Classifying management of Wisconsin pastures using time series satellite imagery

by

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ABSTRACT

While several publicly available landcover databases estimate pasture abundance and distribution across the U.S., these data sources generally combine various types of pastures together that may be managed very differently. Recognizing the environmental impacts of pasture management, differentiating between pasture types on a landscape scale could benefit researchers and community partners seeking this type of data. Our study aimed to explore how time series of satellite-derived vegetation indices could differentiate between categories of pasture management, focusing on a broad classification between rotational and continuous grazing. Rotational systems, defined as those regularly moving livestock between different paddocks during the grazing season, were contrasted with continuous systems, generally allowing livestock full access to an entire pasture throughout the season. Landsat 8 and Sentinel 2 satellite imagery from May to September 2023 were used to derive statistics from vegetation indices (NDVI, EVI, SAVI, MSAVI, NDWI, GLI, NGRDI, SLAVI, GEMI, CIgreen, NBR, and DVI) across the spatial boundaries of pastures and over specific time frames for 75 rotational and 75 continuous pasture locations across Wisconsin obtained from researchers, land county offices, grazing networks, and grazing specialists. Remotely sensed data were used to train and test a random forest classification model, with a resulting model accuracy of ~80% and a kappa value of ~0.6 indicating moderately good fit of the model to the data after accounting for the amount of correct predictions from random chance. When out-of-set predictions (29 continuously grazed and 25 rotationally grazed pastures separate from the dataset used to train the random forest model) were used, the model had an accuracy of ~70% (kappa ~0.4) indicating a fair agreement between the data and the model predictions. The model was used to produce a map estimating rotationally and continuously grazed pastures across Wisconsin, with pasture parcels defined by a 2008 field boundary dataset from the USDA Risk Management Agency (RMA), where most of the given parcels were classified as pasture according to the Wiscland 2.0 dataset. This map predicted that ~59% of the total pasture area in Wisconsin is continuously grazed while ~41% is rotationally grazed. Our research demonstrates the potential of remotely sensed data for landscape-scale pasture management estimates, offering a framework for future studies and policy making.

1 INTRODUCTION

Grasslands are the most widely distributed terrestrial ecosystem (Shen et al., 2022) covering about a third of the earth's terrestrial surface (White et al., 2000). Approximately 70% of global agriculture consists of grasslands (Reynolds and Frame, 2005) and over 40 million km^2 of this area are pastures grazed by livestock (Lambin and Meyfroidt 2011). Given the extent of agricultural pastures, it is important to understand how their associated environmental impacts can be addressed and ecosystem services strengthened through improved management (decisions made regarding fertilization, irrigation, plant species sown, stocking density, and grazing system) (Sollenberger et al., 2019). While there are publicly available data sources that show where pastures are present on a landscape (e.g., USDA NASS Cropland Data Layer), these databases do not describe pasture management. This limitation in pasture management data masks landscape estimates of how pasture land use and land cover influence nutrient cycling, carbon storage, water quality, and biodiversity, which are all known to affect these outcomes (Erb et al., 2016).

One type of management for grazed pastures that impacts various ecosystem services and organismal outcomes is whether a pasture is continuously or rotationally grazed. When a pasture is continuously grazed, livestock have unrestricted access to the full extent of a pasture for the entirety of a growing period. In contrast, if a pasture is rotationally grazed, pastures are subdivided into smaller sections or paddocks that livestock are moved among throughout the season (Heitschmidt and Taylor, 1991). Rotationally grazed pastures result in different outcomes compared to continuously grazed pastures because their design forces changes in the spatial and temporal distribution of livestock feeding, trampling, and excreta (Heady, 1961). Studies directly comparing treatments of continuous and rotational grazing demonstrate that rotational grazing can result in better management of weeds, such as reducing thistles when a period of rest was followed with grazing plots at high stocking rates (Grace et al., 2002), can lead to overall increased relative forage quality, nutritive value, and persistence of legumes within pastures (Paine et al., 1999; Oates et al., 2011; Zegler et al., 2018) as well as greater livestock weight gained (Paine et al., 1999; Walton et al., 1981; Wang et al., 2016).

Some of the most significant benefits of rotational grazing are related to environmental impacts and ecosystem services (Díaz-Pereira et al., 2020; Teague and Kreuter, 2020; Hulvey et al., 2021). Past research suggests that compared to continuous grazing, rotational grazing results in higher levels of soil organic carbon (Conant et al., 2017; Byrnes et al., 2018; Mosier et al., 2021), along with less nitrogen (Park et al., 2017; Dahal et al., 2020) and phosphorous (Toor et al., 2020; Ashworth et al., 2022; Young et al., 2023) loss. Additionally, rotational grazing has greater density and diversity of grassland birds relative to continuously grazed pastures (Temple et al., 1999), and in riparian buffer strips rotational grazed pastures result in less stream bank erosion compared to continuously grazed pastures which can improve fish habitat quality, and benefit fish such as trout that are sensitive to impacts from stream bank erosion (Lyons et al., 2000; Lyons, 1996).

Because of these differences in ecosystem and organismal outcomes under rotationally and continuously grazed pastures, the ability to differentiate and classify these different pasture management types within larger areas would be useful for making more precise estimates on the impacts of pastures at landscape scales. Spatial data showing distribution of different pasture management types could be useful when modeling how pastures in a watershed influence water quality (Vadas et al., 2015; Chaubey et al., 2010) or when trying to quantify how much soil carbon may be held in pastures for a given region (Huang et al., 2019; Sanford et al., 2022; Becker et al., 2022). Estimates of continuously and rotationally grazed pastures across the landscape in Wisconsin would also be useful for community partners (e.g., producer-led watershed groups); local, state, and federal agencies (e.g., county land & water conservation departments, Wisconsin Department of Natural Resources, Wisconsin Department of Agriculture, Trade & Consumer Protection); and non-governmental organizations (e.g., GrassWorks, The Pasture Project, The Land Stewardship Project, Michael Fields Agricultural Institute, Savanna Institute) already working to promote rotational grazing to identify specific areas with the potential to implement more rotational grazing, and to better quantify the amount of pastures where management could be significantly improved.

Satellite data is a useful tool for large scale landscape analysis, and is widely utilized to differentiate between, classify, and map categories of landcover (Lavreniuk et al., 2016; Phiri and Morgenroth, 2017; Wulder et al., 2018), examine landscape degradation, and explore land cover change over time (e.g., Decuyper et al., 2022). Compared with field surveys, aerial imagery from planes, or data collected from Unmanned Aerial Vehicles (UAVs), using satellite imagery for landscape classification and mapping retains certain advantages. Remote sensing of landscapes using satellite imagery for land-use/land-cover (LULC) mapping can be done with less labor, greater efficiency, more cost effectively over large areas, and consistently over long periods (Talukdar et al., 2020; Wang et al., 2022d).

Significant research has explored potential uses of satellite remote sensing for grassland monitoring, and many recent studies have used satellite imagery to estimate specific characteristics/attributes of pastures (Wang et al., 2022a). Examples include quantifying aboveground biomass (ABG) (Zhou et al., 2021) and leaf area index (LAI) (Schwieder et al., 2020). Remote sensing also has been used to monitor pasture use intensity and degradation. Satellite derived NDVI was used to estimate pasture degradation across a River Basin in Brazil

(Calegario et al., 2019). Using multiple satellite derived LAI values over time, Dusseux et al. (2014) detected incidents of mowing and grazing events. We found no examples of studies using satellite data to produce large-scale maps classifying pasture management into continuous or rotationally grazed approaches. Recent reviews of remote sensing grassland literature do not address the topic (Reinnerman et al., 2020; Wang et al., 2022d; Gabrovska-Evstatieva and Evstatiev, 2022).

Because rotationally grazed pastures have individual paddocks that go through periods of intense grazing followed by a period of recovery, we expected that various vegetation indices for greenness, vegetation height, and biomass (Wand et al., 2022) would be more spatially and temporally variable compared to continuously grazed pastures. We hypothesized that we could use these differences, specifically an expected higher variability in rotationally grazed pastures, to differentiate between pasture management. We used an opportunistic dataset of pasture sites with known management (rotationally or continuously grazed) across Wisconsin to train a random forest classification model using temporal summary statistics (across different time frames) of spatial summary statistics (across individual pastures) of vegetation indices (calculated for individual pixels within these pastures) derived from Sentinel 2 and Landsat 8 imagery from May to September 2023. We then mapped Wisconsin pastures based on pasture parcels defined by a 2008 field boundary dataset from the USDA Risk Management Agency (RMA), where we considered parcels as pastures if the majority (> 50%) of the given parcel was classified as pasture according to the Wiscland 2.0 dataset. We used the random forest model to predict these pasture parcels as rotational or continuous grazing.

2 MATERIALS AND METHODS

2.1 Pasture dataset

We were given access to an initial dataset of known continuously and rotationally grazed pastures from a previous research project (Bruce et al., 2021), then expanded on this dataset by reaching out to County Land Conservation Departments, Grazing Networks, grazing specialists, and pasture owners/managers. We compiled locations of pastures shared with us having confirmed management as either continuously or rotationally grazed. In our study we defined continuously grazed pastures as those where livestock had unrestricted access to the full extent of a pasture for long periods of time and were not frequently (less than once a month) moved to new pasture. We defined rotationally grazed as those where livestock were moved between different paddocks at a frequency of at least more than once per week. Because we received more rotationally grazed pasture locations than continuously grazed pastures and did not believe this aligned with actual proportions of management in Wisconsin, we randomly excluded some of the rotationally grazed pastures to balance the dataset (Amrehn et al., 2018). Our resulting dataset contained 75 confirmed rotationally grazed pastures and 75 confirmed continuously grazed pastures dispersed across the state, but clustered in certain regions where more locations were shared with us (Figure 1) (Supplemental Table 1).

Using ArcGIS Pro 3.1.1 mapping software (Esri, 2020) we digitized pasture locations as polygons excluding trees and buildings from the pasture polygons that we would use in our training dataset. As this was an opportunistic dataset, there were spatial patterns (Figure 1) (Supplemental Figure 1) where different management was more prominent in specific regions that may not reflect actual patterns of these management types across Wisconsin. To reduce overfitting models specific to our dataset, we chose not to include weather or soils data because these tended to be strongly correlated with spatial patterns of our dataset. The concern we are addressing with this is avoiding scenarios where specific locations with higher rainfall or a certain soil type coincidentally also have more of a certain pasture management type in our training dataset. This could cause features based on weather and soil data to have greater influence in our predictive model, but functionally the model would be more driven by the spatial patterns that may be unique to our training dataset, and less useful for any out of set predictions.

2.2 Satellite derived vegetation indices

We found a variety of vegetation indices through an online index database (IDB) (Henrich et al., 2009) and selected indices used in prior pasture/grassland research. We chose to calculate a wide range of different indices that we thought might differentiate between rotational and continuous grazing that could be calculated with available bands in Landsat 8 and Sentinel 2 imagery.

