



The Nature Conservancy

# R&D 2023 | Grasslands Health Data



# Introduction

Peer-reviewed literature and supporters of regenerative grazing practices recognize that sustainable grazing and grassland systems are characterized by 1) consistent or increasing production that is responsive to climate and resilient to drought and 2) grass and forb cover that is stable or increasing over time with bare ground cover at low or stable levels. Departures from those conditions that may indicate unsustainable management practices include decreases in production and grass cover, increases in bare ground, deterioration of cover or production following drought, shifts from perennial grass to annual grass dominance, and encroachment of woody species (Jones et al., 2020; Smith et al., 2020; Morford et al., 2022).

Regrow's approach to grasslands monitors key indicators like net primary productivity and percent cover by plant functional type over time and space, and these data allow mapping and identification of productive or stable grazing lands, lands that are degrading, and grassland conversion. This monitoring approach can be applied across scales<sup>1</sup>, is currently available across all CONUS, and does not require grazing data inputs at field or ranch scales that are often difficult to collect and disparate in method. A biogeochemical modeling framework (DNDC) then incorporates remote sensing data to coarsely estimate critical soil metrics including soil organic carbon and emissions over grasslands.

## Regrow Grasslands Products

### Remote Sensing Products

**Herbaceous Annual NPP 2015–2021** – Annual Average Herbaceous Net Primary Productivity (NPP) (gC/m<sup>2</sup>/yr) by HUC8 and CRD.

**Plant Functional Type (PFT) Percent Cover 2015–2021** – Annual Average PFT cover by HUC8 and CRD. PFTs include: Annual Forbs & Grasses, Perennial Forbs & Grasses, Shrubs, Trees, and Bare Ground.

**Herbaceous NPP 2015–2021 Trend** – Percent of area in each HUC8 and CRD exhibiting a significant seven year trend (Positive, Negative.  $p < 0.10$ ) in annual average herbaceous NPP (gC/m<sup>2</sup>/yr) or no trend ( $p > 0.10$ ).

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<sup>1</sup> For this research project, results were aggregated at the HUC8 & CRD scales

**Plant Functional Type (PFT) 2015–2021 Trend** – Percent of area in each HUC8 and CRD exhibiting a significant<sup>2</sup> seven year trend (Positive, Negative.  $p < 0.10$ ) in percent cover by PFT or no trend ( $p \geq 0.10$ ).

**Grasslands productivity that significantly deviates from climatic potential** – Percent of area in each HUC8 and CRD exhibiting a significant trend (Positive, Negative.  $p < 0.10$ ) or no trend ( $p \geq 0.10$ ) in the residuals when applying an environmental model that estimates annual average herbaceous NPP ( $\text{gC}/\text{m}^2/\text{yr}$ ) based solely on climatic conditions. See methods for more detail.

*Note: Original HUC8 boundaries extend into Canada and Mexico. HUC8 boundaries were clipped to CONUS boundaries and the reported ACRES were adjusted accordingly. This is to ensure that Mexico and Canada acres (where no data were available for this project) were not included in the statistical analyses.*

## DNDC Products

**Annual mean DNDC outcomes** (dSOC, CH<sub>4</sub>, Direct N<sub>2</sub>O, Indirect N<sub>2</sub>O) **2015–2021 by USEPA Level 3 Ecoregion** – ( $\text{kg CO}_2 \text{ eq.} / \text{ha} / \text{yr}$ )

- CH<sub>4</sub> CO<sub>2</sub> eq. multiplier =  $(16 / 12) * 28 = 37.33$
- N<sub>2</sub>O CO<sub>2</sub> eq. multiplier =  $(44 / 28) * 265 = 416.43$

## Methodology

The two key inputs to Regrow's remote-sensing based grasslands health data are *net primary productivity* and *plant functional type*.

Net primary productivity (NPP;  $\text{gC}/\text{m}^2$ ) of annual and perennial grasses and forbs **NPP represents the amount of carbon retained in an ecosystem (increase in biomass); it is equal to the difference between the amount of organic carbon production through photosynthesis (GPP) and the amount of energy that is used for respiration.**

The NPP dataset implements a long standing light use efficiency vegetation growth model (MOD17, BIOME-BGC; Running et al., 2004 ) to estimate Gross and Net Primary Productivity (GPP, NPP;  $\text{gC}/\text{m}^2$ ) at 30m resolution with parameters optimized for CONUS (Robinson et al.,

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<sup>2</sup> Pixels denoted as significant included additional criteria. If the slope of the 7-year trend of a PFT indicated a change in cover less than the PFT Model Mean Absolute Error, the pixel trend was considered not significant

2018) and cross-validated against flux tower estimates of GPP. Cross-validation results (from Robinson et al., 2018) of Flux Tower vs 30m GPP for Grasslands sites provide mean absolute bias of 1.46 gC/m<sup>2</sup>/day, an RMSE (%) of 2.01, and a Pearson correlation coefficient (r-value) of 0.72.

