration and stored with the parameter set for later use. Before selecting the best parameter set, a subset of parameter sets was filtered using performance criteria suggested by Moriasi et al. [81,82] (see Section 2.3.4) prior to selecting the best parameter set for given sets of observed data.

The best parameter set for a given runoff dataset is associated with optimal values of performance metrics. The optimal performance metric could be either the maximum Nash-Sutcliffe Efficiency (NSE) [83], maximum Coefficient of Determination (COD, R^2) [84,85], minimum absolute percent bias (PBIAS) [86], or the minimum value of an objective function that incorporates all three metrics. First, the best parameter set with minimum values of objective functions among filtered sets of parameters for discussing the implications of grazing operations was selected. The goodness of the notion in terms of three metrics, including outputs of interest, was also reported.

This study involved running the model 100,000 times, so the approach still requires significant computational resources. To accomplish this, the high-performance computing facility provided by the Office of Scientific Computing, USDA-SCINet, was utilized. In each case, the model ran for four years to warm up the model, the following eleven years as a calibration period, and the remaining years until 2002 for validation.

2.3.4. Model Evaluation

Analyses within the Moriasi criteria [81] were used to compare the simulated surface runoff with observed data. The metrics used in this criterion are COD, NSE, and PBIAS. In addition, objective function used by Monks [83] was also validated:

$$OF_{Monks} = \sqrt{(1 - NSE_i)^2 + \left(|PBIAS_i| + \frac{1}{2}\right)^2} \quad (4)$$

where OF_{Monks} is the objective function suggested by Monks [83] for iteration i , then extended the above objective function by incorporating COD (R^2):

$$OF = \sqrt{(1 - R^2)^2 + (1 - NSE_i)^2 + \left(|PBIAS_i| + \frac{1}{3}\right)^2} \quad (5)$$

Finally, postprocessing reduces the APEX parameter space within the recommended guidelines [81,82], which state $R^2 > 0.6$, $NSE \geq 0.5$, and $|PBIAS| \leq 15\%$ for surface runoff. This resulted in more than one solution for each statistic; therefore, a simplified version the computation by selecting the most optimal parameter set with the smallest OF .

3. Results

3.1. Calibration and Validation Results

3.1.1. Calibrated Parameters

The calibrated parameters for both watersheds with and without grazing are presented in Table 3. These parameters are implied by the lowest values for objective functions (Equation (2)) among the sets within Moriasi et al. [81,82]. The parameter sets associated with maximum NSE and COD and minimum absolute PBIAS are included in Table S9. Note that all parameter values obtained using different metrics are unique in both scenarios from both watersheds. However, there are cases with identical parameter sets, which implies some representations by coupled statistical metrics share parameters regardless

of whether grazing was applied. For instance, parameter sets implied by NSE and COD appear identical for grazing activities in WRE1.

Table 3. Calibrated APEX parameters for native prairie (WRE1) and cropland (WRE8) for surface runoff, obtained by smallest objective function value. Refer to Table 2 for parameter definitions.

PARAM (n)	WRE1: Native Prairie		WRE8: Winter Wheat and Oat	
	Without Grazing	With Grazing	Without Grazing	With Grazing
PARAM [2]	1.299	1.604	1.425	1.425
PARAM [4]	0.327	0.220	0.724	0.724
PARAM [7]	0.411	0.045	0.520	0.52
PARAM [8]	17.890	10.320	18.350	18.350
PARAM [14]	0.335	0.783	0.699	0.699
PARAM [15]	0.085	0.076	0.069	0.069
PARAM [17]	0.130	0.187	0.002	0.002
PARAM [18]	1.325	1.463	1.303	1.303
PARAM [19]	0.049	0.036	0.036	0.036
PARAM [20]	0.400	0.390	0.391	0.391
PARAM [23]	0.0028	0.0028	0.0029	0.0029
PARAM [34]	0.536	0.571	0.598	0.598
PARAM [42]	2.447	2.212	0.828	0.828
PARAM [45]	0.833	1.982	4.509	4.509
PARAM [50]	0.403	0.207	0.326	0.326
PARAM [65]	0.022	0.039	0.086	0.086
PARAM [66]	9.532	4.285	2.152	2.152
PARAM [69]	0.298	0.936	0.887	0.887
PARAM [70]	0.595	1.201	0.871	0.871
PARAM [72]	0.400	0.123	0.329	0.329

Regardless of the best metric values, the parameter values in WRE1 (native prairie) are slightly different as a response to the occurrence of grazing. In contrast, the parameters remain constant with respect to the occurrence of grazing on WRE8 (cropland), perhaps because of a combination of infrequent grazing or similar numbers of activities (planting, fertilizers, and others) that occurred.

3.1.2. Performance Evaluation

Figures 4 and 5 reveal the best representations of surface runoff at the outlets of the two watersheds for both scenarios. These four representations are implied by the four best metrics and associated parameter sets reported in Table 3 and Table S9. These parameters from the subset of the 100,000 parameter sets that satisfy Moriasi et al. [81,82] at the daily temporal scale were used. As such, each representation with (a) the lowest value for the objective function (top row), (b) the highest NSE (second row), (c) the highest COD (third row), and (d) the smallest absolute PBIAS (last row) is tabulated in Table 4.

Figure 4 displays reasonable APEX representations of surface runoff at the outlet of WRE1 for both management scenarios. Although some disparity exists, major features like the location of the peaks and the occurrence of smaller flow events were well captured. Further, COD and NSE exceeded 0.62 and 0.58, respectively, with PBIAS less than 15% and smaller objective functions during calibration (Table 4, top portion).

Likewise, all four representations for WRE8 (Figure 5) are close to measured observations. Except for some discrepancies, most of the major features were well captured. Table 4 (bottom portion) further corroborates the goodness of fit with COD >0.73 and NSE >0.67, though PBIAS exceeded the 15% criterion, which degraded the objective function. Interestingly, performance metrics for WRE8 were almost identical for non-grazing and grazing scenarios, which implies the same optimized parameter set (Table 3 and Table S9), while parameters for WRE1 differed among grazing treatments. This likely occurred because of

the fewer times grazing occurred on WRE8 across the years, especially when compared to WRE1.

It is also important to note that optimized metric values of both fields during calibration were improved with grazing compared to without grazing. This observation is attributed to the measured runoff data corresponding to real-world grazing operations used in the model. As expected, model simulation performance during validation—as observed in Table 4 inside parentheses—was not as good as during calibration for all cases, possibly because the validation data covered a shorter period (1996 to 2000 for WRE1 and 1995–200 for WRE8) of years than the calibration data. Moreover, the comparable results and representation of surface runoff explain how the watershed processes are complex and are non-unique solutions, as the four best representations are equally comparable.