We used Google Earth Engine (Gorelick et al., 2017), a cloud computing platform for processing satellite imagery and other geospatial data to calculate the vegetation indices (NDVI, EVI, SAVI, MSAVI, NDWI, GLI, NGRDI, SLAVI, GEMI, CIgreen, NBR, and DVI) (Supplemental Table 1) for every pixel (30 m^2) within the pasture boundaries on every day that data could be derived from multispectral bands in Landsat 8 (repeat cycle of 16 d) or Sentinel 2 (repeat cycle of 10 d) imagery from 01 May 2023 to 30 Sep of 2023 (Figure 2A). We filtered imagery to exclude clouds, water, and shadows from this data prior to calculating vegetation indices, and after indices were calculated we excluded pixels where the resulting NDVI value was < 0.1 to remove data not likely to represent vegetative cover.

After calculating vegetation indices for all individual pixels within the pastures, we reduced this data to a pasture scale with summary statistics (mean, minimum, max, range, standard deviation, and kurtosis) (Figure 2B). This step resulted in a series of spatial summary statistics at the pasture scale. We generated spatial summary statistics of the vegetation indices with multiple values per pasture collected over time for each of the specified vegetation indices and each of the specified summary statistics (multiple time series of different data associated with each individual pasture, derived from Landsat 8 and Sentinel 2 Imagery).

We used statistical computing software R (R Core Development Team, 2023) to organize the series of spatial summary statistics into specific time frames of May, June, July, August, September, and May through September (2023). We chose to subdivide our data into shorter time frames to better reveal spatial and temporal trends (differences between continuously and rotationally grazed pastures) that had the potential to be lost if averaged over longer periods. We chose to focus mainly on monthly time frames because this appeared to provide enough cloud free imagery consistently to derive temporal summary statistics. We also included May through September of 2023 as one of the periods to discern differences that may be more visible across a longer period. This step resulted in multiple time series of spatial data associated with each individual pasture organized by specific time frames.

After this, we generated temporal summary statistics (variance, mean, minimum, maximum, range, standard deviation, and kurtosis) from the spatial summary statistics that had been organized by the given time frames. This step resulted in a combined temporal/spatial value per timeframe for each unique spatial summary statistic of each specified vegetation index, and these values were the features used in the random forest classification model (Figure 2C).

2.3 Random forest classification model

Since there were thousands of temporal and spatial features generated by this workflow, we decided to first filter for features where differences between rotationally and continuously grazed pastures were plausible, determined through separate t-tests where we selected features with an associated p-value <0.01. In the next stage of feature selection, each time we examined a given set of features in a random forest classification model we would take the average of 100 iterations representing different random partitions of data into training and testing datasets, where the random forest classification model for each iteration would be trained with 70% of the pastures in the dataset and then tested with the remaining 30%. Testing here meant we generated a confusion matrix of the testing data comparing the actual classification (the known management of continuously or rotationally grazed) with the predicted classification of the testing data (what the random forest model trained on 70% of the data predicted the classification was).

Our second stage of feature selection used recursive feature elimination where a random forest classification was run with all the given features, and then the feature with the lowest mean decrease accuracy score (a score indicating the feature had less relative influence in the model compared to the other features) was removed, until we found a model with the greatest overall accuracy that could not be increased by removing any additional features. Models were evaluated by examining the confusion matrix, the overall accuracy (the proportion of correct predictions out of total predictions), omission error rates (the proportion of false negatives out of the total predictions per management type of continuously or rotationally grazed), commission error rates (the proportion of false positives out of total predictions per management type), and kappa value (a value given on a scale from 0-1 indicating how well the model fits the data after accounting for the amount of correct predictions from random chance, with values closer to 1 reflecting better agreement) (McHugh, 2012). All assessment metrics were calculated from the 30% of pastures in each of the random testing datasets averaged across the 100 iterations.

2.4 Model validation

We performed an opportunistic validation of our random forest classification model using a set of pasture locations separate from the training dataset of 150 pastures used to produce the model (out of set pasture locations). This validation dataset was built from an existing dataset we received from the Wisconsin DNR combined with volunteered information of pasture classifications from people within the UW Madison Grassland Ecology Lab who could confirm management of pastures at specific locations from either previous research or local area knowledge (Supplemental Table 3).

Ultimately, this validation dataset contained 54 pasture locations (29 confirmed continuously grazed sites, 25 confirmed rotationally grazed sites). As with the training dataset we digitized polygons of these pasture locations excluding trees and buildings from the pasture polygons and as this was an opportunistic dataset, and we observed potential spatial patterns (Figure 3) (Supplemental Figure 2) where different management was more prominent in specific regions that may not reflect actual patterns of these management types across Wisconsin.

Our random forest classification model was used to predict pasture management (continuously or rotationally grazed) in the validation dataset, and then was compared to the actual management of the pastures. The random forest model when applied to complete out of set pasture locations (our validation dataset) was assessed by examining the confusion matrix, the overall accuracy, omission error rates, commission error rates and the kappa value.

2.5 Mapping of continuously and rotationally grazed pastures

The random forest classification uses features representing spatial and temporal variation that were derived from initial pasture polygons, so to map our predictions made from this model we first had to designate parcels on a map that we considered to be pastures. To delineate pasture parcels in Wisconsin we selected boundaries from the Risk Management Agency (RMA) field boundary dataset (USDA, 2008) where the majority (> 50%) of the area within the field boundary was classified as pasture by the Wiscland 2.0 dataset (Wisconsin Department of Natural Resources, 2016) (Figure 4), calculated using the zonal statistics tool in ArcGIS Pro. The RMA field boundaries do not always align with the pasture boundaries that we had, often either being much larger that our pastures or subdividing our pasture boundaries into smaller sections, and also often including multiple land use types within the same field boundary. Although the RMA field boundary dataset has issues, it did appear better suited to our analysis compared to other publicly available boundary datasets we explored such as the Agricultural Conservation Planning Framework Wisconsin Field Boundary dataset (Tomer et al., 2017), which appeared to aggregate different land use types together into single boundaries more frequently. We chose to use Wiscland 2.0 data, as the raster had a specific category mapped as pasture as opposed to other available datasets that often combined pasture with other grassland types (Wang et al., 2022b), and as it reports a high accuracy (85.9%) for the category of pasture determined from independent ground truth test sites.

After producing this pasture layer, we then produced the spatial/temporal features associated with these pasture parcels following the same workflow with our known pasture locations and used these features to apply the random forest classification model that we had built from our known pasture sites to all the pasture parcels.

We produced an online map (https://arcg.is/14Snb40) of our predictions for rotationally and continuously grazed pastures across the state of Wisconsin which gives users the ability to filter for pastures based on pasture size, proportion of an individual boundary classified as pasture by Wiscland 2.0 data, and the confidence our random forest model had in categorizing them calculated as the number of trees that result in the given classification divided by the total number of trees. We included additional layers on this map that show our predicted estimates for the percent of pastures that are rotationally grazed at both a HUC12 watershed and county level.

3 RESULTS

3.1 Random forest classification model

Our random forest classification model had an average accuracy of 80.18%, omission error rates of 20.36% (continuous) and 19.26% (rotational), commission error rates of 18.89% (continuous) and 20.73% (rotational), and a kappa value of 0.60 (Table 3). Our model included 22 features representing combinations of spatial and temporal summary statistics of 6 vegetation indices (NDWI, NBR, SLAVI, NGRDI, CIgreen, NDVI) at 3 time frames (May, August, and May-September 2023) (Table 2). Compared to the continuously grazed sites, the rotationally grazed sites often had higher values for the features, with the feature mean being higher in the rotationally grazed sites for 18 out of the 22 features included in the model. Additionally, the rotationally grazed sites frequently had higher absolute values for the features that were selected in the model, with the absolute value of the feature mean being greater for rotationally grazed pastures than continuously grazed pastures in all but 1 of the selected features (Figure 5).

3.2 Model validation

Model validation showed an overall accuracy of 70.37%, omission error rates of 13.79% (continuous) and 48% (rotational), commission error rates of 32.43% (continuous) and 7.41% (rotational), and a kappa value of 0.39 (Table 4, Figure 6).

3.3 Map of continuously and rotationally grazed pastures

We generated a map of pasture parcels estimating 482,476 ha of pasture across the state (Figure 4). After applying our random forest classification model to these parcels, we generated maps (Figure 7) showing continuous grazing is more prevalent than rotational grazing in Wisconsin with ~59% (284,660 ha) of this total pasture area continuously grazed and the remaining 41% (197,815 ha) rotationally grazed. The map also predicted a higher frequency of rotational grazing occurring in southwest Wisconsin compared to the rest of the state (Figures 7 and 8).

4 DISCUSSION

4.1 Remotely-sensed vegetation indices useful for discriminating grazing management

Our findings suggest that rotationally grazed pastures, with individual paddocks that go through periods of intense grazing followed by a period of recovery, have greater spatial and temporal variability in a variety of vegetation indices compared to continuously grazed pastures. The differences observed between the average feature values in our random forest classification model between rotationally and continuously grazed pastures supports our finding that time series remotely sensed data can be useful in differentiating between these pasture management types. Using time series remotely sensed data we generated predictions for rotational and continuous grazing across Wisconsin, estimating the relative prevalence and spatial distribution of these types of pasture. These results can be used to better account for known differences between rotationally and continuously grazed pastures in larger landscape scale analyses. While future research ground-truthing pasture management across Wisconsin could improve on our predictions, the model and map that we have generated can help fill a gap in current publicly available data that can be utilized by researchers and community partners.

The mean, minimum, maximum, standard deviation, and kurtosis all showed up as spatial summary statistics used in the selected features for our model, with 'maximum' appearing most frequently as a spatial summary statistic in 9 of the 22 selected features. The prevalence of this spatial summary statistics fits with a possible rationale that in a rotationally grazed pasture, individual paddocks that are not being grazed during a given time frame may have increased biomass and other characteristics that correlate with higher maximum values for certain vegetation indices compared to continuously grazed pastures. The mean, minimum, maximum, range, standard deviation, and kurtosis all showed as temporal summary statistics used in selecting features for our model with 'mean' and 'maximum' both appearing most frequently in 7 of the 22 features, which could still fit with a rationale of individual paddocks having more extreme values of vegetation indices due to periods of intensive grazing and recovery. The combination of spatial and temporal summary statistics together in features makes it difficult to make claims about their respective influence in our random forest model, however as grazing of individual paddocks in rotational pastures varies in both space and time, having features with both combined summary statistics proved useful when developing a model to classify between rotationally and continuously grazed pastures.

