A Satellite Remote Sensing Methodology to Assess Pasture Recovery Time After Grazing Animal Impact

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Introduction

While seeking internships for summer 2018, an incredible opportunity came my way to pursue an independent research project at Caney Fork Farms, located in middle Tennessee (Smith County). The farm, which is only now in its infancy, strives to model economically viable and regenerative land stewardship; its mission, to "inspire others with living proof that carbon farming benefits farmers, the community, and the environment" is undoubtedly ambitious, but with the support of a generous endowment and with a team of highly-educated world-class farmers, its surely within reach. I accepted the opportunity with excitement; I was eager to create value for the Caney Fork Farm team as they pursued their mission, to promote sustainable agriculture more broadly, and to strengthen my own skill set.

One of the core components of stewardship at Caney Fork Farms involves a knowledge-intensive system of grazing livestock known synonymously as management-intensive rotational grazing, regenerative grazing, adaptive grazing, and by other names. A comprehensive 2017 Food Climate Research Network report defines this approach: *"…animals are grazed at very high stocking densities for a short time within a fenced area so that they eat a high fraction of the available vegetation, deposit manure, and intensively trample the soil. They are them moved to another area, and then another, and so forth. The grazed land is left to recover before animals are allowed back on it.*" Benefits of regenerative grazing have been heralded in a number of academic papers and in farmer testimony, and include (1) encouraging desirable forage species over time (species with higher nutritional profiles for livestock), leading to greater animal health and higher pasture carrying capacity, (2) healing degraded land through the trampling action of ruminant hooves which break up soil hard pans and reshape the micro-topography of land to enhance water-capture on site, and (3) promoting soil-carbon sequestration through the cycling of plant-based carbon into manure and through the shedding of carbon by perennial grass root material and sugary exudates deep into the earth (Garnett et al).

At Caney Fork Farms, over 350 acres, divided into 33 permanent pastures (themselves often divided into temporary "sub-paddocks" 1-4 acres in size) are grazed in this manner by a so called "flerd" of cattle, sheep, and goats[1]. Grazing planning is conducted in wintertime. Its an intensive process of mapping animal movements across the landscape, weighing factors such as pasture acreage, forage productivity, vegetation composition (some areas of the farm are dominated by a suite of "cool-season grasses" that have faster recovery rates early and late in the growing season, while other areas are dominated by "warm-season grasses" which are best grazed during the heart of the season), peak palatability (cattle prefer vegetation fresh and tender before it goes to seed and lignifies), convenient movement regime (its easier for the farmer to move animals from one paddock to an adjacent one instead of across the entire site!), and winter preparation (i.e. some pastures need to be hayed to ensure adequate feed year-round). It's also a speculative process, based on predicted flerd size, keen observation of historic growing seasons, and deep knowledge of site. The plan is continually adjusted throughout the growing season based on continuous site observation. Images 1 and 2 showcase pasture on Caney Fork Farms.

[1] The term for a group of cattle is "herd," while the term for a group of sheep or goats is a "flock," thus colloquially becoming a "flerd" when grazed together as a single unit!

Image 1

Cattle grazing on pasture at Caney Fork Farms

Image 2

Birds-eye-view of most of the 33 permanent pastures on site

After arriving on site and learning about the farm operations, I couldn't shake the idea that remote sensing analysis- the practice of observing earth from aerial sensors – in concert with other geospatial data and techniques might offer real value for regenerative grazing strategy. I was especially enthusiastic because I saw opportunity to apply some breakthrough tools to a domain of geospatial analysis that few, if any, people have yet explored.

Consider that most remote historic remote sensing analysis has been conducted at the county-wide, regional, or even larger scales because most (if not all) publicly available satellite imagery has relatively poor spatial resolution (i.e. two commonly used satellite systems MODIS and Landsat have spatial resolutions of 250-500 and 30 meters respectively). Likewise, most satellite imagery analysis is conducive to relatively long-term investigations (i.e. monthly, seasonal, or annual timescale) because most satellites in orbit snap a picture of a given spot on the earth's surface once every handful of days or weeks (i.e. Landsat has a so-called "return time" of 16 days). However, in only the last few years, there has been an extraordinary revolution in satellite data products. For example, Planet Labs' PlanetScope constellation, which has only been in orbit since August 2016, offers high spatial resolution (3.5-4 meters) and high temporal resolution (1-day "return time") satellites, providing the possibility of more targeted analysis (a few hundred acres) over shorter time periods (a few days). Truly cutting edge! Similarly, while gathering background information prior to my arrival on the farm, I discovered that in December 2017 the Tennessee Department of Finance Administration, STS-GIS services was awarded a $730,000 grant from the USGS to collect LIDAR data across 17-counties in middle Tennessee. LIDAR is a remote-sensing technology that relies on a laser pointed at targets to collect sub-inch point-distance data. When the data is published in early 2019, it will permit an ultra-accurate model of elevations across the farm, and subsequently an ultra-accurate mapping of water flows- valuable information that could be integrated into my analysis, however far I had progressed. Lastly, like the revolution is satellite technology, there has been a huge breakthrough recently in our ability to efficiently process satellite data. This is thanks to Google's Earth Engine platform, which avails massive cloud-based computing power and storage capabilities to the average user. This is all to say that I was excited about the possibility of conducting innovative work that would arise from using state-of-the-art data products, with the high-octane Earth Engine platform. Satellite remote sensing is today what the cell-phone was 25 years ago; sleek iPhones are in the making.

Objectives

My primary objective was (1) to trial and assess a methodology in which pasture recovery time after animal impact could be predicted based on a set of relevant variables, including weather, soil condition, grazing intensity, and hydrology. A secondary objective was (2) to develop such a model for Caney Fork Farms.

An aside: I strongly believe that acute on-the-ground observation and record-keeping by thoughtful natural resource managers is the main driver of successful natural resource management. I want to highlight that in my several years working with attentive land-stewards, the managers of Caney Fork Farms are particularly wizard-like in their deep knowledge of site ecology and animal and crop health. The impetus of this tool is to complement keen human observation with a data-driven approach to pasture management, possibly exposing new insight into whole-site carrying capacity, variability across pastures, and management prescriptions.