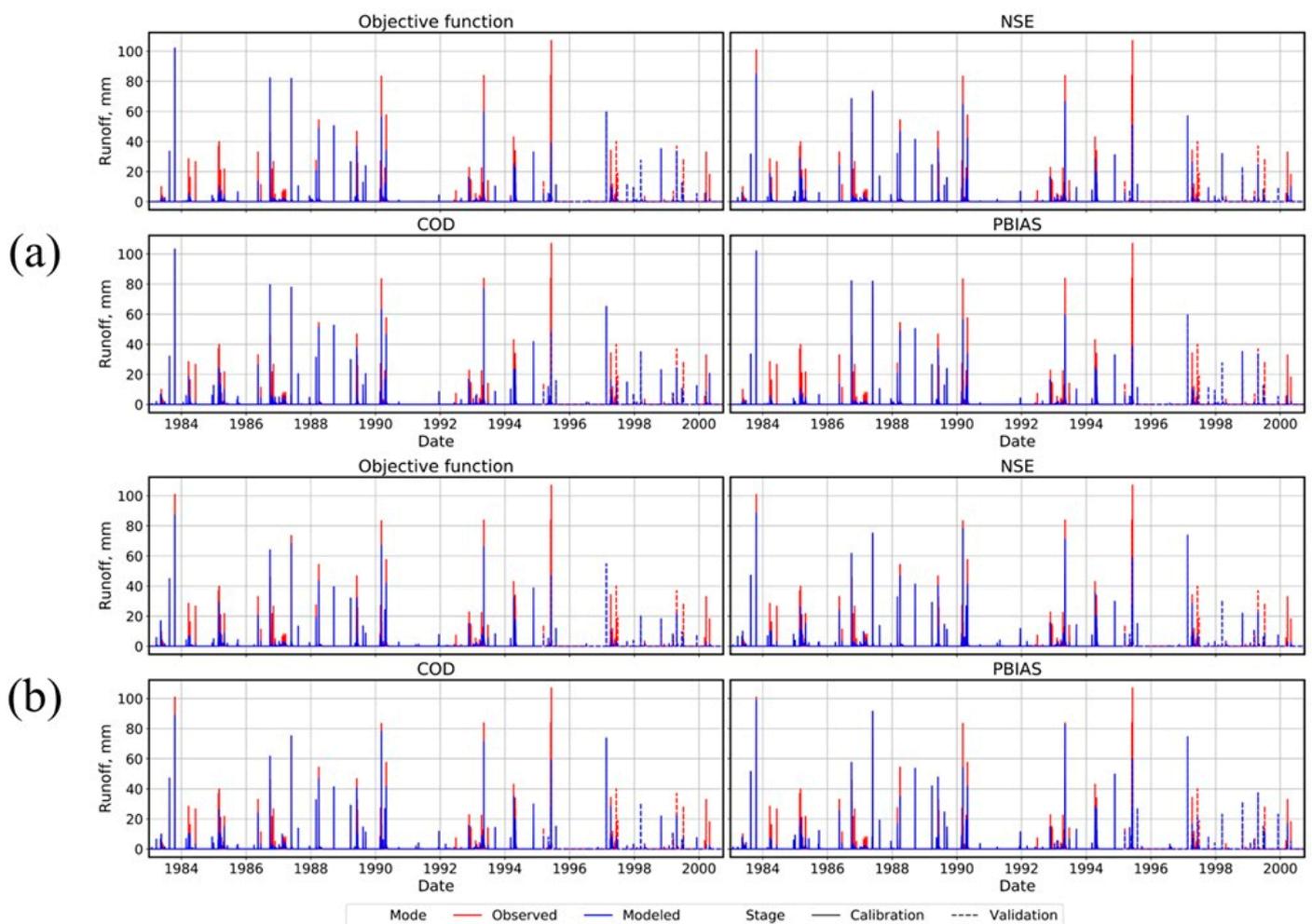


Figure 4. Daily time series of best representations of surface runoff (January 1983 to September 2000) optimized at daily scale for native prairie, WRE1. (a) Without grazing (top), (b) with grazing (bottom).

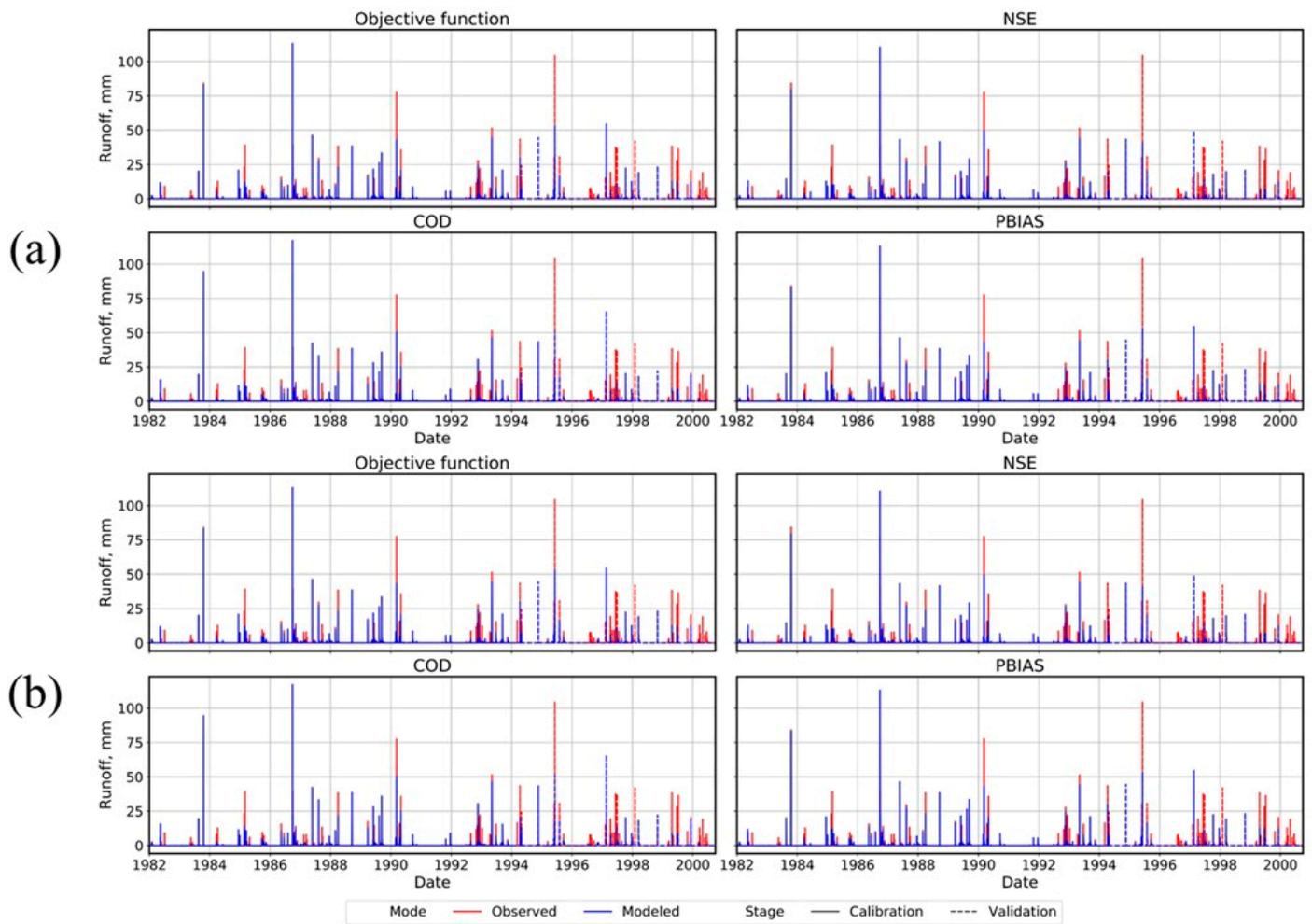


Figure 5. Daily time series of best representations of surface runoff (January 1982 to September 2000) optimized at daily scale for cropland, WRE8. (a) Without grazing (top), (b) with grazing (bottom).

