

Article

Tools for Predicting Forage Growth in Rangelands and Economic Analyses—A Systematic Review

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Abstract: Farmers and ranchers depend on annual forage production for grassland livestock enterprises. Many regression and machine learning (ML) prediction models have been developed to understand the seasonal variability in grass and forage production, improve management practices, and adjust stocking rates. Moreover, decision support tools help farmers compare management practices and develop forecast scenarios. Although numerous individual studies on forage growth, modeling, prediction, economics, and related tools are available, these technologies have not been comprehensively reviewed. Therefore, a systematic literature review was performed to synthesize current knowledge, identify research gaps, and inform stakeholders. Input features (vegetation index [VI], climate, and soil parameters), models (regression and ML), relevant tools, and economic factors related to grass and forage production were analyzed. Among 85 peer-reviewed manuscripts selected, Moderating Resolution Imaging Spectrometer for remote sensing satellite platforms and normalized difference vegetation index (NDVI), precipitation, and soil moisture for input features were most frequently used. Among ML models, the random forest model was the most widely used for estimating grass and forage yield. Four existing tools used inputs of precipitation, evapotranspiration, and NDVI for large spatial-scale prediction and monitoring of grass and forage dynamics. Most tools available for forage economic analysis were spreadsheet-based and focused on alfalfa. Available studies mostly used coarse spatial resolution satellites and VI or climate features for larger-scale yield prediction. Therefore, further studies should evaluate the use of high-resolution satellites; VI and climate features; advanced ML models; field-specific prediction tools; and interactive, user-friendly, web-based tools and smartphone applications in this field.

Keywords: decision support tools; economic analysis; machine learning; modeling; remote sensing; systematic literature review



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1. Introduction

Grasslands dominate the landscape of the western and central United States, covering more than 60% of the land surface [1]. Pastures, rangelands, shrublands, meadows, steppes, and woodlands fall under the category of grasslands, and are primarily maintained to support the livestock industry, among other operations. Ranchers rely on natural forage in these environments to feed cattle, sheep, goats, horses, and other domestic livestock. The northern Great Plains, which cover parts of Montana, Wyoming, Colorado, North Dakota, South Dakota, and Nebraska, are primarily rural areas and contain roughly 25% of the national livestock population [2]. Forage crops known as the edible part of the plant are

crucial in maintaining livestock health, as they provide essential nutrients and encourage proper digestion. Therefore, ranchers and farmers must ensure a continuous supply of forage to maintain the viability of the livestock industry. Proper monitoring, management, and economic benefit analysis of rangeland and pastureland dynamics are necessary to make effective enterprise decisions.

Although several individual scientific studies on forage growth, models, predictions, economics, and tools were available, a comprehensive review on the knowledge domain of forage growth prediction and economic analysis tools is not available. Therefore, this study surveyed the scientific literature, specifically peer-reviewed journal articles published from 2010 to 2021, to provide a comprehensive knowledge review and identify research gaps.

Due to the importance of forage, predicting growth patterns in advance aids ranchers in resource planning and management. In addition to ensuring forage availability and productivity, effective management practices also benefit the pasture ecosystem. An important indicator of proper pasture ecosystem function is biomass yield, which is traditionally measured using destructive methods such as clipping. Such analyses are often constrained to small areas due to the intensive time and labor required, and hence not carried out frequently [3–5].

A possible replacement for traditional methods is non-destructive remote sensing (RS) with proper validation and calibration. In this method, satellites and unmanned aerial vehicles (UAVs) monitor green vegetation based on its spectral reflectance properties [6]. Optical sensors attached to the satellite platforms efficiently collect and secure information, which can be used for detecting greenness, estimating vegetation density, distinguishing different vegetation classes, and other applications [7–9]. Satellite information can be valuable for large-scale monitoring of spatial and temporal patterns of grasslands while significantly reducing time and labor.

Satellite datasets can be easily obtained, allowing reproducible studies to be performed. The most commonly used optical sensor satellites are the Landsat, Sentinel-2, Moderate Resolution Imaging Spectroradiometer (MODIS), and Advanced Very-High-Resolution Radiometer (AVHRR). In recent years, the use of satellites to monitor pasture biomass has gained popularity because the data are readily available and freely accessible. Vegetation indices (VI) estimated from the spectral wavelength data have been used as a proxy for the biomass yield in pastures [10].

Along with remote sensing data, soil and climate characteristics are used to predict biomass yield [11,12]. A simple linear relationship can be used to understand the importance of VI, soil, and/or climate factors in predicting pasture biomass. However, the complex, interlinked connections between these parameters are better explained using machine learning (ML) approaches.

Interactive tools are critical to farmer success by informing decisions regarding management strategies and budget planning [13,14]. Both prediction models and economic analyses can be developed with user-friendly tools for farmers. For example, tools using a developed prediction model might aid farmers in monitoring pastures and planning stocking rates. Economic analysis tools take planning a step further by measuring farm profit, evaluating the effectiveness of management strategies, and comparing scenarios. Although several individual scientific studies regarding models, predictions, economic analysis, and tools for forage management have been published, a comprehensive review of this knowledge is not yet available. A review is crucial for farmers and researchers alike to be cognizant of the currently available forage technology and tools for forage production and management.

This study aims to survey the scientific literature, specifically peer-reviewed journal articles published from 2010 to 2021, and intends to provide a comprehensive review and identify research gaps. The objective is to review the input features (VI, soil, and climate), prediction models (regression and ML), and tools used for grass and forage monitoring and economic analysis using a systematic literature review (SLR) process. Potential research

gaps in a specific knowledge domain were effectively identified, and are expected to serve as a guide to researchers in this subject seeking to improve forage and grassland management.

2. Material and Methods

2.1. Review Methodology

The review methodology followed the SLR guidelines outlined by Keele et al. [15]. A review protocol is emphasized in SLR which includes developing specific research questions to be addressed and planning the methods for successfully performing the review (Figure 1).

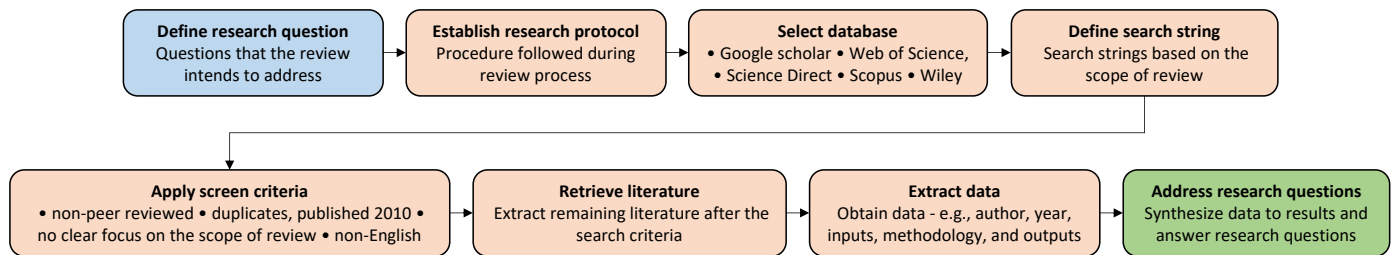


Figure 1. Flowchart for conducting systematic literature review showing planning, conducting, and reporting stages.

The database sources used to select relevant literature included Science Direct, Web of Science, and Google Scholar. The selected publications were screened using various inclusion and exclusion criteria to assess their relevance to each research question. According to SLR guidelines, the review process was classified into three stages; (i) planning, (ii) conducting, and (iii) reporting.

The review process was carried out after defining the scope of the review, developing a draft review protocol, validating and revising the review protocol based on the research questions, and finally extracting information from the selected literature. Basic information regarding the authors, year of publication, type of research, methodology, results, and recommendations were stored. The stored data were analyzed to provide an outline of the relevant literature published. The final stage was review reporting, whereby the results were used to answer the developed research questions and the review was concluded.

2.1.1. Defining Research Questions

This review is focused on literature published in the selected domain of “biomass yield prediction models, and tools for pasture grass and forage, and economic analysis tools for forage.” The specific research questions were:

- Q1: What significantly influences grass and forage biomass yield prediction?
- Q2: What regression and machine learning modeling techniques can be used for biomass yield prediction?
- Q3: What tools are currently available for grass/forage monitoring and yield prediction?
- Q4: What tools are available for forage economic analysis?

2.1.2. Literature Search

A general search of the chosen knowledge domain yielded published literature outside the scope of this review. Therefore, the search included relevant concepts from the research questions. A primary search was conducted to identify and list search terms and their synonyms based on the literature abstracts. The search terms identified were used as “search strings” in the publication databases (Table 1).

Table 1. Identified search item strings for systematic literature review.

Search Aspect	Search Item Strings
Grassland	grassland *, pasture *, steppe *, rangeland *, meadow *
Climate	precipitation, rainfall, evapotranspiration, humidity, solar radiation, temperature, soil temperature
Remote Sensing	remote sensing, satellite, drone *, UAV *
Vegetation indices	vegetation ind*, NDVI, GNDVI, EVI
Methodology	machine learning, artificial intelligence, regression
Yield	biomass, produc*, monitoring, harvest, cut, quantity, yield

Note: * indicates placeholder that captures related forms (e.g., plural expression). UAV—unmanned aerial vehicle, NDVI—normalized difference vegetation index, GNDVI—green NDVI, and EVI—enhanced vegetation index.

2.1.3. Exclusion Criteria

Studies outside the scope of this review were excluded based on the following set of criteria:

- C1: Literature that did not have a clear focus on grass or forage prediction
- C2: Literature not in English
- C3: Duplicate publications already retrieved from another database source
- C4: Literature published before 2010 (latest 10+ years considered)
- C5: Literature published in conference proceedings and magazines

The total number of literature entities (manuscripts) downloaded from the selected 4 database sources was 147 (Table 2). Only 85 manuscripts qualified for further analysis after applying exclusion criteria. Among the databases, more relevant manuscripts were retrieved from Google Scholar (64%) than from Web of Science (17%) and Science Direct (Table 2). The list of the 85 selected manuscripts, based on the research questions (Section 2.1.1) and used for data analysis and the results, is presented in Table A1 (Appendix A).

Table 2. Distribution of compiled literature from the three database sources from 2010 to 2021.

Database	Downloaded	Excluded	Selected (%)
Google Scholar	83	46	54
Web of Science	36	20	24
Science Direct	28	19	22
Total	147	85	100

3. Results

3.1. Important Features Predicting Grass/Forage Yield

Data from the selected literature were extracted to analyze the most significant factors used to estimate pasture grass and forage dynamics. Remotely sensed vegetation indices (VI), as well as soil and climate features, were individually analyzed and are presented separately.

3.1.1. Vegetation Indices

The use of satellite sensors to measure grass and forage production in grassland, pasture, rangelands, meadow, and steppe environments was recorded in 52 manuscripts. The term “Landsat” included platforms such as Landsat 5, 7, and 8, whereas results for “Sentinel” included Sentinel 1 (Synthetic Aperture Radar, SAR) and 2 (optical satellites). Analyzing the satellites revealed that MODIS, Landsat, and Sentinel were the most commonly used platforms for predicting pasture or forage yield (Table 3). The finer spatial resolution predictions provided by the PlanetScope satellite were used in literature published after 2019. UAVs equipped with hyperspectral sensors were also widely used for grass and forage yield prediction. Figure 2 shows the results of the number of publications against the various vegetation indices considered. Band information of the vegetation indices is presented in Table A2 (Appendix B).

Table 3. Distribution of satellite platforms found in the selected literature.