Plant Functional Type percent cover (PFT; %)

**Plant functional types refers to grouping or classifying plant species based on similar physiological, structural and/or phenological properties, and also reflect plant responses to resources or environmental conditions.**

The PFT data providing percent cover of annual forbs and grasses, perennial forbs and grasses, bare ground, trees, and shrubs is produced using Landsat satellite data and a machine learning model trained on tens of thousands of field plots (Jones et al., 2018; Allred et al., 2021). To capture the diversity of plant functional types across grazing lands the MOD17 model was adapted to use the PFT percent cover data to calculate NPP, where NPP for each pixel is partitioned to each PFT. For example, a mixed pixel containing perennial forbs & grasses, annual forbs and grasses, and shrubs will have an NPP estimation for each PFT that accounts for the PFT's percent cover and regional phenology. (Robinson et al., 2019)

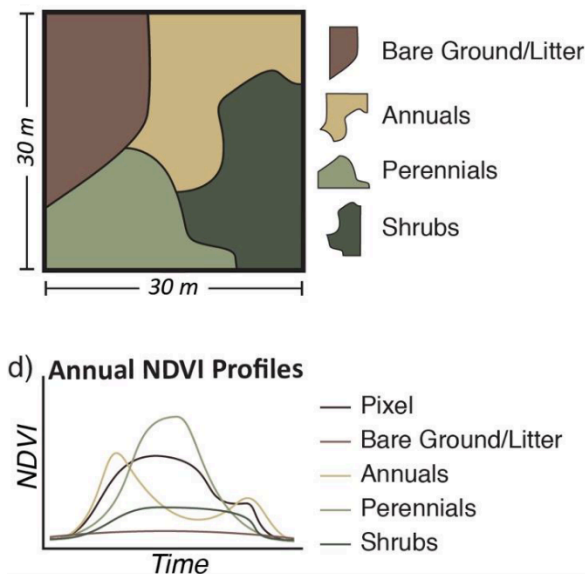


Figure 1. Conceptual diagram (from Robinson et al., 2019) displaying pixel-scale percent cover of PFTs (top) and the Normalized Difference Vegetation Index (NDVI) phenological profiles of each PFT (bottom). Phenological profiles allow partitioning of the pixel's NDVI for use in the NPP PFT calculation, which accounts for both the fractional area of the PFT and its phenological state.

Validation of model results for each PFT used 7,500 field plots not used in the model training (Table 1; Allred et al., 2021).

Table 1: Error metrics of the PFT percent cover model; Mean Absolute Error (MAE), Root Mean Square Error(%), and coefficient of determination ( $r^2$ )

Error Metric	Annuals	Perennials	Shrubs	Trees	Bare Ground	Average
MAE(%)	7.0	10.3	5.8	2.8	6.7	6.3
RMSE (%)	11.0	14.0	8.3	6.8	9.8	9.6
$r^2$	0.58	0.77	0.57	0.65	0.73	

Data used for analysis and displayed in maps were masked using the USGS National Land Cover Dataset (NLCD). Pixels categorized as crop, development, or water (including wetlands) were masked using the NLCD 2016 data to mask years 2015–2018, and the NLCD 2019 data to mask years 2019–2021 in all analyses.

### Spatially aggregated summaries of NPP & PFT

Trends in yearly PFT and herbaceous NPP were calculated for the 2015–2021 period. A Kendall’s Tau-b rank correlation (Kendall 1938) was used to test for significant trends ( $p < 0.10$ ) and the Theil-Sen (Thiel 1950; Sen 1968) estimator (Sen’s slope) to determine the slope of trends using 2015–2021 annual data for each 30m pixel. These methods are nonparametric, less sensitive to outliers, and provide a robust estimate of trends and slopes when analyzing time series data. Each pixel is then classified as no trend ( $p > 0.10$ ) or significant positive or negative trend ( $p < 0.10$ ).

Trends in perennial herbaceous cover and herbaceous NPP provide insight on the effects of woody encroachment and annual grass invasion; degrading grazing lands where cover and production of valuable forage show significantly negative trends concurrent with advancing tree cover and annual grasses. Each NPP aggregation contains the fraction of area exhibiting stable productivity, an increasing trend in productivity, and a decreasing trend in productivity (degradation) from years 2015 – 2021, as well as the fraction of area not included in the analysis (categorized as crop, development, or water/wetland in the 2019 NLCD land cover).

