

How Spatial Variation Affects Plant Phenology

By: Zach Madsen

Mentor: Dr. Ian Breckheimer

Submitted to

Rocky Mountain Biological Laboratory

Final Report

Abstract

Climate change effects the timing of phenology, which can have consequences on plants and their pollinators. A critical reason for this is due to early snowmelt. However, there are other variables that could affect phenology. In heterogenous environments, plants could be buffered by these variables, thus understanding them will help understand the different effects climate change has over space. This study aims to focus on environmental variability within the East River Watershed. The results of this observational study shows that environmental variability has an effect on the timing of phenology. Moreover, three variables were discovered to have a correlation with phenology timing; elevation, timing of snow melt, and maximum soil moisture. Further studies that observe other variables, along with previous ones that could be reperformed with more data, will help us further understand how landscape affects our ecosystems.

Introduction

In the context of climate change, alpine areas are experiencing earlier snow melt due to shifts in temperature and precipitation. Studies done at the Rocky Mountain Biological Laboratory in Gothic Colorado have shown that early snowmelt influences plant phenology and reproductive success. With warmer climates, plants bloom earlier, and in conjunction with late season frosts, plant species can experience bud abortion, decreases in seed production, drought stress, and changes in phenotypic traits (Pardee et al., 2019). In addition to increased risk of frost, early snow melt can cause species to experience less soil moisture throughout the summer season, which can have severe impacts on their rates of survival (Iler, 2019). Furthermore, angiosperm species and their interactions with their pollinators have been disrupted in some cases, although rewiring of plant-pollinator networks can help to buffer some of these effects

(CarraDonna et al., 2017). Whereas the effects of early snow melt have been observed, and are actively studied, there are other environmental variables that could play a role in plant phenology and flower life cycle (Burghardt et al., 2015). Investigating into these other variables especially in heterogenous environments are a crucial step for understanding possible buffering effects.

Unlike some ecosystems, alpine areas have environments that are highly heterogenous at small spatial scales, and this plays an important role in the resilience of these ecosystems to climate change and other stressors (Aalto et al., 2013). Environmental heterogeneity affects the relationships between communities across space and within many functional components of an ecosystem. This is due to buffering effects that protect against mismatches (Hindle et al., 2015). Furthermore, heterogenous communities have an increased spatial storage effect, where they benefit from environmental changes within micro ecosystems, while also preventing from any one species from being to dominate or go extinct (Tan et al., 2017).

Although heterogeneity in phenology has important functional consequences, much is unknown about spatial patterns of patterns of phenology and what drives them. The contributions of below-ground environmental factors such as soil moisture are particularly poorly studied. The amount of water that soils can hold can determine how well a population can do within an environment. There are several factors that can determine soil moisture such as solar radiation, canopy cover, and the texture of the soil (Billings, 1974; Chapin et al., 2005). Soil that is made of clay will hold water longer, whereas soil made of igneous will not (Poulenard, Podwojewski, 2004). In addition, the canopy cover can determine moisture by regulating evapotranspiration (Stoy et al., 2006). This is due to the vegetation reflecting solar radiation, which can heat the soil and cause water to evaporate. Understanding these factors and how they connect with each other, can help us understand how spatial heterogeneity works.

To get a better understanding of these spatial patterns requires observations distributed across large landscapes, and technology such as remote sensing makes this large-scale data collection much more feasible. Remote sensing has become very popular and is used by a variety of industries to help make better analysis of the space around them (Wim et al., 2000). However, when it comes to ecology, there seems to be little information on soil moisture's effect on phenology in heterogenous communities (Wundram et al., 2010; Graham et al., 2012). Yet ecologists believe these belowground patterns are critical to better understanding environmental heterogeneity (Alto et al., 2010) Therefore, investigation into these spatial patterns should be performed and analyzed to see what connections exist.

This project is focused on answering three questions about how environmental heterogeneity affects the phenology of twelve species of subalpine meadow plants. First, I ask if plants growing in different micro-environments flower at different times. Second I examine which aspects of phenology are most heterogeneous across space. Finally, if environmental heterogeneity does play a role, what are the major environmental factors that contribute? To find these answers, we conducted an observational study utilizing both remote sensing and field collected data in conjunction with one another to predict phenology patterns between site locations. We hypothesize that environmental variation will affect the flowering start date, end date and duration. Additionally, we believe that there are seven potential variables that could affect plant phenology. Those are the timing of snow melt, elevation, amount of soil moisture, solar radiation, amount of greenness, soil texture, and vertical distance from stream slope.

Methods:

Site Locations:

This study was conducted at ten different site locations in the vicinity of the town of Crested Butte, Colorado. Though relatively close to each other, each site is distinct from the next. All sites have different environments, whether it be in a higher altitude, on a rocky hill, or in a soft clay area. The ten areas include up to Rustler's Gulch road, near Snodgrass Trailhead, at the bottom of Slide Rock Rd, on the hill of Elkton, on the south side of Mnt. Baldy, up in Paradise Basin, at the base of Lupine Trail, a quarter mile in East River Trail, at Strand Hill, and at the end of Deer Creek Trail. These site locations have a transect line, which is where observational data was collected.

Determination of Phenology and Species

The key dependent variable in this study is the timing of flowering. To observe this variable, we collected flower phenology data for all animal-pollinated plants at ten sites along a 50m transect at each site. Dr. Breckheimer chose these transect lines to be broadly representative of environments across the upper East River watershed. The transect is fifty meters long and sectioned into 25 two by two-meter segments. From when the transect shows greenery, data about the flower phenology is collected. We visited each site every 5-10 days across the growing season, averaging 12 visits per site per year. At each site visit, we recorded budding, flowering, and fruiting reproductive stages for all animal-pollinated plant species in each transect segment.