Methods

The model relies upon a widely accepted indicator of green vegetative cover used in remote sensing called the NDVI, or *normalized difference vegetative index*. This index takes advantage of the stark differences in the reflective properties of near infrared wavelengths of the electromagnetic spectrum and visible red wavelengths of the electromagnetic spectrum for green vegetative material[2]. NDVI is formally defined as (NIR-R)/(NIR+R), with a range of values between -1 and 1, where higher values describe greater green vegetation cover. NDVI has been used to predict vegetative biomass and has been used as a proxy for gross primary productivity (Pettorelli). Here, it is assumed that higher NDVI values indicate greater amounts of vegetative forage. Thus, the rate of increase of NDVI describes the incremental recovery of a given pasture after animal impact. Limitations of this index are described in depth in the discussion section below.

In theory, the full model would be parametrized as such:

Model 1: *Theorized ideal*

$$NDVI = \beta_0 + \sigma_0(DailyWeather)_{T-30:0} + \lambda_0\left(\frac{AU}{Acre}\right)_{T-30:0} + \delta_0(Soils) + \theta_0(Hydrology) + \mu_0(Species) + \epsilon$$

where (i) *NDVI* equals the NDVI value for a given pixel in a given paddock on a given day of the 2017 growing season, (ii) $(DailyWeather)_{T-30:0}$ equals a suite of weather variables, including precipitation, temperature high, and temperature low, for each of 30 days prior to each pixel-day observation, (iii) $\left(\frac{AU}{Acre}\right)_{T-30:0}$ equals animal units per acre for each of 30 days prior to each pixel-day observation[3], (iv) $(Soils)$ equals a set of two variables that describe soil condition for each pasture including percent organic matter[4], and total exchange capacity[5], (v) $(Hydrology)$ equals the flow accumulation for a given pixel on the farm taken from a LIDAR-derived DEM of the site, where flow accumulation describes the area of each pixel's upstream watershed and can be used to account for water availability in a given location on pasture, and (vi) $(Species)$ equals a classification of the dominant forage species for a given pixel (given some idealized classification approach that does not yet exist).

[2] Green vegetation is highly reflective in the near-infrared, while it is highly absorbent in the red. Plant material typically reflects near-infrared light at upwards of five times the rate it reflects visible green light.

[3] An "animal unit" is a commonly used measure to equate the forage consumption of differing species of grazing livestock, whereby for example one 1000lb beef cow is equal to 1 AU, while six 130 lb sheep are equal to 1 AU.

[4] Soil organic matter content leads to higher water-holding capacity and greater aeration, increases cation exchange capacity, acts as a source of essential plant nutrients, and feeds the soil food web.

[5] Exchange capacity describes the nutrient holding capacity of soil, whereby small soil particles, like clays and organic materials, are better able to bind nutrients in soil solution than larger soil particles, like sand.

Ultimately, I was unable to organize the data on a per pixel basis due to the extensive memory requirements needed to convert a raster image into a vector-based file. Ultimately, data was organized at the sub-paddock level; the *NDVI* variable above was amended to equal the average NDVI value for a given sub-paddock on a given date of the 2017 growing season, and $(Hydrology)$, which exists on a per-pixel level, and $(Species)$, which data is unavailable, were removed from the equation:

Model 2: *True model used for analysis*

$$\boldsymbol{NDVI} = \boldsymbol{\beta_0} + \boldsymbol{\sigma_0}(\boldsymbol{DailyWeather})_{\boldsymbol{T_{-30:0}}} + \boldsymbol{\lambda_0}\left(\frac{\boldsymbol{AU}}{\boldsymbol{Acre}}\right)_{\boldsymbol{T_{-30:0}}} + \boldsymbol{\delta_0}(\boldsymbol{Soils}) + \boldsymbol{\epsilon}$$

Data Collection and Processing

NDVI: NDVI values were acquired from Planet Labs' PlanetScope satellite constellation Level 3A surface reflectance product[6]. The level 3A data is preprocessed by Planet, including orthorectification (removal of terrain distortions), sensor and radiometric corrections[7], and atmospheric corrections, facilitating image preparation. 38 cloud-free[8] image date zip-packages for the 2017 growing season (April 8- October 31) were initially acquired from the Planet Explorer data portal. Three of those datasets did not include an atmospherically corrected image product in the download; manual correction was decided against due to uncertainties around the Planet atmospheric correction algorithm and thus these image dates were discarded. An additional image date (that for April 8) was discarded because it was an outlier in time with over a month before a subsequent image date (May 9) was available. Consequently, a total of 34 images were incorporated into the model (Table 1).

Table 1

05/09	05/10	05/14	05/16	06/07	06/09
06/27	07/01	07/10	07/11	07/17	07/18
07/19	07/20	07/21	07/22	07/26	07/30
07/31	08/03	08/18	08/19	08/20	08/22
09/04	09/08	09/09	09/16	09/26	10/04
10/06	10/17	10/19	10/31		

List of dates in the 2017 growing season incorporated into the model.

All images were imported as independent assets into Google Earth Engine, along with their corresponding "unusable-data mask" (udm), a file that indicates cloud-cover, and missing or suspect data for each band (generated by Planet Labs). The udm was applied to each image, along with a second mask which eliminated all pixels with reflectance value 0 for any of the bands (a few such pixels occurred for some images. These would have slipped through Planet's udm; though some pixels might have truly low reflectance values, indicating a black surface, a value of 0 would be extremely unlikely, and would skew subsequent operations; see next paragraph). Each masked image was clipped to isolate Caney Fork Farms.

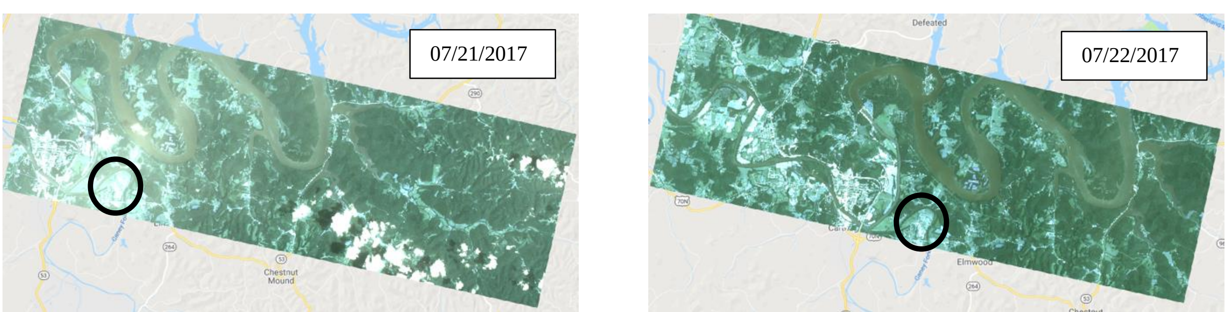
[6] For the PlanetScope satellites, $\text{NDVI} = (\text{NIR}_{(780-860nm)} - \text{R}_{(590-670nm)}) / (\text{NIR}_{(780-860nm)} + \text{R}_{(590-670nm)})$