Table 4. Model performance for the four best representations shown in Figures 4 and 5, obtained using four statistics: OF: objective function (Equation (2)), NSE: Nash–Sutcliffe efficiency, COD: coefficient of determination, and PBIAS: percent bias in %. Without and with represent the presence or absence of grazing management, respectively. Values inside the parentheses are metrics for validation.

Watershed	Metrics	OF		NSE		COD		PBIAS, %	
		Without	With	Without	With	Without	With	Without	With
WRE1 (Grass-land)	OF	0.66 (4.13)	0.60 (26.52)	0.60 (0.16)	0.66 (0.25)	0.61 (0.20)	0.66 (0.26)	0.00 (3.63)	−0.03 (26.17)
	NSE	2.07 (9.71)	8.80 (1.23)	0.63 (0.25)	0.69 (0.23)	0.64 (0.26)	0.70 (0.27)	−1.67 (9.32)	−8.46 (0.29)
	COD	6.36 (2.40)	8.80 (1.23)	0.62 (0.20)	0.69 (0.23)	0.65 (0.24)	0.70 (0.27)	−6.01 (−1.79)	−8.46 (0.29)
	PBIAS	0.66 (4.13)	0.64 (4.14)	0.60 (0.16)	0.60 (0.21)	0.61 (0.20)	0.63 (0.28)	0.00 (3.63)	0.00 (3.67)
WRE8 (Crop-land)	OF	30.74 (24.22)	30.67 (25.10)	0.67 (0.43)	0.68 (0.42)	0.73 (0.43)	0.73 (0.42)	−30.40 (23.88)	−30.33 (24.75)
	NSE	32.61 (22.21)	32.56 (22.24)	0.70 (0.37)	0.70 (0.36)	0.73 (0.37)	0.73 (0.36)	−32.27 (21.86)	−32.22 (21.89)
	COD	32.74 (23.16)	32.73 (22.94)	0.70 (0.38)	0.70 (0.39)	0.76 (0.39)	0.76 (0.39)	−32.40 (22.81)	−32.39 (22.59)
	PBIAS	30.74 (24.22)	30.67 (25.10)	0.67 (0.43)	0.68 (0.42)	0.73 (0.43)	0.73 (0.42)	−30.40 (23.88)	−30.33 (24.75)

3.2. Grazing Impacts

3.2.1. Water Balance Components

Figure 6 shows the time series of major water components for both watersheds aggregated monthly for the two scenarios. These series represent the entire simulation period as implied by the calibrated sets of parameters that were associated with the lowest values for objective functions that produced representations in the top rows of Figures 4 and 5.

Grazing cattle in grassland (WRE1, left) increases evaporation and decreases runoff and deep percolation. However, negligible impacts of grazing in cropland (WRE8, right) were observed until 1997, after which changes were noted. This response may relate to a lower incidence of grazing applied to WRE8 over the years. As expected, the error in water balance (precipitation, water yield, deep percolation, evapotranspiration) decreased from 0.82 mm (0.10%) to -3.90 mm (-0.40%) after grazing in native prairie. In comparison, the error slightly increased from 11.70 mm (1.02%) to 11.83 mm (1.03%) in cropland. Similar behavior in water balance was observed for the other representations for NSE, COD, and PBIAS.

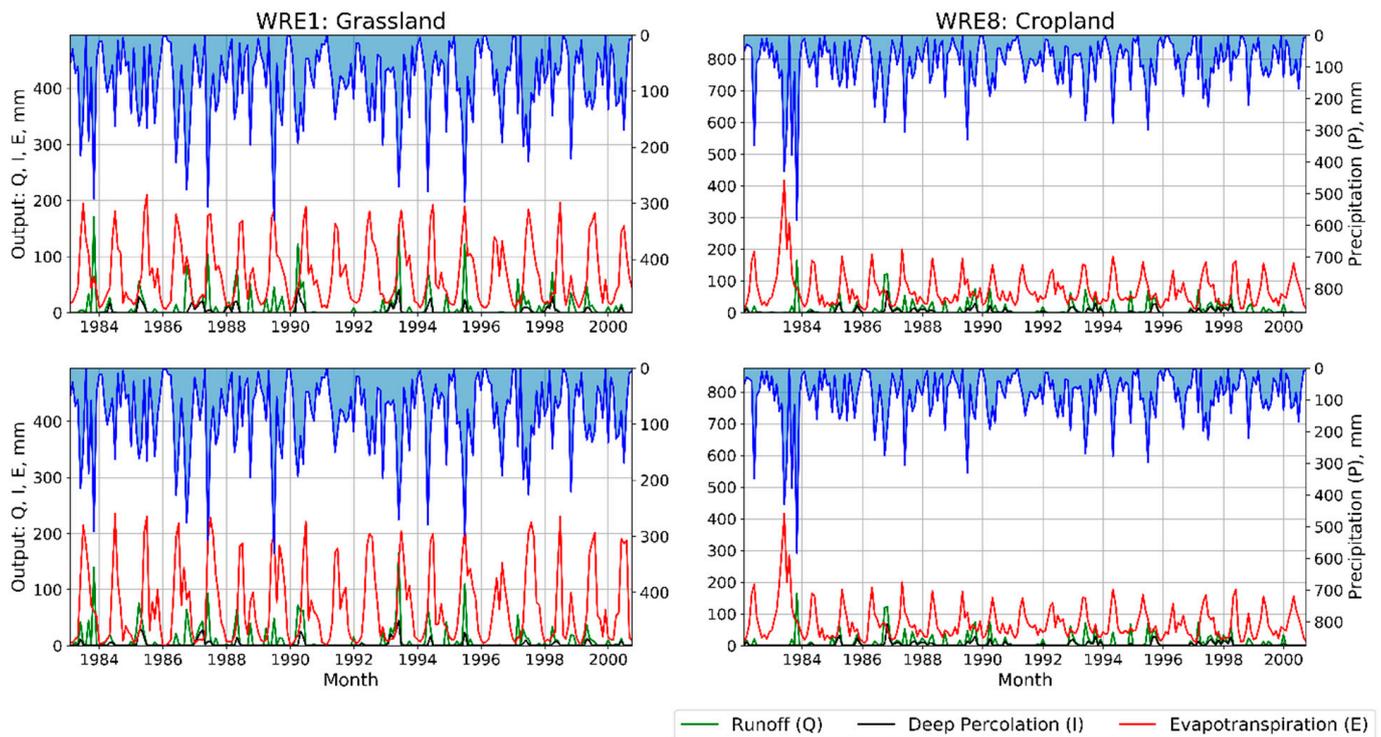


Figure 6. Water balance components at a monthly scale implied by the calibrated parameter sets for WRE1 (native prairie) over 1983–2000 and WRE8 over 1982–2000 (cropland) without (**top**) and with (**bottom**) grazing operations.

3.2.2. Changes in Major Response Variables

Key response variables related to hydrology, agronomy, and environment from the model were examined to determine the impacts of grazing operations on the watersheds. The response variables implied by all four metrics were aggregated annually and summarized throughout the calibration and validation period in Table S10 for WRE1 and Table S11 for WRE8. For illustration purposes, only changes in these variables with respect to management without grazing are summarized over the simulation period in Table 5 for WRE1 and Table 6 for WRE8. Variabilities of response variables observed during calibration, validation, and the entire period are inconsistent.