Previous research on the remotely-sensed vegetation indices of NDWI (Serrano et al., 2022), NBR (Su et al., 2021), SLAVI (Damdinsuren et al., 2023), NGRDI (Shimada et al., 2012), CIgreen(Li et al., 2017) and NDVI (Amies et al., 2021) demonstrated their use to estimate pasture characteristics such as biomass, forage quality, and evidence of grazing showing that they can be used as proxies for the characteristics that vary between rotationally and continuously grazed pastures across space and time. Other indices that we tested but did not appear as components in any of our selected features in our final model were DVI, GEMI, GLI, MSAVI, SAVI, and EVI. While these indices have demonstrated value in estimating various pasture characteristics (e.g., Luna et al., 2023; Fava et al., 2009;Wagle et al., 2020), they appeared to be less useful compared to indices in our selected features for our specific workflow and goal of differentiating between rotationally and continuously grazed pastures. An additional pattern that we noticed in our selected features was the occurrence of the time frames of May, June, August and May-September 2023, with the absence of July and September. This could potentially be explained by the variability in data availability across the season as some data is lost due to cloud cover, compared to the other time frames July and September had less data which may have decreased the ability of features from these time frames to differentiate between rotationally and continuously grazed pastures.

4.2 Spatial patterns of continuously and rotationally grazed pastures

Our model predicted ~59% of total pasture area in Wisconsin as continuously grazed with 41% predicted as rotationally grazed. A 2022 survey of producers across the northern and southern Great Plains in the U.S., where out of 875 respondents (of 4,500 producers receiving the survey) 40.5% reported use of continuous grazing while about 59.5% reported some form of rotational or management intensive grazing (Wang et al 2022c). Although our model predicted more continuous grazing compared to estimates based on surveys, it is important to note that the survey was for a larger region while our map and model were focused specifically on Wisconsin.

Our model predicted a similar level of rotational grazing as USDA NASS estimates of about 42% of beef farms in Wisconsin using rotational grazing (USDA, 2007). As there are currently no other large scale datasets differentiating pastures by continuous and rotational grazing, we have been comparing our predictions to survey estimates, which could be influenced by response bias, or through respondents claiming to use rotational grazing when actual management is more similar to continuous grazing (Ostrum and Jackson-Smith, 2000). Despite variability across current estimates, our model-based estimate and previous survey-based estimates of pasture management agree that there are significant opportunities to promote rotational grazing with all of its attendant ecosystem service benefits.

We noticed patterns in our generated map with a greater relative amount of rotational grazing located in southern Wisconsin. The general patterns appear to align with maps in a report on rotational grazing across the U.S. (O'Hara et al., 2023), where the county level rotational grazing frequency estimates do appear to also demonstrate trends of more rotational grazing in southwest Wisconsin. The steeper and more erosion-prone geography of southwestern Wisconsin makes this area more amendable to grazing rather than row-crop agriculture, and historical social norms around grazing in this region may reinforce the management that we see of the pastures here (Strauser and Stewart, 2023; Pradhananga et al., 2019).

4.3 Caveats of modeling

Our model was trained and validated with small opportunistic datasets, so extrapolating predictions across the entire state must be done cautiously. Future research could use our current map to develop an approach for randomly selecting locations for systematic observations of pastures across Wisconsin and validation data collection. With a larger pasture dataset more representative of the entire state, it would be possible to properly validate the current model we have generated, and to build upon our workflow. Another advantage of collecting an extensive validation dataset would be reduction in the risk of bias introduced by patterns that appear in small opportunistic datasets, so variables such as soil characteristics and precipitation, which we intentionally excluded from our model to avoid overfitting, could be included to potentially improve the model accuracy.

4.3 Implications for research, management, and policy

Previous research has indicated how continuously- and rotationally-grazed pastures result in different environmental outcomes (Díaz-Pereira et al., 2020; Teague and Kreuter, 2020; Hulvey et al., 2021). Compared to continuous grazing, rotational grazing has benefits of higher soil carbon (Conant et al., 2017; Byrnes et al., 2018; Mosier et al., 2021), less runoff of nitrogen (Park et al., 2017; Dahal et al., 2020) and phosphorous (Toor et al., 2020; Ashworth et al., 2022) and reduced soil loss and erosion (Lyons et al., 2000). Based on these differences, pasture management should be considered when performing analysis seeking to understand the influence of pastures on nutrient cycling, carbon storage, and water quality at a landscape scale. The results of our research show the potential of time series remotely sensed data for classifying pasture management, and our initial estimates could provide useful data for a variety of different landscape scale analyses.

Our estimates of the spatial distribution of continuously and rotationally grazed pastures could also be integrated into or otherwise complement existing models and tools used by researchers, farmers, agencies, watershed groups and community partners concerning ecosystem services, nutrient cycling, and soil erosion associated land use. For example, SmartScape is a decision support system that examines how crop change scenarios can influence ecosystem services such as soil carbon, phosphorous loading, and biodiversity (Tayyebi et al., 2016), it utilizes GIS landcover data and could potentially benefit from a dataset that differentiates pasture management. Another tool that could be complemented by our pasture management data is the Revised Universal Soil Loss Equation (RUSLE) model, this model is used for estimating soil erosion and it has a parameter called the cover management factor which incorporates how vegetative cover influences soil erosion (Luvai et al., 2022). This is another scenario where our dataset could be used with a tool that already incorporates GIS landcover data and could refine landcover classifications to help improve predictions.

The model and estimates we generated could also be used in a variety of ways by grazing networks, watershed groups, and other community partners interested in the spatial variability of continuously and rotationally grazed pastures and how this could be leveraged for the promotion of rotational grazing. The map and model could be used as content for education and outreach and can also be used to directly identify areas where more rotational grazing could be occurring with the right support. Showing maps with these pasture management estimates could also serve a practical communication purpose when applying for funding, as a way for local communities to demonstrate the need for resources and opportunity for positive land use change.

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TABLES

Table 1. The first 4 columns indicate the components of each feature that was included in the final random forest classification model, with Vegetation Index indicating which vegetation index is summarized by the corresponding spatial summary statistic, Time frame (2023) indicating month or range of months of data that the temporal summary statistic was calculated from, Temporal Summary Statistic indicating how the spatial summary stats were summarized across time, and Spatial Summary Statistic indicating how the vegetation indices were summarized across each pasture (spatial boundary). The 5th column indicates the Mean Decrease Accuracy Value (arranged in descending order) associated with the given feature, with high values indicating the feature has a greater relative influence over the random forest classification model. The 6th and 7th columns indicate the t statistic and p-values associated with two sample t tests that were performed on these features comparing continuously grazed and rotationally grazed pastures (n=150, 75 continuously grazed and 75 rotationally grazed pastures). Positive and negative t statistics are used to communicate direction, with positive values indicating the mean of the feature is greater in the continuous pastures, and negative values indicating the mean of the feature is greater in the rotational pastures (directionality also indicated by color in these columns with yellow indicating a higher mean for continuous pastures and green indicating a higher mean for rotational pastures). The 8th column is a letter code that matches with figures 4 and 5, that can be used to more easily check what features are being referenced, and what the components of these features are.

Vegetation Index	Time frame (2023)	Temporal Summary Statistic	Spatial Summary Statistic	Mean Decrease Accuracy	t-statistic	p-value	Code
NDWI	May	Minimum	Mean	0.021	4.87	<1e-04	A
NBR	May	Maximum	Maximum	0.018	-4.06	<1e-04	B
NDWI	May	Maximum	Mean	0.016	3.73	<1e-03	C
SLAVI	May	Maximum	Maximum	0.015	-4.75	<1e-05	D
NGRDI	June	Range	Mean	0.015	-4.06	<1e-04	E
CIgreen	May	Minimum	Mean	0.015	-4.00	<1e-03	F
NGRDI	August	Mean	Maximum	0.014	-5.04	<1e-05	G
CIgreen	May	Maximum	Mean	0.013	-5.41	<1e-06	H
NGRDI	August	Mean	Standard Deviation	0.011	-3.91	<1e-03	I
NDVI	August	Mean	Maximum	0.011	-4.73	<1e-05	J
NBR	August	Kurtosis	Mean	0.010	3.76	<1e-03	K
NDWI	August	Mean	Minimum	0.010	4.65	<1e-05	L
SAVI	May- September	Kurtosis	Kurtosis	0.0096	-3.67	<1e-03	M
SLAVI	August	Maximum	Maximum	0.0091	-3.95	<1e-03	N
SLAVI	May	Standard Deviation	Minimum	0.0089	-4.08	<1e-04	O
NBR	August	Maximum	Maximum	0.0083	-3.94	<1e-03	P
SLAVI	May	Standard Deviation	Mean	0.0081	-4.86	<1e-05	Q
NBR	May- September	Maximum	Mean	0.0079	-4.18	<1e-04	R
CIgreen	August	Mean	Maximum	0.0074	-3.73	<1e-03	S
CIgreen	August	Mean	Mean	0.0071	-3.56	<1e-03	T
CIgreen	May	Minimum	Maximum	0.0066	-4.31	<1e-04	U
NDVI	May- September	Mean	Maximum	0.0066	-4.08	<1e-04	V

Table 3. Confusion matrix, overall accuracy, kappa value, and omission and commission error rates for continuous and rotationally grazed pastures for our selected random forest classification model, calculated by comparing actual and predicted pasture management averaged from 100 iterations of data partitioning where a random 30% of the pasture data (from the initial training dataset of 150 pasture sites) was used for testing (excluded from being used to train the random forest model in the given iteration, and used to examine the accuracy of the model by comparing actual to predicted management of pastures).

Confusion Matrix		
	Predicted Continuous	**Predicted Rotational**
Actual Continuous	17.84	4.56
Actual Rotational	4.16	7.44

Accuracy Assessment Metrics	
Overall Accuracy	80.18%
Kappa value	0.60
Omission Error Rate for Continuously Grazed Pastures	20.36%
Omission Error Rate for Rotationally Grazed Pastures	19.26%
Commission Error Rate for Continuously Grazed Pastures	18.89%
Commission Error Rate for Rotationally Grazed Pastures	20.73%

Table 4. Confusion matrix, overall accuracy, kappa value, and omission and commission error rates for continuous and rotationally grazed pastures for our selected random forest classification model, calculated by comparing actual and predicted pasture management on out of set pastures not used in building the random forest model, a validation dataset of 54 pastures (25 continuously grazed, 29 rotationally grazed) were used for testing the random forest model to examine accuracy of the model by comparing actual to predicted management of pastures.

Confusion Matrix		
	Predicted Continuous	**Predicted Rotational**
Actual Continuous	25	4
Actual Rotational	12	13

Accuracy Assessment Metrics	
Overall Accuracy	70.37%
Kappa value	0.3907
Omission Error Rate for Continuously Grazed Pastures	13.79%
Omission Error Rate for Rotationally Grazed Pastures	48%
Commission Error Rate for Continuously Grazed Pastures	7.41%
Commission Error Rate for Rotationally Grazed Pastures	48%

Supplemental Table 1. The column Unique Pasture IDs gives identification codes for the 150 pasture sites where Pasture IDs beginning with C are continuously grazed pastures, and IDs beginning with R are rotationally grazed pastures, these IDs are also available to reference in the online version of the map: https://arcg.is/1a0vCS. The column Hectares gives the size of each pasture in Hectares. The column Wisconsin County indicates what county the pasture is in, and the column Data Source indicates where we received this pasture location and management classification from, pasture locations came from various county departments and grazing specialists, and directly from graziers who could volunteer information on their pastures in an online form that was distributed by extension agents and land county offices.