Satellite Platforms	Frequency
MODIS	16
Landsat 5, 7, & 8	15
Sentinel 1 & 2	12
UAV	9
PlanetScope	5
LIDAR	2
EOSDIS	1
NOAA/AVHRR	1
PROBA-V	1

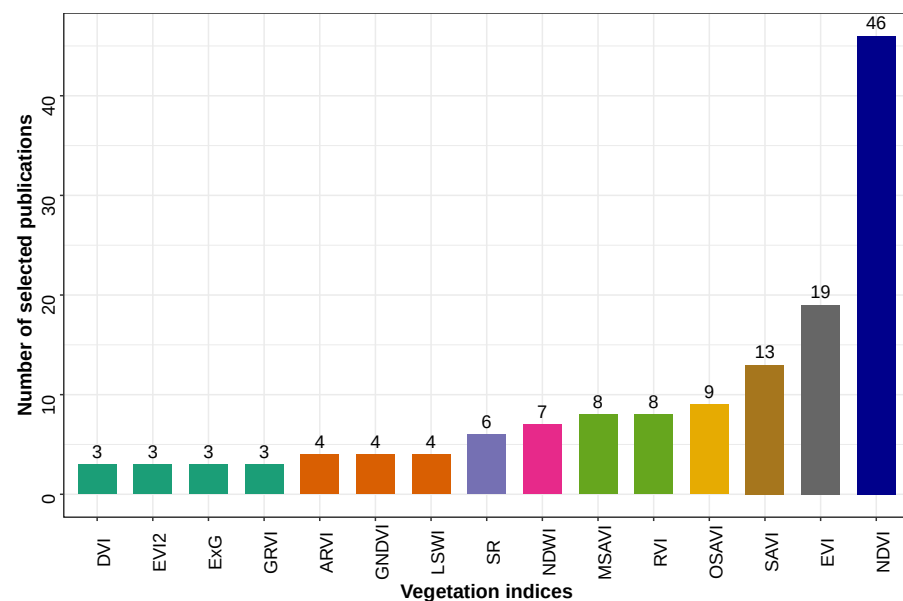


Figure 2. Vegetation indices versus the number of selected publications collected from database sources. Frequency of use of vegetation indices is sorted from lowest to highest. NDVI—normalized difference vegetation index, EVI—enhanced vegetation index, SAVI—soil-adjusted vegetation index, OSAVI—optimized soil-adjusted vegetation index, RVI—relative vigor index, MSAVI—modified soil-adjusted vegetation index, NDWI—normalized difference water index, SR—simple ratio, LSWI—land surface water index, GNDVI—green NDVI, ARVI—atmospherically resistant vegetation index, GRVI—green and red ratio vegetation index, ExG—excess green, EVI2—2-band EVI, and DVI—difference vegetation index.

3.1.2. Weather and Soil Features

Many studies have explored the use of climate and soil features to forecast annual forage yield, inform decisions on livestock stocking rates, and monitor plant communities of interest. In the reviewed literature (Table A1), the most commonly used weather features were air temperature, precipitation, solar radiation, relative humidity, and wind speed (Figure 3). The variable ‘weather’ mainly included the minimum, average, and maximum air temperature and solar radiation observations, and the term ‘precipitation’ included rain and snowfall. Soil moisture, pH, organic matter, and soil nutrients were categorized under soil variables.

3.2. Overview of Forage/Grass Prediction Models

Forage and grass yield showed a complex relationship with the weather, soil, and VI factors. Studies have reported using linear regression (LR) for cases where the yield was correlated to individual features, and both multiple linear regression (MLR) and partial least squares regression (PLSR) are appropriate when combined factors are used for yield

prediction. In the last few years, new approaches, such as ML, have been developed to capture complex, non-linear relationships between yield and environmental factors.

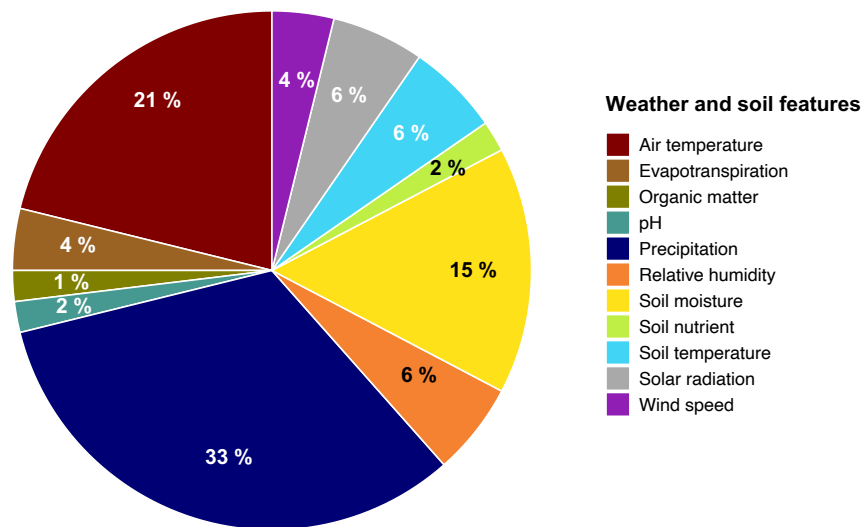


Figure 3. Distribution of weather and soil features for grass and forage prediction observed in selected literature.

Common ML methods used to predict grass and forage yield in the studied literature were artificial neural network (ANN), gradient boosting (GB), k-nearest neighbor (kNN), random forest (RF), and support vector machine (SVM) techniques. The prediction performance (R^2) for the eight most-used regression and ML methods and their variation along with the number of publications used in the analysis is presented in Figure 4.

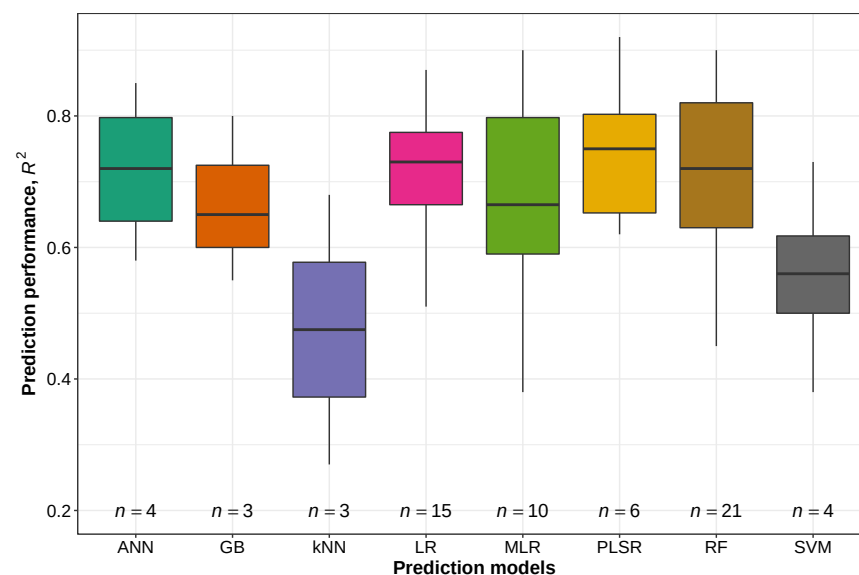


Figure 4. Box plot of prediction performance (R^2) for the eight most-used regression and machine learning methods. ANN—artificial neural network, GB—gradient boosting, kNN—k-nearest neighbor, LR—linear regression, MLR—multiple linear regression, PLSR—partial least squares regression, RF—random forest, and SVM—support vector machine.

3.3. Existing Tools for Grass/Forage Prediction

Few user-interactive tools that use the above-described grass and forage yield prediction models have been built. These tools aid ranchers to compare management practices, aid decision-making, develop forecast scenarios, and plan livestock stocking rates. The ex-

isting tools mostly use climate features such as precipitation as inputs for predicting the biomass yield. Described in the following are the tools developed for forage and grass prediction that include spreadsheet- and web-based applications.

3.3.1. North Dakota Drought Calculator

The North Dakota Drought Calculator (NDDC) is a spreadsheet-based linear decision tool developed by the United States Department of Agriculture (USDA) Agricultural Research Service (ARS) and the USDA Natural Resources Conservation Service (NRCS) to predict the effect of drought on forage production [16]. The NDDC uses linear regression models of average monthly precipitation to predict the forage growth potential (FGP) based on generic forage/biomass growth curves for specific zones. This tool is intended for farmers and ranch managers to aid in early stocking decisions during droughts (Figure 5). The FGP represents the above-ground forage biomass during the growing season, and is measured using the peak standing crop factor [17]. The calculator tool was developed and evaluated using data from the Great Plains of Colorado, North Dakota, and Wyoming. The overall accuracy of the NDDC tool, applicable to North Dakota, was determined to be approximately 75% [16].

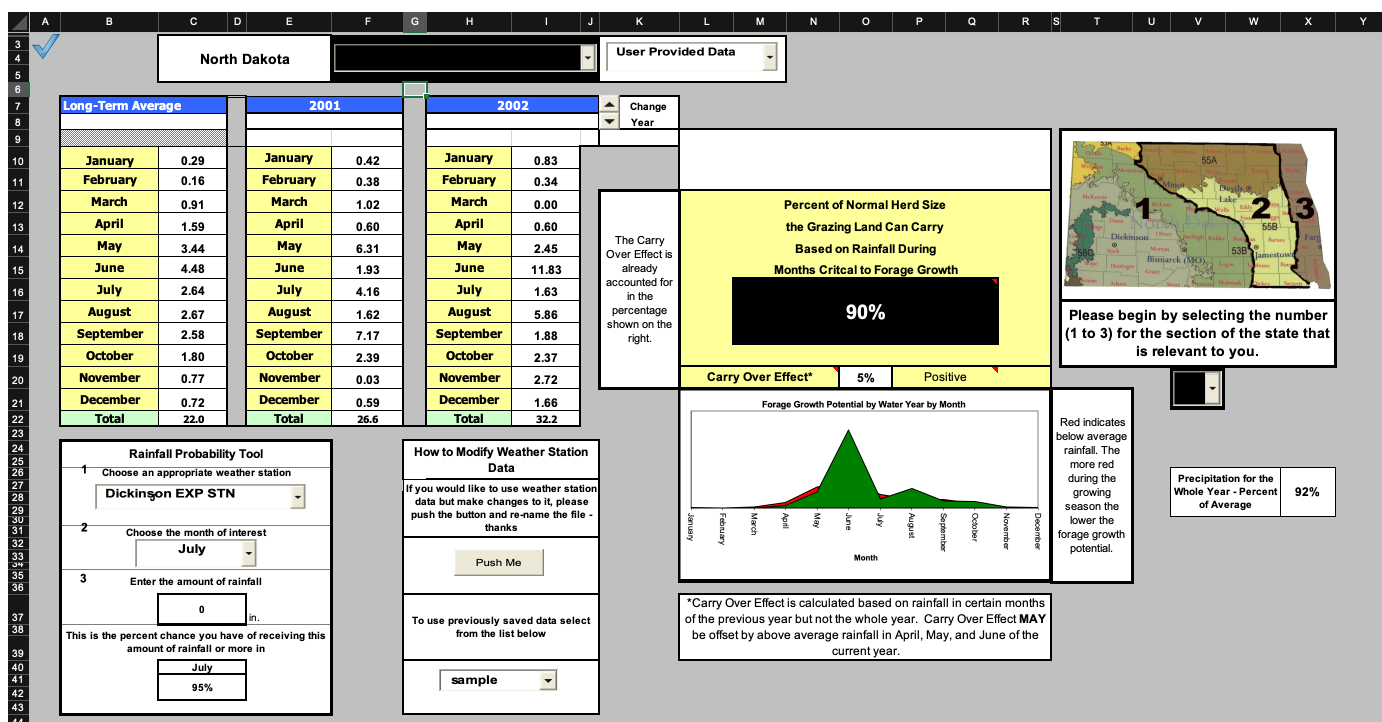


Figure 5. Previous version of the North Dakota Drought Calculator (NDDC) rainfall input page for predicting forage growth potential from three growth zones. The colored cells in the screenshot were meant to draw the attention of the users to various inputs and outputs.