Table 5. Summary of response variables averaged annually in grassland (WRE1), implied by four best-calibrated parameter value sets associated with four metrics and respective changes (D) in % after grazing over the simulation period (1983–2000). Shaded cells with positive changes refer to decreased response variables after grazing.

Response Variables	OF		NSE		COD		PBIAS	
	Without	D%	Without	D%	Without	D%	Without	D%
Water yield, mm	130.59	5.9	130.29	−7.5	138.31	−1.2	130.59	−0.01
Deep percolation, mm	32.07	21.6	28.22	3.4	23.77	−14.7	32.07	58.9
Sediment, t/ha	2.21	65.2	1.87	20.1	3.25	54.1	2.21	8.3
Soil erosion, t/ha	2.20	65.1	1.86	19.8	3.25	54.0	2.20	8.2
Evapotranspiration, mm	805.69	−2.4	814.48	1.1	810.98	0.6	805.69	−2.9
Potential ET, mm	1495.47	−9.6	1741.62	8.1	1691.97	5.4	1495.47	4.1
Total phosphorus, kg/ha	0.26	48.7	0.20	−40.9	0.27	−4.7	0.26	−25.1
Total nitrogen, kg/ha	5.17	42.0	4.93	9.9	6.20	28.3	5.17	−21.8
Plant biomass, t/ha	13.19	−98.1	14.99	−18.9	10.79	−65.3	13.19	−23.5
Forage yield, t/ha	9.33	65.6	10.79	83.2	7.58	76.1	9.33	83.7
Standing dead biomass, t/ha	5.98	−258.9	7.88	−89.7	5.96	−150.8	5.98	−129.9
Standing live biomass, t/ha	0.28	−380.3	0.39	−131.1	0.26	−242.9	0.28	−192.7
Drought stress, d	6.14	−530.5	22.24	−19.8	16.39	−62.5	6.14	−283.1
Temperature stress, d	137.48	−1.6	139.94	3.1	135.98	0.3	137.48	2.8
Nitrogen stress, d	76.91	98.1	23.98	8.5	0.21	−100	76.91	69.9
Phosphorus stress, d	72.12	−37.5	100.71	−10.2	149.05	25.6	72.12	−65.6

Table 6. Summary of response variables, averaged annually in cropland (WRE8), implied by four best-calibrated parameters associated with four metrics and respective changes (D) in % after grazing operations over the simulation period (1982–2000). Shaded cells with positive changes refer to decreased response variables after grazing.

Response Variables	OF		NSE		COD		PBIAS	
	Without	D%	Without	D%	Without	D%	Without	D%
Water yield, mm	142.33	0.4	144.86	0.04	144.46	−0.1	142.33	0.4
Deep percolation, mm	40.27	−0.4	48.29	−0.9	41.24	0.3	40.27	−0.4
Sediment, t/ha	5.92	10.3	14.85	0.4	10.46	−3.4	5.92	10.3
Soil erosion, t/ha	5.92	10.3	14.85	0.4	10.46	−3.4	5.92	10.3
Evapotranspiration, mm	949.65	−0.02	936.97	0.04	947.17	−0.01	949.65	−0.02
Potential ET, mm	2040.10	0.0	2002.75	0.0	2040.10	0.0	2040.10	0.0
Total phosphorus, kg/ha	2.03	7.5	4.50	−0.5	3.55	−3.4	2.03	7.5
Total nitrogen, kg/ha	11.97	6.4	15.35	−1.0	15.53	−3.4	11.97	6.4
Crop biomass, t/ha	19.20	−0.6	18.62	−0.7	20.85	−0.8	19.20	−0.6
Forage yield, t/ha	4.27	−3.0	3.77	−2.1	4.56	−3.7	4.27	−3.0
Standing dead crop residue, t/ha	13.44	−0.2	13.07	−0.2	14.61	−0.5	13.44	−0.2
Standing live plant biomass, t/ha	1.26	−0.2	1.23	−0.2	1.37	−0.6	1.26	−0.2
Drought stress, d	4.27	−3.0	3.77	−2.1	4.56	−3.7	4.27	−3.0
Temperature stress, d	58.37	−0.2	57.10	0.1	62.19	−0.3	58.37	−0.2
Nitrogen stress, d	18.49	−0.1	22.86	−0.02	1.06	11.7	18.49	−0.1
Phosphorus stress, d	-	0.0	-	0.0	5.94	4.8	-	0.0

Table 5 shows the changes in response variables based on four different performance metrics during the entire simulation period (1983–2000). These changes show uneven changes in terms of their magnitude. For example, water yield was reduced only with the representations associated with the lowest objective function value and absolute PBIAS, while NSE and COD showed increased water yield. In contrast, except for COD, the other three representations showed reduced deep percolation with grazing. All four model representations consistently showed decreased simulated sediment yield, soil erosion, and forage yield but increased plant biomass, crop residue, and drought stress. NSE, COD, and PBIAS showed reduced evapotranspiration rates and increased temperature stress, while OF showed an increase. Furthermore, representations associated with maximum COD revealed increased nitrogen and decreased phosphorus stress.

In contrast, the simulated response of grazing operations in native prairie notably varied from calibration to validation period and among the four representations provided by optimal statistics (Table S10). For example, decreased yields of water were revealed in validation except for NSE-based representations. Grazing operations increased deep percolation associated with COD, while other metrics showed a decrease. Although changes in total phosphorus and nitrogen appeared inconsistent among the four metrics over the simulation period (Table 5), Table S10 shows a consistent decrease in total phosphorus and nitrogen during calibration and validation among all metrics. Interestingly, changes in plant biomass, forage yield, crop residue, and phosphorus stress observed over the simulation period were consistent with calibration and validation.

In contrast, changes in the response variables are less apparent in cropland (Table 6) regardless of increase or decrease. This observation was also valid for monthly water balance components (Figure 6). As observed in Tables 5 and S10, response variables change inconsistently, though the magnitudes of change are relatively small. Over the entire simulation period, grazing in cropland generated decreased water yields when optimized for OF, NSE, and PBIAS, but only the COD-based representation revealed decreased deep percolation (Table 6). However, a decrease in water yield was noted during the calibration and validation stage in all metrics except COD, which displayed decreased water yield during calibration and increased yields during validation (Table S11). Except for COD, all other optimized sets resulted in reduced sediment yield and soil erosion for the entire simulation period, while OF and PBIAS displayed reduced sediment yield and soil erosion during calibration, and the validation period revealed increased sediment yield and soil erosion with COD (Table S11). The overall simulation showed a slight decrease in plant evapotranspiration and temperature stress when optimized for NSE.

Nevertheless, optimized NSE and COD reduced plant evapotranspiration only during validation and calibration, respectively, while an increase in temperature stress was observed during validation when optimized for NSE. Decreased total phosphorus and nitrogen were consistently observed with OF and PBIAS over calibration, validation, and even the entire simulation period, except for the validation period with NSE only (Table S11). All optimized metrics showed consistently increased potential evapotranspiration, crop biomass, crop yield, and drought stress at all time scales. The entire simulation showed decreased nitrogen and phosphorus stress while optimized for COD. However, while optimized for all four metrics, nitrogen stress appeared to drop, and COD showed reduced phosphorus stress only during validation.