The data was then put into a spreadsheet with site location, date, flowers observed in that area, section of transect, and whether the flower is in bud, flower, or seed. Although we collected data for more than 80 species, most were relatively uncommon, so we chose 12 species for this study: *Boechera stricta*, *Delphinium nuttalianum*, *Hydrophyllum capitatum*, *Lathyrus leucanthus*, *Lomatium dissectum*, *Mertensia fusiformis*, *Noccea fendleri*, *Pseudocymopteris*

montanus, *Senecio integerrimus*, *Taraxicum officinale*, *Valeriana occidentalis*, and *Viola praemorsa*. These species were chosen because of three factors: they were recorded at more than one transects, and more than 20 segments, and the both the start and end of flowering were consistently observed (i.e. they did not occur before or after the start or end of data collection). Additionally, these species have been given code abbreviations in order; BOESTR, DELNUT, HYDCAP, LATLEU, LOMDIS, MERFUS, NOCFEN, PSEMON, SENINT, TAROFF, VALOCC, and VIOPRA. Although this data was collected for 2019 and 2020, we will focus on the 2019 data in this analysis because 2020 data collection is still in progress.

Measuring the environment

We explored the drivers of spatial heterogeneity in phenology by relating flowering time to four different types of environmental information, vegetation structure and topography information from drone imagery, snow data from satellite observations, potential solar radiation data from a GIS-based model, and soils data collected in the field.

Drone imagery

The drone imagery was collected from twelve sites, including the 10 transect areas included in this analysis, using two models of consumer drone: a DJI Phantom 4, and a DJI Mavic 2 Pro. At each site, images were taken once per week at an altitude of 120 meters above the ground with a 20-megapixel built-in camera (similar for both drones). These images were then processed to 3cm resolution georeferenced orthomosaics using Agisoft Metashape software, and radiometrically calibrated using information from a 4-panel MapIR calibration target. Each calibrated mosaic was analyzed with an algorithm that tracks plant greenness over time using a statistic called Green Chromatic Coordinates (GCC, Reid et. al, 2016). Additionally, the

photogrammetry software produced 3D point clouds which were processed to 9cm resolution vegetation height and topography maps using CloudCompare software v2.1 (Girardeau-Montaut 2016), using a cloth-simulation filter (Zhang et al. 2016), to extract ground heights.

We estimated snow disappearance dates using a time-series of Landsat 8 and Sentinel 2 satellite imagery, collected approximately every 5 days from March to September 2019. Surface reflectance data from both satellites were processed to generate the Normalized Difference Snow Index (NDSI), which was then capped at a value of 0.42 to separate snow and non-snow pixels. We used an algorithm developed with Dr. Breckheimer (Breckheimer et al., *in prep*) to interpolate between these images to extract the date of seasonal snow disappearance.

We estimated clear-sky potential solar radiation using the “r.sun” module in GRASS GIS (Šúri, & Hofierka 2004). This model takes into consideration the shading effects of topography, and was implemented at 3m resolution across the domain. We chose the date for solar radiation calculations to be May 5th, near the start of the growing season.

Shapefiles

All of the remotely sensed environmental measures came in the form of gridded (raster) datasets. We extracted information from these datasets for each transect segment using two different GIS programs. First, we created a vector dataset for each transect line in ESRI ArcMAP, using GPS point information for the start and end of each transect. There are two GPS point vectors per site that mark the beginning and the end of the transect. They were observed in relationship to transect markers on the drone-based orthoimage and were moved accordingly to exactly match these markers. Then, new feature classes were created to make a line between vector points. Once the line was created, a geoprocessing tool called “split” was used to divide the line into 25 sections, matching the physical transect line. Then, each line was buffered 1

meter on each side to represent the 2x2 meter transect. Unfortunately, these lines are not perfect in length due to elevation not being considered by ArcMap. However, they are within relative proximity of 2 meters long per section.

After all the transects were created, they were then exported into shapefiles, so that they could be manipulated in QGIS. QGIS was necessary for this next step to avoid hefty fees by ESRI to use the same feature in ArcMap. Once in QGIS, the tool 'zonal statistics' was used to summarize all raster files, including vegetation height, ground height, solar radiation, and snow melt, inside all transect segments. The summaries used were to create new fields in the vector file that showed the mean, maximum value, and standard deviation of each raster within each section.

Soil Moisture

The final type of environmental data was soil measurements collected in the field at each site. There were two sample types, soil moisture and soil texture. Soil moisture was collected with a Field Scout TDR150 at all ten sites on three separate occasions. The samples were taken using a soil moisture probe, and they consisted of five samples per section per site in each visit. The first samples were collected at random, typically following a day of afternoon showers. The second sample was collected on the same day for all ten sites, and all sites had experienced a week of no rain. The third sample was collected a couple days after several days of rain, to see how much water evaporated at each site. Then each site was summarized to show the average soil moisture for each section at each site.

Soil Core Samples

Additionally, we collected soil samples to investigate soil texture. We collected samples of surface soil using a soil corer, which was lent by Dr. Jennie DeMarco's team. The core

samples were five inches in diameter and 12 inches in depth. There were three cores taken from each site, and they were taken along the transect line, but outside the 2x2 meter sections where field phenology data was collected. The samples were taken at the beginning, the middle, and the end of the transect. They were placed in plastic bags, which were labeled accordingly, and then placed in a cool area to prevent water loss. These samples are approved in the permit given to the mentor of this project, Dr. Ian Breckheimer.

These samples were then processed for several variables. First, they were weighed before being handled. Then, they were sifted to get rid of the rock and fraction and only leave >2mm fraction soil. The rocks were weighed and then placed in a graduated cylinder filled with water, to measure the rock volume. The fraction was also weighed, and then thrown away. The >2mm fraction soil was then weighed for the collected weight. Then each sample was separated into tiny tin cups at approximately 13-20g per cup, which were then placed in an oven at 105C for 4-5 days. The then dried soil was reweighed, subtracted by the tin weight, and then added together for the dried weight. These numbers were used to calculate soil moisture percentage. Finally, all the data mentioned previously was used to estimate soil bulk density.