This NDDC tool was not active for several years, sparking a recent update to the “dashboard and no-macro” version, termed as Updated North Dakota Drought Calculator (UNDDC), which was developed by Agricultural and Biosystems Engineering, North Dakota State University (NDSU) and can be downloaded and run using Microsoft Excel (Figure 6). The updated tool (UNDDC) is a stripped-down version of the original, and was developed as a direct tool without macros and with Visual Basic programming (no-macro) to ensure better security.

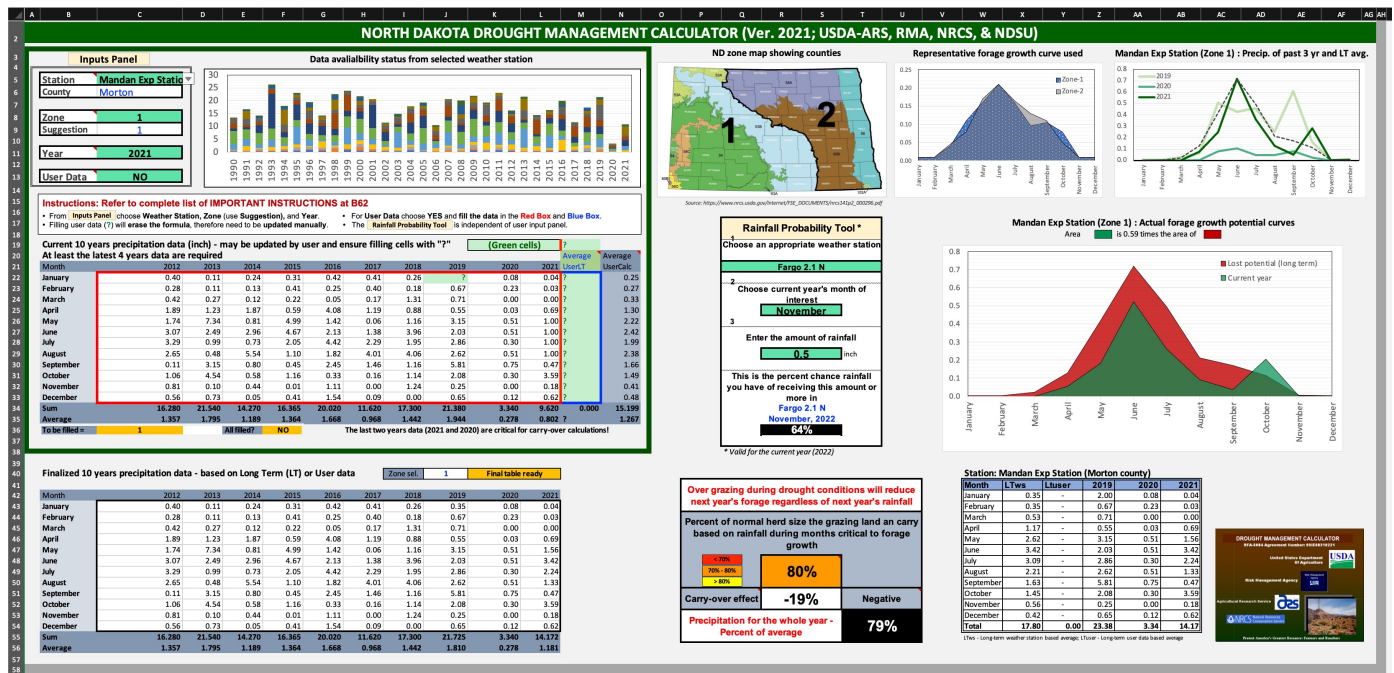


Figure 6. No-macro Updated North Dakota Drought Calculator (UNDDC) dashboard for predicting forage growth potential using monthly precipitation for two growth zones. The green cells indicate input fields; the red, orange, and yellow are color codes for the indicated ranges of percent of normal herd size; and black cells with white text are respective outputs.

3.3.2. US Drought Monitor

The US Drought Monitor (USDM) is a web-based map tool that provides weekly updates on the regions of the United States affected by drought [18]. The USDM has been functional since 1999, and is maintained and operated by a team of agencies, including the USDA, the National Drought Mitigation Center (NDMC) at the University of Nebraska-Lincoln, and the National Oceanic and Atmospheric Administration (NOAA). The primary users of this tool are banks, farm service agencies, and internal revenue services.

Drought is classified into five different zones on the map: abnormally dry (D0), moderate (D1), severe (D2), extreme (D3), and exceptional (D4, Figure 7). The categorization of the different drought zones is not based on statistical or forecasting models; however, input variables such as temperature, soil moisture, and snow cover, as well as indices such as standard precipitation index (SPI) and palmer drought severity index (PDSI), are used in determining the drought zones. These input variables are analyzed by the drought experts and compared with long-term averages to produce drought maps.

The outputs of the USDM tool include (i) side-by-side comparison and slider options for drought maps of consecutive weeks with a selectable area type, area, and statistical type; (ii) visualization of time-series analysis (2000–2022) of different USDM indexes; (iii) archives of all maps published weekly since 2000; (iv) animated maps for drought conditions over the selected period, which can be downloaded in a ‘gif’ format; and (v) downloadable archive data in table format.

3.3.3. Grass-Cast

Grass-Cast was developed exclusively to forecast grassland productivity in the Great Plains and southwest regions of the United States. This web-based tool was developed in a collaboration between Colorado State University, the USDA, the NDMC, and the University of Arizona [19]. Potential users of this tool include researchers, extension specialists, producers, and land managers.

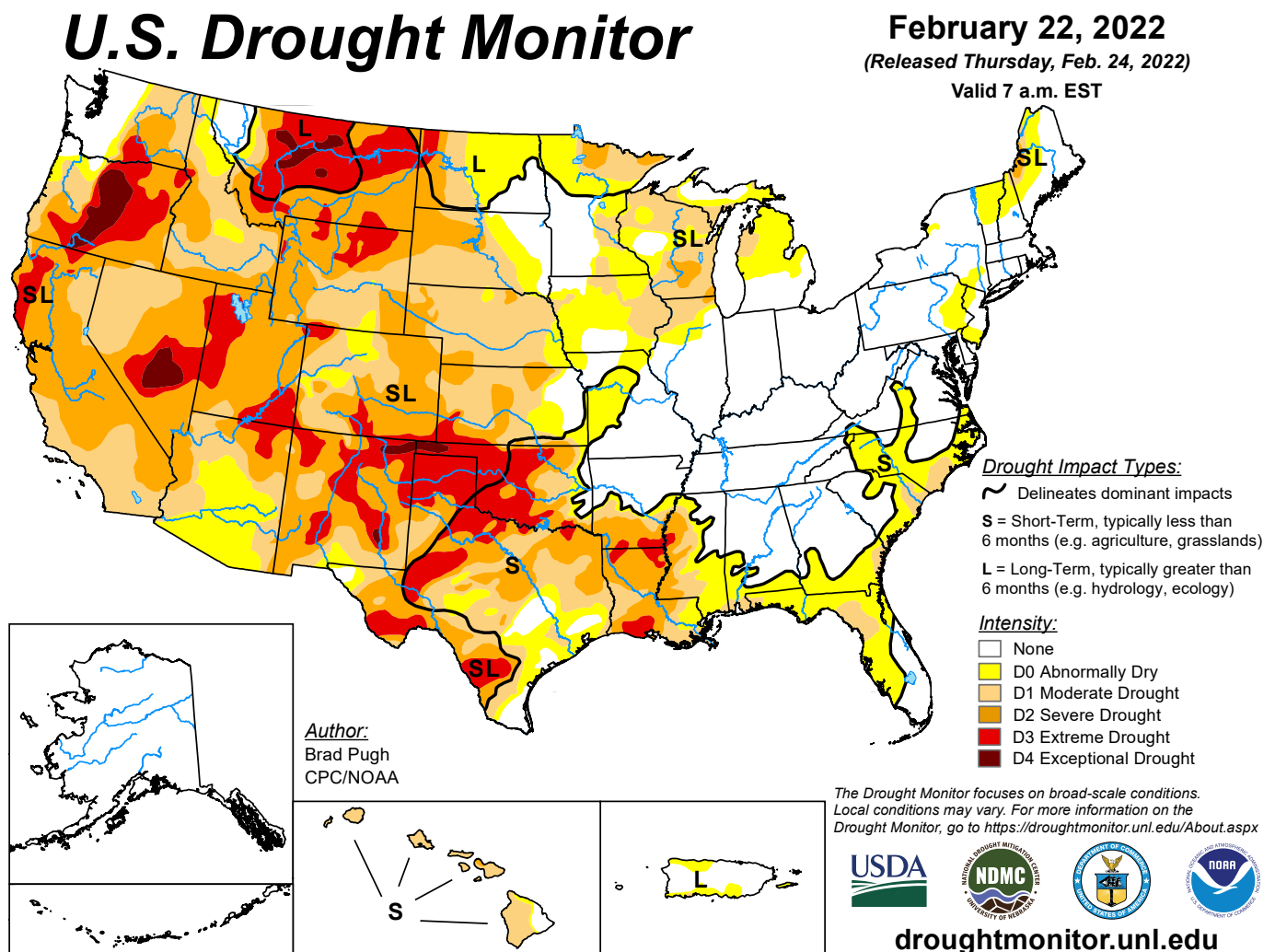


Figure 7. US Drought Monitor map categorized into abnormally dry (D0), moderate (D1), severe (D2), extreme (D3), and exceptional (D4). Accessed 24 February 2022.

The Grass-Cast tool employs a reliable grassland ecological model, DayCent, to forecast forage biomass of grasslands. Models are based on 38 years of historical weather and vegetation growth data, current weather data, and seasonal climate outlook data from the NOAA climate prediction center [20]. The outcomes of the model include forecasted productivity in pounds per acre (for a spatial grid size of 10 km × 10 km, or approximately ~6 miles × 6 miles), and produces separate maps showing above-normal, near-normal, and below-normal scenarios in terms of above-ground net primary productivity (ANPP), which is a measure of peak biomass, when compared to 30 years of historic data from the respective area (Figure 8; [21]).

The choropleth colors indicate the possibility of the grassland vegetation (ANPP) to be higher or lower than that recorded over 30 years. Grass-Cast forecast maps are first released at the beginning of spring (April) and are published every two weeks until the end of summer (August). Because recently observed weather data is added regularly, the accuracy of the model increases with time. Printer-friendly versions of the maps are available online, and the previous maps and CSV data (since 2017) can be accessed as archives.