3.2.3. Examples of Grazing Response in Temporal Dynamics

For brevity, representations obtained by minimizing the objective function (OF) to demonstrate the grazing response on watershed processes, concentrating on plant biomass and crop or forage yields are shown. For instance, Figure 7 (top) shows that grazing operations significantly increased crop biomass over the simulation period for WRE1 (Table 5). However, simulations for cropland (WRE8) showed slight increases in biomass after grazing (Figure 7, bottom) throughout the simulation period (Table 6).

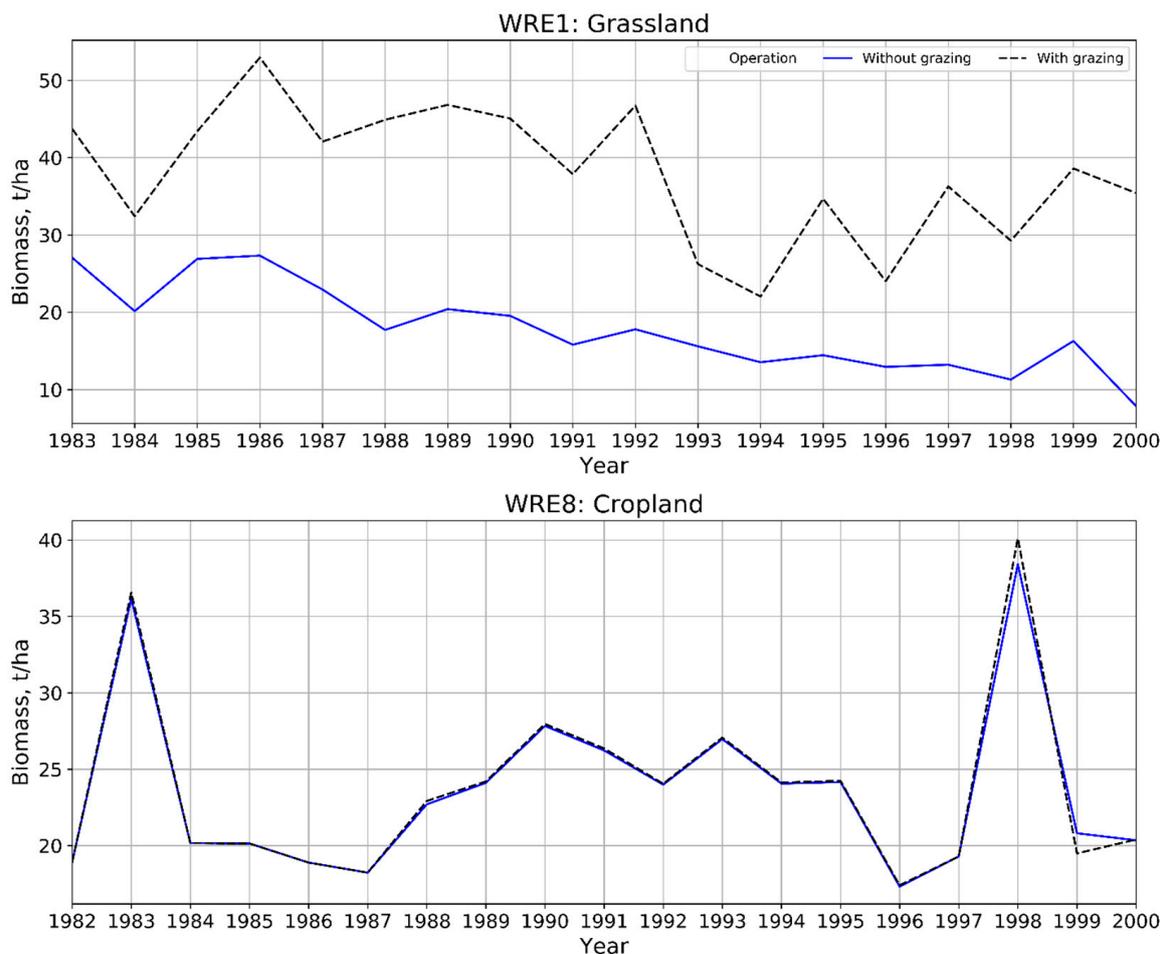


Figure 7. Annual average biomass generated from WRE1 (grassland) and WRE8 (cropland) under without and with grazing operations.

Figure 8 illustrates how forage production on WRE1 and crop yield on WRE8 responded to grazing. While forage yield from native prairie (WRE1) inter annually varied from nearly 6 t/ha to 15 t/ha, after grazing, almost all forage was consumed by cattle, except for the four years when there were no grazing activities (1993–1996) (Figure 8, top). For this reason, forage yield, on average, is particularly less during grazing operations than without grazing operations, as noted in Table 5. Notably, these four years showed increased forage after grazing over WRE1. The cropland system in WRE8 (Figure 8, bottom) experienced almost similar crop yield without and with grazing operations. However, a slight increase in crop yield was observed during the years 1988, 1991, 1993–1996, and 1998. Hence, a slight increase in crop yields is noted in Table 5 and Table S10 for WRE8. But the year 1999, when stockers grazed for more than 140 days in WRE8, shows some decrease in crop yield, while grazing heifers for a month in 1983 did not impact crop yield (Table S4). This analysis discriminates between the intensity of grazing operations; the amount of grain yield heavily depends on the level of applied grazing pressure. For instance, crop yields were less affected by the milder grazing operations in WRE8.