Once all the data was processed, we proceeded with consolidating all of the information into one data sheet. This was performed using R, which allowed us to filter and join files together.

Filtering was done to get rid of extra columns created in the processing files.

Data analysis

With all the data collected and joined together, we completed our data analysis in the R programming language (R Core Team 20202). The data sheets were filtered and joined together until we had a master data sheet where we could fit statistical models. We first performed exploratory data analysis and created plots using the *dplyr* and *ggplot2* packages (Wickham

2014, Wickham 2011), and they were used to see if there were any relationships between the variables and our dependent predictors. The selected variables were examined by using the Bayesian Linear Mixed Effects Models implemented in the *rstanarm* package. This class of models is designed to measure multiple independent variables' effects on a single dependent variable. For each dependent variable (start of flowering, flowering duration, soil moisture), we created several candidate models using anywhere from one to three variables. They were then compared using leave-one-out cross validation using the `loo()`, `loo_compare()` functions in the package *loo* (Vehtari et al. 2017). These comparisons, along with literature review, lead us to select our final models which represent the key statistical relationships in our results.

Results

Environmental Variation and Flowering

Using histograms and averages, we were able to see variation among all the species when it came to the start of flowering, the end of flowering, and the duration of flowering. The histograms shown in Figure 1.1 20 bins produced the best visual results. Some species showed more variation than others, however, all showed a wide range of observed flowering times, ending times, and duration (see Figure 1, Figure 2) Additionally, the mean of each of these factors are significantly different amongst species (see Table 1).

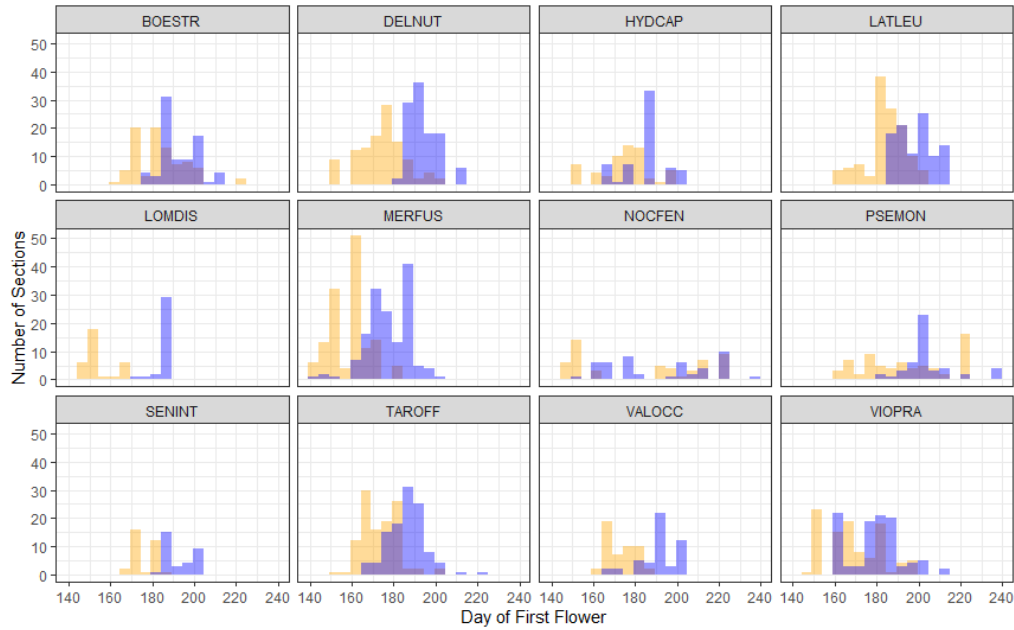


Figure 1 Number of Observations for First and Last Day of Flowering

This figure shows that among all the transect locations and each section within those transect there is variation in the start and end date of flowering. Some like “VALOCC” are more evenly distributed, whereas others like “TAROFF” are more favorable to certain days.

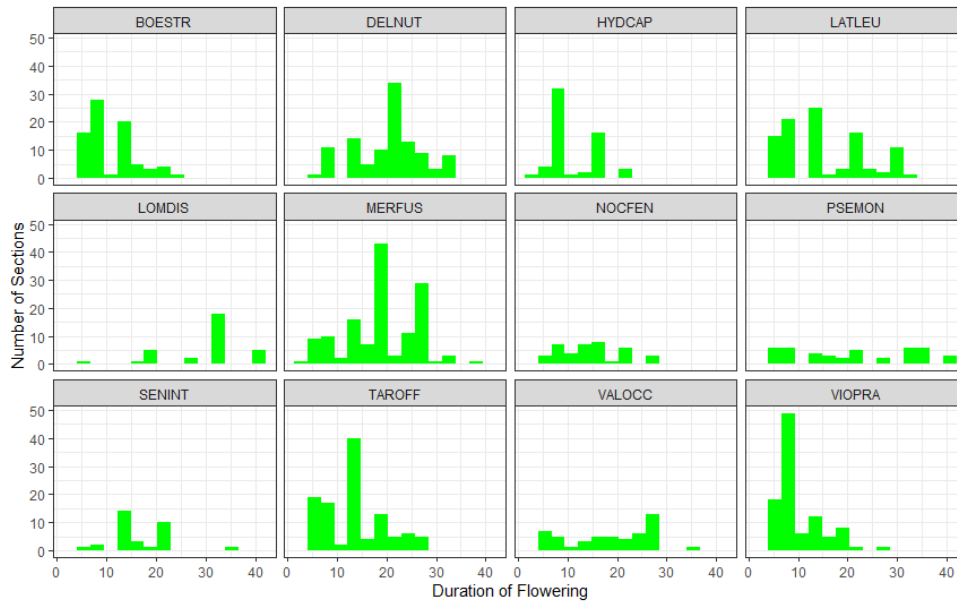


Figure 2 Number of Observations for Flower Duration

This figure shows that among all the transects and their sections, there is variation amongst the duration that plant have flowers. Similar to the previous Figure1.1, some species favor a certain amount of duration amongst a large amount of sites; ex: “VIOPRA”, while others are more uniformly distributed; ex: “PSEMON”.