[8] PlanetScope satellites pass over the farm consistently at ~4PM CT

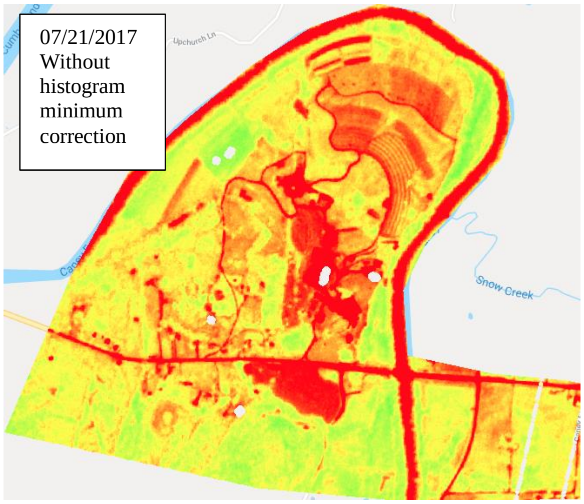
I then applied a *histogram minimum* correction to all of the masked and clipped images, whereby for each band (B, G, R, NIR), the minimum value across the entire image was subtracted from each pixel value for that band. This correction acts as a control for haze, which is not corrected for in Planet's atmospheric correction algorithm. The premise here is that across all images, there exists a dark pixel (valued near zero) for each band, whereby any light reaching the satellite sensor is assumed to be a result of light reflection from atmospheric haze, and *not light reflected from the underlying earth surface*. Subtracting this minimum value from all other pixels in the scene would theoretically remove any haze from the scene, thus normalizing band values across all days in the timeseries where the atmosphere might be more contaminated with haze on some days than on others.

Two crucial assumptions are made here. The first is that in each image, there exists a similarly dark pixel for each band. I am confident that this assumption holds because the Caney Fork River, which wraps around the farm and exists in each image, likely contains the lowest reflecting pixel within each band[9]. The second assumption holds that for a given day, the haze would be equally distributed across the landscape. Though, there were probably slight differences in the thickness of haze from one location to another across the farm on a given day, the land-area of the farm is sufficiently small that differences should be sufficiently negligible. Image 3, displays the NDVI images from July 21 (particularly hazy) to July 22 (not hazy) before the histogram minimum correction is applied, and after the histogram minimum correction is applied. Before the histogram minimum correction, a drastic increase in NDVI is seen from one day to the next, surely not indicative of any on-the-ground changes. After the histogram minimum correction, changes in NDVI from one day to the next become more diluted.

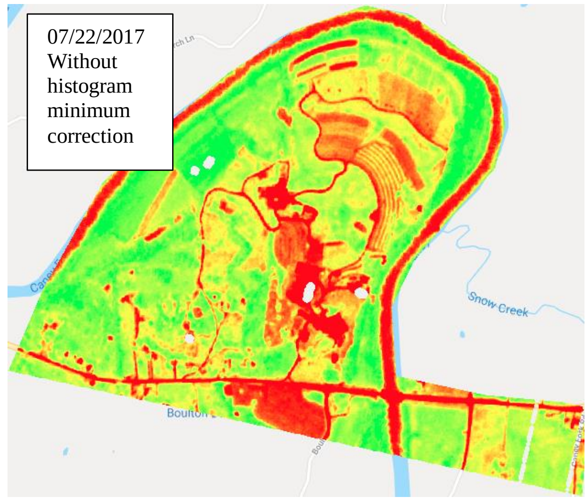
Image 3



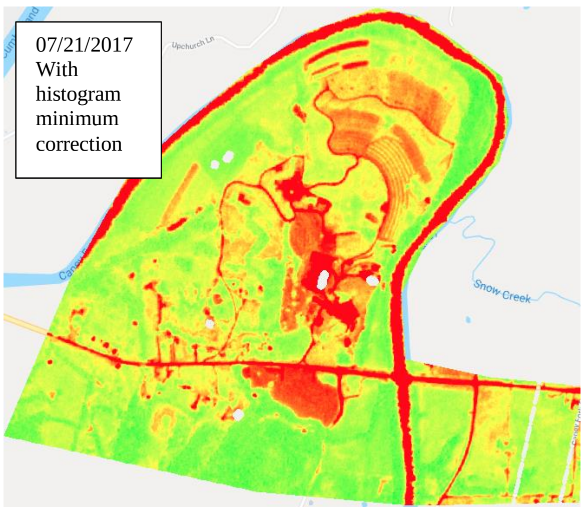
[9] An alternative and similar approach known as "Dark Object Subtraction" might have been a good choice for elementary haze correction as well. Here, a dark location assumed to be constant across images would have been manually selected, and used to normalize all images. However, I opted against this approach because I feared that the differing nadir angles of the satellites on a differing days might lead to inconsistent glare effects at a chosen spot on the water



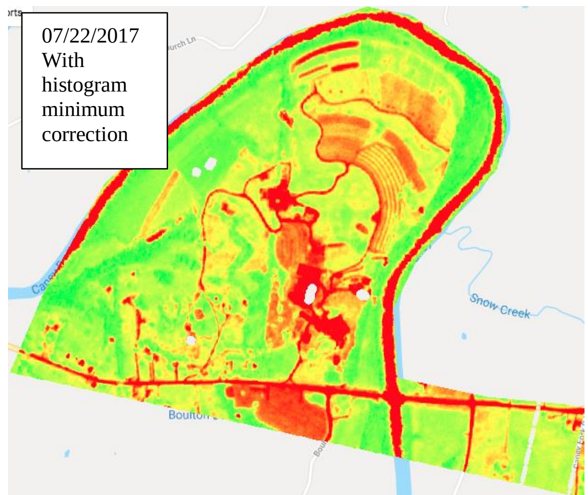
Mean NDVI = .6160



Mean NDVI = .6568



Mean NDVI = .6962



Mean NDVI = .6995

Top: Complete true color image file over Caney Fork Farm and greater geography on July 21 and July 22. It is clear that weather is cloudy/hazy on July 21 image date.

