Analysis of the effects of climate and environment on *Fritillaria gentneri* flowering

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Report to the Bureau of Land Management, Medford District

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Institute for Applied Ecology

PREFACE

This report is the result of a cooperative project between the Institute for Applied Ecology (IAE) and a federal agency. IAE is a non-profit organization dedicated to natural resource conservation, restoration, research, and education. Our aim is to provide a service to public and private agencies and individuals by developing and communicating information on ecosystems, species, and effective management strategies and by conducting research, monitoring, and experiments. IAE offers educational opportunities through 3-4 month internships. Our current activities are concentrated on rare and endangered plants and invasive species.

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Cover photograph: Gentner's fritillary (*Fritillaria gentneri*)

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EXECUTIVE SUMMARY

- We used non-parametric multiplicative regression (NPMR) to model the effects of climate and environmental variables on flowering of *Fritillaria gentneri* from 57 sites throughout its range in southern Oregon. We report 4 models using different sites in an attempt to find the strongest predictors for flowering of *F. gentneri*:
    - In Model 1(51 sites), number of flowering *F. gentneri* was best explained by the previous winter's precipitation (in), and the previous spring's minimum temperature (F). While this model had a strong *p* value, these variables were able to capture only 7.5% of the variability in the data.
    - For Model 2, sites with a mean of less than one were deleted, resulting in 36 sites. In this model, spring precipitation (in) and the previous spring's minimum temperature (F) were the strongest predictors, explaining 9.7 % of the variability, which was a slight improvement from Model 1.
    - For Model 3, we deleted sites that had zero plants in 5 or more years, resulting in 32 sites. Number of flowering plants was best explained by spring precipitation (in), previous spring's minimum temperature (F), and previous winter maximum vapor pressure deficit. Collectively these predictors explained 15% of the variability in the data, resulting in the strongest model.
    - For Model 4, we used a more long-term data set of 24 sites monitored from 1999-2017. Number of flowering plants was best explained by previous winter maximum vapor pressure deficit and winter maximum vapor pressure deficit; these predictors only explained 5.8% of the response.
- While our best models only explained up to 15% of the variability in the data, they do suggest climate variables that were consistently chosen as predictors are likely to impact flowering of *F. gentneri* across its range.

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REPORT TO THE BUREAU OF LAND MANAGEMENT, MEDFORD DISTRICT

INTRODUCTION

Fritillaria gentneri (Gentner's fritillary) is a rare member of the lily family (Liliaceae) that is currently listed as endangered by the U.S. Fish and Wildlife Service and State of Oregon (ORBIC 2016). *Fritillaria gentneri* is endemic to southwestern Oregon and northern California. In Oregon, it is known only in Jackson and Josephine Counties; in California, it is only known in Siskiyou County. Most populations are small, containing fewer than 100 individuals, and are within open oak woodland and chaparral shrub communities along the lower slopes of the Rogue Valley basin. There are several hypotheses about the evolutionary origin of *F. gentneri*. The prevailing hypothesis suggests that *F. gentneri* is a stabilized hybrid between *Fritillaria recurva* and *Fritillaria affinis* (= *F. lanceolata*) (see Figure 1). Both hypothesized parents overlap in geographic range with *F. gentneri* (and both are present at many populations) and share several morphological, genetic and physiological traits with *F. gentneri* (Knight 1991, Guerrant 1992).

The Institute for Applied Ecology (IAE) monitored one population, Pickett Creek, from 2002 to 2014 (Giles-Johnson et al. 2014). At Pickett Creek, the population was censused for number of flowering individuals, and number of individuals (both vegetative and reproductive) has been counted in long term monitoring plots where it has been determined that only *F. gentneri* is present. Over the thirteen years of this study we noted a decline in the number of flowering individuals of *F. gentneri* from 400 to 51, while the number of vegetative plants has remained stable at around 13,300 plants (Giles-Johnson et al. 2014). To explore which factors might be contributing to the population trends observed, we created statistical models using long-term climate data (temperature and precipitation) as predictors for number of plants at Pickett Creek. Using climate models, we were able to determine that the Pickett Creek population tends to thrive under warmer/drier conditions. While these climate models can indicate potential influences on the population, they also suggest that the decrease in the number of flowering plants was not explained by climate factors alone and thus was likely that other environmental or biological variables are driving the decrease in the number of flowering individuals.

Figure 1. Three closely related *Fritillaria* species. *Fritillaria affinis* (left) and *F. recurva* (right) are the putative parents of *F. gentneri* (center).