Unique Pasture ID	Hectares	Wisconsin County	Data Source
C01	18.42	Brown	Brown County Land and Water Conservation Department
C02	21.19	Brown	Brown County Land and Water Conservation Department
C03	3.64	Brown	Brown County Land and Water Conservation Department
C04	2.75	Brown	Brown County Land and Water Conservation Department
C05	1.90	Sheboygan	Response from grazier
C06	0.77	Green	Previous research project (Bruce et al., 2021)
C07	2.73	Lafayette	Previous research project (Bruce et al., 2021)
C08	6.17	Iowa	Previous research project (Bruce et al., 2021)
C09	36.88	Iowa	Previous research project (Bruce et al., 2021)
C10	41.80	Crawford	Previous research project (Bruce et al., 2021)
C11	2.48	Crawford	Previous research project (Bruce et al., 2021)
C12	5.90	Crawford	Previous research project (Bruce et al., 2021)
C13	1.27	Vernon	Jim Munsch, grazing specialist
C14	0.66	Vernon	Jim Munsch, grazing specialist
C15	15.44	Vernon	Jim Munsch, grazing specialist
C16	16.88	Vernon	Jim Munsch, grazing specialist
C17	10.67	Vernon	Jim Munsch, grazing specialist
C18	2.95	Vernon	Jim Munsch, grazing specialist
C19	2.69	Vernon	Jim Munsch, grazing specialist
C20	15.27	Vernon	Jim Munsch, grazing specialist
C21	4.79	Vernon	Jim Munsch, grazing specialist
C22	4.01	Vernon	Jim Munsch, grazing specialist
C23	9.35	Vernon	Jim Munsch, grazing specialist
C24	2.69	Vernon	Jim Munsch, grazing specialist
C25	2.61	Vernon	Jim Munsch, grazing specialist
C26	4.52	Vernon	Jim Munsch, grazing specialist
C27	2.60	Vernon	Jim Munsch, grazing specialist
C28	1.92	Vernon	Previous research project (Bruce et al., 2021)
C29	2.12	Vernon	Jim Munsch, grazing specialist
C30	4.78	Vernon	Previous research project (Bruce et al., 2021)
C31	1.00	La Crosse	Jim Munsch, grazing specialist
C32	5.04	La Crosse	Jim Munsch, grazing specialist
C33	7.32	La Crosse	Jim Munsch, grazing specialist
C34	7.45	Columbia	Previous research project (Bruce et al., 2021)

C35	27.14	Taylor	Taylor County Land Conservation Department
C36	12.63	Taylor	Taylor County Land Conservation Department
C37	7.53	Taylor	Taylor County Land Conservation Department
C38	13.92	Taylor	Taylor County Land Conservation Department
C39	8.61	Taylor	Taylor County Land Conservation Department
C40	4.47	Taylor	Taylor County Land Conservation Department
C41	14.48	Taylor	Taylor County Land Conservation Department
C42	8.68	Taylor	Taylor County Land Conservation Department
C43	17.53	Taylor	Taylor County Land Conservation Department
C44	9.01	Taylor	Taylor County Land Conservation Department
C45	7.89	Taylor	Taylor County Land Conservation Department
C46	2.99	Taylor	Taylor County Land Conservation Department
C47	5.26	Taylor	Taylor County Land Conservation Department
C48	4.19	Taylor	Taylor County Land Conservation Department
C49	4.61	Taylor	Taylor County Land Conservation Department
C50	2.70	Taylor	Taylor County Land Conservation Department
C51	8.65	Taylor	Taylor County Land Conservation Department
C52	5.08	Taylor	Taylor County Land Conservation Department
C53	4.49	Taylor	Taylor County Land Conservation Department
C54	2.00	Taylor	Taylor County Land Conservation Department
C55	3.51	Taylor	Taylor County Land Conservation Department
C56	12.55	Taylor	Taylor County Land Conservation Department
C57	3.07	Taylor	Taylor County Land Conservation Department
C58	6.61	Taylor	Taylor County Land Conservation Department
C59	8.56	Taylor	Taylor County Land Conservation Department
C60	2.57	Taylor	Taylor County Land Conservation Department
C61	15.21	Taylor	Taylor County Land Conservation Department
C62	8.54	Taylor	Taylor County Land Conservation Department
C63	67.90	Taylor	Taylor County Land Conservation Department
C64	97.22	Taylor	Taylor County Land Conservation Department
C65	23.40	Taylor	Taylor County Land Conservation Department
C66	11.21	Taylor	Taylor County Land Conservation Department
C67	9.92	Taylor	Taylor County Land Conservation Department
C68	10.76	Taylor	Taylor County Land Conservation Department
C69	10.34	Taylor	Taylor County Land Conservation Department
C70	10.49	Clark	Taylor County Land Conservation Department
C71	172.43	Adams	Adams County Land and Water Division
C72	71.62	Adams	Adams County Land and Water Division
C73	1.50	Adams	Adams County Land and Water Division
C74	2.19	Adams	Adams County Land and Water Division
C75	168.87	Adams	Adams County Land and Water Division
R01	8.66	Polk	Response from grazier
R02	2.73	Dunn	John Sippl, NRCS Conservationist
R03	26.73	Trempealeau	Steve Okonek, Jackson & Trempealeau County Agriculture Agent
R04	19.63	Jackson	Steve Okonek, Jackson & Trempealeau County Agriculture Agent
R05	66.98	Jackson	Steve Okonek, Jackson & Trempealeau County Agriculture Agent
R06	15.43	Shawano	Shawano Land Conservation Department
R07	19.28	Shawano	Shawano Land Conservation Department
R08	8.86	Brown	Brown County Land and Water Conservation Department
R09	58.46	Outagamie	Brown County Land and Water Conservation Department
R10	9.65	Brown	Brown County Land and Water Conservation Department

R11	9.96	Brown	Brown County Land and Water Conservation Department
R12	8.11	Brown	Brown County Land and Water Conservation Department
R13	2.35	Brown	Brown County Land and Water Conservation Department
R14	2.29	Brown	Brown County Land and Water Conservation Department
R15	10.85	Brown	Brown County Land and Water Conservation Department
R16	6.35	Waupaca	Winnebago Land and County Conservation Department
R17	0.60	Winnebago	Winnebago Land and County Conservation Department
R18	3.59	Winnebago	Winnebago Land and County Conservation Department
R19	0.78	Winnebago	Winnebago Land and County Conservation Department
R20	1.82	Winnebago	Winnebago Land and County Conservation Department
R21	15.66	Winnebago	Winnebago Land and County Conservation Department
R22	7.20	Winnebago	Winnebago Land and County Conservation Department
R23	7.62	Sheboygan	Direct response from information request distributed to graziers
R24	13.69	Ozaukee	Direct response from information request distributed to graziers
R25	29.73	Jefferson	Direct response from information request distributed to graziers
R26	25.23	Green	Previous research project (Bruce et al., 2021)
R27	27.95	Green	Previous research project (Bruce et al., 2021)
R28	21.19	Green	Previous research project (Bruce et al., 2021)
R29	12.51	Iowa	Previous research project (Bruce et al., 2021)
R30	5.10	Iowa	Previous research project (Bruce et al., 2021)
R31	50.81	Crawford	Previous research project (Bruce et al., 2021)
R32	9.13	Vernon	Previous research project (Bruce et al., 2021)
R33	17.50	Vernon	Jim Munsch, grazing specialist
R34	9.40	Vernon	Jim Munsch, grazing specialist
R35	9.48	Vernon	Jim Munsch, grazing specialist
R36	14.28	Vernon	Previous research project (Bruce et al., 2021)
R37	9.82	La Crosse	Jim Munsch, grazing specialist
R38	18.30	La Crosse	Jim Munsch, grazing specialist
R39	6.41	Sauk	Previous research project (Bruce et al., 2021)
R40	28.07	Sauk	Previous research project (Bruce et al., 2021)
R41	9.87	Sauk	Previous research project (Bruce et al., 2021)
R42	1.98	Sauk	Previous research project (Bruce et al., 2021)
R43	9.26	Sauk	Previous research project (Bruce et al., 2021)
R44	10.99	Sauk	Previous research project (Bruce et al., 2021)
R45	1.51	Columbia	Previous research project (Bruce et al., 2021)
R46	32.64	Columbia	Previous research project (Bruce et al., 2021)
R47	28.00	Columbia	Previous research project (Bruce et al., 2021)
R48	38.55	Rusk	Response from grazier
R49	6.10	Taylor	Response from grazier
R50	12.84	Rock	Response from grazier
R51	9.06	Waupaca	Response from grazier
R52	7.39	Waupaca	Response from grazier
R53	1.46	Marquette	Response from grazier
R54	56.23	Taylor	Taylor County Land Conservation Department
R55	15.44	Taylor	Taylor County Land Conservation Department
R56	18.55	Taylor	Taylor County Land Conservation Department
R57	11.89	Taylor	Taylor County Land Conservation Department
R58	8.79	Taylor	Taylor County Land Conservation Department
R59	16.06	Taylor	Taylor County Land Conservation Department
R60	9.74	Taylor	Taylor County Land Conservation Department
R61	6.50	Taylor	Taylor County Land Conservation Department
R62	29.732	Taylor	Taylor County Land Conservation Department
R63	40.09	Taylor	Taylor County Land Conservation Department

R64	22.10	Clark	Taylor County Land Conservation Department
R65	3.98	Taylor	Taylor County Land Conservation Department
R66	20.72	Taylor	Taylor County Land Conservation Department
R67	25.64	Taylor	Taylor County Land Conservation Department
R68	11.01	Taylor	Taylor County Land Conservation Department
R69	21.08	Taylor	Taylor County Land Conservation Department
R70	6.74	Sauk	Sauk County Land Resources and Environment Department
R71	11.41	Sauk	Sauk County Land Resources and Environment Department
R72	7.34	Sauk	Sauk County Land Resources and Environment Department
R73	11.78	Sauk	Sauk County Land Resources and Environment Department
R74	4.36	Sauk	Sauk County Land Resources and Environment Department
R75	8.79	Sauk	Sauk County Land Resources and Environment Department

Supplemental Table 2. Vegetation Indices and their respective abbreviations and formulas calculated from Landsat 8 and Sentinel 2 imagery were that tested for potential use in training our random classification model.