Variables Affecting Start Flower Date

After examining the different variables, only snow disappearance and maximum soil moisture showed some correlation with flowering start date. However, both had some variation in their results across species. For snow, the majority of species showed a positive correlation with the exception of *Senecio integerrimus*, and *Valeriana occidentalis*. In contrast, maximum soil moisture showed a negative correlation (i.e. earlier flowering with greater soil moisture) with the exception of *Valeriana occidentalis*, *Lomatium dissectum*, *Lathyrus leucanthus* and *Pseudocymopterus montanus* (see Figure 2). A single outlier point of high soil moisture was removed from the graph in Figure two. This outlier was taken in the last section at the Paradise Basin transect, which is extremely saturated, possibly due to underground streams passing through.

Elevation was strongly positively correlated with flowering start date. However, after running a correlation, or “cor” test in RStudios between elevation and snowmelt, it was decided not to be included in the next model because we felt it wasn’t a causal relationship. This is due to the correlation test being above .7, and the knowledge that elevation was used to estimate snow disappearance timing. These relationships make it irrelevant when being compared with snow disappearance. However, it should be noted that there was no strong correlation found between elevation and soil moisture.

With the two variables chosen, they were then put into several Bayesian models, which included them being separate and together. After running a leave one out comparison test, we chose the model that included both variables (See Table 1). This model suggests that for every day that snow stays on the ground, flowering is delayed by .8 days. Additionally, for every 1% increase in soil moisture, flowering begins sooner by .5 days (See Table 2).

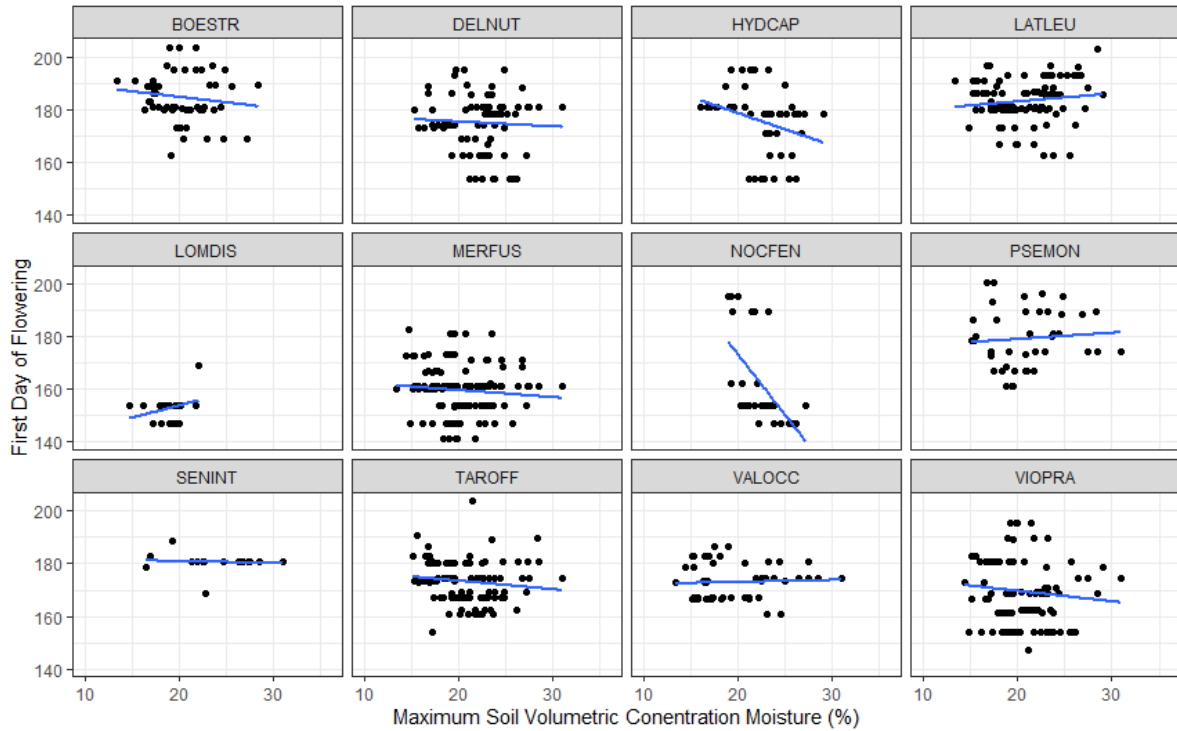


Figure 3

Each species shows a different trend in response to soil moisture. The trend favors a negative correlation, however, amongst those with a negative correlation, there are several whom show very weak correlations. These include “SENINT”, “MEFUS”, and “DELNUT”. However, as a whole the relationship seems strong enough to show effect in Bayesian Model.

Table 1 Leave One Out Comparison Test

m4 represents all three variables, m3 is only snow and soil moisture, m3.2 is snow and stream slope. M3 was chosen due to the non casual relationship between elevation and snow

	elpd_diff	se_diff
m4	0.0	0.0
m3	-3.9	3.5
m3.2	-13.4	4.7

Table 2 Bayesian Model Results for Snow Disappearance and Maximum Soil Moisture

Variables	Mean	SD	1%	5%	10%	50%	90%	95%	99%
Intercept	75.5	3.8	66.6	69.3	70.8	75.5	80.3	81.7	84
Snow mean	0.8	0	0.7	0.7	0.7	0.8	0.8	0.8	0.8
Max SM	-0.5	0.1	-0.6	-0.6	-0.6	-0.5	-0.4	-0.4	-0.3

Variables Affecting Flower End Date

Out of all of the variables, only elevation seemed to have a real impact on the flowering end date.

The only species which did not follow the regression trend was *Pseudocymoptis montanus* (See Figure 4). Furthermore, the maximum soil moisture and distance from stream slope did not show very strong relationships with the majority of the species.