Center: July 21 and July 22 ndvi of Caney Fork Farms before histogram minimum correction is applied. Green represents high NDVI values, red represents low NDVI values. Drastic increase in NDVI is apparent across the entire image from one day to the next, certainly not a result of any land-driven changes from one day to the next. Mean NDVI values across the entire farm vary approximately 4 points.

Bottom: July 21 and July 22 ndvi of Caney Fork Farms after histogram minimum correction is applied. Mean NDVI values across the entire farm vary by .3 points.

Then, with the bands normalized for haze effects, I calculated NDVI across all pixels in each image. I manually drew out the shape for each known sub-paddock on site, (see *Animal Units/Acre* discussion below), stored these as geometric vectors on Earth Engine, determined acreage for each geometry (for *Animal Units/Acre*, described below), and used these geometries to determine the average NDVI value for each sub-paddock for each image date. Data points for all NDVI sub-paddock dates were exported from Earth Engine as a .csv file and imported into R for further analysis.

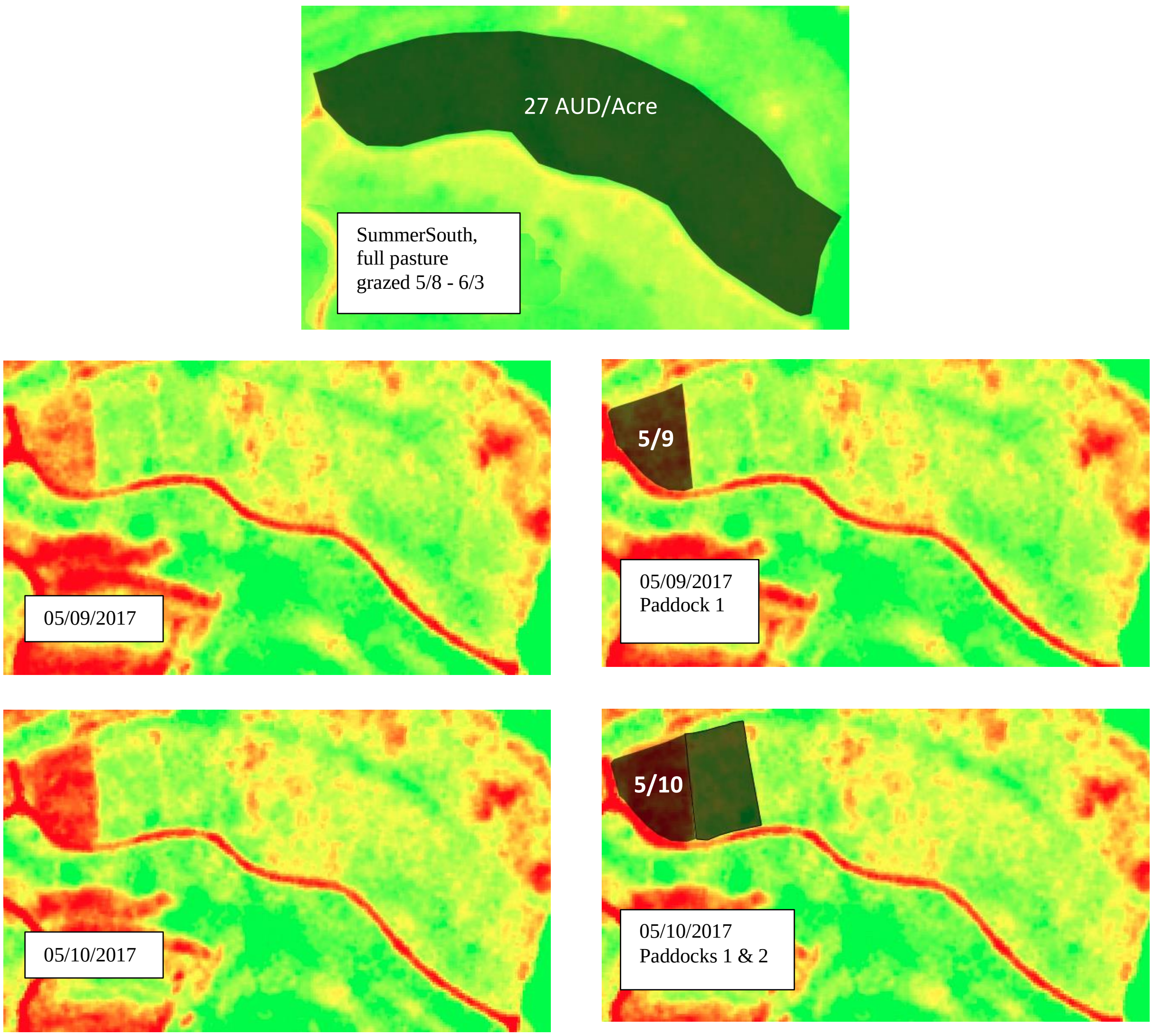
Weather: Daily weather data was downloaded from the NOAA National Centers For Environmental Information historic weather archive for Lebanon, Tennessee, the nearest weather station to Caney Fork Farm (~20 miles southwest). Weather data was appended to the NDVI-paddock-date data in R. Temperature lows and highs in Lebanon would be strongly representative of on-farm conditions. However, daily precipitation data might vary significantly given the pattern of strong scattered summertime fronts that frequent central Tennessee. Precipitation data would be more valuable if monitored directly on the farm.

Soils: Soils data was based on a September, 2015 pasture-specific (6 in depth) soil test conducted by Logan Labs, LLC. Soils data was appended to the NDVI-paddock-date data in R. Soils data was not taken during the 2016 or 2017 seasons. The 2015 data may or may not be representative of true soil conditions during the 2017 growing season; pastures had been grazed during the following 2016 season which might have affected conditions, though no soil amendments had been applied between the date of the soil test and the 2017 growing season.