Fifty-seven populations of *F. gentneri*, managed by the Medford District BLM, in SW Oregon have been monitored annually. The number of flowers has been counted at these populations from 1998 to the present (Pacific Crest Consulting 2016, Figure 2). We used these long-term datasets to create statistical models to increase understanding of the environmental factors that impact flowering in *F. gentneri* across its range. While flowering is a clear measurable trait, it does not fully represent plant reproductive fitness given that this species reproduces mostly vegetatively.

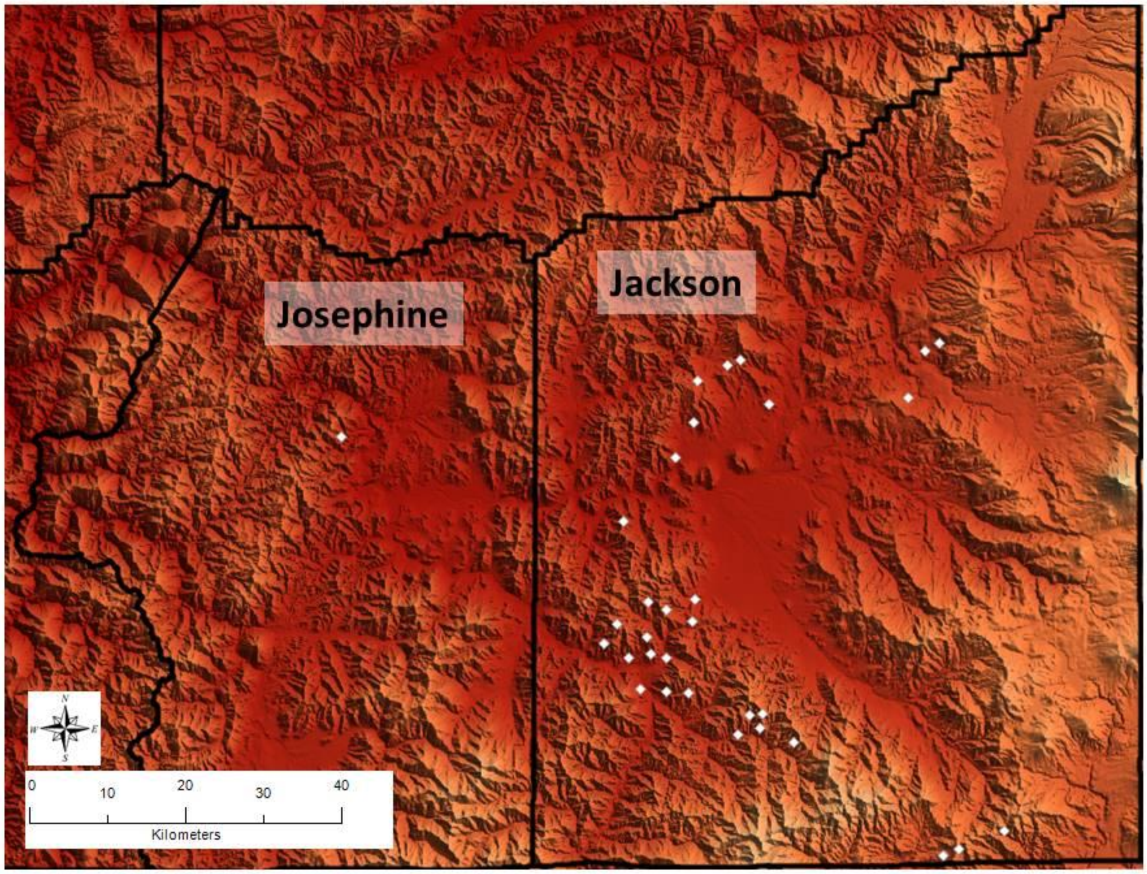

Figure 2. Distribution of *57 F. gentneri* populations used in analysis. Sites are represented by white dots and occur in Josephine and Jackson counties in SW Oregon, and have been monitored annually from 1998 to the present.

METHODS

To assess whether climate and environmental variables could be used to predict *F. gentneri* flowering, we used non-parametric multiplicative regression (NPMR; McCune 2006) in HyperNiche v. 2.10 (McCune and Mefford 2009). NPMR accommodates the fact that species respond to multiple interacting environmental factors by incorporating interactions among predictors and it also assumes nothing about the shape of the response surface (McCune 2006). NPMR uses an iterative process to create multiple potential models of many combinations of predictors and selects those of best fit, using cross-validation to avoid overfitting.