After running through similar Bayesian models like with flowering start date, and then running through the comparison test, the results show that the best fit model has all three variables.

However, the next best model was elevation by itself, and after running some more correlation tests, it seemed to be the most appropriate fit. What the model tells us is that for every 1-kilometer increase in elevation, the flower end date is delayed by 44.7 days.

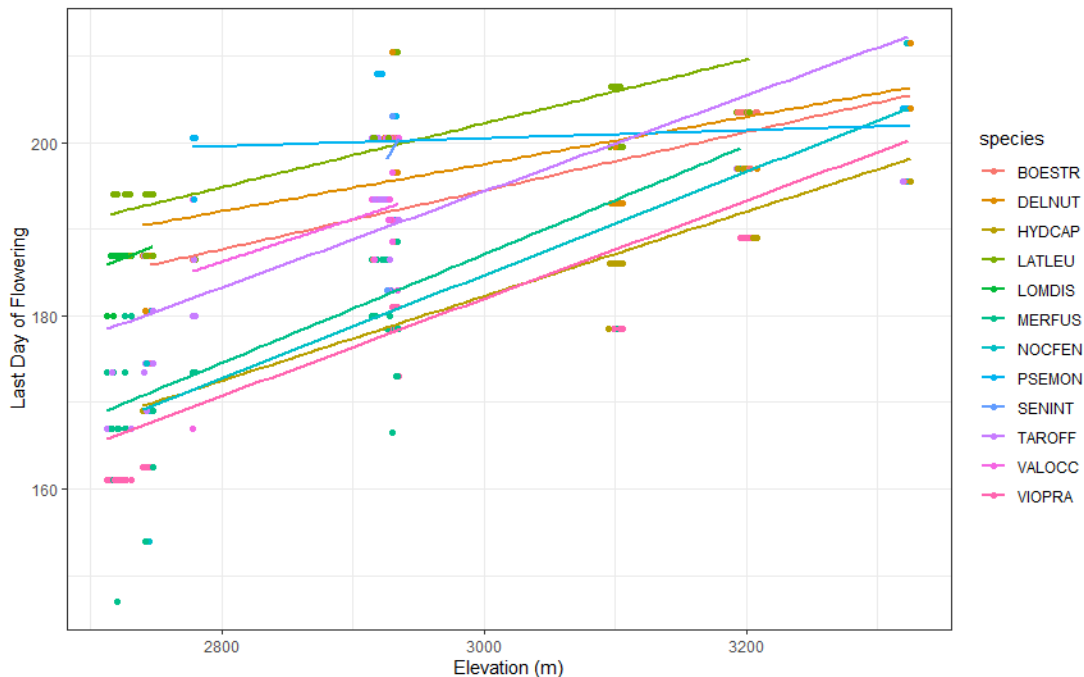


Figure 4 Elevation Affects the Last Day of Flower

Whereas the majority of flowers show a strong positive correlation, once exception is "PSEMON" (light blue), which shows no correlation.

Variables Affecting Flower Duration

Similar to the flowering end date, the same three variables showed correlation to the flowering duration in the linear models. However again, there were some species that did not fit the trend. These were *Boechera stricta*, *Hydrophyllum capitatum*, *Lomatium dissectum*, *Lathyrus leucanthus*, *Noccea fendleri*, *Taraxicum officinale*, and *Valeriana occidentalis*. Some of them, like *Valeriana occidentalis*, showed opposite or no correlation trends from the other species in all three variable models (See Figure 5).

After running the Bayesian models and making the comparisons. The best fit trend was having all three variables. However, there were some issues with these results. Though the standard deviation was low in all models, both stream distance and maximum soil moisture had values of 0 in their 95 and 99 percentiles. This could be due to the species that do not fit the regression trend, which could skew some of the data. However, since there seemed to be some evidence in the linear models, this Bayesian model with all three variables was the best fit for the data (See Figure 3).

For elevation, the model showed that for every 1-kilometer increase, there was a 7.3 day decrease in flower duration. For every one-meter increase in distance from stream slope, there is a .2 day decrease in flower duration. Finally, for every 1% increase in soil moisture, flower duration decreases by 0.1 days (See Table 4).