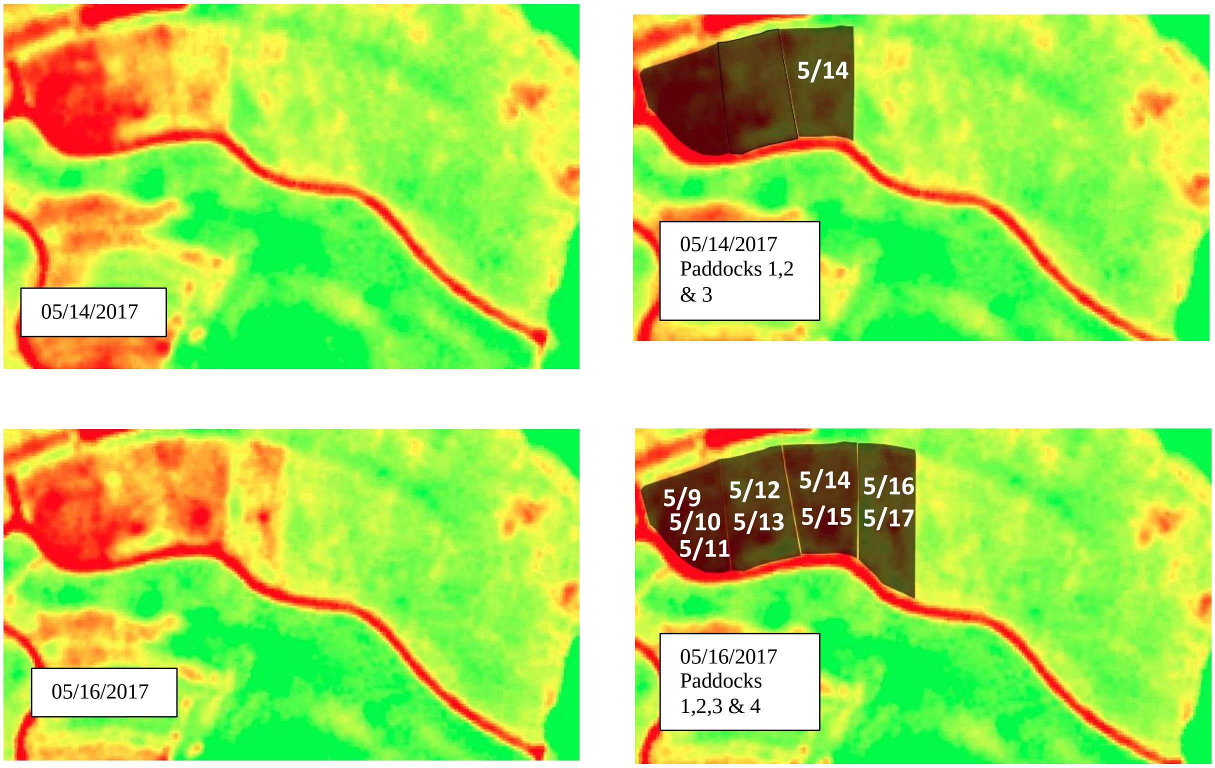
Animal Units/Acre: Animal units data was based on historic records kept by the Caney Fork Farms livestock manager from the 2017 growing season. Records included animal units on a given pasture on a given date. These records were necessary for this study, though they were imperfect for several reasons: First, although the records described which *permanent* pasture animals were grazing, the records failed to describe animal movements from one sub-paddock to the next within that permanent block. For example, the records noted that the flerd was grazing *SummerSouth*, a permanent 20-acre pasture, for a period of 27 days between May 8 and June 3, 2017. However, *SummerSouth* was itself broken up into 10 separate approximately 2-acre temporary sub-paddocks, each of which was grazed independently for a period of 2-3 days. Second, though the exact location of each permanent pasture was known, the exact location of each sub-paddock varied slightly based on where the farm team set up temporary fencing for a given flerd movement.

To best reconstruct the exact location of each sub-paddock and the exact location of the flerd on a given day, satellite images were rigorously scrutinized. Where steep NDVI gradients are seen in a given pasture during a period when grazing animals were recorded to have been in that pasture, gradient contrast would have denoted the edge of one sub-paddock before the next. Low NDVI values would have indicated which sub-paddocks were already grazed, while higher NDVI values would indicate sub-paddocks yet to be grazed. Image 4 demonstrates an example of this methodology. Here, the May 9, May 10, May 14, and May 16 satellite images (NDVI) were observed. Knowing that animals were recorded to have been on *SummerSouth* between May 8 to June 3, I was able to trace the shape of a given sub-paddock, determine acreage of a traced sub-paddock on Google Earth Engine, and infer timing of animal movements. In total, I was able to reconstruct precise locations of 23 sub-paddocks, and infer the flerd location on 95 days of the growing season[10]. An interview with the head livestock manager regarding personal recollections of the 2017 grazing season (general flerd movement patterns, general shape of pasture divisions into sub-paddocks) served to validate image inspection[11]. Animal units data was appended to the NDVI-paddock-date data in R. Data points were divided by sub-paddock acreage in R, resulting in an animal units/acre variable.

Image 4



[10] I characterized these inferences on a 3-point scale, noting whether I was "completely confident," (36 data-points) whether the inference was "strongly evidence-based" (22 data-points) or whether the inference was "evidence-based" (37 data-points). All data points were used in the full analysis, though this characterization could be used to create additional models where only the most reliable data is used as input.



Example reconstruction of sub-paddock geometry and flerd location based on inference from satellite imagery NDVI edges. Historic grazing records were paired with sub-paddock image reconstruction and farmer livestock manager personal recollections to describe total animal units on a given sub-paddock on a given date during the 2017 growing season.

See Appendix 1 for structure of full data set. The data includes 690 NDVI-sub-paddock day observations for which the data is complete.

Results

A linear regression was performed according to Model 2 (described above). Model estimators are detailed in Appendix 2. 64 of the 127 predictor variables (TMAX and TMIN variables as well as a few PRCP variables) were undefined because of singularities in the data.

Discussion

Come wintertime, when its time again to plan for the 2019 grazing season, theoretically, pending valid underlying data and accurate model parametrizations, the Caney Fork Farms grazing manager would be able to test a draft grazing plan for the upcoming season by inputting given soils parameters, weather expectations, and proposed animal units on a given sub-paddock at a given period. The model, theoretically, again pending valid underlying data and accurate parametrizations, would be able to predict the NDVI on a given sub-paddock, so that presuming a defined NDVI value conversion that signals “go ahead and graze!,” the farm manager would know when a sub-paddock is ready to be grazed and re-grazed. In turn, this, theoretically, would offer insight on efficient forage usage across pasture on Caney Fork Farms and over the time of the growing season. For now, for the below reasons, these theoretical propositions ought to remain merely theoretical:

On the validity of satellite data used for model construction: A fundamental assumption that underlies this methodology is that the day-to-day atmospherically corrected image reflectance values derived from the PlanetScope constellation are a true depiction of surface reflectance alone across time. I already described one instance where this assumption does not hold- in the case of haze- though this issue was accounted for using the histogram minimum operation prior to data analysis. A more basic issue yet to be addressed requires examination of the PlanetScope satellite constellation and its sensors. Whereas heavily relied upon systems like Landsat or Modis are individual satellites, PlanetScope is not. Rather, it's a constellation of over 130 satellites, each identically constructed, and launched into orbit at varying times. Significant problems seem to be linked to image capture from a multiplicity of sensors.