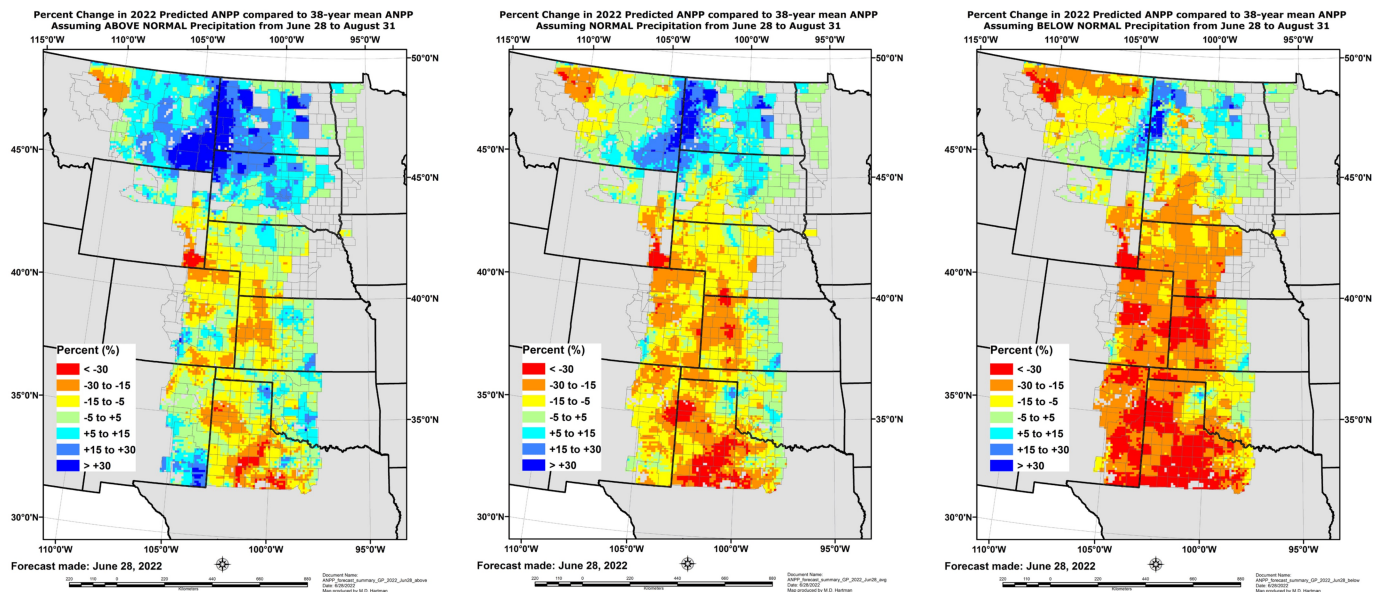


Figure 8. Grass-Cast maps of above-ground net primary productivity (ANPP) with scenarios for precipitation above normal (**left map**), near normal (**middle map**), and below normal (**right map**). Map archive data of Great Plains for date 28 June 2022.

3.3.4. Rangeland Analysis Platform

The Rangeland Analysis Platform (RAP) is a free online interactive tool that provides rapid access to geospatial data from United States rangelands (Figure 9). The RAP is a collaborative product of the University of Montana, the Department of Interior Bureau of Land Management, and the USDA—Natural Resources Conservation Service [22]. The target audience of this tool is anyone looking to make a land management decision based on the changes in vegetation cover and productivity, including ranchers, landowners, managers, and conservationists.

The RAP combines datasets describing nearly 57,000 field plots from sources such as the National Resources Conservation Service National Resources Inventory (NRI); the Bureau of Land Management Assessment, Inventory, and Monitoring (AIM) groups; and historical Landsat data. The tool uses cloud computing and ML techniques (temporal convolutional networks) to monitor rangelands, and includes pasture-, landscape-, and regional-scale data dating back to 1984 [23].

The RAP provides options such as shapefile upload and drawing features to select the area of interest. The tool then generates time-series analysis results based on the chosen location. Results show trends in vegetation cover (%) and biomass availability (lb/acre) for the selected area (Figure 9). The generated results can be downloaded in PDF, form, and the tabular data can be downloaded in CSV or Excel formats for future reference.

3.4. Tools Available for Forage Economic Analysis

Along with forage/biomass yield prediction, one of the most important pieces of information for producers and farmers is the bottom-line economic status of the ranching or agricultural enterprise. Furthermore, ranchers/farmers must constantly evaluate options for growing or buying forage for their livestock population in a sustainable manner. However, studies in the domain of forage/biomass economic analysis are scarce. Described in the following are the existing spreadsheet-based calculators that replace the manual estimation of forage economic analysis.

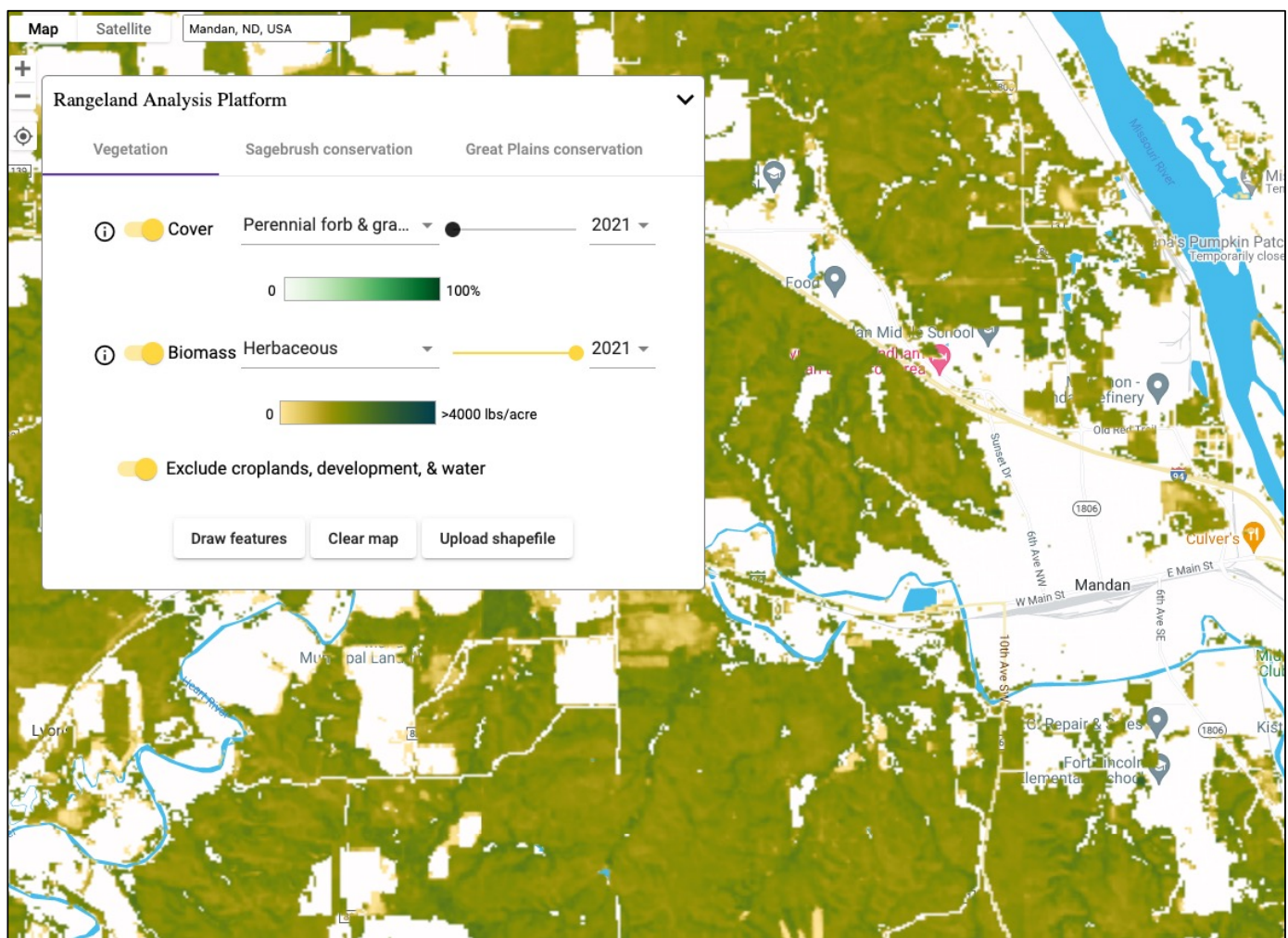


Figure 9. Range analysis platform, interactive web-based tool for forbs and grass percentage cover and herbaceous biomass yield.

3.4.1. Alfalfa Cost Calculator

Based on a research trial conducted at the University of Wisconsin-Extension establishing that short rotations of alfalfa were more profitable than long-term rotations, a spreadsheet-based calculator was developed [24]. This economic analysis tool was designed using fixed and variable costs (including machinery operation and land rent) of a four-year stand alfalfa crop (Figure 10), and study results were incorporated into a calculator where inputs include factors such as alfalfa yield, price, fertilizer cost, and land rent cost [25]. The costs of alfalfa production from years one to four are provided in the calculator as default choices to calculate the profit.

3.4.2. Haying System Enterprise Budgeting

The Montana State University Extension developed a detailed calculator to determine the operating and ownership cost of different haying systems for alfalfa [26]. The general inputs of the tool include total acres of hay grown, estimated yield, cuttings per year, number of machine operations per year, and fuel price (Figure 11). In addition, other specific machinery information (speed, field efficiency, type of fuel, and percent utilized) for tractors, swathers, rakes, bailers, and hauling equipment is collected as input to calculate the machine cost per ton, and the operating and ownership costs. The tool also generates enterprise budgeting for irrigated alfalfa hay establishments. The inputs and the generated results are printable for future use.




Enter most values in yellow boxes.

Enter alfalfa base yield: (tdm/A)
(For established fields) 4.00

Enter alfalfa hay price: (\$/ton) \$130.00

Enter fertilizer costs in blue cells: (\$/ton)

Enter chosen phosphorus fertilizer cost:

Phosphorous	MAP	DAP	TSP
Price/ton	\$0.00	\$590.00	\$0.00
% P ₂ O ₅	52	46	46
Cost / unit P ₂ O ₅	\$0.00	\$0.64	\$0.00

Phosphorus Cost / unit P₂O₅ \$0.64

Potassium Cost / unit K₂O \$0.72

Enter land cost: (\$/a) \$85.00

Enter cost choice (cells B50 to G50 in green) 2

For costs to establish, produce and harvest the alfalfa (fuel, depreciation, etc) ,
use the following default values based on base yield ranges or enter your values –

Cost choice	1	2	3	4	5	6
Yield range	2.6-3.5	3.6-4.5	4.6-5.5	5.6-6.5	6.6-7.5	My Costs
	tdm/A	tdm/A	tdm/A	tdm/A	tdm/A	
	(\$/A)	(\$/A)	(\$/A)	(\$/A)	(\$/A)	(\$/A)
Establishment Yr.	\$242.33	\$242.33	\$242.33	\$242.33	\$242.33	
Alfalfa - Yr. 1	\$137.79	\$137.79	\$137.79	\$137.79	\$137.79	
Alfalfa - Yr. 2	\$137.79	\$137.79	\$137.79	\$137.79	\$137.79	
Alfalfa - Yr. 3	\$137.79	\$137.79	\$137.79	\$137.79	\$137.79	
Alfalfa - Yr. 4	\$137.79	\$137.79	\$137.79	\$137.79	\$137.79	

Your Expected Alfalfa Yield and Profit per Acre

	Yield (tdm/A)	Gross Income (\$/A)	Total Costs ¹ (\$/A)	Profit (\$/A)
Establishment Yr. (-45%)	2.20	\$328.75	\$418.58	(\$89.83)
Alfalfa - Yr. 1 (0%)	4.00	\$597.72	\$426.79	\$170.93
Alfalfa - Yr. 2 (+2%)	4.08	\$609.67	\$426.79	\$182.88
Alfalfa - Yr. 3 (-17%)	3.39	\$506.57	\$377.39	\$129.18
Alfalfa - Yr. 4 (-34%)	2.69	\$401.97	\$377.39	\$24.58

¹ All establishment, production and harvesting costs (fuel, depreciation, etc) including fertilizer and land charges.