Vegetation Index	Abbreviation	Formula
Normalized Difference Vegetation Index	NDVI	(nir-red)/(nir+red)
Enhanced Vegetation Index	EVI	2.5 * ((nir - red) / ((nir + 6 * red - 7.5 * blue + 1))))
Soil Adjusted Vegetation Index	SAVI	(nir - red) / ((nir + red + 0.5) * 1.5))
Modified Soil Adjusted Vegetation Index	MSAVI	0.5 * (2 * nir + 1 - sqrt((2 * nir + 1)^2 - 8 * (nir - red))))
Normalized Difference Water Index	NDWI	(green - nir) / (green + nir))
Green Leaf Index	GLI	(2*green)+red+blue)/((2*green)-red-blue))
Normalized Green Red Difference Index	NGRDI	(green-red) / (green + red))
Specific Leaf Area Vegetation Index	SLAVI	nir / (red + swir1))
Global Environment Monitoring Index	GEMI	sqrt(2 * ((nir^2 - red^2) / (nir + 1.5 * red + 0.5))))
Chlorophyll Index Green	CIgreen	(nir/green)-1
Simple Ratio NIR/Red Difference Vegetation Index	DVI	(nir) / (red))
Normalized Difference Burn Ratio	NBR	(nir-swir1)/(nir+swir)

Supplemental Table 3. The column Unique Pasture IDs gives identification codes for the 54 pasture sites in the validation dataset where the first letter in the ID is V (to indicate it is in the validation dataset)with the second letter of C or R indicating if the pasture is continuously or rotationally grazed respectively, these IDs are also available to reference in the online version of the map. The column Hectares gives the size of each pasture in Hectares. The column Wisconsin County indicates what county the pasture is located in, and the column Data Source indicates where we received this pasture location and management classification from, pasture locations for the validation dataset came from a dataset shared with us by Mary Anderson at with Wisconsin DNR along with volunteered pasture locations from members of the Grassland Ecology Lab (representing pastures from previous research or other locations that people were familiar with the management).

Unique Pasture ID	Hectares	Wisconsin County	Data Source
VC01	146.30	Portage	Mary Anderson, Conservation Agriculture Specialist, Wisconsin DNR
VC02	120.66	Portage	Mary Anderson, Conservation Agriculture Specialist, Wisconsin DNR
VC03	8.15	Winnebago	Mary Anderson, Conservation Agriculture Specialist, Wisconsin DNR
VC04	3.84	Richland	Mary Anderson, Conservation Agriculture Specialist, Wisconsin DNR
VC05	2.24	Dunn	Lexi Shank, UW Madison Grassland Ecology Lab
VC06	2.92	Buffalo	Lexi Shank, UW Madison Grassland Ecology Lab
VC07	8.54	Buffalo	Lexi Shank, UW Madison Grassland Ecology Lab
VC08	7.80	Buffalo	Lexi Shank, UW Madison Grassland Ecology Lab
VC09	3.35	Trempealeau	Lexi Shank, UW Madison Grassland Ecology Lab
VC10	0.73	Buffalo	Lexi Shank, UW Madison Grassland Ecology Lab
VC11	3.75	Trempealeau	Lexi Shank, UW Madison Grassland Ecology Lab
VC12	1.60	Trempealeau	Lexi Shank, UW Madison Grassland Ecology Lab
VC13	6.60	Trempealeau	Lexi Shank, UW Madison Grassland Ecology Lab
VC14	2.40	Trempealeau	Lexi Shank, UW Madison Grassland Ecology Lab
VC15	4.85	Trempealeau	Lexi Shank, UW Madison Grassland Ecology Lab
VC16	3.73	Trempealeau	Lexi Shank, UW Madison Grassland Ecology Lab
VC17	0.51	Trempealeau	Lexi Shank, UW Madison Grassland Ecology Lab
VC18	4.42	Trempealeau	Lexi Shank, UW Madison Grassland Ecology Lab
VC19	1.01	Trempealeau	Lexi Shank, UW Madison Grassland Ecology Lab
VC20	1.94	Trempealeau	Lexi Shank, UW Madison Grassland Ecology Lab
VC21	2.03	Trempealeau	Lexi Shank, UW Madison Grassland Ecology Lab
VC22	2.18	Trempealeau	Lexi Shank, UW Madison Grassland Ecology Lab
VC23	0.68	Waupaca	Ashley Becker, UW Madison Grassland Ecology Lab
VC24	2.29	Vernon	Gregg Sandford, UW Madison Grassland Ecology Lab
VC25	3.28	Vernon	Gregg Sandford, UW Madison Grassland Ecology Lab
VC26	11.24	Richland	Gregg Sandford, UW Madison Grassland Ecology Lab
VC27	7.81	Richland	Gregg Sandford, UW Madison Grassland Ecology Lab
VC28	0.69	Sheboygan	Jessica Mehre, UW Madison Grassland Ecology Lab
VC29	1.55	Sheboygan	Jessica Mehre, UW Madison Grassland Ecology Lab
VR01	61.67	Winnebago	Mary Anderson, Conservation Agriculture Specialist, Wisconsin DNR
VR02	28.42	Portage	Mary Anderson, Conservation Agriculture Specialist, Wisconsin DNR

VR03	23.79	Portage	Mary Anderson, Conservation Agriculture Specialist, Wisconsin DNR
VR04	126.67	Portage	Mary Anderson, Conservation Agriculture Specialist, Wisconsin DNR
VR05	91.51	Portage	Mary Anderson, Conservation Agriculture Specialist, Wisconsin DNR
VR06	21.08	Wood	Mary Anderson, Conservation Agriculture Specialist, Wisconsin DNR
VR07	8.04	Portage	Mary Anderson, Conservation Agriculture Specialist, Wisconsin DNR
VR08	12.26	Columbia	Mary Anderson, Conservation Agriculture Specialist, Wisconsin DNR
VR09	12.14	Fond du Lac	Mary Anderson, Conservation Agriculture Specialist, Wisconsin DNR
VR10	126.67	Adams	Mary Anderson, Conservation Agriculture Specialist, Wisconsin DNR
VR11	297.42	Portage	Mary Anderson, Conservation Agriculture Specialist, Wisconsin DNR
VR12	23.28	Crawford	Mary Anderson, Conservation Agriculture Specialist, Wisconsin DNR
VR13	114.09	Portage	Mary Anderson, Conservation Agriculture Specialist, Wisconsin DNR
VR14	299.47	Portage	Mary Anderson, Conservation Agriculture Specialist, Wisconsin DNR
VR15	24.49	Wood	Mary Anderson, Conservation Agriculture Specialist, Wisconsin DNR
VR16	7.81	Dane	Mary Anderson, Conservation Agriculture Specialist, Wisconsin DNR
VR17	6.02	Sauk	Mary Anderson, Conservation Agriculture Specialist, Wisconsin DNR
VR18	2.17	Rock	Mary Anderson, Conservation Agriculture Specialist, Wisconsin DNR
VR19	107.28	Wood	Mary Anderson, Conservation Agriculture Specialist, Wisconsin DNR
VR20	35.67	Green	Ashley Becker, UW Madison Grassland Ecology Lab
VR21	4.63	Waupaca	Ashley Becker, UW Madison Grassland Ecology Lab
VR22	6.11	Iowa	Ashley Becker, UW Madison Grassland Ecology Lab
VR23	3.30	Marinette	Ashley Becker, UW Madison Grassland Ecology Lab
VR24	8.06	Iowa	Ashley Becker, UW Madison Grassland Ecology Lab
VR25	8.55	Chippewa	Ashley Becker, UW Madison Grassland Ecology Lab

FIGURES

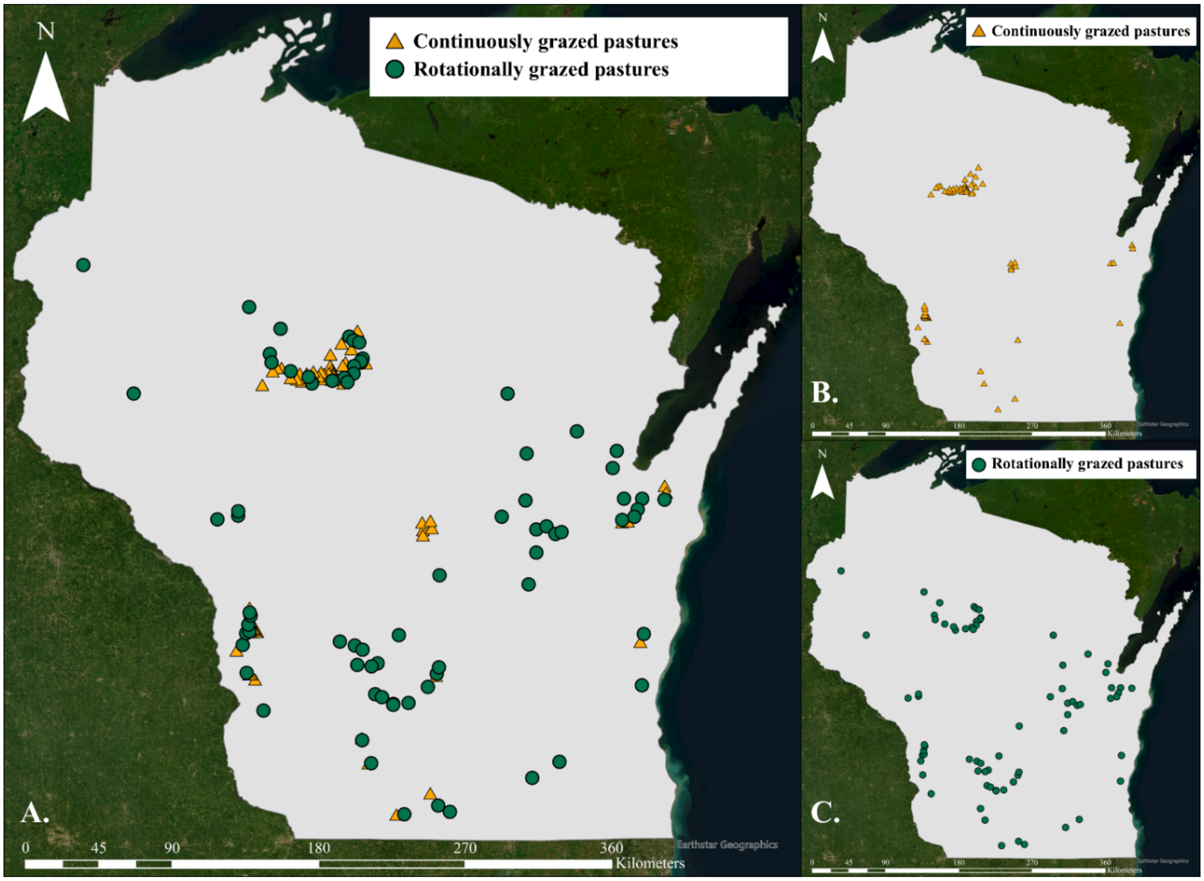


Figure 1. (A) Map of Wisconsin with the locations of our 75 confirmed continuously grazed pastures (shown with yellow triangles) and 75 rotationally grazed pastures (shown with green circles) on the left. (B) Just the continuous pastures are shown in upper right map. (C) Just the rotationally grazed sites are shown in lower right map. An online version of this map layer can also be viewed here: https://arcg.is/14Snb40