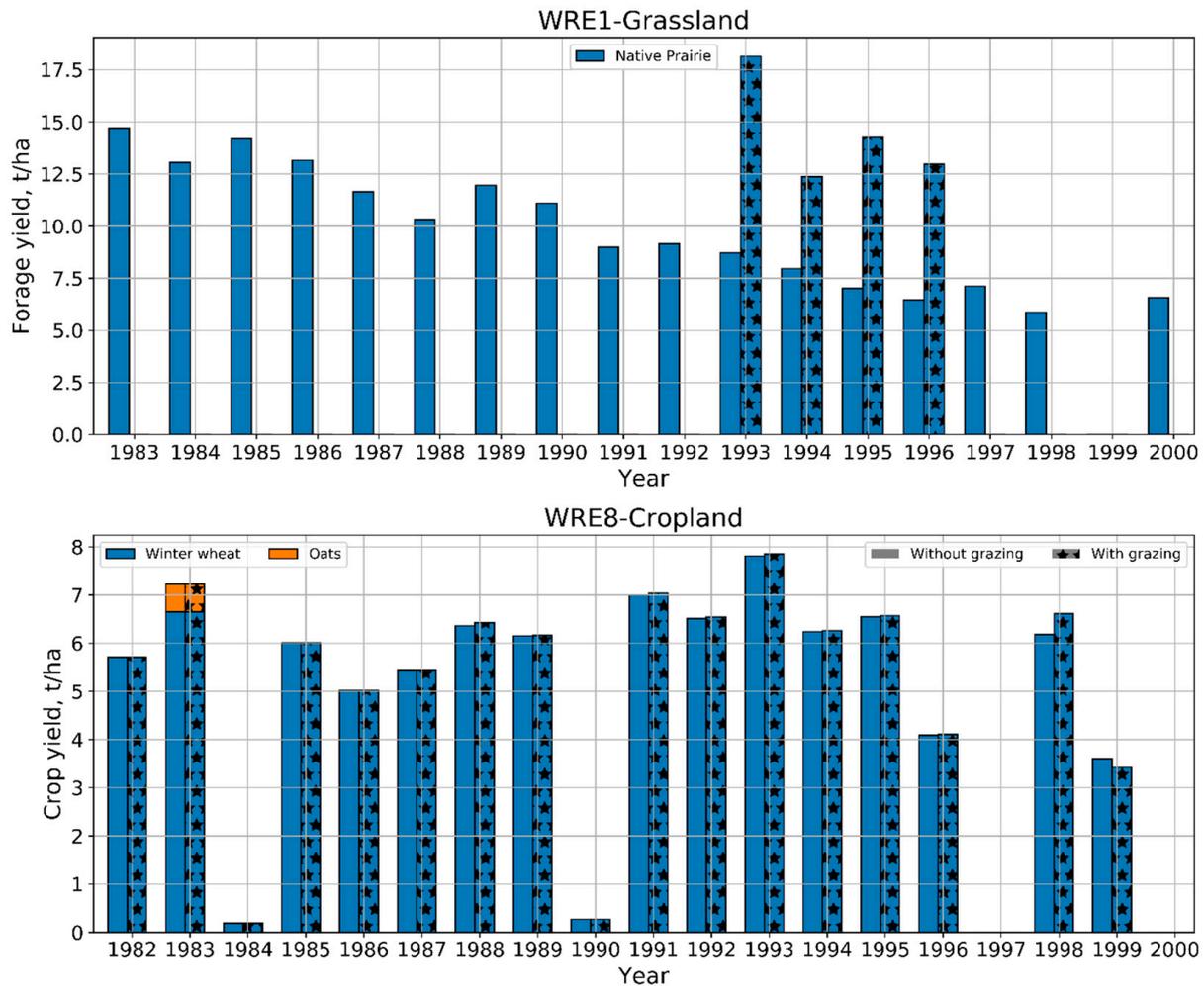


Figure 8. Annual yields generated by WRE1 (native prairie, **top**) and WRE8 (cropland, **bottom**) without and with grazing operations. Bar chart with stars refer to crop yield while farm is under grazing activities.

4. Discussions

This study explored the APEX model's capability to assess grazing impacts on surface runoff in small-scale watersheds. It investigated the possibility of simplifying schemes for parameterizing hydrological models with more than ten parameters, followed by sensitivity analysis. The simple calibration framework, which considers the normal probability distribution of model parameters, appeared reasonable in capturing the features of water yield in watersheds with (a) native prairie and (b) a partial combination of winter wheat and oats (cropland) without and with grazing.

Out of 100,000 independent iterations, there was more than one reasonable representation of water yield within the Moriasi Criteria, implied by different metrics selected for the optimization process. Such observations indicate that watershed processes before and after grazing activities exhibit non-unique solutions, as Beven [84] suggested. Such multiple solutions for a given observation set can be developed to address epistemic uncertainties by the nature of hydrological modeling and predictions [85]. As expected, representations of water yield in Figures 4 and 5 exhibit reasonable model simulation performance based on Moriasi et al. [81,82]. However, the other watershed responses are unique for different optimized parameter value sets and at different time scales, which could be due to inherent uncertainty in the observations (Tables 5, 6, S10 and S11). For brevity, the response of grazing activities concentrating on the parameter set optimized for the objective

function expressed in Equation (5) as it incorporates all three performance measures that discriminate the temporal dynamics between observed and modeled sets is the focus.

Regardless of the calibration and validation period, simulated results reveal that water yield decreased by 6% and deep percolation declined by 22%. In comparison, crop and potential evapotranspiration increased by 10% and 2% from grassland with native prairie after grazing (Figure 6, Table 5). In contrast, cropland showed a <1% decrease in water yield coupled with a <1% increase in deep percolation (Figure 6, Table 6, second column). A decrease in simulated runoff and deep percolation from native prairie can be attributed to increased evapotranspiration from regrowth after grazing [86]. Younger leaves tend to be more efficient in the use of soil water than more mature leaves, so grazing should enhance water use in the production of biomass by grazed plants [87]. However, grazing also results in reduced effects of transpiration from existing plants (with removal of plant canopies) on the water balance of pastures, as noted for wheat pastures near the study site [88]. Therefore, grazing should generate some increase in available moisture in soil profiles. In contrast, grazing also removes the plant canopy that provides shade to the soil surface, which increases the potential for evaporation and runoff from less protected (and compacted from grazing) surfaces [89,90]. The simulated annual evapotranspiration in the study area falls within the reported range of annual accumulated evapotranspiration by Wagle et al. [91].

Decreased sediment, soil erosion, and nutrients (total nitrogen and phosphorus) simulated in both farms after grazing (Tables 5 and 6) were consistent with the literature [92,93]. Yu et al. [94] explained that a reduction in soil erosion may occur in light grazing due to litter accumulation in the form of feces and urine, improving surface soil structure via decomposition. A decrease in sediment deposition can be attributed to an increase in vegetation cover after grazing [95,96]. Grazing has been shown to affect biomass based on intensity and frequency. Biomass is commonly used as an indicator to show effective grazing as it increases soil carbon and porosity (and, therefore, infiltration) [97,98]. Although most literature reported that grazing decreases total aboveground and belowground biomass [99,100], this study shows increased biomass, including standing dead crop residue and standing live plant biomass. At the same time, this observation is consistent with some literature [101,102]. The nature of increased biomass rather than decreased may confirm that grazing in this study fell under moderate grazing [103]. Decreased forage in native prairie (WRE1) of more than 65% (Table S10) after grazing is attributed to the consumption of forage while cattle graze on the farm. Such a decrease appears consistent in the other scenarios and at all time scales (Tables 5 and S10). However, grazing cattle over cropland (WRE8) increases rather than decreases grain yield (Tables 6 and S11). Such observation is realistic and can be due to a reduction in lodging or grazing termination date before the elongation of the reproductive stems [60,104]. Increased drought stress in both watersheds after grazing operations were also observed. It is not surprising that grazing often leads to increased water loss through soil evaporation, even though transpiration from plants often decreases [105]. In native prairie, most optimized sets showed reduced nitrogen stress (Table 5) but increased in cropland (Table 6). Likewise, increased phosphorus stress was observed in native prairies, but there was no change in phosphorus stress in cropland.

Overall, a difference in calibrated parameters for native prairie between grazing operations were noted, while parameters were similar in cropland (Tables 3 and S9). Consistent with parameter variation, the dynamics in water balance (Figure 6) appeared identical before and after grazing in cropland compared to native prairie. Such observations are attributed to differences in grazing frequency and intensity and fertilizer and pesticide applications. However, similar parameters were observed before and after the grazing operations in cropland and with different optimized metrics, though not necessarily with the same magnitudes of response (Tables 6 and S11).