## Grasslands productivity that significantly deviates from climatic potential (Residuals)

Climate change and human activity are two main factors driving vegetation dynamics in herbaceous systems. Net primary production (NPP) interannual variations are mainly controlled by annual precipitation in most rangeland ecosystems (Lauenroth & Sala, 1992). Compared with climatic factors, however, the influence of human activities is difficult to estimate, but quantification of deviation from productivity that would have been expected due to climate alone can be a useful tool to assess human-driven effects.

Identification of lands that demonstrated herbaceous production that significantly deviated from climate driven potential production required the implementation of geographically complex, ecoregion specific, environmental models to properly capture NPP responses to localized bioclimatic conditions. The main objective was to distinguish vegetation NPP changes due to climate variations from those induced by land use/land management (e.g., grazing, seeding, etc.). The methods were two-fold. First, the NPP interannual variation due to climate factors was estimated by an environmentally driven model. Second, after the model was applied, analysis of the temporal trends of the residuals of the model would provide an indication of the non-climatic impacts on production.

Yearly herbaceous NPP data from 2003–2021 served as the dependent variable with local environmental controls (serving as independent variables) represented by three groups of climate factors:

- [precipitation](#) (annual, two, and three years accumulated precip.),
- [temperature](#) (annual mean, maximum, and minimum), and
- [aridity](#) (several arid indices supplied on different time scales corresponding to the time aggregation of the primary variable).

Ecoregion Level III boundaries ([CEC](#), 1997) were used to identify areas with similar environmental conditions. Dependent and independent variable data were extracted over random points in each ecoregion; 1000 to 2000 points dependent on ecoregion extent and excluding pixels not classified as pasture/hay, grassland/herbaceous, forests, or shrubs in the NLCD land cover. Statistically significant ( $p$ -value < 0.10) independent variables that explained the highest level of interannual variation of NPP were retrieved. The ecoregion specific independent variables were then used in a linear regression (for each ecoregion) to calculate climatically driven potential production. The residuals of the resulting ecoregion specific models (representing the deviation from expected production) were then used in a

Kendall's Tau-b rank correlation, where statistically significant increasing or decreasing trends (and non-significant trends) in the residuals were mapped. **Positive trends indicate areas where production was greater than the climatic potential, negative trends were indicative of production lower than climatic potential, and no trends were indicative of production aligned with climatic expectations.**

Coarse DNDC model assessment of current trends in SOC and GHG over grasslands Remote-sensing (RS) data provide top-down observations of the land surface but do not provide observations about conditions below-ground. While the process-based biogeochemical model DNDC simulates these above-ground processes and biomass, it further simulates below-ground soil processes to provide estimates of hard-to-observe biogeochemical processes that contribute to changes in soil carbon sequestration and greenhouse gas emissions. RS data provide key information on plant dynamics and growth that is directly observed and estimated from spectral information and the NPP light-use efficiency model.

In this coarse model assessment of DNDC over CONUS grasslands, we assimilated time-series of RS-NPP into DNDC to improve simulations of plant growth dynamics above-ground (DNDC-NPP) and therefore provide better estimations of above-ground biomass accuracy and improve below-ground processes that align with the RS observed production.

DNDC is a point based (single field/location) model and executing the model at a scale matching RS data (e.g. at every 30m grazing land pixel across CONUS) is not a scalable option from a computation perspective, nor is it explicitly necessary when conducting a coarse scale assessment of model performance as the primary grassland soil flux drivers are soil properties and climate, which do not vary at such fine (i.e. 30m) resolutions. Therefore, for this model assessment DNDC was run at the field-level at 180 locations within each USEPA Level 3 Ecoregion scale for a total of ~15k simulations across CONUS.

The 180 samples in each ecoregion were weighted by the area of each soil texture in the ecoregion. These results were then aggregated to the ecoregion scale. When selecting representative sample locations within each ecoregion, two masking layers were used to ensure that locations grew perennial grasses. The inner join was taken of these masks to be conservative.

- National Land Cover Database (NLCD) data layer, where included all locations (pixels) labeled as Grassland/herbaceous, Pasture/hay, Shrub/scrub, Barren land and Dwarf scrub.

- Regrow data layers of Net Primary Production (NPP) for four classes of plant functional group: perennial grasses, annual grasses, trees, and shrubs. Locations (pixels) were only included if perennial grasses dominated all other plant functional groups during the peak of the growing season over the last 10 years.

Simulations were run with a spin up of 40 years, with outputs for 2015–2021. In these simulations, no management was applied, there was no weighting for climate variables and manure was not an input to DNDC.

## Resources

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