Artemis Software (*Normalized Difference Vegetation Index*) elegantly describes (1) sensor degradation and (2) off-nadir effects as limitations of using NDVI in remote sensing analysis:

(1) Sensor degradation effects: *"...the overall relationship between the radiation received by the satellite and the pixel value is given by the radiometer's calibration. However, the satellite radiometer degrades over time. Consequently, the calibration coefficients are not constant... When using NDVI imagery, care must be taken to ensure the data has been corrected."*

(2) Off-nadir effects: *"...the viewing angle at which the radiometer surveys vegetation has an influence on the NDVI value. For example, directly above a region of crops the crops and the soil will be visible to the radiometer. However, viewed at an angle, the region may seem to have continuous vegetative cover. In this case, the NDVI values will be lower directly beneath the radiometer."*

With regards to point (1), because each of the 130+ SkyScope satellites were constructed and launched at different times, sensor degradation would vary across the satellites. Thus, calibration would be particularly important; any imperfections would lead to errors in data consistency across images taken by different satellites. Planet Labs describes "vigorous" sensor calibration techniques in their 2017 Product Specification sheet,[12] and so I am inclined to trust that sensor degradation effects would be controlled for.

With regards to point (2), this seems to be a more serious problem. Each satellite in the PlanetScope constellation captures DN values with variable view angles of ~0-4 degrees (as of 2017), though most- based on informal perusal of satellite imager have view angles between 0 and 1 degree. These discrepancies in view angles were not controlled for in this analysis and therefore lead to some data inconsistency across time. An example illustrates this problem: On

[12] "based on lab calibration, regular checks of statistics from all incoming image data, temporal monitoring using lunar calibration, and on-orbit absolute calibration using instantaneous crossovers with well calibrated satellites and vicarious campaigns."

July 10, 2017, two separate satellites of the PlanetScope constellation (ID 1022 and ID 0f12) both took images over Caney Fork Farms at 3:43PM and 3:44PM respectively (within 2 minutes of each other!). Satellite 0f12 had a view angle of 1.4 degrees off-nadir while satellite 1022 had a view angle of 3.8 degrees off-nadir. I processed each image to acquire an NDVI band for each scene, calculated the average NDVI value over the whole of Caney Fork Farms and for *SummerSouth* alone (a permanent pasture used for the model), for each image, and found the difference in values. Average NDVI difference over the whole of Caney Fork Farms between the two images was .022, though the difference was smaller at .019 over *SummerSouth*[13]. Based on this informal test, we might assume confidence for NDVI as an indicator of land-based change alone of ±.019, enough to obstruct the accuracy of the model, but not reason to fully neglect it. This methodology would be more valid if it properly controlled for discrepancies in satellite view angle via specification of a specific view angle in image selection (seemingly, the vast majority of PlanetScope satellites capture images at a view angle of .1 degree off-nadir, based on informal perusal).

On the validity of other data sources: (1) Precipitation data would have been more valid if monitored directly at the hyper-local level. (2) Soils data would have been more valid if soil tests were available for 2017, the year that NDVI data was analyzed. (3) Animal Units data would have been more valid if records were kept at the sub-paddock level instead of at the permanent pasture level (where image visualization and inference were necessary). (4) Sub-paddock location would have been more valid if temporary fences were georeferenced with a high-accuracy (preferably sub-meter) gps receiver each time animals were moved across pasture. At Caney Fork Farms, some such transitions to ensure higher quality data for future analysis are already underway[14]. Others, like proposals (1) and (4) might be more invasive to farm operations, though they might be worth considering if rigorous on-site data collection is deemed to be important for the farm's mission.

On the strength of the model: The statistical approach presented in this paper, needs further examination. Improvements to the model would likely involve reducing the number of regressors so that insight could be generated from fewer data points. A reasonable approach might be to include historic weather and AU//Acre variables for each of 15 or 20 days prior to each pixel-day observation instead of for each of 30 days, as was the case here.

On determining "Go ahead and graze!" from NDVI values: For any real utility, a predicted NDVI value would need to be translated into an actionable management recommendation: something to the effect of "go ahead and graze!" or "land not yet fully recovered!". One means to set such a translation would be to establish (a) threshold NDVI value(s) through a ground-truthing exercise. Here, a grazing expert would point out the optimal moment in time when (a given) pasture(s) is ready to be re-grazed, and this data would be paired with pasture NDVI data at time of characterization. Ideally multiple thresholds would be conceived, one for each pasture

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[13] Interestingly, the difference in NDVI values was greatest on the river (~.038 from large sample of points) and metal-roofed farm buildings (~.027 from large sample of points), which is likely attributed to sun-glare effects specific to these surfaces.

[14] The farm is currently transitioning to a record-keeping platform called *PastureMap*, whereby animal units per sub-paddock will be monitored digitally. The app also encourages documentation of the exact timing (to the nearest hour) of animal movements across pasture. The farm is also implementing annual and more intensive soil testing. Such a system of records will raise confidence around data for future studies.

of Caney Fork Farms, due to the varying composition of forage species[15]. Another means to set such a translation would be to establish the "go-ahead" when NDVI reaches some pre-animal-impact value. This would be a more convenient conversion because no ground-truthing would be necessary. However, this method trusts that historically, animals had been allowed onto pasture at an optimal moment in time when biomass accumulation was sufficient to ensure forage endurance, but not too late that forage had begun to go to seed. The first option seems more promising.

Future Work

I believe that future iterations of this tool have the potential to overcome challenges, and to offer significant value not only to a single farm, but at scale. Caney Fork Farms is continuing to keep records for the 2018 grazing season. Those records alone could double the reliability of the model. Likewise, with some outreach via NRCS, Holistic Management International, and sustainable farming thinktanks, certifying bodies, professional associations, and social network groups, data from additional regenerative grazing operations probably could be accessed and funneled into the model. With each additional data contribution, the strength of the model would grow.