The response variable for our models was number of flowering *F. gentneri*. Count data provided from the BLM encompassed 57 sites monitored from 1998 to 2017 (Pacific Crest Consulting 2016). Although some of the sites had been monitored from 1998 to 2017, all sites were visited consistently from 2008-2017, so those years were used in the majority of the models. We removed sites that had zero flowering during the time period, resulting in 51 sites. The annual count data were log(x+1) transformed to normalize their distribution, and the mean of the log-transformed values was calculated for each site across all years. The data were then relativized by subtracting the log-transformed site mean from the log-transformed count data to yield the distance from the mean rather than the absolute values. These values were put into a matrix where there was a relativized response for each site/year combination. An additional model was created using only the sites that were monitored consistently from 1998-2017, using the same data transformation for number of *F. gentneri* flowers.

Predictors were evaluated and selected based upon data availability and environmental variables that could be impacting flowering for these individuals. Climate data were downloaded for each site using the PRISM data explorer (PRISM 2012). Variables extracted were monthly total precipitation (rain+melted snow), monthly minimum temperature (F, averaged over the month), monthly temperature (F, averaged over the month), monthly maximum temperature (F, averaged over the month), daily mean dew point temperature (F, averaged over the month), daily minimum vapor pressure deficit (averaged over the month), and daily maximum vapor pressure deficit (averaged over the month). Monthly climate variables were then used to calculate seasonal means (Winter= December-February, Spring= March-May, Summer =June-August, Fall=September-November). The previous years' seasonal means along with the current year's winter and spring means were included in a predictor matrix for each site/year. The current year's summer and fall means were not included as they occurred after flowering of *F. gentneri* for that year. Elevation, aspect, and slope were calculated from a 10m digital elevation model provided by the Medford BLM in ArcGIS (ESRI 2016). Using these data and latitude from each site, we calculated heat load and potential direct incident radiation (PDIR) using non-parametric multiplicative regression (McCune and Keon 2002, McCune 2007). PDIR is a value for the potential radiation experienced at a given point on Earth. PDIR is symmetrical across the north-south axis, but temperatures are not due to the heat experienced on a slope differing depending on time of day. Heat load was calculated to take these differences into account (McCune 2007).

To avoid overfitting the model with too many potential predictors, we screened some environmental variables in early models to see if they had an impact on the model, and if not, they were removed. Fire data (year of burn) were obtained using a shapefile provided by the BLM and data were extracted using ArcGIS, and we calculated the number of years since the most recent fire. Using these data, we found that fire only occurred at 5 of the sites, and so it was not a robust enough predictor to use in the model. Data for fuels management treatments were provided by the BLM and consisted of treatment type (hand pile burn, under burn, and broadcast burn) and the year of treatment. Data were added to the predictor matrix as year since the most recent treatment; treatments occurred at 16 sites and were not found to influence the model so were not included in the final predictor matrices. Soils data were extracted from the NRCS Web Soil Survey, and were lumped into groups based upon their map unit description. They were included in early models, but were removed when they were not selected as significant predictors because keeping the additional potential predictors in the models increased the chance of over-fitting.

NPMR Models were created using the local mean setting, which estimates the response as an average of observed values, with an automatic minimum neighborhood size (N*). N* indicates the amount of data used to obtain a point estimate on the response surface. In NPMR, the estimate for a point on the response surface is weighted depending on its proximity to a data point, with these weights diminishing according to a Gaussian smoothing parameter. Best fit models were selected based on the leave-one-out cross-validated statistic for fit (xR^2) which is similar to the conventional R^2, however point data are excluded when calculating the mean, resulting in the possibility of a negative xR^2 for a weak model (McCune 2006). Predictors were evaluated using sensitivity analysis, in which sensitivity of a predictor is determined by the magnitude of change in response of the model caused by altering that predictor; predictors with higher sensitivity have more influence on model response. Statistical significance of the whole model was evaluated using a randomization test to determine if the fit of the selected model is better than that expected by chance (McCune 2006).

After a model with the full number of sites (51) was run (Model 1), we ran subsequent models with sites removed to increase the strength of the model and reduce noise. In Model 2, sites that had a mean number of flowers of less than one across all years were removed, resulting in 36 sites. In Model 3, sites that had no plants in 5 or more years were deleted, resulting in 32 sites. An additional model (Model 4) was run using the original data set but limiting the data to the number of sites that had been monitored consistently from 1999-2017 (24 sites); this was to see if looking at fewer sites over a longer time frame would result in a stronger model.