5. Challenges and Limitations

5.1. Challenges

During this analysis, a few questionable outcomes with regard to either APEX or APEXgraze were discovered. For example, the amount of total biomass that was generated in the native prairie was almost doubled with grazing (98%, Table 5). These results do not seem realistic since the disturbance of grazing removes the leaf area required to capture photosynthates that generate growth and accumulation of biomass. Further, the total amounts of biomass produced by the simulation of native prairie far exceeded the production potential for the site. Production guidelines for soils on this site indicate a range of 1 ton/ha under drought conditions and 4 tons/ha under favorable growing conditions [106]. In comparison, earlier research on sites in proximity to WRE 1 reported total amounts of biomass generated on an annual basis ranging from 1 to 6 tons/ha, depending on growing conditions [107–109]. In contrast, the amounts of biomass produced by winter wheat fell within the upper part of ranges noted for neighboring pastures [88,108].

The origins of the form of the equation that was used to describe increases in biomass or how the effects of environmental factors on production were derived are uncertain. However, increases in live biomass in grasslands during growing seasons are intrinsically nonlinear in form and are impacted by different factors that limit growth [108,110]. Plant growth in native prairie and pastures of winter wheat is sigmoidal, characterized by an initial quiescent phase of slow growth early in growing seasons, followed by a period of exponential increase and eventual slowing of growth as the growing season ends. Peak biomass is attained, and plants begin to senesce [108,110]. This type of growth curve represents carbon capture by the plant community as affected by environmental factors, including availability and timing of moisture, ambient temperature, and day length [87,88,111]. More documentation is required from the model developers to grasp how this relationship is being represented.

In addition, there were issues with how the model represented biomass and leaf area index (LAI) at smaller scales. For example, the cropland in 1983 (Figure 9a,c) showed a bi-modal curve for biomass and LAI, with LAI greatly outpacing biomass. This is a somewhat illogical result as leaf area is dependent on the presence of leaf biomass, which is an ever-decreasing portion of aboveground growth with a time of the growing season due to increases in stem growth as plants mature [87]. However, there were no differences in the graphs (Figure 9a) among grazing treatments despite grazing being applied that year (as depicted with the overlapping lines). Part of the explanation for the lack of differences in the cropland between grazing treatments was a low level of grazing pressure. However, one would expect differences to show in those years with grazing. Given the number and size of cattle applied, their intake requirements, and length of grazing period in 1983 (Table S4), a total of roughly 3 tons/ha of biomass would be removed by grazing. Alternatively, there was no grazing in the native prairie in 1983 (Figure 9b,d). Yet, the grazing simulation showed a bi-modal dip in biomass in August, followed by a rebound in plant growth from September through October. In contrast, the non-grazing simulation for native prairie did not show the rebound. Also, the LAI in native prairie remained high under grazing despite the removal of leaf biomass by cattle but showed a seasonal decline without grazing. Therefore, further discussion of LAI was omitted from this analysis. However, more information is needed to describe why these patterns occur and their effects on the outcomes of simulations. There were also issues with the daily outputs of biomass, crop (forage) yield, etc., not equaling the pre-calculated annual outputs, which requires further investigation.

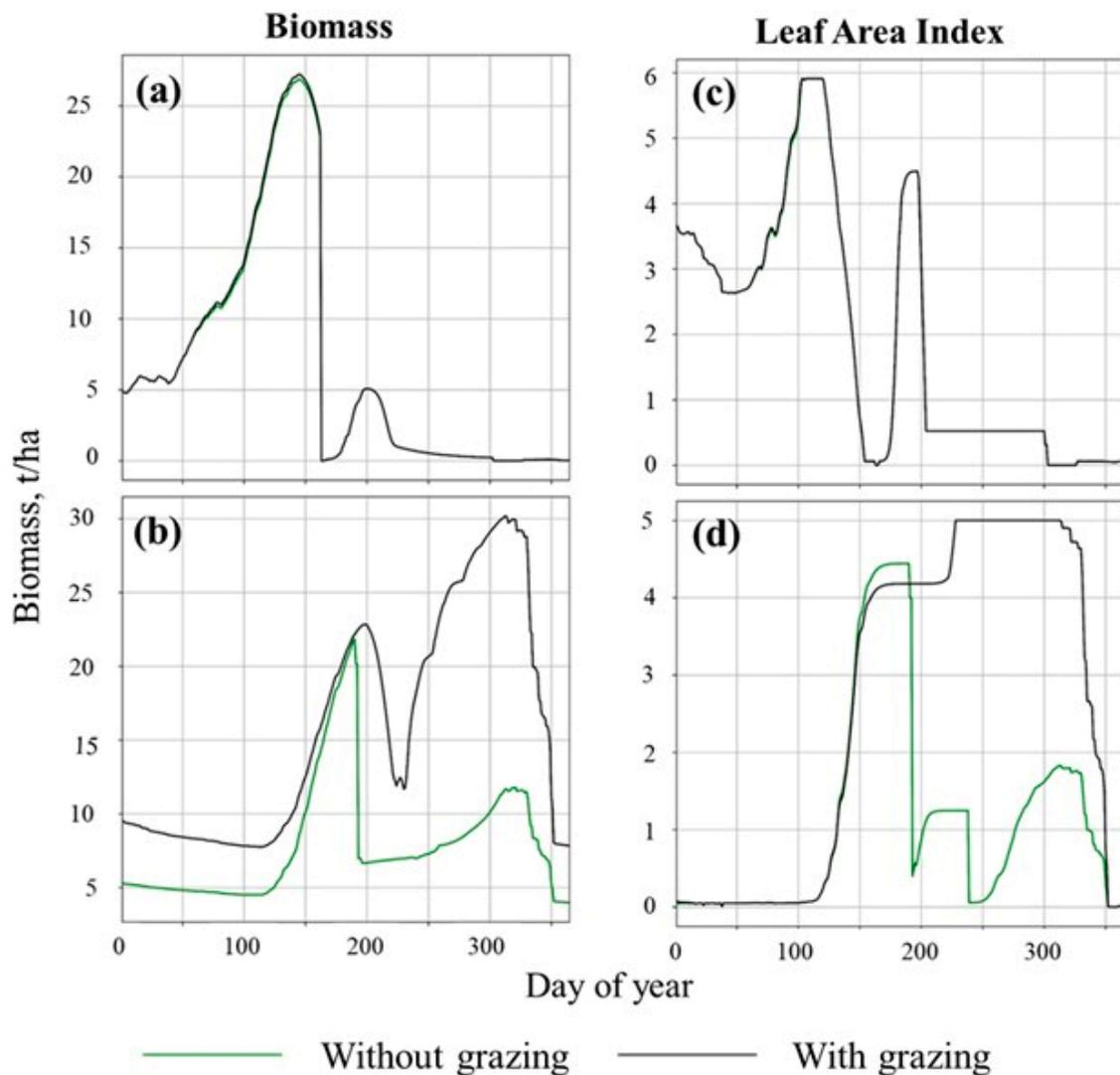


Figure 9. Biomass and leaf area index with and without grazing activities for the year 1983. Top (a,c): cropland (WRE8); bottom (b,d): native prairie (WRE1).

This study relied on published data sets on management practices, grazing schedules, runoff, and sediment at the outlet of each watershed [54,55]. However, the dataset did not include much documentation regarding sampling, quality assurance, and analysis. One area of need is the effects of grazing or applied management to wheat pasture. An earlier, short-term study on the WRE pastures reported significant levels of compaction in the upper 75 mm of the profile of wheat pasture that was managed by conservation tillage and grazed [90]. Longer and more detailed studies are required to define the effects of conservation tillage and grazing applied to wheat or oat pasture on soil compaction. The results of the current study and long-term measurements will augment the understanding of more sustainable livestock production that enhances water use efficiency.