Speculation about future possibilities might be futile, but all trends point to continued rapid development of geospatial technology, data availability, and data processing capabilities. Perhaps, sometime soon Google Earth Engine will be equipped with enough memory to process the model on a per-pixel basis, in which case hydrological flows could be appended to the model, cuing insight on forage recovery based on topographic position in the landscape. Perhaps, high resolution UAV imagery, paired with improvements in object-based classification algorithms will enable identification of individual forage species. This type of classification data in concert with pixel-based data processing would enable the prediction of species-by-species recovery curves across a range of soil, weather, and grazing intensity conditions.

In this study, my primary objective to trial and assess a methodology by which pasture recovery time after animal impact could be predicted based on a set of relevant variables was successful. My secondary objective to build a functional model for Caney Fork Farm failed. I am excited about opportunities to build upon techniques and methods described here for functional use in the future.

*A special thank-you to the team at Caney Fork Farms for their gracious hospitality this summer and for making this work possible.

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[15] within a sward, there are several different species of grasses (beyond the broader categories of "cool" and "warm" season), each with its own color profile and growth patterns, which would lead to differing NDVI signatures at a given regrowth stage. For example, at Caney Fork Farms, common pasture grasses include Kentucky Bluegrass (Poa pratensis), Tall Fescue (Festuca arundinaceae), Johnson Grass (Sorghum halepense), and others. Kentucky Bluegrass is a sod-forming grass that reaches height of 12-18 inches, can be grazed down to 1-2 inches, and requires extensive recovery time after impact. Tall Fescue is a bunch-type grass that reaches height of 30-36 inches, can be grazed down to 4 inches, and is both drought and flood tolerant. Johnson Grass can reach heights of 72-96 inches, can be grazed down to 6-8 inches, and is prone to overgrazing if cattle are left to continuously graze a single location.

Appendix 1

RowID	Date	Paddock_ID	Day	Acres	nd	AU_T0	Confidence	AUPAT0	(AUPA_TM_1:30)	PRCP	(PRCP_TM_1:30)	TMAX	(TMAX_TM_1:30)	TMIN	(TMIN_TM_1:30)	OM	pH	TEC
368	5/9/17	22	15	1.99	0.82979712	0	2	0		0		79		48		4.08	5.4	7.5
369	5/10/17	0	16	1.82	0.55256218	20.769	2	11.4115385		0		86		60		3.66	5.8	8.1
370	5/10/17	1	16	2.01	0.67908018	0	2	0		0		86		60		3.66	5.8	8.1
371	5/10/17	2	16	1.96	0.68170899	0	2	0		0		86		60		3.66	5.8	8.1
372	5/10/17	3	16	2.13	0.65921508	0	2	0		0		86		60		3.66	5.8	8.1
373	5/10/17	4	16	2	0.65571599	0	2	0		0		86		60		3.66	5.8	8.1
374	5/10/17	5	16	1.65	0.66005133	0	2	0		0		86		60		3.53	6.1	7.32
375	5/10/17	6	16	2.02	0.67901929	0	2	0		0		86		60		3.53	6.1	7.32
376	5/10/17	7	16	1.77	0.65790177	0	2	0		0		86		60		3.53	6.1	7.32
377	5/10/17	8	16	1.65	0.66030159	0	2	0		0		86		60		3.66	5.8	8.1
378	5/10/17	9	16	1.85	0.67721232	0	2	0		0		86		60		3.53	6.1	7.32
379	5/10/17	10	16	1.98	0.68073549	0	2	0		0		86		60		3.53	6.1	7.32
380	5/10/17	11	16	1.87	0.68435641	0	2	0		0		86		60		3.53	6.1	7.32
381	5/10/17	12	16	1.89	0.65708948	0	2	0		0		86		60		3.53	6.1	7.32
382	5/10/17	13	16	2.04	0.6211576	0	2	0		0		86		60		3.45	6.3	8.7
383	5/10/17	14	16	2.25	0.63720213	0	2	0		0		86		60		3.45	6.3	8.7
384	5/10/17	15	16	1.87	0.65898136	0	2	0		0		86		60		3.45	6.3	8.7
385	5/10/17	16	16	1.63	0.62532843	0	2	0		0		86		60		3.45	6.3	8.7
386	5/10/17	17	16	1.51	0.61787024	0	2	0		0		86		60		3.45	6.3	8.7
387	5/10/17	18	16	2.01	0.64080349	0	2	0		0		86		60		3.45	6.3	8.7
388	5/10/17	19	16	1.36	0.7095288	0	2	0		0		86		60		3.45	6.3	8.7
389	5/10/17	20	16	4.85	0.69638541	0	2	0		0		86		60		3.35	5.4	8.11
390	5/10/17	21	16	2.3	0.73641861	0	2	0		0		86		60		4.08	5.4	7.5
391	5/10/17	22	16	1.99	0.74825204	0	2	0		0		86		60		4.08	5.4	7.5
392	5/11/17	0	17	1.82	NA	20.769	1	11.4115385		0		85		61		3.66	5.8	8.1
393	5/11/17	1	17	2.01	NA	0	2	0		0		85		61		3.66	5.8	8.1
394	5/11/17	2	17	1.96	NA	0	2	0		0		85		61		3.66	5.8	8.1
395	5/11/17	3	17	2.13	NA	0	2	0		0		85		61		3.66	5.8	8.1
396	5/11/17	4	17	2	NA	0	2	0		0		85		61		3.66	5.8	8.1
397	5/11/17	5	17	1.65	NA	0	2	0		0		85		61		3.53	6.1	7.32
398	5/11/17	6	17	2.02	NA	0	2	0		0		85		61		3.53	6.1	7.32
399	5/11/17	7	17	1.77	NA	0	2	0		0		85		61		3.53	6.1	7.32
400	5/11/17	8	17	1.65	NA	0	2	0		0		85		61		3.66	5.8	8.1
401	5/11/17	9	17	1.85	NA	0	2	0		0		85		61		3.53	6.1	7.32
402	5/11/17	10	17	1.98	NA	0	2	0		0		85		61		3.53	6.1	7.32
403	5/11/17	11	17	1.87	NA	0	2	0		0		85		61		3.53	6.1	7.32
404	5/11/17	12	17	1.89	NA	0	2	0		0		85		61		3.53	6.1	7.32
405	5/11/17	13	17	2.04	NA	0	2	0		0		85		61		3.45	6.3	8.7
406	5/11/17	14	17	2.25	NA	0	2	0		0		85		61		3.45	6.3	8.7
407	5/11/17	15	17	1.87	NA	0	2	0		0		85		61		3.45	6.3	8.7
408	5/11/17	16	17	1.63	NA	0	2	0		0		85		61		3.45	6.3	8.7
409	5/11/17	17	17	1.51	NA	0	2	0		0		85		61		3.45	6.3	8.7
410	5/11/17	18	17	2.01	NA	0	2	0		0		85		61		3.45	6.3	8.7
411	5/11/17	19	17	1.36	NA	0	2	0		0		85		61		3.45	6.3	8.7
412	5/11/17	20	17	4.85	NA	0	2	0		0		85		61		3.35	5.4	8.11
413	5/11/17	21	17	2.3	NA	0	2	0		0		85		61		4.08	5.4	7.5
414	5/11/17	22	17	1.99	NA	0	2	0		0		85		61		4.08	5.4	7.5
415	5/12/17	0	18	1.82	NA	0	2	0		1.72		85		64		3.66	5.8	8.1
416	5/12/17	1	18	2.01	NA	20.769	1	10.3328358		1.72		85		64		3.66	5.8	8.1