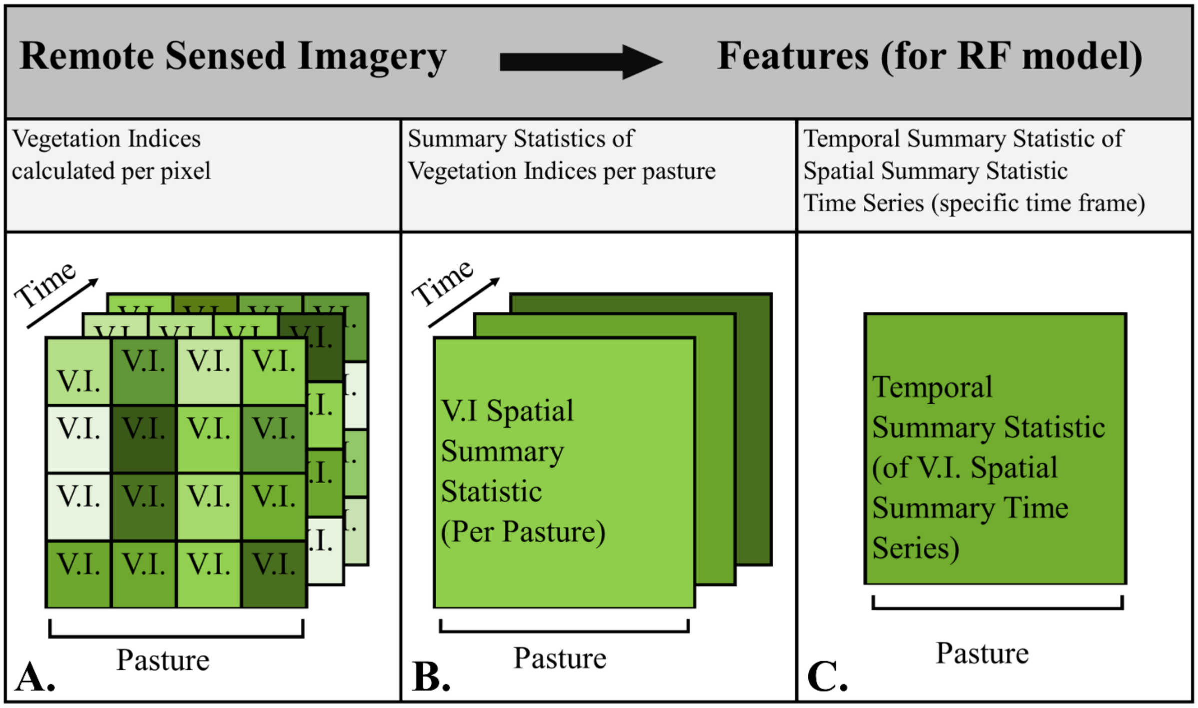


Figure 2. Diagram summarizing our workflow, giving an example of how a vegetation index (V.I. in diagram) derived from satellite imagery would be (A) calculated for individual pixels across pastures, across time. (B) Reduced to a pasture scale to produce a time series of spatial summary statistics per pasture. (C) Summarized over a specified time frame to produce a feature that could then be used in a random forest classification model (RF model).

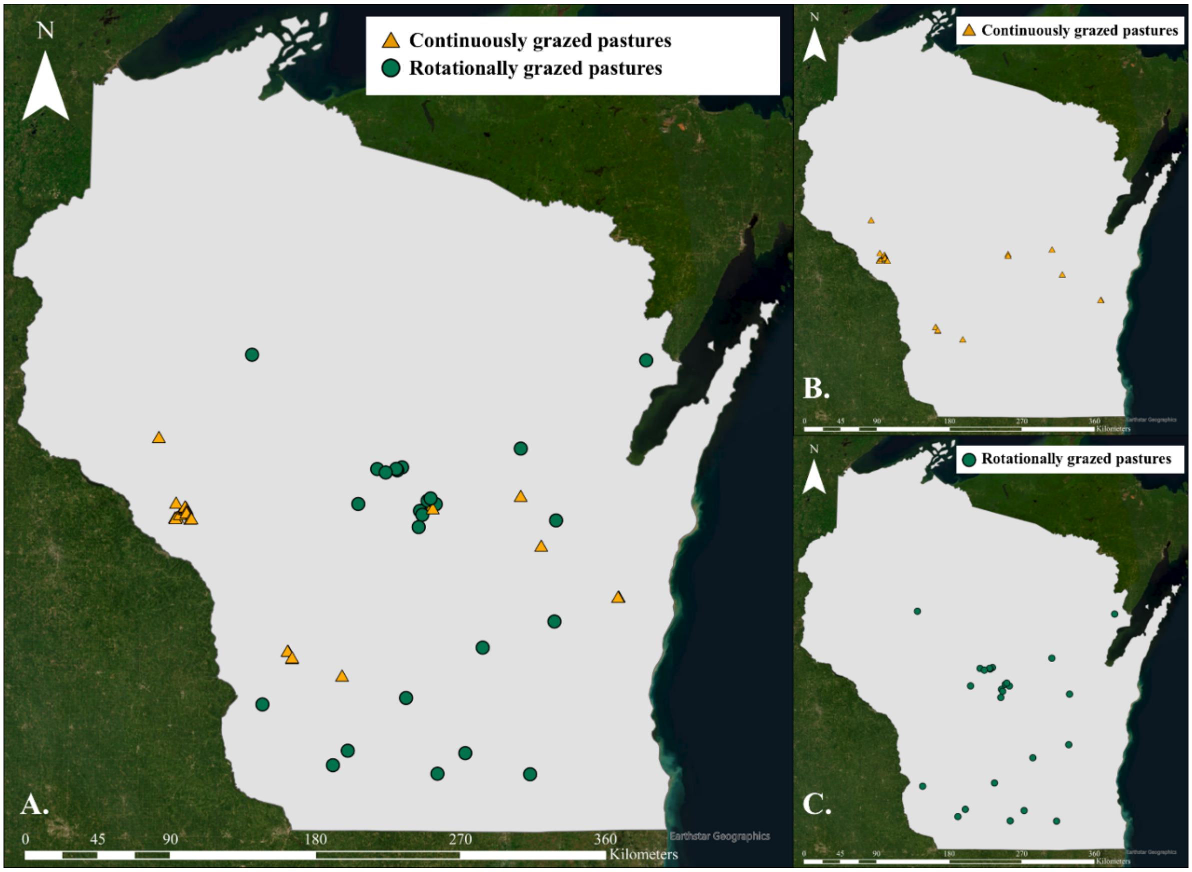


Figure 3. (A) Map of Wisconsin with the locations of 29 confirmed continuously grazed pastures (shown in yellow triangles) and 25 rotationally grazed pastures (shown in green circles) used for an initial validation of our model. (B) Just the continuously grazed sites are shown in the upper left map. (C) Just the rotationally grazed sites are shown in the map on the right. An online version of this map layer can also be viewed here: https://arcg.is/14Snb40

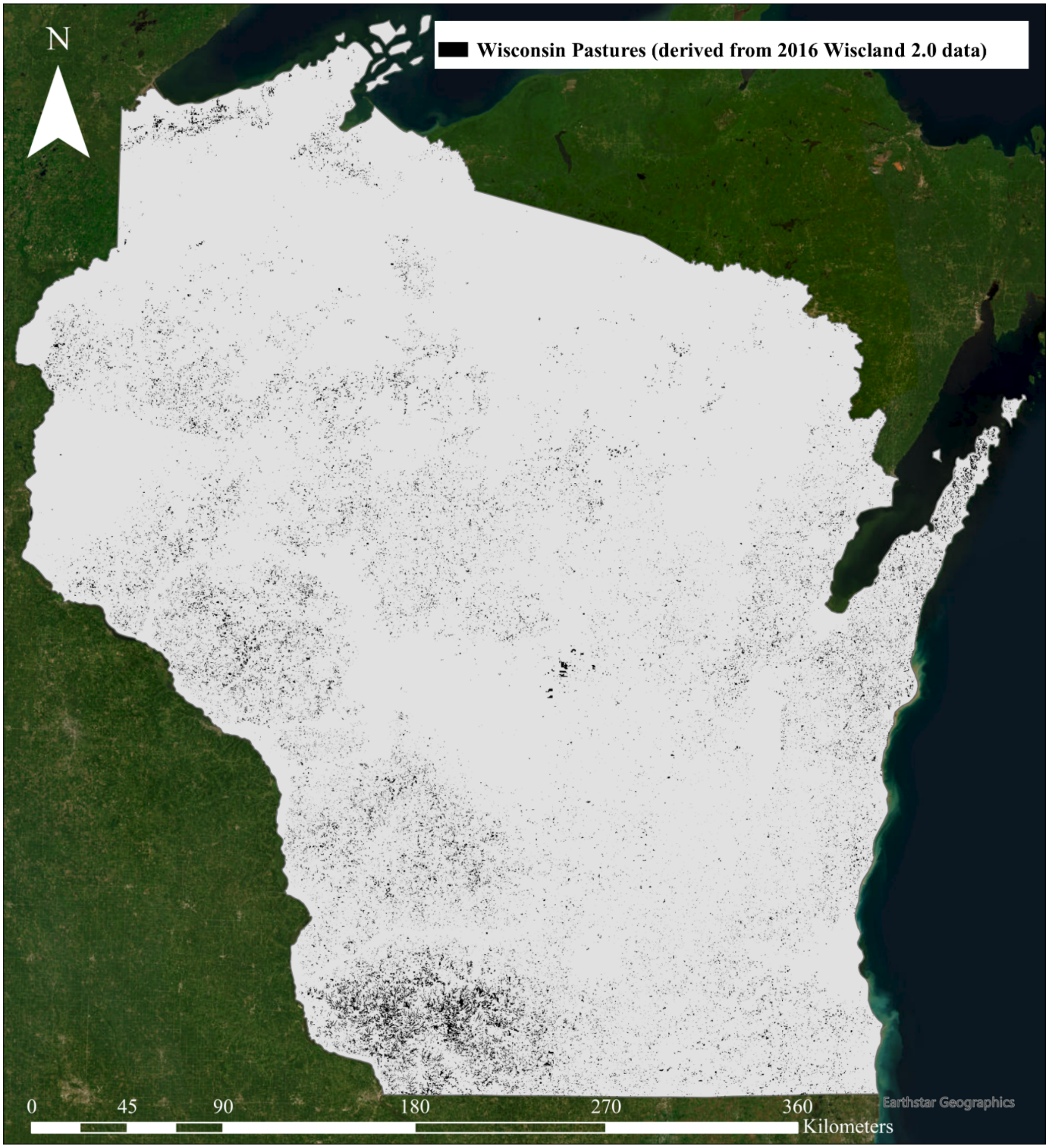
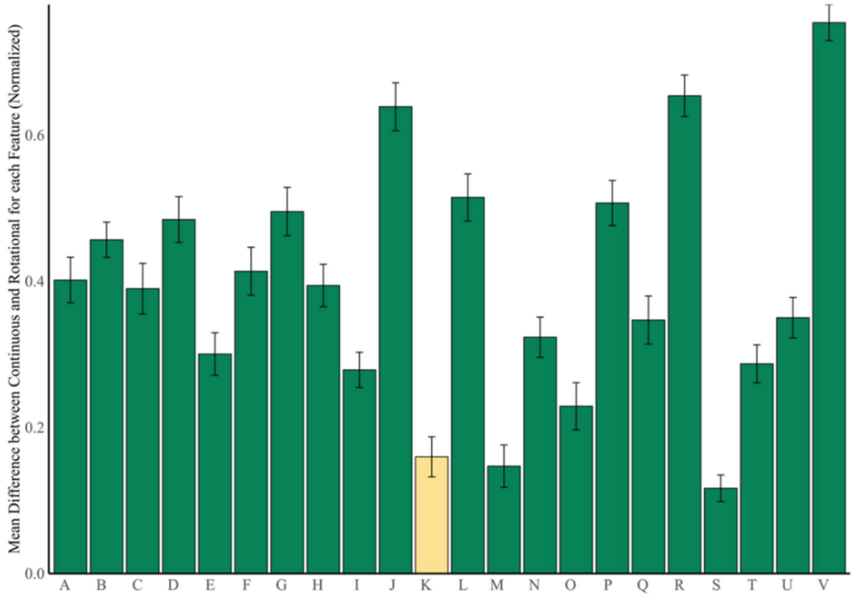