Interestingly, the model did not calculate forage yield for the year 1999 in WRE1 and crop yield for the year 1997 in WRE8 regardless of grazing management (Figure 8). This observation suggests detailed investigations of databases as well as parameter settings are needed.

Significant differences in response variables were observed between calibration and validation, possibly due to the short periods that were applied to the validation phase of this study. Recommendations for calibrations require extended periods of measurement for machine learning methods and usually require 70% of the measured data, which limits

validations to 30% of the data. Differences in response variables when optimizing for the different statistics were noted. Different statistics give different sets of parameters, as explained by the equifinality nature of hydrological models [84]. These solutions suggest creation of a framework that addresses epistemic uncertainties of equifinality in hydrological modeling and predictions [85,112,113]. Equifinal solutions in hydrological modeling can arise from differences in antecedent conditions, limited measurements, and the nature of distributed models [114,115]. Therefore, combining parameter values from different sources does not guarantee optimal results.

Disparity in changes in response variables at different time scales (calibration, validation, and simulation period) can be attributed to inconsistent management schedules in addition to the unpredictability behavior of the model. For instance, according to the least objective function value, simulated water yield in native prairie increased and decreased during calibration and validation periods, respectively (Table S10). However, the overall simulation period showed decreased water yields from native prairie (Table 5). Although such behavior is surprising, the beginning and termination dates for grazing could have been different during the calibration and validation phases. Note that although the model generated different runoff sets, the climate conditions, such as precipitation and temperature, were the same.

The hydrological process, in terms of other key variables like crop evapotranspiration, sediment, crop (forage) yields, and crop biomass, becomes worth investigating if these variables were collected reliably. However, the impacts of different elements of grazing management, such as stocking rates or rotational forms of grazing management were not examined. It is also possible to study the impacts of different forms of seasonal grazing with cattle effects on grain yields by wheat at watershed scales [116].

5.2. Future Direction

Though simple and capable of producing reasonable results for some response variables, the current approach needs improvement, mostly due to the non-unique solutions that are implied by the different performance metrics. To avoid such multiple representations, stochastic methods may provide an avenue for parameterizing such process-based hydrological models. In addition, recent advances may allow the use of deterministic methods of sensitivity analysis [117–121]. These methodologies may improve the current results that model livestock management in grasslands and croplands.

A similar calibration protocol can be implemented in other process-based models such as the Soil and Water Assessment Tool (SWAT), Root Zone Water Quality Model (RZWQM), and Decision Support System for Agrotechnology Transfer (DSSAT). Since the scope of this work is concentrated on calibration, future research will involve investigating sensitive parameters and their uncertainty range and response variables. Further, calibrated parameters could be used to enumerate the ranges of different response variables under climate conditions derived from global circulation models. These scenarios will be useful for designing management practices in the future.

6. Concluding Remarks

The impact of grazing on watershed processes, such as surface runoff, biomass, forage (crop) yield, etc., in native prairie and cropland was examined by employing a recently modified version of APEX, an agro-hydrological model that incorporates the grazing module APEXgraze. A simple approach to parameterize the APEXgraze model by expanding parameter space relying on normal distribution that utilized lower and upper bounds of each parameter instead of a priori probability distributions was proposed. With measured runoff at the outlets of two watersheds, this approach provided reasonable model simulation performance using various metrics. These multiple reasonable solutions imply that the watershed processes exhibit non-unique solutions due to nonlinear relations among processes. The behavior of two watersheds within the same subarea under different forms

of management and grazing intensities was reported. Despite having multiple solutions under the same management, the response variables were unique.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/hydrology11040042/s1>, Table S1: Planting schedule for watersheds 1 and 8 including plant populations (plants/m²) as reported in Nelson et al. [54,55]; Table S2: Fertilizer application schedule for watersheds 1 and 8 including species and applicator rates (kg/ha), as reported in Nelson et al. [54,55]; Table S3: Pesticides application schedule for watersheds 1 and 8 including species and applicator rates (kg/ha), as reported in Nelson et al. [54,55]; Table S4: Grazing schedule for watersheds 1 and 8, as reported in Nelson et al. [54,55]; Table S5: APEX crop database for crops in WRE [63,79]; Table S6: Fertilizers applied in WRE watersheds during monitoring period and implied characteristics in APEX database [63,79]; Table S7: Pesticides applied in WRE watersheds during monitoring period and implied characteristics in APEX database [63,79]; Table S8: Grazer characteristics for WRE watersheds during monitoring period and implied characteristics in APEX database [63,79,118]; Table S9: Calibrated APEX parameters for native prairie (WRE1) and cropland (WRE8) for surface runoff implied by maximum NSE and absolute PBIAS. Refer to Table 2 for parameter definitions; Table S10: Annual average of selected response variables, including environmental indicators in grassland (WRE1), implied by the calibrated parameter set and respective changes in % with respect to grazing operations during calibration (1983–1995) and validation (1996–2000) periods, implied by four different best metrics. Values in gray-shaded cells refer to decreased response variables after grazing; Table S11: Annual average of selected response variables, including environmental indicators in cropland (WRE8), implied by calibrated parameter set and respective changes in % with respect to grazing operations during calibration (1982–1994) and validation (1995–2000) periods, implied by four different best metrics. Values in gray-shaded cells refer to decreased response variables after grazing.

Author Contributions: Conceptualization, A.M.N. and M.L.M.; methodology, M.L.M. and D.N.M.; software, M.L.M.; validation, A.M.N. and M.L.M.; formal analysis, M.L.M.; investigation, A.M.N. and M.L.M.; resources, A.M.N., B.K.N. and D.N.M.; data curation, A.M.N.; writing—original draft preparation, M.L.M.; writing—review and editing, A.M.N., M.L.M., B.K.N. and D.N.M.; visualization, M.L.M.; supervision, A.M.N.; project administration, A.M.N. and D.N.M.; funding acquisition, A.M.N., B.K.N. and D.N.M. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: Data will be made available on request.

Acknowledgments: Resources for this research were provided by USDA towards CEAP and LTAR endeavors. This research used resources provided by the SCINet project and the AI Center of Excellence of the USDA Agricultural Research Service, ARS project number 0500-00093-001-00-D. We want to thank Brian Stucky and Huang Haitao from the Office of Scientific Computing, USDA-SCINet, who supported us in providing high computational facilities. We also thank the pioneering soil, water, plant, and environmental research team at Blackland Research & Extension Center and USDA Grassland, Soil, and Water Laboratory in Temple, Texas, who gave us valuable contributions in setting up the model and relevant databases. We acknowledge Hydrologist Phillip R Busted from USDA-ARS Grazinglands Research Laboratory, who compiled climate data for our simulation tasks. Also, we credit James Dean from the USDA-ARS Sustainable Water Management Research Unit for his sincere help in compiling pesticide and fertilizer datasets. Finally, comments from the associate editor and anonymous reviewers improved the quality of the manuscript. Mention of trade names or commercial products in this publication is solely for the purpose of providing specific information and does not imply recommendation or endorsement by the USDA. USDA is an equal-opportunity employer.

Conflicts of 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.

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