RESULTS & DISCUSSION

NPMR models for flowering *F. gentneri* had fits that were better expected than chance (*P*= 0.0099, Table 1), though the amount of variability explained by these models was the 15% at the highest. In Model 1(51 sites), number of flowering *F. gentneri* was best explained by the previous winter's precipitation (in), and the previous spring's minimum temperature (Table 1, Figure 3). While this model had a strong *p* value, these variables were able to capture only 7.5% of the variability in the data. With Model 2, sites with a mean of less than one were deleted, resulting in 36 sites. In this model, spring precipitation (in) and the previous spring's minimum temperature (F) were the strongest predictors, explaining 9.7 % of the variability, which was a slight improvement from Model 1 (Figure 4). For Model 3, we deleted sites that had zero plants in five or more years, resulting in 32 sites. The model had the same predictors as Model 2 and added previous winter maximum VPD as another predictor, explaining 15% of the variability, which was our strongest model (Figure 5). Model 4 was run with data from sites that were monitored from 1999-2017 (24 sites); this model only explained 5.8% of the variability (Figure 6), and had different predictors: winter maximum vapor pressure deficit and previous winter maximum vapor pressure deficit (Table 1).

While our models may not have strong predictors that explain all *F. gentneri* flowering, they do indicate climate variables that have some impact on flowering across the populations. The response surfaces of our models were multimodal, making them difficult to interpret (Figures 3-6). The previous spring's minimum temperature was selected as a predictor in models 1-3. This indicates that the temperature in the previous spring, particularly how cool it was, could have an impact on flowering of *F. gentneri* in the successive year. Looking at the response surfaces, all models indicated a dip in the high end of the temperature range and an increase in flowering in the cooler temperatures (Figures 3-5). This suggests that cooler temperatures experienced in the previous spring could positively impact flowering the following year. In Model 1, previous winter's precipitation came out as a predictor, indicating that precipitation in the previous winter could impact flowering the following spring, however the response surface is not linear (Figure 3). Models 2 and 3 shared spring precipitation as a predictor, which suggests that precipitation impacting the site in spring can impact flowering for that season. It is interesting that models 2 and 3 share two of the same predictors, even though they were created with different sites in the model. Model 3 also selected the previous winter's maximum vapor pressure deficit as an additional predictor, a predictor also selected in Model 4. In Model 3, flowering decreased with increased winter maximum vapor pressure deficit in the year prior to flowering (Figure 5). This suggests that in times of high winter vapor pressure deficit (or low relative humidity), flowering decreases. Model 4 was created using a more long-term dataset but resulted in a weak model; despite this it also selected previous winter maximum vapor pressure deficit and the current year winter maximum vapor pressure deficit, which occurs just before flowering (Table 1). While our models were not particularly strong, this corroborates that these climate factors do have some impact *F. gentneri* flowering.

Table 1. Non-parametric multiplicative regression modeling of the number of flowering *F. gentneri* in relation to climate/environmental predictors. xR^2 =leave-one-out cross-validated statistic for fit. Average N* = amount of data used to obtain a particular point estimate. Tolerance = the range of predictor space over which data values are used to estimate response (sensitive to scale of data); predictors with narrow tolerances have greater effects on the model than do those with broad tolerances. Model 1 indicates that model run with the full dataset. Model 2 used the response where sites with a mean of less than 1 were removed. Model 3 used the response where sites with 5 or more years with no plants were removed. Model 4 used the response for sites monitored over a longer time period (1999-2017).

Response	Model 1	Model 2	Model 3	Model 4
Number of sites	51	36	32	24
Year range	2008-2017	2008-2017	2008-2017	1999-2017
xR^2	0.0747	0.0968	0.1511	0.0583
p	0.0099	0.0099	0.0099	0.0099
Average N*	41	20	16.6	27.8
Predictor	**Sensitivity (Tolerance)**	**Sensitivity (Tolerance)**	**Sensitivity (Tolerance)**	**Sensitivity (Tolerance)**
Previous Winter Precipitation (in)	0.24(0.41)	-	-	-
Spring Precipitation (in)	-	0.32(0.24)	0.17(0.48)	-
Previous Spring Minimum Temperature (F)	0.18(1.1)	0.21(1)	0.45(0.55)	-
Previous Winter Maximum VPD	-	-	0.03(1.65)	0.17(0.55)
Winter Maximum VPD	-	-	-	0.38(0.22)