Figure 4. Map of Wisconsin pastures produced by selecting RMA field boundaries (USDA, 2008) where the majority (over 50%) of the area was covered by pasture as according to the Wiscland 2.0 (2016) pasture class.

Group with higher absolute mean feature value	
Continuous	Rotational



VI	TF	Time	Space	Code
NDWI	May	Min	Mean	A
NBR	May	Max	Max	B
NDWI	May	Max	Mean	C
SLAVI	May	Max	Max	D
NGRDI	Jun	Range	Mean	E
CIgreen	May	Min	Mean	F
NGRDI	Aug	Mean	Max	G
CIgreen	May	Max	Mean	H
NGRDI	Aug	Mean	St Dev	I
NDVI	Aug	Mean	Max	J
NBR	Aug	Kurt	Mean	K
NDWI	Aug	Mean	Min	L
SAVI	May- Sep	Kurt	Kurt	M
SLAVI	Aug	Max	Max	N
SLAVI	May	St Dev	Min	O
NBR	Aug	Max	Max	P
SLAVI	May	St Dev	Mean	Q
NBR	May- Sep	Max	Mean	R
CIgreen	Aug	Mean	Max	S
CIgreen	Aug	Mean	Mean	T
CIgreen	May	Min	Max	U
NDVI	May- Sep	Mean	Max	V

Figure 5. The absolute value difference between the mean of continuously and rotationally of 22 features included in the random forest classification model, features normalized (values scaled between 0-1) to better show features derived from different indices together. Features shown left to right in descending order of mean decrease accuracy scores (indicating relative importance of features in the model) Error bars show 95% confidence intervals of the difference between the means. Letter codes shown reference individual features detailed in corresponding table to the left (corresponding with Table 2), where the V.I. column indicates Vegetation Index, TF column indicates time frame (all 2023), Time column indicates the temporal summary statistic (summary per pasture time series), Space column indicates spatial summary statistic (summary per pasture), Code indicates the letter code that references to the graph. The yellow color indicates the mean absolute value of the feature is higher for continuously grazed pastures compared to rotationally grazed pastures (only seen in feature K). The green color indicates the mean absolute value of the feature is higher for rotationally grazed pastures compared to continuously grazed pastures (seen in all features except K).

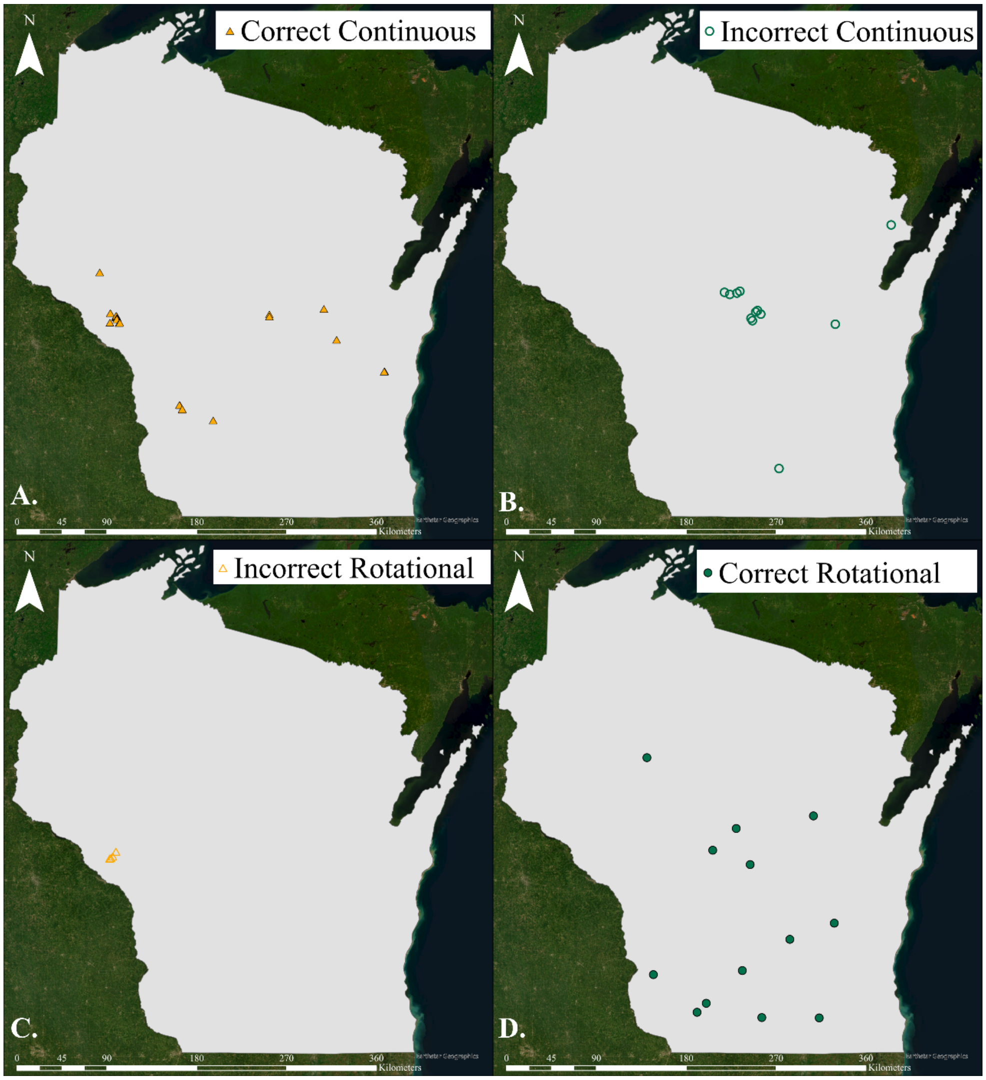


Figure 6. Results from our map validation using out of set locations, (A) Pastures correctly identified as continuous labeled as Correct Continuous (upper left). (B) Pastures incorrectly identified as continuous labeled as Incorrect Continuous (false positive for continuous grazing, false negative for rotational grazing) (upper right). (C) Pastures incorrectly identified as rotational labeled as Incorrect Rotational (false positive for rotational grazing, false negative for continuous grazing) (lower left). (D) Pastures correctly identified as rotational labeled as Correct Rotational (lower right). An online version of this map layer can be viewed here: https://arcg.is/14Snb40

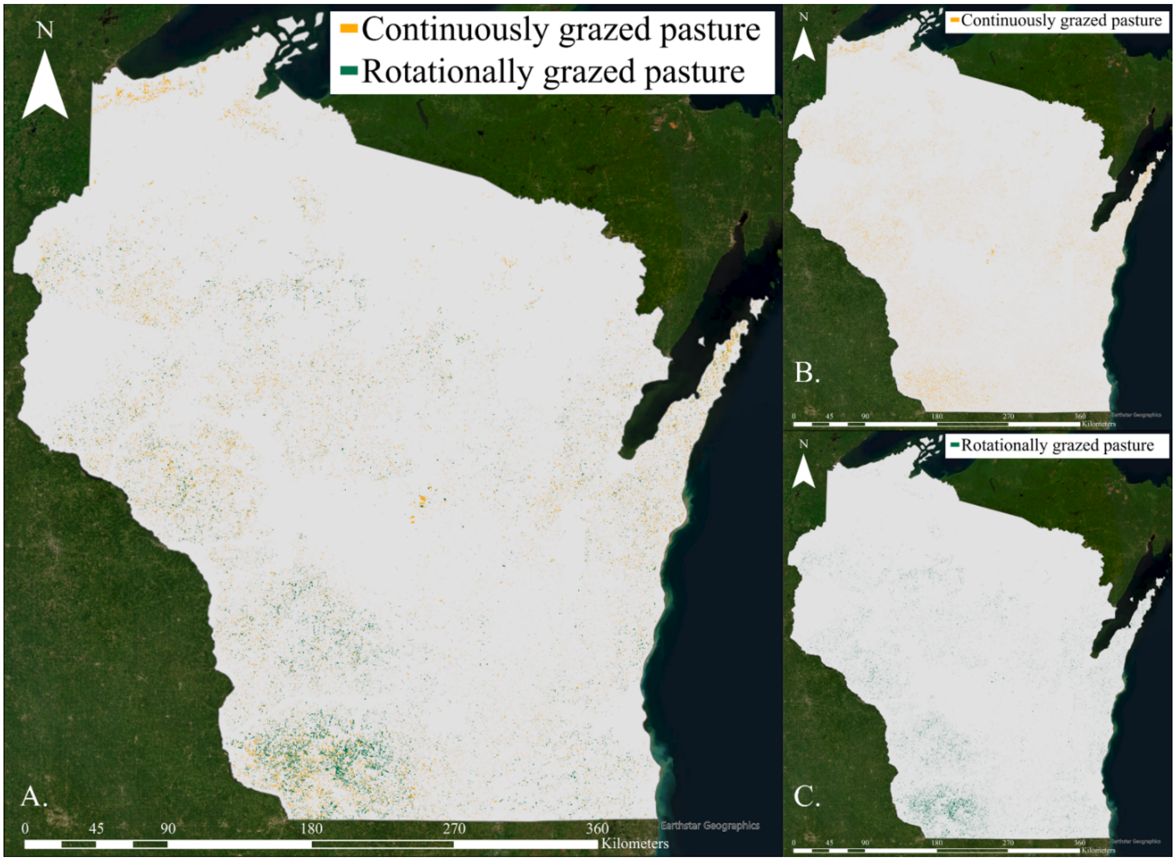


Figure 7. Maps of our model's prediction for continuously and rotationally grazed pastures. (A) Estimates of continuously and rotationally grazed pastures across the state of Wisconsin shown on the map on the left. (B) Just the estimates of continuously grazed pastures shown in the map on the upper right. (C) Just the estimates of rotationally grazed pastures are shown in the map on the lower right. An online version of this map layer can be viewed: https://arcg.is/14Snb40