For further details on the values used in this spreadsheet, refer to the paper
["Value of Short Rotations for Alfalfa Productivity".](#)

Developed by Ken Barnett, April 2009
 University of Wisconsin Center for Dairy Profitability

Figure 10. Alfalfa profitability and fertilizer cost calculator developed by University of Wisconsin-Extension. The yellow, light blue, and light green cells indicate user inputs, and the orange generated outputs.

3.4.3. Enterprise Budgeting for Producing Irrigated Alfalfa

A study was conducted by the Washington State University Extension to analyze the economics of establishing a central pivot irrigation system for alfalfa production [27]. The results were based on a 120-acre central-pivot-irrigated alfalfa field. The study revealed that the cumulative net returns recaptured the irrigation establishment cost by the end of the third year. Because this establishment cost is met, the net return of alfalfa significantly increases after three years. The budgets from this study are presented in an Excel spreadsheet and serve as a reference for growers to compare and analyze their own cost data (Figure 12). The reference spreadsheet includes operational costs for fertilization, irrigation,

and herbicide/pesticide application. Other costs factored in include haying (swath, rake, baling, and haul) as well as fixed, variable, and land costs.

Hay/Forage Production System Cost Worksheet

by Larry Brence & Duane Griffith
Montana State University Extension Service
<http://www.montana.edu/softwaredownloads/cropdownloads.html>

Total Acres of Hay Grown Annually	200
Estimated Annual Yield Tons/Acre	7.0
Average Number of Cuttings Per Year	3.0
Total Acres Covered by machinery (times over * acres)	600
Tons Harvested Annually (Acres Hay * Avg. Yield/Ac)	1,400
Fuel Price--Gasoline (On Farm Price)	\$2.25
Fuel Price--Diesel (On Farm Price)	\$2.50
Discount Rate (Interest Rate minus Inflation Rate)	5%
Millage Rate (Local Mill Levee Rate, for Tax Calculation)	300
Insurance Cost (Dollars per \$1000 of Machine value)	\$4.50
Taxable Value Rate	4.00%

Tractor Information, Select up to 5 tractors that are used in the haying operation

Tractors (Choose up to 5)

Model	Power Unit #	Gas/Diesel (G or D)	Annual Use (hours)
26 180 HP 2WD, DUALS	1	d	400
14 115 HP MFWD	2	d	400
10 95 HP MFWD	3	d	250
00 None	4		
00 None	5		

View or Change Tractor Database

Cutting Hay -- Select the number and type of Swathers used.

Self Propelled Swathers (Choose up to 3)

Model	Speed MPH	Field Efficiency	Gas/Diesel	Percent Utilized	Cost/Acre	Cost/Ton
11 Swather 120 HP 14 Ft	4	80%	d	100%	\$ 17.03	\$ 2.43
00 None					\$ -	\$ -
00 None					\$ -	\$ -

View or Change Self Propelled Swather Database

Pull Type Swather (Choose up to 3)

Model	Speed MPH	Field Efficiency	Power Unit #	Percent Utilized	Cost/Acre	Cost/Ton
00 None					\$ -	\$ -
00 None					\$ -	\$ -
00 None					\$ -	\$ -

View or Change Pull Type Swather Database

Bi-directional tractor with cutter head plus a pull type swather (enter the bi-directional tractor as a power unit)

Pull type, pulled with a bi-directional	Speed MPH	Field Efficiency	Power Unit #	Percent Utilized	Cost/Acre	Cost/Ton
00 None					\$ -	\$ -
Cutter Head for the bi-directional					\$ -	\$ -
00 None					\$ -	\$ -

Check sum 100%

Help Blue text and double lined box = Input Cell
Yellow shading and heavy lined box = Use the drop down arrow that appears to select from a list.
For boxes with yellow shading, you must click on that cell. After you click on one of these cells, a small drop down arrow will appear to the right of the cell. Click on this drop down arrow and then select (click on) one of the items in the drop down list.

Figure 11. Haying system budget estimator developed by Montana State University Extension. The functions of the colored cells were indicated in the tool.

3.4.4. Price of Standing Hay Crop Forage

A spreadsheet calculator was developed by Penn State Extension to estimate prices for standing hay crop forage from buyer and grower perspectives based on current hay prices, estimated hay yield/acre, and dry matter of haylage [28]. From the grower perspective, costs of mowing, conditioning, raking, baling, and wrapping were considered. From the buyer standpoint, a comparison of costs for silo haylage versus standing dry hay was provided (Figure 13). The machinery costs involved in the cost analysis represented custom rates for the year 2016 published by the National Agricultural Statistics Service for Pennsylvania.

3.4.5. Decision Support Tool for Hay Production vs. Hay Cost

A decision support spreadsheet tool was developed by the NRCS for alfalfa and grass hay [29]. This tool helps farmers and ranchers evaluate profits and make informed decisions to produce or purchase hay (Figure 14). Two default examples of the production estimation for alfalfa and grass hay are provided as a reference, and a provision for entering user data is included. Costs of land rent, fertilizer, seed, herbicide, and respective machinery are provided as direct inputs. Another feature of this tool is that it determines the hay requirement after storage loss, which helps farmers understand the costs and benefits

of hay storage. The storage loss analysis tool and worksheet were developed by Iowa State University.

TABLE 13. SHORT FORM YEARS 2 and 3 FULL PRODUCTION SMALL 2 TIE BALES

GROSS RETURNS:	YIELD Tons/acre	PRICE \$/ton	GROSS RETURN \$/acre	YOUR FIGURES
Alfalfa Hay	8	\$220.00	\$1,760.00	_____
CULTURAL OPERATIONS:	LABOR, MACHINERY, CUSTOM HIRE \$/acre	MATERIALS \$/acre	TOTAL \$/acre	YOUR FIGURES
Fertilizing	\$9.30	\$206.58	\$215.88	_____
Herbicide Ap. (2 lb/a Velpar Alfamax)	\$9.00	\$33.40	\$42.40	_____
Irrigation (Labor and Pivot Expenses)	\$65.00	\$45.00	\$110.00	_____
Gopher Control	\$3.00	\$2.00	\$5.00	_____
HAYING:				
Swathing 4X	\$20.00		\$80.00	_____
Raking 4X	\$10.00		\$40.00	_____
Baling (\$0.95/bale 80 lb bales)	\$0.95		\$190.00	_____
Haul and Stack (\$0.40/bale)	\$0.40		\$80.00	_____
Tarping (\$7.00/ton)	\$7.00		\$56.00	_____
Hay Insurance		\$16.00	\$16.00	_____
OTHER CHARGES:				
Fuel, Repairs, Labor and other expenses	\$1.80	\$9.92	\$11.72	_____
General Overhead 5% of variable costs			\$42.35	_____
Operating Capital Interest 6.50%, 6 mo			\$27.53	_____
Fixed Costs - Depreciation, Insurance, Taxes, etc.			\$11.29	_____
Management Return			\$61.41	_____
Land Cost			\$300.00	_____
Amortized Establishment Cost			\$193.77	_____
TOTAL COST PER ACRE PER YEAR			\$1,483.35	_____
NET RETURN PER ACRE PER YEAR			\$276.65	_____
Notes:				

Figure 12. Alfalfa budget workbook guidelines developed by Washington State University Extension. Green bordered box indicates the currently selected cell while navigating the spreadsheet.

3.4.6. Forage Economics Calculator

The forage economics calculator is a user-friendly, web-based tool developed by North Dakota State University in collaboration with the USDA Northern Great Plains Research Laboratory–Mandan (Figure 15). The tool focuses on the bale collection logistics, which is often ignored but is a labor-intensive operation that significantly influences economic outcomes [30]. Other operations such as harvesting, baling, and hauling are included as direct inputs. The tool accommodates 10 different forage types, including annual, perennial, and grain (remaining hay after grain harvest) forages. The tool includes 29 input variables and generates 37 output parameters dynamically. It serves as a decision support tool, allowing scenario analysis to help farmers make informed decisions. Downloadable and printable reports are available and show selected inputs and estimated outputs. Potential users of this tool include hay producers, farmers, custom hay operators, financial personnel, educators, and others interested in the economics of handling bales.

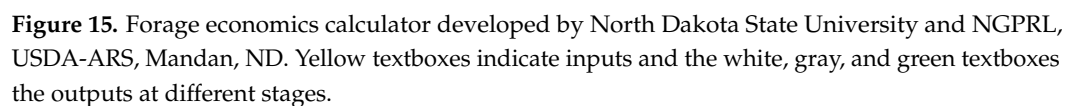
Price per ton of Dry hay	\$	203.00	\$/ton	\$	0.091	Price per lb of Dry Matter
Potential Dry Hay Yield (tons/acre)		1.25	tons/acre		2,500	lbs of dry matter harvested/acre
Dry Matter of Harvested Silage		50.00	%	\$	228.38	Value of dry matter harvested per acre
Market price for haylage	\$	91.35	\$/ton	\$	114.19	Moisture-adjusted value per acre
Hay Quality Discount (\$ per ton)	\$	-	\$/ton	\$	91.35	Value per ton of haylage
Hay Grower's Perspective				Buyer's Perspective		
(to Net the same amount from selling Standing Hay as if harvesting dry hay)				(to Pay the same as buying haylage from a silo)		
		Per Acre	Per Ton		Buy Standing Hay	
					Per Ton	
Grower's Gross Income (ton x price)	\$	253.75	\$ 203.00	Price of haylage from silo*	\$ 91.35	*includes delivery charge
Mowing and Conditioning, Raking	- \$	25.85	\$ 20.68	Mowing and Conditioning, Raking	- \$ 10.34	
Baling and Wrapping Cost	- \$	41.90	\$ 33.52	Chop/Haul/Fill	- \$ 8.10	
Hay Delivery Charge	- \$	5.00	\$ 4.00	Storage Cost	- \$ 5.05	
Hay Quality Discount (\$/ton)	- \$	-	\$ -	Dry Matter Loss ¹	- \$ 7.31	
Total Dry Hay Net	= \$	181.00	\$ 144.80	Subtotal	= \$ 60.55	
Standing Forage price, breakeven with dry hay	= \$	72.40	\$ 57.92			
Potential chopped haylage yield (Tons/acre)		2.50				
Price per Ton of Standing Hay Crop needed to Equal Dry Hay Net	= \$	57.92		Price per Ton of Standing Hay Crop Forage	= \$ 60.55	
Hay Making Costs:				Silage Making Costs:		
		Your Farm:			Your Farm:	
Mowing and Conditioning		16.40	\$/acre	Mowing and Conditioning	\$ 16.40	\$/acre
Raking		9.45	\$/acre	Raking	\$ 9.45	\$/acre
Baling Cost	\$	7.70	\$/bale	Chop/Haul/Fill	\$ 8.10	\$/Ton
Bale Weight		895	lbs.	Storage Cost Silage (Bagging or Silo Cost)	\$ 5.05	\$/Ton
Wrapping Bales	\$	7.30	\$/bale	Dry Matter Loss ¹	8	%
Hay Delivery Charge	\$	4.00	\$/ton	Silage Delivery Charge	\$ 5.00	\$/Ton
Bales per acre		2.79	/acre			
Baling and Wrapping per acre	\$	41.90	/acre			
1 Man 1 Truck \$64.90/hour	\$	64.90	/hour			
	\$	4.06	/Ton for 16 Ton Load - 1 Load per Hour			

Figure 13. Price of standing hay crop from buyer and grower perspectives developed by PennState Extension. Yellow cells are input fields and the green bordered box indicates the currently selected cell while navigating the spreadsheet.