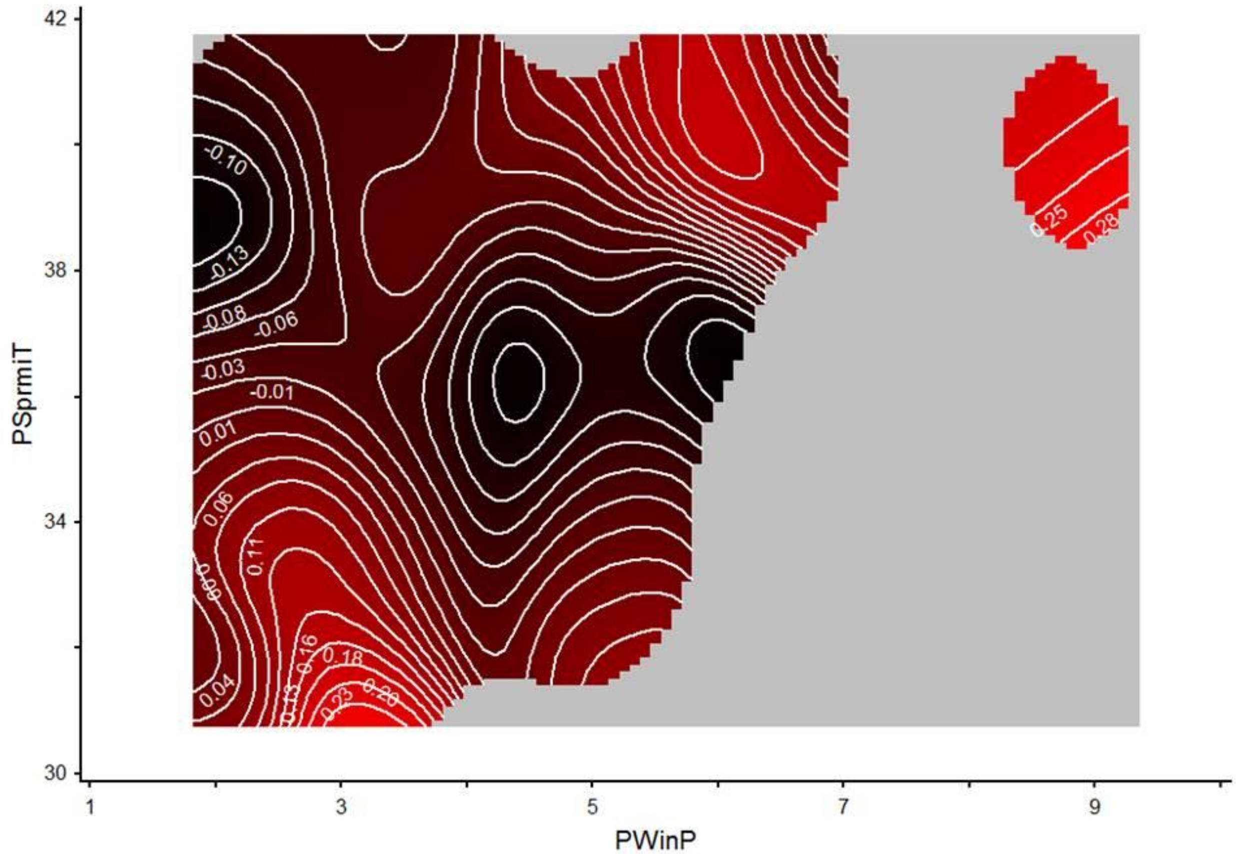

Figure 3. Response surface for Model 1, the number of flowering F. gentneri, predicted by previous spring minimum temperature (PSprmiT) and previous winter's precipitation (PWinP). Model 1 was created using data from 51 sites.