Sample data structure used for final model input. "(TM_1:30) data not displayed here to fit full data structure on single page.

Appendix 2

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	0.9674827	0.1650300	5.862	7.38e-09	***
AUPAT0	-0.0016779	0.0009031	-1.858	0.06366	.
AUPA_TM1	-0.0022910	0.0011838	-1.935	0.05340	.
AUPA_TM2	-0.0037196	0.0013350	-2.786	0.00550	**
AUPA_TM3	-0.0036187	0.0014864	-2.435	0.01519	*
AUPA_TM4	-0.0025984	0.0014834	-1.752	0.08033	.
AUPA_TM5	-0.0042476	0.0018372	-2.312	0.02110	*
AUPA_TM6	-0.0026017	0.0017454	-1.491	0.13656	
AUPA_TM7	-0.0043196	0.0019352	-2.232	0.02596	*
AUPA_TM8	-0.0017957	0.0017763	-1.011	0.31245	
AUPA_TM9	-0.0022697	0.0018072	-1.256	0.20961	
AUPA_TM10	-0.0023862	0.0016225	-1.471	0.14188	
AUPA_TM11	-0.0009859	0.0012448	-0.792	0.42866	
AUPA_TM12	-0.0027926	0.0013497	-2.069	0.03895	*
AUPA_TM13	-0.0012059	0.0013693	-0.881	0.37885	
AUPA_TM14	-0.0024950	0.0013384	-1.864	0.06278	.
AUPA_TM15	-0.0005454	0.0012741	-0.428	0.66876	
AUPA_TM16	-0.0025842	0.0014138	-1.828	0.06805	.
AUPA_TM17	-0.0011056	0.0014875	-0.743	0.45759	
AUPA_TM18	-0.0026046	0.0016911	-1.540	0.12401	
AUPA_TM19	-0.0002773	0.0016728	-0.166	0.86837	
AUPA_TM20	-0.0011371	0.0016500	-0.689	0.49098	
AUPA_TM21	-0.0007629	0.0016569	-0.460	0.64537	
AUPA_TM22	-0.0007710	0.0017451	-0.442	0.65878	
AUPA_TM23	-0.0004174	0.0017187	-0.243	0.80818	
AUPA_TM24	-0.0010594	0.0011753	-0.901	0.36773	
AUPA_TM25	-0.0003504	0.0012273	-0.285	0.77537	
AUPA_TM26	-0.0025214	0.0015008	-1.680	0.09345	.
AUPA_TM27	0.0006232	0.0015798	0.394	0.69337	
AUPA_TM28	-0.0026570	0.0015168	-1.752	0.08031	.
AUPA_TM29	0.0011891	0.0014569	0.816	0.41470	
AUPA_TM30	-0.0011779	0.0011295	-1.043	0.29741	
PRCP	0.0745555	0.9815129	0.076	0.93948	
TMAX	-0.0125075	0.0021860	-5.722	1.64e-08	***
TMIN	0.0064570	0.0032456	1.989	0.04708	*
PRCP_TM1	-0.3474050	0.0679643	-5.112	4.25e-07	***
PRCP_TM2	0.2890290	0.0519085	5.568	3.83e-08	***
PRCP_TM3	-0.0912758	0.0278756	-3.274	0.00112	**
PRCP_TM4	-0.0192226	0.0201006	-0.956	0.33928	
PRCP_TM5	-0.0186517	0.0285922	-0.652	0.51442	
PRCP_TM6	-0.1637366	0.0390533	-4.193	3.15e-05	***
PRCP_TM7	0.0232818	0.0195606	1.190	0.23440	
PRCP_TM8	-0.0061170	0.0171348	-0.357	0.72122	
PRCP_TM9	0.0028917	0.0121849	0.237	0.81249	
PRCP_TM10	-0.0979158	0.0477368	-2.051	0.04067	*
PRCP_TM11	-0.0232564	0.0085028	-2.735	0.00641	**
PRCP_TM12	-0.0031027	0.0372680	-0.083	0.93368	
PRCP_TM13	0.0610149	0.0148468	4.110	4.49e-05	***
PRCP_TM14	0.0189195	0.0150578	1.256	0.20942	
PRCP_TM15	0.0557268	0.0194729	2.862	0.00435	**
PRCP_TM16	-0.0550193	0.0133090	-4.134	4.05e-05	***
PRCP_TM17	0.1032025	0.0470223	2.195	0.02855	*
PRCP_TM18	0.1416413	0.0274893	5.153	3.45e-07	***
PRCP_TM19	0.0080343	0.0194663	0.413	0.67995	
PRCP_TM20	0.1437022	0.0776275	1.851	0.06461	.
PRCP_TM21	0.2250871	0.0685555	3.283	0.00108	**
PRCP_TM22	-0.0646076	0.0413555	-1.562	0.11873	
PRCP_TM23	0.0867957	0.1719103	0.505	0.61381	
PRCP_TM24	-0.0553571	0.0401359	-1.379	0.16831	
PRCP_TM25	0.0335971	0.0167832	2.002	0.04573	*
PRCP_TM26	-0.0301394	0.0270324	-1.115	0.26531	
PRCP_TM27	NA	NA	NA	NA	
PRCP_TM28	NA	NA	NA	NA	
PRCP_TM29	NA	NA	NA	NA	
PRCP_TM30	NA	NA	NA	NA	
TMAX_TM1:30	NA	NA	NA	NA	
TMIN_TM1:30	NA	NA	NA	NA	

Model output. Bottom variables undefined due to singularities in data.

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