Alfalfa Hay Production Costs Calculation									
Costs Based Upon 8.5 T/A (High Management Default Example)					Costs Based Upon 3.5T/A (Average Management Default Example)				
	Establish	year 2	year 3	year 4		Establish	year 2	year 3	year 4
Rent (\$/Acre)	\$ 300.00	\$300.00	\$300.00	\$300.00	Rent (\$/Acre)	\$ 300.00	\$300.00	\$300.00	\$300.00
Lime (\$/Acre)	\$ 36.00				Lime (\$/Acre)	\$ 36.00			
Fertilizer (\$/Acre)	\$ 88.75	\$266.68	\$266.68	\$266.68	Fertilizer (\$/Acre)	\$ 88.75	\$115.63	\$115.63	\$115.63
Micronutrients (\$/Acre)		\$ 20.00	\$ 20.00		Micronutrients (\$/Acre)				
Insecticides (\$/Acre)			\$ 16.00		Insecticides (\$/Acre)				
Seed (\$/Acre)	\$ 140.00				Seed (\$/Acre)	\$ 140.00			
Herbicides (\$/Acre)	\$ 24.38	\$ 17.25	\$ 17.25	\$ 17.25	Herbicides (\$/Acre)	\$ 24.38	\$ 17.25		
Apply fert (\$/Acre)	\$ 5.65	\$ 16.95	\$ 16.95	\$ 11.30	Apply fert (\$/Acre)	\$ 5.65	\$ 16.95		
Apply chem (\$/Acre)	\$ 5.65	\$ 5.65	\$ 11.30	\$ 5.65	Apply chem (\$/Acre)	\$ 5.65	\$ 5.65		
Work ground (\$/Acre)	\$ 18.80				Work ground (\$/Acre)	\$ 18.80			
Plant (\$/Acre)	\$ 15.00				Plant (\$/Acre)	\$ 15.00			
TOTAL	\$ 634.23	\$626.53	\$648.18	\$600.88	TOTAL	\$ 634.23	\$455.48	\$415.63	\$415.63
Mow/co (\$20.70/A x 2)	\$ 41.40	x4 cut \$ 82.80	\$ 82.80	\$ 82.80	Mow/co (\$20.70/A x 2)	\$ 41.40	x4 cut \$ 82.80	\$ 82.80	\$ 82.80
Tedder (\$7.80/A x 2)	\$ 15.60	x4 cut \$ 31.20	\$ 31.20	\$ 31.20	Tedder (\$7.80/A x 2)	\$ 15.60	x4 cut \$ 31.20	\$ 31.20	\$ 31.20
Rake (\$6.70/A x 2)	\$ 13.40	x4 cut \$ 26.80	\$ 26.80	\$ 26.80	Rake (\$6.70/A x 2)	\$ 13.40	x4 cut \$ 26.80	\$ 26.80	\$ 26.80
Bale (\$24.60/A x 2)	\$ 49.20	x4 cut \$ 98.40	\$ 98.40	\$ 98.40	Bale (\$24.60/A x 2)	\$ 49.20	x4 cut \$ 98.40	\$ 98.40	\$ 98.40
Stack/store (\$8/T x 4.25T)	\$ 34.00	8.5T \$ 68.00	\$ 68.00	\$ 68.00	Stack/store (\$8/T x 1.75T)	\$ 14.00	3.5T \$ 28.00	\$ 28.00	\$ 28.00
TOTAL	\$ 153.60	\$307.20	\$307.20	\$307.20	TOTAL	\$ 133.60	\$267.20	\$267.20	\$267.20
Grand Total per Year	\$ 787.83	\$933.73	\$955.38	\$908.08	Grand Total per Year	\$ 767.83	\$722.68	\$682.83	\$682.83
Grand Total all years	#####				Grand Total all years	#####			
total production (Tons)	29.75				total production (Tons)	12.25			
(assumes full production years 2-4, 1/2 production in year 1)					(assumes full production years 2-4, 1/2 production in year 1)				
\$Cost/Ton	\$ 120.50				\$Cost/Ton	\$ 233.16			

YOUR COSTS				
Enter your input values in shaded cells.				
	Establish	year 2	year 3	year 4
Rent (\$/Acre)				
Lime (\$/Acre)				
Fertilizer (\$/Acre)				
Micronutrients (\$/Acre)				
Insecticides (\$/Acre)				
Seed (\$/Acre)				
Herbicides (\$/Acre)				
Apply fert (\$/Acre)				
Apply chem (\$/Acre)				
Work ground (\$/Acre)				
Plant (\$/Acre)				
TOTAL	\$ -	\$ -	\$ -	\$ -
Mow/co (\$/A x cut)				
Tedder (\$/A x cut)				
Rake (\$/A x cut)				
Bale (\$/A x cut)				
Stack/store (\$/T x Tons)				
TOTAL	\$ -	\$ -	\$ -	\$ -
Grand Total per Year	\$ -	\$ -	\$ -	\$ -
Grand Total all years	\$ -			
Total production (Tons)				
\$Cost/Ton	#DIV/0!			

Figure 14. Decision support tool for grass and alfalfa production developed by Natural Resource Conservation Service (NRCS). Yellow cells are input fields.



4. Discussion

4.1. Important Features Predicting Grass/Forage Yield

4.1.1. Vegetation Indices

Among the publications collected (Table A1), normalized difference vegetation index (NDVI) was the most frequently used VI (28%) for predicting grass and forage production (Figure 2), followed by enhanced vegetation index (EVI), soil-adjusted vegetation index (SAVI), and optimized soil-adjusted vegetation index (OSAVI). A study comparing eight VIs derived from Sentinel 2 and Landsat 8 satellite data showed that prediction models developed using the EVI, NDVI, SAVI ($R^2 = 0.61\text{--}0.65$) had similar performance to those developed using above-ground biomass and leaf area index [31]. Another recent study estimating pasture biomass revealed NDVI as the most accurate method, with a prediction performance of R^2 between 0.74 and 0.94 using Sentinel 2 and PlanetScope images [32]. Integration of vegetation indices from C-band SAR images from Sentinel-1 (vertical and horizontal waves) and optical images from Sentinel-2 and Landsat 8 (LSWI, EVI, and NDVI) resulted in a better prediction ($R^2 = 0.67$) of above ground biomass than for an individual satellite [33]. In a drone-based forage biomass estimation study, modified soil-adjusted vegetation index (MSAVI) produced a strong positive correlation ($r = 0.94\text{--}0.99$) in predicting forage and dry matter yield [34].

While satellite images might help in repeated scouting and monitoring of vast areas of grasslands, it is also important to note that the images are not always captured at the ideal resolution, frequency, and times, which might impede the data quality. Satellites that capture large areas are often coarse in resolution, resulting in loss of data. Moreover, the frequency of the coverage is limited by the orbital repeat cycle of the satellite. Additionally, satellite data collection becomes problematic in areas with frequent cloud cover. In essence, the grass/forage prediction model's accuracy using VIs is heavily dependent on the quality of the data.

4.1.2. Weather and Soil Features

The most commonly used climate and soil features for predicting forage and grass biomass were precipitation, air temperature, and soil moisture, noted in 33%, 21%, and 15% of studies, respectively (Figure 3). Other common variables included relative humidity, soil temperature, and solar radiation (6% each). The least commonly used features for grass and forage prediction were soil pH, organic matter, and soil nutrients.

A study conducted to estimate the stability of forage cover with respect to climate revealed that annual precipitation influences the dry matter yield of pure alfalfa and of sequenced oats and maize [35]. Another study in alpine grassland showed that the start of the growing season (January to May) was positively correlated with the mean air temperature and negatively correlated with cumulative precipitation [36]. The effects of soil features on herbage yield were studied in different pastures, and a decrease in yield was observed with decreasing soil moisture and increasing soil temperature [37].

Weather or climate data collected from the actual location or measured at several locations within the grassland are highly reliable variables in predicting the spatially variable forage yield; however, most studies relied on the data from the nearest weather station, which might not reflect the actual weather conditions of the grassland location. Even though using spatial climate data might resolve this issue, the associated errors between the actual and spatial data are often assumed negligible. This limits the credibility of the models that use spatial climate data. Similarly, soil grid samples can be collected to represent the spatial yield variability in grasslands; however, collecting that information for a vast area is an exhaustive undertaking and manually demanding.

Overall, more literature focused on VI ($n = 55$) than on climate features ($n = 26$), suggesting a steadily increasing trend in the adoption of remote sensing technology for monitoring forage and grass yield (Table A1). To address Q1: "What significantly influences grass and forage biomass yield prediction?", the factors that showed a significant relationship with grass and forage yield were NDVI, precipitation, air temperature, and soil moisture.

4.2. Overview of Forage/Grass Prediction Models

ANNs are computational models inspired by the function of neurons in the human brain [38]. The models are developed using the interconnection of neurons in different layers, weights of the interconnections, and the activation function for converting the weighted inputs to outputs. An ensemble of decision trees was developed in GB where a new tree improved the prediction of the previous one by fitting the residual errors [39]. The trees are grown repeatedly for a specific number of iterations to predict new residuals. Further, kNN is a non-parametric approach that uses k samples of the training data that are at the nearest distance to the testing data for accurate predictions [40]. The RF model is another ensemble-based approach that used decision trees for prediction [41]. The subset of features for each tree varies, generating a large number of random trees, and the predictions are obtained from averaging the randomized trees. SVM is a supervised method that aims at minimizing errors while reducing model complexity [42]. A set of mathematical functions called kernels are used in the SVM models to transform features from a lower- to a higher-dimensional space.

Based on the examined publications (Table A1; Figure 4), a large number of studies written since 2015 used RF ($n = 21$), followed by LR ($n = 15$), MLR ($n = 10$), PLSR ($n = 6$), SVM plus ANN ($n = 4$), and GB plus kNN ($n = 3$). The highest median R^2 (analyzed summary data from relevant publications; Figure 4) in predicting the grass and forage yield from various input parameters used in the studies was obtained with PLSR (0.75), closely followed by LR (0.73). High median R^2 values were observed for LR models because the biomass predictions were based on individual VI or weather features; however, this is not generally desirable because forage and grass biomass yield is influenced by a combination of features. Among the ML prediction models, ANN as well as RF produced the highest median R^2 value (0.72). The lowest median R^2 among all methods was obtained using kNN (0.48).

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In studies that used multiple prediction models, ML models (especially RF) generally performed better than the LR models. For example, a model comparison study conducted to estimate grass biomass using drone-based VI showed that the RF ($R^2 = 0.77$) model consistently performed better than the MLR model [34]. Another study comparing linear regression and ML models to predict grassland biomass established that the RF model produced a better prediction accuracy ($R^2 = 0.63$) than linear regression, SVM, and kNN methods [43]. Higher accuracy of RF can be explained through the default algorithm mechanism that includes the selection of a random subset of features while growing uncorrelated trees. This helps to decrease overfitting issues and therefore better variance–bias trade-offs were achieved, which successively leads to better prediction performance.

To answer research question Q2: “What regression and machine learning modeling techniques can be used for biomass yield prediction?”, the results from the literature data show that the ML models had better performance than LR models. Variables such as climate, soil, environmental factors, and their interactions influence biomass growth. The combination of factors and interactions is nonlinear in nature and is often not captured by linear regression as it assumes linearity. However, ML techniques are promising when dealing with complex and nonlinear datasets. This demonstrates the consistent and higher performance of ML over LR models in studies predicting biomass yield. Among ML models, studies showed that RF was widely used for its proven performance due to its lower risk of overfitting and higher prediction accuracy.

4.3. Existing Tools for Grass/Forage Prediction

4.3.1. North Dakota Drought Calculator

The updated tool (UNDDC), compared to the previous version (Figure 5), includes input information based on the weather station, county, zone, year, and user data. The tool can perform automatic FGP calculations based on the data stored from 150 weather stations across North Dakota (Figure 6). The user data option with YES allows users to feed in their own precipitation data for analysis and save session data for future access. The output is a printable summary report that includes information on the predicted FGP, precipitation data used, and a graphical comparison between the recent and long-term potential for the selected county.