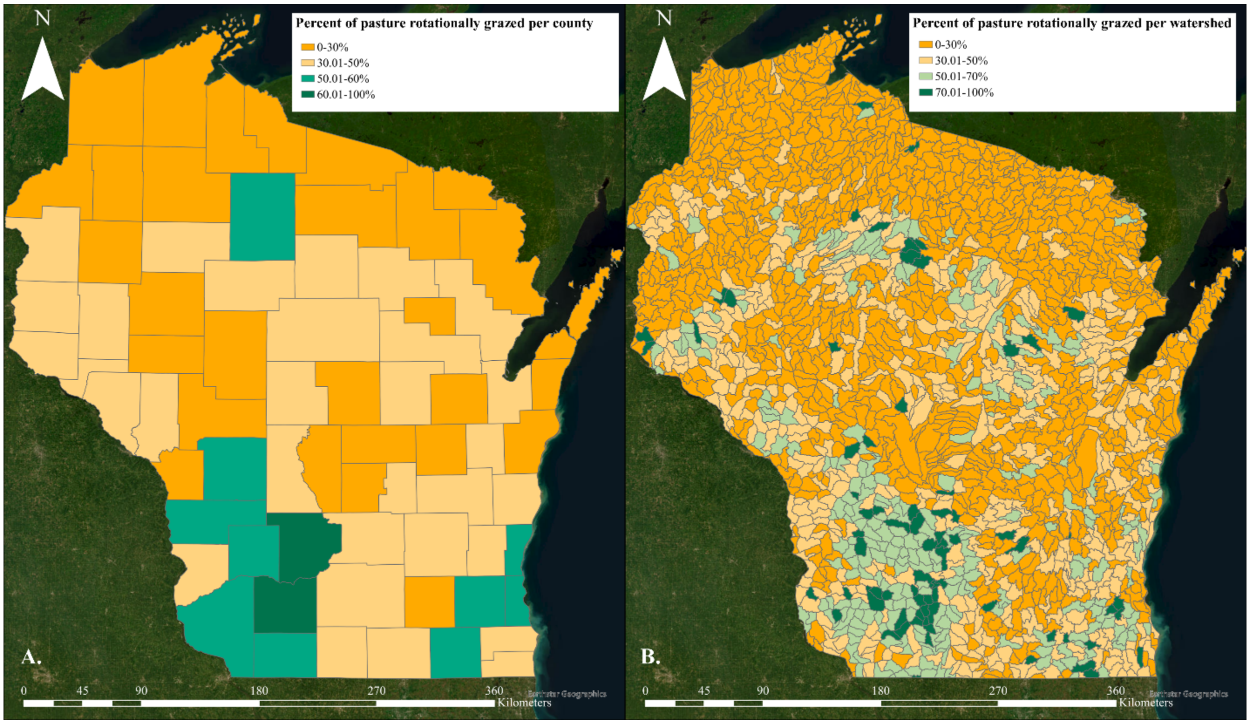
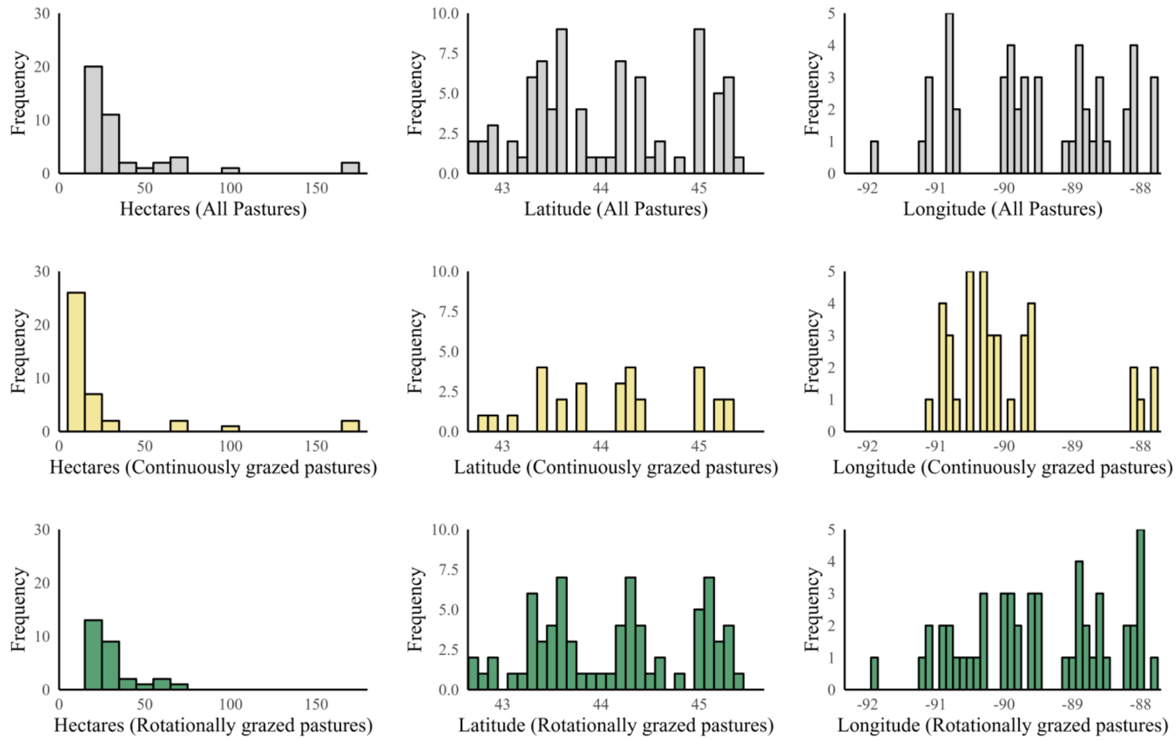
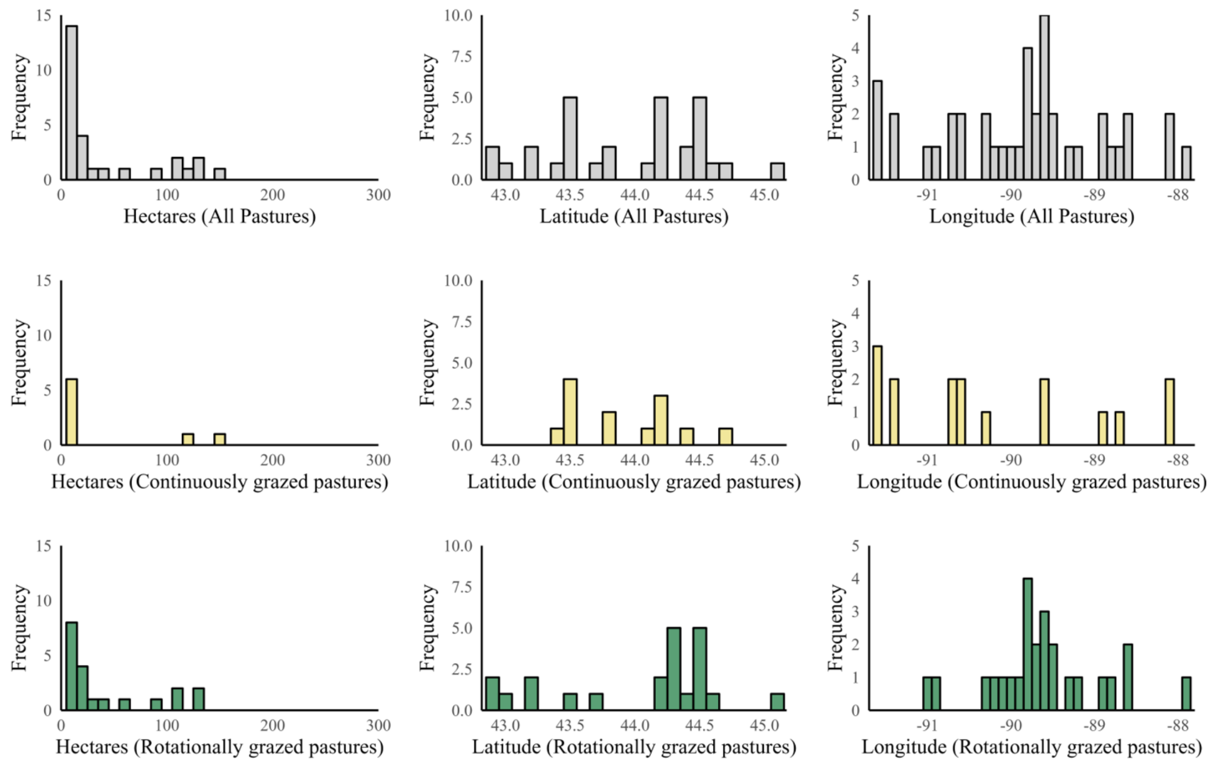


Figure 8. (A)Map showing our predicted estimates for the percent of total pastures in a given Wisconsin county that our rotationally grazed shown on the map on the left. (B) Map showing our predicted estimates for the percent of total pastures in a given HUC-12 watershed that are rotationally grazed shown on the right. Online versions of these map layers can be viewed here: https://arcg.is/14Snb40



Supplemental Figure 1. Various histograms displaying potential trends that existed in our dataset of 150 pastures (75 continuously grazed pastures, and 75 rotationally grazed pastures, the following histograms show (A) size (in hectares) across all pasture (B) size (in hectares) across continuously grazed pastures (C) size (hectares) across rotationally grazed pastures (D) latitude across all pastures (E) latitude across continuously grazed pastures (F) latitude across rotationally grazed pastures (G) longitude across all pastures (H) longitude across continuously grazed pastures (I) longitude across rotationally grazed pastures.



Supplemental Figure 2. Various histograms displaying potential trends that existed in our validation dataset of 54 pastures (29 continuously grazed pastures, and 25 rotationally grazed pastures, the following histograms show (A) size (in hectares) across all pasture (B) size (in hectares) across continuously grazed pastures (C) size (hectares) across rotationally grazed pastures (D) latitude across all pastures (E) latitude across continuously grazed pastures (F) latitude across rotationally grazed pastures (G) longitude across all pastures (H) longitude across continuously grazed pastures (I) longitude across rotationally grazed pastures.