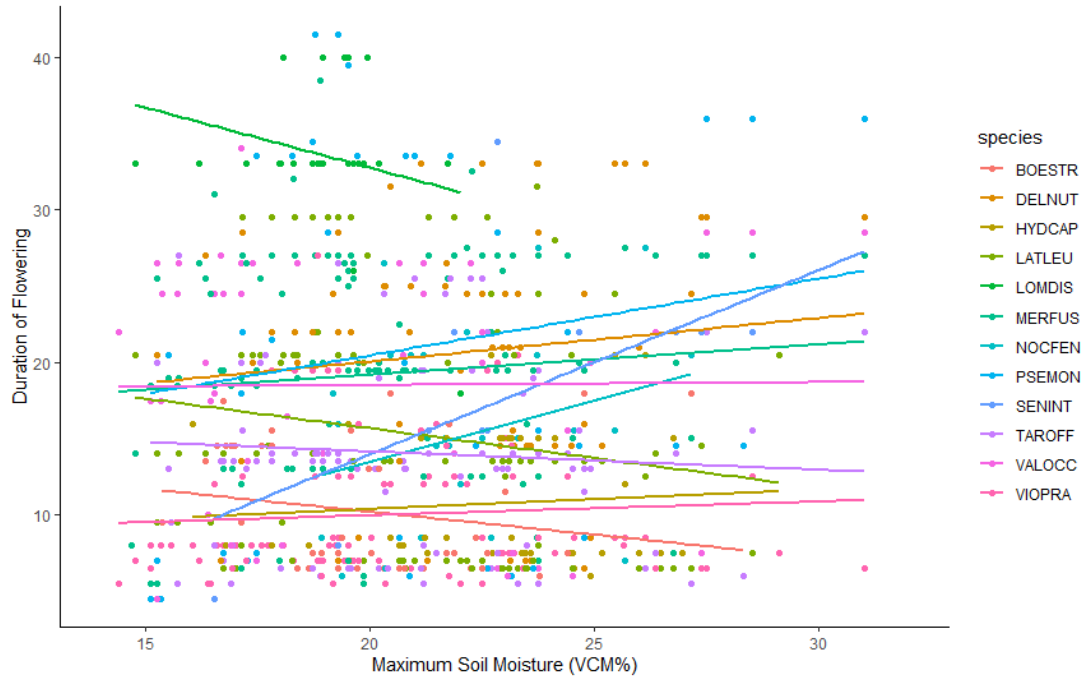


Figure 5 Maximum Soil Effects on Flower Duration

There is a lot of uncertainty around the role of soil moisture when comparing these particular species. Some like "LOMDIS" show negative relationships while others like "SENINT" shows strong positive relationships. Others such as "VIOPRA" (pink) have very weak relationships between their duration and soil moisture. These species that do not fit the trend might be the cause for 0 values in Bayesian Model in Table 3.

Table 3 Leave One Out Comparison

Table shows the model with the best fit value and the difference from that value for the other models. m6.9 and m6.6 represent all three variables, and two variables, elevation and stream distance. m6.3 and 6.8 reflect models that include snow as a variable.

	elpd_diff	se_diff
m6.9	0.0	0.0
m6.6	-0.1	1.8
m6.3	-0.9	2.0
m6.8	-1.2	1.7

Table 4 Bayesian Model Showing Effects of the Distance from Stream Slope, and the Maximum S

Variables	Mean	SD	1%	5%	10%	50%	90%	95%	99%
Intercept	42.5	5.2	30.5	33.9	33.9	42.5	49.3	51.1	54.6
Slope Distance	-0.2	0	-0.2	-0.2	-0.2	-0.2	-0.1	-0.1	-0.1
Max SM	-0.1	0.1	-0.3	-0.3	-0.2	-0.1	0	0	0
Elevation/1000	-7.3	1.6	-11	-9.9	-9.3	-7.3	-5.3	-4.8	-3.4

Variables Affecting Soil Moisture

In addition to testing relationships between environmental variables and phenology, we also explored which environmental factors were related to each other to seek out further connections and relationships. The linear models that best fit soil moisture were the amount of greenness and the distance from stream slope. After running the linear regression model, it was clear neither were very significant, however, both showed positive correlation with soil moisture. Again, there were some variations, but this time amongst the sites. For example, South Baldy and Paradise Basin transects showed more consistent relationships with both greenness and slope distance (See Figures 6, 7)

Regardless, the Bayesian model that seemed the most appropriate was where both variables were included. The model suggests that for every 1 GCC unit increase, there is 27.5 % increase in soil moisture. Whereas these numbers seem high, it should be noted that the GCC scale is from 0-1, therefore, a 1-unit increase is the maximum value of increase possible. Regarding distance from stream slope, the results indicate that for every 1-meter increase away from the streams slope, soil moisture decreases by 0.1%.

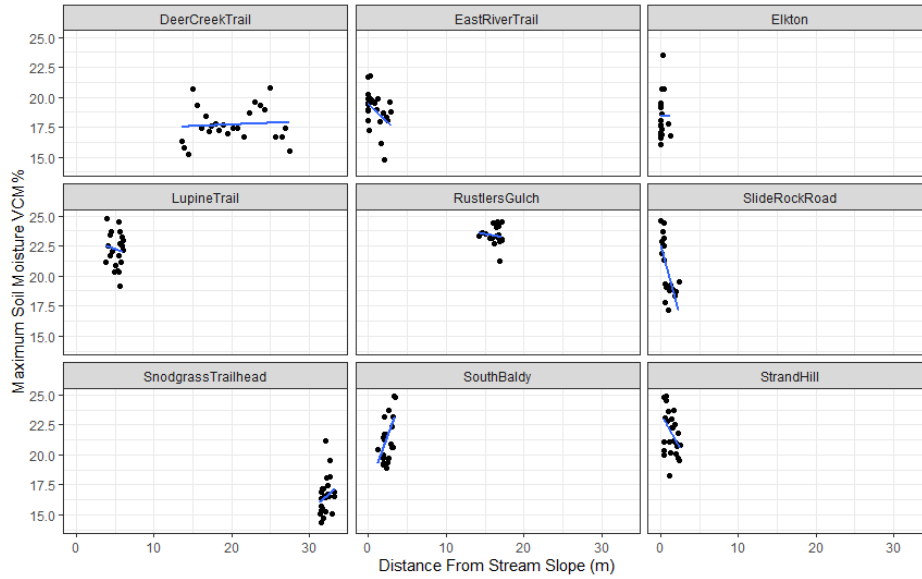


Figure 6 Relationship Between the Vertical Distance from Stream Slope and Maximum Soil Moisture

This figure shows that there is a negative correlation between the distance from the slope stream(m) and the maximum soil moisture (VCM%). Variation is off at some site locations, which could signify weak relationship. Examples: South Baldy, Elkton, Deer Creek. It is possible that those sites' transects obtain soil moisture a different way than from slope streams.