The UNDDC (Figure 6) was recommended as a decision-making tool for cattle ranchers by accounting for the varying weather and climatic conditions in the northern Great Plains area [44]. Another study that reviewed drought management options for ranchers also suggested using the UNDDC tool because it was developed based on the direct relationship between precipitation and forage growth [45]. Overall, the UNDDC is a science-based tool that enables livestock producers in North Dakota to incorporate suitable plans based on the information accessible to them [46].

4.3.2. US Drought Monitor

A study conducted to estimate the drought impact on field crops and income, as defined by USDM (Figure 7), showed that the USDM was most accurate for the High Plains, Midwest, and southern regions, and less accurate for northeast and southeast regions [47]. Another study predicted the drought categories in the US with the initial conditions derived from the USDM along with seasonal climate forecasts from the North American Multimodel Ensemble [48]. Because forage biomass is dependent on drought conditions, the USDM is useful for ranchers as an information tool, allowing them to adapt management frameworks and adjust cattle populations based on drought conditions [49].

4.3.3. Grass-Cast

A comparative study of Grass-Cast (Figure 8) and MODIS NDVI (data used for validation) for predicting forage production revealed that Grass-Cast was more accurate overall, particularly from May to mid-June [50]. Another paper studying critical decision dates for drought management in the rangelands of the central and northern Great Plains recommended Grass-Cast as a forage prediction tool for ranchers to match animal demand to forage availability [51,52].

4.3.4. Rangeland Analysis Platform

Several studies monitoring grassland and estimating the expansion of invasive grass species have used geospatial products from RAP (Figure 9). For instance, a study tracking the spread of exotic grasses in the western United States used RAP geospatial data from 1985 to 2018 [53]. Another similar study used remote sensing products from RAP to quantify the rate of spread of annual grass dominance in the Great Basin area of the United States [54].

To address research question Q3: “What tools are currently available for grass/forage monitoring and yield prediction?,” based on the review results presented in this section, the existing tools for forage prediction are NDDC, USDM, Grass-Cast, and RAP.

4.4. Tools Available for Forage Economic Analysis

Although grasses and forages are naturally available in pastures, grasslands, meadows, and steppes, to meet the annual feed supply for livestock, some forage crops may need to be cultivated and stored by farmers. In some cases, remaining hay after a grain harvest can be collected and used as supplemental animal feed. Studies show that a large portion of livestock production costs is attributed to producing, harvesting, baling, and storing forage [55,56]. Therefore, the economic analysis of forage operations is critical for forage

growers to make informed decisions on aspects such as equipment purchases for farm operations and forage sale prices. The economic analysis of forage includes numerous variables and complex calculations that are tedious, time-consuming, and difficult to perform manually, leading to the development of tools/calculators and details of these have already been presented (Section 3.4; Figures 10–15).

To answer research question Q4: “What tools are available for forage economic analysis?,” several spreadsheet-based tools and one web-based tool are available for the economic analysis of forage. Most of the spreadsheet tools were developed for alfalfa forage crops, whereas the web-based tool includes ten different crop varieties.

4.5. Research Gaps and Future Research Recommendations

This comprehensive review highlights the techniques and tools available for forage yield prediction and economic analysis through common semantics and research questions. Based on the literature collected and analyzed using the SLR methodology, 49% of the analyzed studies used MODIS and Landsat remote sensing satellites (spatial resolution 110–30 m), whereas only 8% of the studies used PlanetScope (spatial resolution 3 m). Even though the satellites are limited by the coarse spatial resolution and cloud cover, they are still preferred for scouting, monitoring, and predicting, because of the availability of data covering large areas and at appropriate time intervals. With the advent of satellites such as PlanetScope, fine spatial resolution data can be readily obtained which represents more detailed information, and should therefore produce more accurate biomass yield predictions than those made with lower resolution. In addition, finer spatial resolution is likely to be more important for yield predictions in heterogeneous pastures, as with fine resolution it is possible to delineate species that will otherwise be lost/merged in low resolution. Therefore, the application of high-resolution images (using satellite or UAV) that enable multi-species heterogeneous pasture analysis is a logical recommendation for future research. Future studies should also compare different satellite platforms to determine the influence of spatial resolution.

Most studies used either VI or climate features in predicting biomass. Using both VI and climate can help clarify the influence of the input features as predictors, and is expected to yield better prediction results. In recent years, ML methods have improved prediction performance for non-linear scenarios, and further models must be evaluated to improve predictions of grass and forage yield. Therefore, investigations of VI and climate features to evaluate the best factors for predicting forage and grass biomass as well as application of other advanced ML models (e.g., deep learning) that will be useful for comparing and evaluating models prediction performance should be carried out as future research directions.

The available forage prediction tools, generally for large-scale applications, primarily focus on the single-county or -state scale using satellite images, meaning that weather, soil, and plant species variation in a specific location (e.g., a producer’s field) are not accounted for, although they play a vital role in rangeland forage prediction. Therefore, models for “field-specific” prediction using the local weather, soil, and plant species composition should be developed based on ground truth and satellite data. As a recommendation for future research, user-friendly web tools should be developed, allowing users to input location-specific variables for more accurate predictions of grass and forage yields.

Given that the existing tools for forage economic analysis are predominantly developed for alfalfa forage, the incorporation of more forage crops for economic analysis is recommended. Most of the tools are spreadsheet-based; therefore, the development of more interactive, user-friendly, web-based tools and smartphone applications is recommended for future research to encourage easy management while avoiding critical errors and security issues associated with spreadsheet programs.

5. Conclusions

A systematic review methodology was successfully planned and conducted (2010 to 2022) to gain insights and report findings regarding forage yield prediction (input features, models, and tools) and economic analysis tools. Among the selected database sources, Google Scholar yielded the most literature results ($n = 46$; total 85 qualified manuscripts) for selected search terms. More literature was available for forage yield prediction using remotely sensed VI ($n = 55$) than using climate features ($n = 26$), showing a strong increasing trend of remote grassland and pasture monitoring. Reported forage and grass yield prediction studies either used VI or climate features, but not both.

The frequencies of studies using satellite platforms were unequally distributed; among the satellite methods, MODIS ($n = 16$) was the most-used, followed by Landsat and Sentinel. About 28% of the literature collected on remote sensing prediction of grass and forage yield used NDVI, which represents the most frequently used VI. Precipitation (33%) and soil moisture (15%) were the most frequently used features for predicting grass and forage yield. The prediction performance of ML models was superior to that of the linear and multiple linear regression models. Among ML methods, the random forest model was the most widely used ($n = 21$) and produced the highest median R^2 with 0.72.

Established grass and forage prediction tools include the NDDC, UNDDC, USDM, Grass-Cast, and RAP, which focus on large-scale prediction and may not be sensitive to variability within the field of an individual producer. Most of the forage economics tools are spreadsheet-based and developed for cropped alfalfa; however, the NDSU forage economics calculator is interactive and web-based, including 10 forage crops.

The potential future research scopes include a comparison between satellite platforms; combined vegetation index and climate features to predict biomass yield; advanced ML models and comparison of forage prediction performance; development of user-friendly field-, local-weather-, and soil-plant-specific forage prediction web-based tools and smartphone applications; and the inclusion of more crop varieties and operations both for forage prediction and economics assessment. The findings of this review have the potential to boost research in the direction of the development of robust prediction methods and tools for grassland production while addressing the challenge of sustainable forage production for maintaining a viable livestock industry.

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Appendix A. Selected Publications from Literature Review

Table A1. Details of selected articles through systematic literature review and their citation scores.

S.No.	Database	Year	Title	Citations	Reference
1	Sci-Dir	2022	A non-destructive method for rapid acquisition of grassland aboveground biomass for satellite ground verification using UAV RGB images	*	Zhang et al. [57]
2	Sci-Dir	2022	Classification of Zambian grasslands using random forest feature importance selection during the optimal phenological period	1	Zhao et al. [58]
3	Sci-Dir	2022	Estimating pasture quality of Mediterranean grasslands using hyperspectral narrow bands from field spectroscopy by Random Forest and PLS regressions	*	Fernández-Habas et al. [59]
4	Sci-Dir	2022	Monitoring standing herbaceous biomass and thresholds in semiarid rangelands from harmonized Landsat 8 and Sentinel-2 imagery to support within-season adaptive management	*	Kearney et al. [60]
5	Sci-Dir	2022	Monitoring the available forage using Sentinel 2-derived NDVI data for sustainable rangeland management	*	İleri and Koç [61]
6	Goo-Sch	2021	A machine learning method for predicting vegetation indices in China	3	Li et al. [62]
7	Sci-Dir	2021	A novel UAV-based approach for biomass prediction and grassland structure assessment in coastal meadow	7	Pecina et al. [63]
8	Goo-Sch	2021	A practical satellite-derived vegetation drought index for arid and semi-arid grassland drought monitoring	5	Chang et al. [64]
9	Goo-Sch	2021	Applicability of different vegetation indices for pasture biomass estimation in the north-central region of Mongolia	*	Bayaraa et al. [65]
10	Sci-Dir	2021	Changes and controls of aboveground net primary production in response to grassland policy in Inner Mongolian grasslands of China	*	Zheng et al. [66]
11	Sci-Dir	2021	Comparing vegetation indices from Sentinel-2 and Landsat 8 under different vegetation gradients based on a controlled grazing experiment	*	Qin et al. [31]
12	Goo-Sch	2021	Enhanced drought detection and monitoring using sun-induced chlorophyll fluorescence over Hulun Buir Grassland, China	4	Liu et al. [11]
13	Goo-Sch	2021	Estimating pasture biomass using Sentinel-2 imagery and machine learning	9	Chen et al. [67]
14	Goo-Sch	2021	Estimation of rangeland production in the arid oriental region (Morocco) combining remote sensing vegetation and rainfall Indices: Challenges and lessons learned	2	Lang et al. [68]
15	Goo-Sch	2021	Grassland productivity estimates informed by Soil moisture measurements: Statistical and mechanistic approaches	2	Krueger et al. [12]
16	Goo-Sch	2021	Improving the estimation of alpine grassland fractional vegetation cover using optimized algorithms and multi-dimensional features	*	Lin et al. [69]
17	Goo-Sch	2021	Monitoring rainfed alfalfa growth in semiarid agrosystems using Sentinel-2 imagery	*	Echeverría et al. [70]
18	Web-Sci	2021	National mapping of New Zealand pasture productivity using temporal Sentinel-2 data	4	Amies et al. [71]
19	Goo-Sch	2021	Precipitation rather than evapotranspiration determines the warm-season water supply in an alpine shrub and an alpine meadow	5	Li et al. [72]
20	Sci-Dir	2021	Remote sensing inversion of grassland aboveground biomass based on high accuracy surface modeling	5	Zhou et al. [73]
21	Goo-Sch	2021	Remote sensing of aboveground grass biomass between protected and non-protected areas in savannah rangelands	*	Dube et al. [74]
22	Web-Sci	2021	Remote-sensing inversion method for aboveground biomass of typical steppe in inner Mongolia, China	4	Lyu et al. [75]
23	Sci-Dir	2021	The superiority of the normalized difference phenology index (NDPI) for estimating grassland aboveground fresh biomass	3	Xu et al. [76]
24	Goo-Sch	2021	Cool-season grass productivity estimation model evaluating the effects of global warming and climate adaptation strategies	1	Tarumi et al. [77]
25	Web-Sci	2021	A new method for grassland degradation monitoring by vegetation species composition using hyperspectral remote sensing	12	Lyu et al. [78]
26	Goo-Sch	2020	Estimating grassland parameters from Sentinel-2: A model comparison study	6	Schwieder et al. [79]
27	Sci-Dir	2020	Effects of climate change on the growing season of alpine grassland in Northern Tibet, China	5	Zhang et al. [36]
28	Goo-Sch	2020	Estimating plant pasture biomass and quality from UAV imaging across Queensland's Rangelands	10	Barnetson et al. [80]

Table A1. Cont.