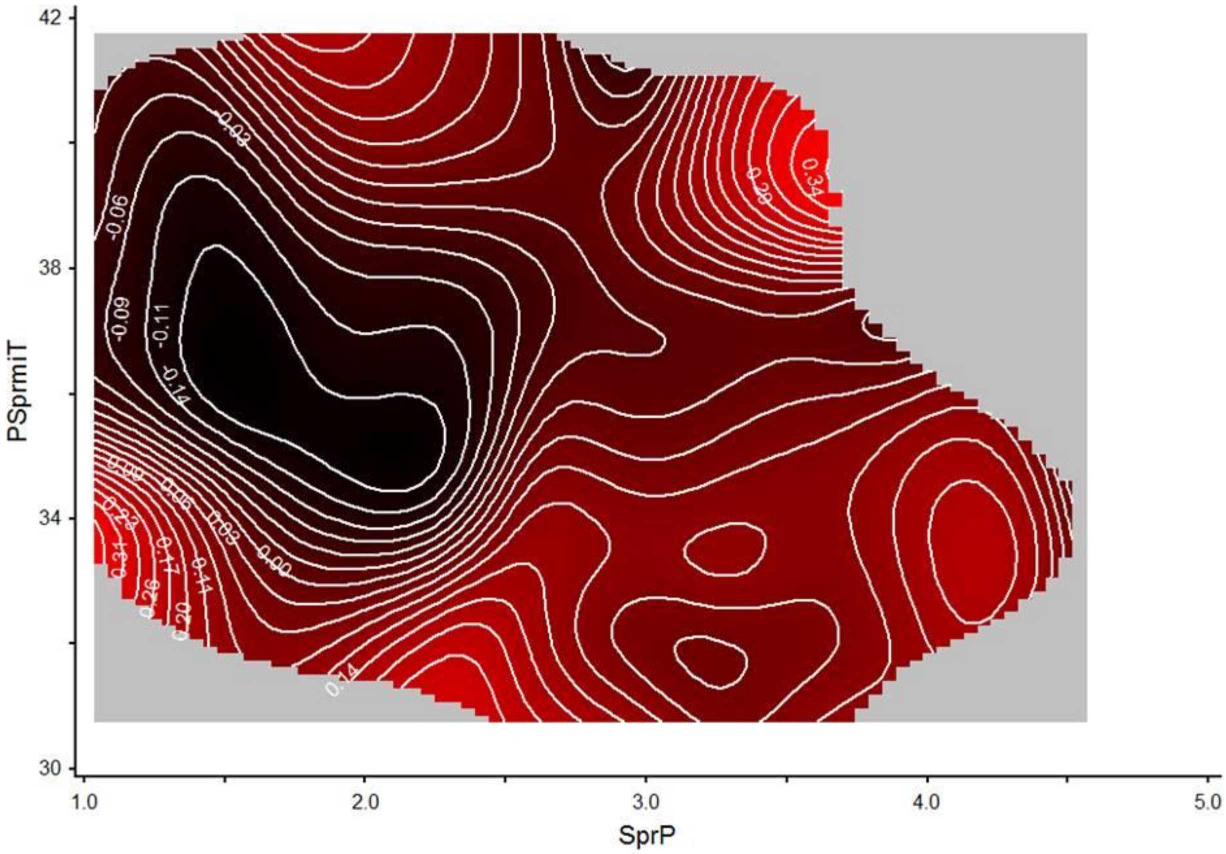

Figure 4. Response surface for Model 2, the number of flowering F. gentneri, predicted by previous spring minimum temperature (PSprmiT) and spring precipitation (SprP). Model 2 was created using data from 36 sites.