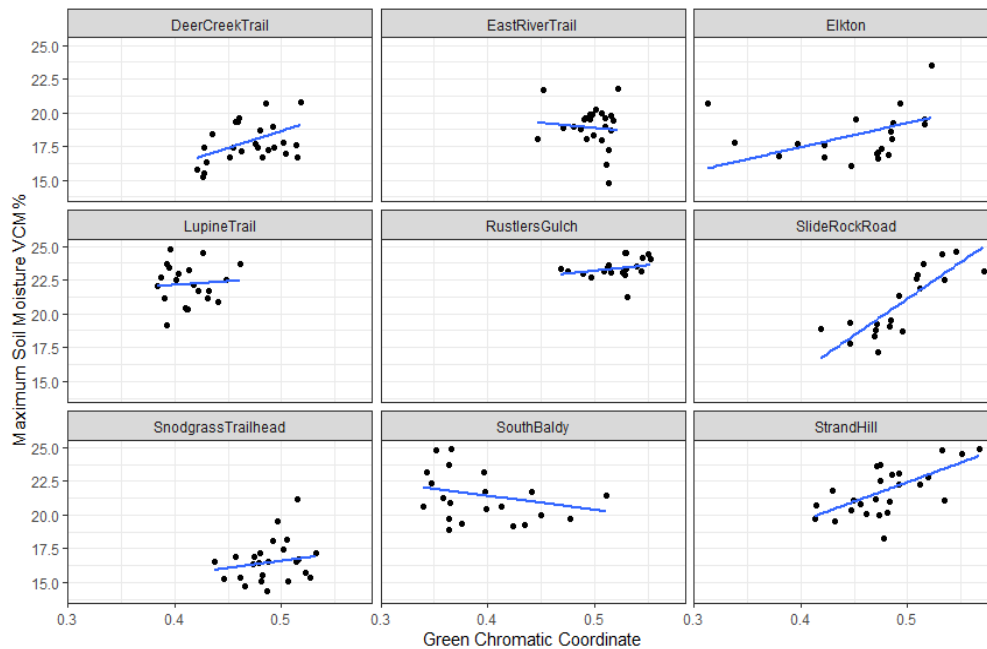


Figure 7 Relationship between GCC and Max Soil Moisture

This relationship shows positive trends amongst sites, showing that more green areas increase the soil moisture maximum. However, there are some places this is not true. Example: South Baldy and East River Trail. Others like Lupine Trail show weak relationships. Both could be explained by the type of terrain and type of vegetation. Lupine Trail has more sage brush, and east river has more rose bushes.

Discussion:

Environmental Variation and Phenology

The study of plant phenology, along with the relationships between the environment and the flower life cycle has been ongoing for many years. As climatic temperature continues to rise, environmental effects, like early snow melt, can accelerate the timing of flowering (CaraDonna et al. 2017). However, there are other environmental variabilities that could affect plant phenology along with the duration and end time of that flower that have not been fully explored. The aim of this study was to see if there is a relationship between spatial patterns in the environment and the timing of flowering. Through this study and the results it produced, we found that there is variability between the timing of flowering, the ending of flowering, and the duration of flowering throughout all ten transect sites.

Variables that Affect Phenology

We tested six variables to see if they could have an effect flower life cycle. Of those six, only disappearance of snow, soil moisture, distance from stream slope, and elevation displayed some effect on flower phenology and life cycle. Solar radiation, which was expected to have some effect based off of literature, showed no effect (Juha et al. 2013). However, after observation of the raster file, it was clear that solar radiation was uniform throughout all the site transects. Surprisingly, it all had little correlation with snow melt, which is interesting considering the timing of snow melt raster file was created using data from solar radiation. More investigation may be needed.

Additionally, the amount of greenness only had an effect on soil moisture, though there were some site locations where this was not the case. For this could be an error of data and should be reperformed several times with more collected data to get more accurate readings. Additionally,

soil texture was assumed to be an important factor based off of preliminary data from samples. However, due to shortage of time, they were not able to be compared in any statistical model. Further work will be needed to be done to get a more accurate result in soil texture.

Effects on Flowering Start Date

The two strongest variables that affected the flowering start date were disappearance of snow and maximum soil moisture, with disappearance of snow having a stronger relationship. This is consistent with previous observations and studies that have predicted the effects of early snow melt (Inouye 2008). However, when examining each species individually, there were several that did not follow the negative trend. For example, *Lomatium dissectum* had a positive correlation when it came to soil moisture affecting its flowering start date. This makes sense considering that this species is found in dry rocky areas (Marisco, Hellman 2009). If species who show no relationship or a positive relationship were removed, we could see a stronger correlation between soil moisture and flowering start date. Additionally, elevation showed had a strong relationship with flower start date but was excluded from the model due to its strong relationship with snow.

Effects on Flowering End Date

Initially, maximum soil moisture and distance from slope were used in models to be compared. Among some species, there seemed to be a trend, however, when summarizing the Bayesian Models, it was clear that there was not clear evidence of an association across all species. However, if some species like *Valeriana occidentalis* were to be removed, we might see different relationships. Elevation showed that it would prolong flowering end dates as it increased. This is consistent with the fact that elevation also played a role in flowering start date. However, as previously discussed, elevation was an umbrella variable that affects snow and other

microclimate variables, whereas in this case, snow does not play a role in flower end date. This also seems logical considering snow is generally gone by the time flowers start going to seed. There is probably a more precise variable that affects the flower ending time and more tests should be run.

Effects on Flowering Duration

Of the three chosen variables, elevation seemed to have the strongest effect on flower duration. However, elevation seems to be more relevant between site locations more so than within sites. Soil moisture and distance from slope were also used in the model, though they had weaker relationships. Soil moisture showed the weakest relationship in the Bayesian Model, however, the assumption that it was relevant if certain species to be included had to be removed. This will of course have to be tested and will be in a future project coming this fall.

Effects on Soil Moisture

In addition to wanting to understand environmental variability on plant phenology, there was also interest in if these variables were related to each other. Soil moisture was the primary focus because elevation and solar radiation were used to estimate the disappearance of snow. The two main factors seemed to be the amount of greenness and vertical distance from stream slopes. Though neither were strongly correlated when compared with all sites, there was distinctions amongst individual sites. Sites like South Baldy and Elkton were among the sites that showed no relationship between the two variables and soil moisture. This becomes clear with visual observation. Both Elkton and South Baldy transects have rocky terrain (see Figure 6, therefore have little greenness to begin with. Additionally, sites could be less affected by stream slope if they have a different means of obtaining water.



Figure 8 Elkton and South Baldy

Elkton (left) has rocky terrain at top of transect. South Baldy (Right) has rocky terrain throughout.

Limitations

There were several limitations that could reflect in the accuracy of these results. The first is the amount of data. This data was primarily collected last year during a heavy snow year.