S.No.	Database	Year	Title	Citations	Reference
29	Goo-Sch	2020	Influence of climate variability on the potential forage production of a mown permanent grassland in the French Massif Central	7	Gómará et al. [81]
30	Goo-Sch	2020	Long-term grass biomass estimation of pastures from satellite data	4	Clementini et al. [82]
31	Goo-Sch	2020	Monitoring and modeling rangeland health with remote sensing	1	Soubry and Guo [83]
32	Goo-Sch	2020	Monitoring pasture aboveground biomass and canopy height in an integrated crop livestock system using textural information from PlanetScope imagery	8	Dos Reis et al. [10]
33	Goo-Sch	2020	Remote sensing applications for insurance: A predictive model for pasture yield in the presence of systemic weather	6	Brock Porth et al. [84]
34	Goo-Sch	2020	Spatial and temporal pasture biomass estimation integrating electronic plate meter, Planet CubeSats and Sentinel-2 satellite data	9	Gargiulo et al. [32]
35	Goo-Sch	2020	The fusion of spectral and structural datasets derived from an airborne multispectral sensor for estimation of pasture dry matter yield at paddock scale with time	10	Karunaratne et al. [85]
36	Goo-Sch	2020	Estimating natural grassland biomass by vegetation indices using Sentinel 2 remote sensing data	34	Guerini Filho et al. [86]
37	Goo-Sch	2019	A new approach to predict normalized difference vegetation index using time-delay neural network in the arid and semi-arid grassland	8	Wu et al. [87]
38	Sci-Dir	2019	Application of the MODIS MOD 17 net primary production product in grassland carrying capacity assessment	24	De Leeuw et al. [88]
39	Web-Sci	2019	Canopy height measurements and non-destructive biomass estimation of <i>Lolium perenne</i> swards using UAV imagery	31	Borra-Serrano et al. [89]
40	Goo-Sch	2019	Drought-induced decline of productivity in the dominant grassland species <i>Lolium perenne</i> L. depends on soil type and prevailing climatic conditions	15	Buttler et al. [90]
41	Goo-Sch	2019	Effect of irrigation management on pasture yield and nitrogen losses	20	Vogeler et al. [91]
42	Web-Sci	2019	Estimating grassland aboveground biomass on the Tibetan Plateau using a random forest algorithm	21	Zeng et al. [92]
43	Web-Sci	2019	Estimating leaf area index and aboveground biomass of grazing pastures using Sentinel-1, Sentinel-2 and Landsat images	85	Wang et al. [33]
44	Goo-Sch	2019	Estimating rangeland forage production using remote sensing data from a small unmanned aerial system (sUAS) and PlanetScope satellite	18	Liu et al. [93]
45	Goo-Sch	2019	Yield estimates by a two-step approach using hyperspectral methods in grasslands at high latitudes	11	Ancin-Murguzur et al. [94]
46	Goo-Sch	2019	Estimating the basis risk of rainfall index insurance for pasture, rangeland, and forage	21	Yu et al. [95]
47	Web-Sci	2019	Evaluation of grass quality under different soil management scenarios using remote sensing techniques	21	Askari et al. [96]
48	Web-Sci	2019	Grassland ecosystem services in a changing environment: The potential of hyperspectra monitoring	19	Obermeier et al. [97]
49	Goo-Sch	2019	Integrating traditional ecological knowledge and remote sensing for monitoring rangeland dynamics in the Altai Mountain region	12	Paltsyn et al. [98]
50	Web-Sci	2019	LIDAR provides novel insights into the effect of pixel size and grazing intensity on measures of spatial heterogeneity in a native bunchgrass ecosystem	10	Jansen et al. [99]
51	Sci-Dir	2019	Quantitative estimation of biomass of alpine grasslands using hyperspectral remote sensing	14	Kong et al. [100]
52	Sci-Dir	2019	The classification of grassland types based on object-based image analysis with multisource data	9	Xu et al. [101]
53	Web-Sci	2018	Grassland canopy cover and aboveground biomass in Mongolia and Inner Mongolia: Spatiotemporal estimates and controlling factors	65	John et al. [102]
54	Goo-Sch	2018	A novel machine learning method for estimating biomass of grass swards using a photogrammetric canopy height model, images and vegetation indices captured by a drone	108	Viljanen et al. [34]
55	Web-Sci	2018	Characterizing the spatio-temporal variations of C3 and C4 dominated grasslands aboveground biomass in the Drakensberg, South Africa	15	Shoko et al. [103]
56	Web-Sci	2018	Estimates of grassland biomass and turnover time on the Tibetan Plateau	35	Xia et al. [104]
57	Web-Sci	2018	Estimating vegetation biomass and cover across large plots in shrub and grass dominated drylands using terrestrial lidar and machine learning	57	Anderson et al. [105]
58	Goo-Sch	2018	Innovation in rangeland monitoring: Annual, 30 m, plant functional type percent cover maps for us rangelands, 1984–2017	115	Jones et al. [106]

Table A1. Cont.

S.No.	Database	Year	Title	Citations	Reference
59	Web-Sci	2018	Modeling grassland above-ground biomass based on artificial neural network and remote sensing in the Three-River Headwaters Region	105	Yang et al. [107]
60	Goo-Sch	2018	Modelling inter-annual variation in dry matter yield and precipitation use efficiency of perennial pastures and annual forage crops sequences	25	Ojeda et al. [35]
61	Sci-Dir	2018	Predicting habitat quality of protected dry grasslands using Landsat NDVI phenology	36	Weber et al. [108]
62	Goo-Sch	2018	Remote sensing as a tool to assess botanical composition, structure, quantity and quality of temperate grasslands	4	Wachendorf et al. [109]
63	Goo-Sch	2018	Spatial and temporal variability of grassland yield and its response to climate change and anthropogenic activities on the Tibetan Plateau from 1988 to 2013	28	Zhang et al. [110]
64	Goo-Sch	2017	Constructing Italian ryegrass yield prediction model based on climatic data by locations in South Korea	17	Peng et al. [111]
65	Sci-Dir	2017	Estimating grassland LAI using the Random Forests approach and Landsat imagery in the meadow steppe of Hulunber, China	36	LI et al. [112]
66	Sci-Dir	2017	Estimation and prediction of grassland cover in western Mongolia using MODIS-derived vegetation indices	6	Paltsyn et al. [113]
67	Goo-Sch	2017	Evaluation of remote sensing inversion error for the above-ground biomass of alpine meadow grassland based on multi-source satellite data	32	Meng et al. [114]
68	Goo-Sch	2017	Multi-model simulation of soil temperature, soil water content and biomass in Euro-Mediterranean grasslands: Uncertainties and ensemble performance	52	Sandor et al. [115]
69	Goo-Sch	2017	Identification of high nature value grassland with remote sensing and minimal field data	54	Stenzel et al. [116]
70	Goo-Sch	2017	Remote sensing of above-ground biomass	119	Kumar and Mutanga [117]
71	Goo-Sch	2017	The relationship between soil moisture and temperature vegetation on Kirklareli city Luleburgaz district a natural pasture vegetation	5	Sen and Ozturk [118]
72	Goo-Sch	2017	The signature of sea surface temperature anomalies on the dynamics of semiarid grassland productivity.	21	Chen et al. [119]
73	Goo-Sch	2017	Modelling biomass of mountainous grasslands by including a species composition map	23	Magiera et al. [120]
74	Web-Sci	2016	Modeling managed grassland biomass estimation by using multitemporal remote sensing data—A machine learning approach	80	Ali et al. [121]
75	Goo-Sch	2016	Calibration of GrassMaster II to estimate green and dry matter yield in Mediterranean pastures: Effect of pasture moisture content	24	Serrano et al. [122]
76	Web-Sci	2016	Comparison of machine-learning methods for above-ground biomass estimation based on Landsat imagery	52	Wu et al. [43]
77	Web-Sci	2016	Grassland and cropland net ecosystem production of the US Great Plains: Regression tree model development and comparative analysis	10	Wylie et al. [123]
78	Sci-Dir	2016	Modeling grassland aboveground biomass using a pure vegetation index	50	Li et al. [124]
79	Web-Sci	2016	Application of synthetic NDVI time series blended from Landsat and MODIS data for grassland biomass estimation	76	Zhang et al. [125]
80	Goo-Sch	2016	Modeling phenological responses of Inner Mongolia grassland species to regional climate change	24	Li et al. [126]
81	Sci-Dir	2015	Estimating above-ground biomass on mountain meadows and pastures through remote sensing	64	Barrachina et al. [127]
82	Web-Sci	2015	Estimating plant traits of grasslands from UAV-acquired hyperspectral images: A comparison of statistical approaches	98	Capolupo et al. [128]
83	Goo-Sch	2015	Water use efficiency of six rangeland grasses under varied soil moisture content levels in the arid Tana River County, Kenya	19	Koech et al. [129]
84	Goo-Sch	2013	The North Dakota drought calculator: Decision support tool for predicting forage growth during drought	8	Dunn et al. [17]
85	Sci-Dir	2010	Using remote sensing and GIS technologies to estimate grass yield and livestock carrying capacity of alpine grasslands in Golog Prefecture, China	98	Long et al. [130]

Note: Sci-Dir—Science Direct; Goo-Sch—Google Scholar; Web-Sci—Web of Science; and * Citations not reported for these latest publications.

Appendix B. Visual and Hyperspectral Vegetation Indices from Literature Review

Table A2. List of RGB and multispectral-based vegetation indices.

Vegetation Index	Equation	Reference
Normalized difference vegetation index (NDVI)	$(NIR - R) / (NIR + R)$	[131]
Enhanced vegetation index (EVI)	$2.5 \times (NIR - R) / (1 + NIR + 6R - 7.5B)$	[132]
Soil-adjusted vegetation index (SAVI)	$1.5(NIR - R) / (NIR + G + 0.5)$	[133]
Optimized soil-adjusted vegetation index (OSAVI)	$(1 + 0.16) \times (NIR - R) / (NIR + R + 0.16)$	[134]
Modified soil-adjusted vegetation index (MSAVI)	$(2NIR + 1 - \sqrt{(2NIR + 1)^2 - 8(NIR - R)}) / 2$	[135]
Normalized difference water index (NDWI)	$(G - NIR) / (G + NIR)$	[136]
Simple ratio index (SR)	NIR / R	[137]
Land surface water index (LSWI)	$(NIR - SWIR) / (NIR + SWIR)$	[138]
Green normalized vegetation index (GNDVI)	$(NIR - G) / (NIR + G)$	[139]
Atmospherically resistant vegetation index (ARVI)	$(NIR - 2R - B) / (NIR + 2R - B)$	[140]
Green red vegetation index (GRVI)	$(G - R) / (G + R)$	[141]
Excess green (ExG)	$2G - B - R$	[142]
Enhanced vegetation index 2-band (EVI2)	$2.5 \times (NIR - R) / (NIR + 2.5R + 1)$	[143]
Difference vegetation index (DVI)	$NIR - R$	[144]

Note: R—red, B—blue, G—green, NIR—near infrared, and SWIR—short-wave infrared bands recorded from the satellite platforms. The cited references in this table were the sources of the vegetation index equations and do not feature in research questions and hence do not belong to the selected literature (Table 2) in this review study.

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