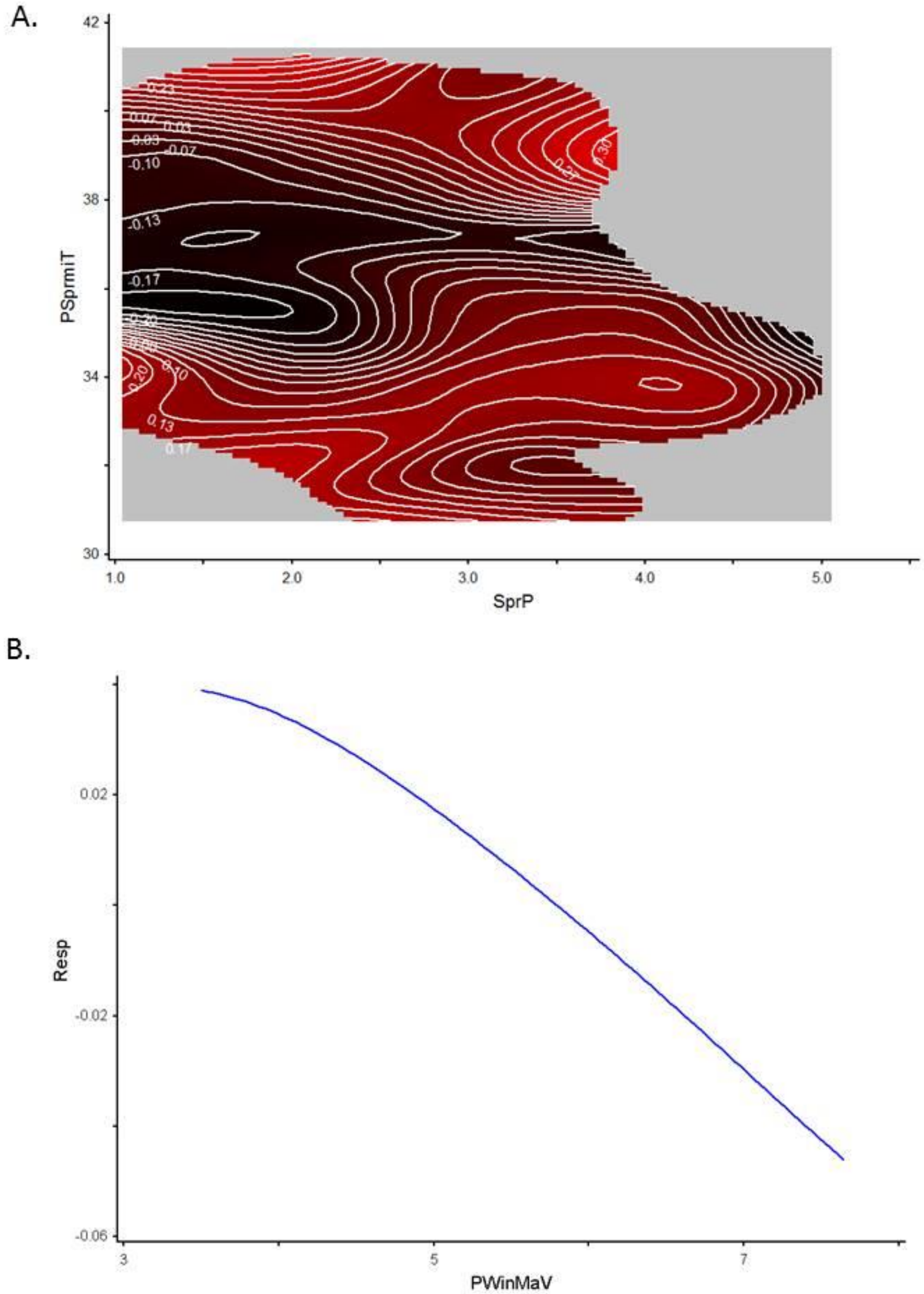

Figure 5. Response surfaces for Model 3, the number of flowering F. gentneri, predicted by (A.) previous spring minimum temperature (PSprmiT) and spring precipitation (SprP), and (B.) the number of flowering F. gentneri (Resp) predicted by previous winter maximum vapor pressure deficit (PWinMaV). Model 3 was created using data from 32 sites.