Additionally, the soil moisture was collected this year during a light snow year. This could be irrelevant since soil samples were collected in mid to late July, long after most sites have been melted. Still, more data should be collected and tested against this year's data to see a more accurate trend.

Additionally, the number of species and choice of species could have an impact. As the results showed, certain species consistently fell outside the trend, and this could lead to different results. Furthermore, investigating other species could have different results. Species were chosen on abundance and timing, therefore, if we changed parameters for abundance and time, we may have different observations.

Finally, this is an observational study and hidden variables could be further correlated with snow and soil moisture. Experimental tests that explore these variables further and in more detail could help us understand the deeper mechanics. In addition, more observations and models testing other variables will also help us get better insight of different environmental variables and their effects on phenology.

Final Thoughts

This is just the first step in understanding how environmental variability plays a role in plant phenology and flower life cycle. Though these results are only preliminary, there is reason to believe that further studies and more data will help us further understand the significance location has on plants. Further studies should look at other variables, along with reanalyzing the current variables with more data to see if there is a trend. Discovery of these trends can help us better understand the effects of climate change in our mountain environment.

Reference:

- Asbjornsen, H. , Goldsmith, G. R. , Alvarado-Barrientos, M. S. , et al., 2011 : Ecohydrological advances and applications in plant-water relations: a review. *Journal of Plant Ecology* , 4: 3–22.
- Billings, W. D. , 1974: Adaptations and origins of alpine plants. *Arctic and Alpine Research* , 6: 129–142
- Burghardt, L.T., Metclaf, J.E., Wilczek, A.M., Schmitt, J., Donohue, K., 2015. Modeling the Influence of Genetic and Environmental Variation on the Expression of Plant Life Cycles Across Landscapes. *The American Naturalist*, Vol 185, Num 2.
<https://doi.org/10.1086/679439>
- CaraDonna, P.J., Petry, W.K., Brennan, R.M., Cunningham, J.L., Bronstein, J.L., Waser, N.M. and Sanders, N.J. (2017), Interaction rewiring and the rapid turnover of plant–pollinator networks. *Ecol Lett*, 20: 385-394. doi:10.1111/ele.12740
- Chapin, F. , Sturm, M. , Serreze, M. , et al., 2005: Role of the land-surface changes in Arctic summer warming. *Science* , 310: 657–660. [Google Scholar].
- Girardeau-Montaut, D. (2016). Cloud Compare: 3D point cloud and mesh processing software, open-source project. *On-line: [http://www. danielgm. net/cc](http://www.danielgm.net/cc), Accessed, 4(03).*
- Hindle, B. J., Kerr, C. L., Richards, S. A., & Willis, S. G. (2015). Topographical variation reduces phenological mismatch between a butterfly and its nectar source. *Journal of Insect Conservation*, 19(2), 227-236.
- Iler AM, Compagnoni A, Inouye DW, Williams JL, CaraDonna PJ, Anderson A, Miller TEX 2019. Reproductive losses due to climate change? Induced earlier flowering are not

- the primary threat to plant population viability in a perennial herb. *Journal of Ecology* 107:1931-1943.
- Inouye D, 2008. Effects of Climate Change on Phenology, Frost Damage, and Floral Abundance of Montane Wildflowers. *Journal of Ecology* <https://doi.org/10.1890/06-2128.1>
- Juha A, Peter C. le Roux & Miska Luoto (2013) Vegetation Mediates Soil Temperature and Moisture in Arctic-Alpine Environments, Arctic, Antarctic, and Alpine Research, 45:4, 429-439, DOI: 10.1657/1938-4246-45.4.429
- Marsico TD, Hellmann JJ, 2009. Dispersal Limitation Inferred From an Experimental Translocation of *Lomatium* (Apiaceae) Species Outside Their Geographic Ranges. *Oikos*, Vol 118, Is 12. <https://doi.org/10.1111/j.1600-0706.2009.17698.x>
- Pardee G., Jensen I, Inouye DW, Irwin RE 2019. The individual and combined effects of snowmelt timing and frost exposure on the reproductive success of montane forbs. *Journal of Ecology* 107:1970-1981.
- R Core Team (2020). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. URL <http://www.R-project.org/>
- Reid, A. M., Chapman, W. K., Prescott, C. E., & Nijland, W. (2016). Using excess greenness and green chromatic coordinate colour indices from aerial images to assess lodgepole pine vigour, mortality and disease occurrence. *Forest Ecology and Management*, 374, 146-153.
- Soy, P.C., Katul, G.G., Siqueira, M.B.S., et al., (2006), Separating the effects of climate and vegetation on evapotranspiration along a successional chronosequence in the southeastern US. *Global Change Biology*, 12: 2115-2135. doi:10.1111/j.1365-2486.2006.01244.x

- Šúri, M., & Hofierka, J. (2004). A new GIS-based solar radiation model and its application to photovoltaic assessments. *Transactions in GIS*, 8(2), 175-190.
- Vehtari, A., Gelman, A., & Gabry, J. (2017). Practical Bayesian model evaluation using leave-one-out cross-validation and WAIC. *Statistics and computing*, 27(5), 1413-1432.
- Wim G.M Bastiaanssen, David J Molden, Ian W Makin (2000), Remote sensing for irrigated agriculture: examples from research and possible applications, *Agricultural Water Management*, Vol 46, Iss 2, pg 137-155[https://doi.org/10.1016/S0378-3774\(00\)00080-9](https://doi.org/10.1016/S0378-3774(00)00080-9).
- Wundram, D. , Pape, R. , and Löffler, J. , 2010: Alpine soil temperature variability at multiple scales. *Arctic, Antarctic, and Alpine Research* , 42: 117–128.
- Zhang, W., Qi, J., Wan, P., Wang, H., Xie, D., Wang, X., & Yan, G. (2016). An easy-to-use airborne LiDAR data filtering method based on cloth simulation. *Remote Sensing*, 8(6), 501.