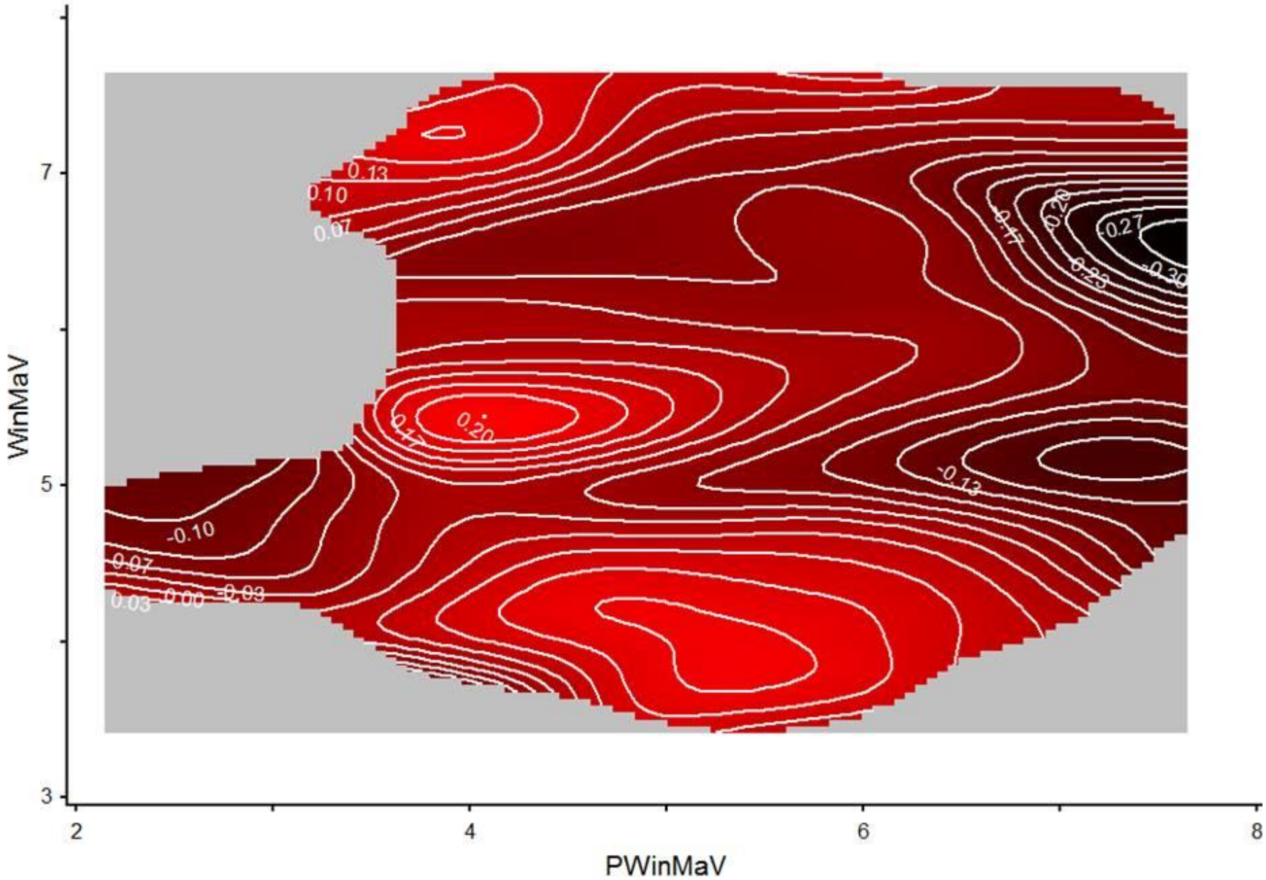

Figure 6. Response surface for Model 4, the number of flowering F. gentneri, predicted by winter maximum vapor pressure deficit (WinMaV) and previous winter maximum vapor pressure deficit (PWinMaV). Model 4 was created using data from 24 sites monitored from 1999-2007.

The low xR^2 values in all our models suggests that while we were able to find climate factors that may impact flowering of *F. gentneri*, other factors are likely to be impacting flowering that were not represented with our models. While soils data were incorporated in our models in early runs, they were based on broad soils series data (Map Unit Descriptions) from the Web Soil Survey (NRCS 2017), and were not found to predict flowering across the sites modeled. This species might be responding to soil characteristics that differ at a more localized or microclimate scale, which we were unable to capture. Likewise, the plant community was something we were unable to add into our models due to insufficient data, but could affect population dynamics of *F. gentneri*. Competition from non-native species, particularly annual grasses, could affect population dynamics for this species. This species has been reported in numerous plant community types across its range (USFWS 2003), which could vary greatly in moisture and light. While we were able to test heat load and PDIR as potential predictors, we were limited in not having data pertaining to the plant community and other microclimatic factors.

Figure 7. Small bulblets of F. gentneri produced from the mother bulb. Photo by Jordan Brown (ODA).

While flowering in *F. gentneri* is the most consistent method to identify the species amid closely related species, this species reproduces vegetatively as its primary means (USFWS 2003). Number of flowers often represents only a small percentage of true population size, given its ability to produce small rice-like bulblets from the mother bulb (Figure 7). There are many unknowns associated with the demography of these species, including the lifetime of individual plants and the number of years to sexual maturity. Flowering plants have been observed to flower numerous years in a row, or to flower and then return to a vegetative state or go dormant (USFWS 2003). Understanding the environmental cues that impact these changes is an important step towards conservation and recovery of this rare species.

While our models do suggest some climate drivers that may be impacting flowering, they do not fully explain the environmental and climate factors that impact flowering of *F. gentneri*. This method of statistical modeling could be applied to other rare species, with appropriate data available, where there is an increased need for understanding response(s) to the environment and climate change. Similar models can take into account the inherent variability and site specific differences and could help land managers increase understanding of the factors that are impacting population dynamics.

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