Pocket gopher (*Thomomys talpoides*) soil disturbance peaks at mid elevation and is associated with air temperature, forb cover, and plant diversity

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Supplementary Material

Table S1. GPS coordinates and elevation of each site within a transect.

Peak	Latitude (°)	Longitude (°)	Elevation (m)
Avery	38.86548	-106.91236	2711
Avery	38.86523	-106.91238	2812
Avery	38.95136	-106.98636	2896
Avery	38.96224	-106.98546	2982
Avery	38.96594	-106.98281	3135
Avery	38.97142	-106.98428	3192
Avery	38.97529	-106.97827	3347
Avery	38.92741	-106.97823	3455
Avery	38.98407	-106.97021	3655
Cinnamon	38.88163	-106.96172	2749
Cinnamon	38.89727	-106.97899	2799
Cinnamon	38.93460	-107.01078	2932
Cinnamon	38.94540	-107.02822	3025
Cinnamon	38.96168	-107.03091	3181
Cinnamon	38.96189	-107.03879	3223
Cinnamon	38.97018	-107.02955	3366
Cinnamon	38.99111	-107.06497	3416
Cinnamon	38.99356	-107.06754	3579
Cinnamon	38.99463	-107.06913	3665
Cinnamon	38.99495	-107.07043	3726
Hunters Hill	38.84759	-106.81964	2824
Hunters Hill	38.90366	-106.78383	3060
Hunters Hill	38.92538	-106.77776	3171
Hunters Hill	38.92596	-106.79232	3249
Hunters Hill	38.92683	-106.79105	3322
Hunters Hill	38.92963	-106.78896	3430
Hunters Hill	38.93297	-106.78699	3531
Hunters Hill	38.93762	-106.78742	3629
Hunters Hill	38.94084	-106.78776	3724
Hunters Hill	38.94595	-106.78773	3827
Ruby	38.86430	-107.03173	2822
Ruby	38.85617	-107.06954	2945
Ruby	38.86447	-107.10579	3055
Ruby	38.87421	-107.10598	3128
Ruby	38.88382	-107.11328	3199
Ruby	38.89454	-107.11722	3333
Ruby	38.90226	-107.11630	3447

Ruby	38.90104	-107.12194	3539
Ruby	38.89997	-107.12580	3633
Ruby	38.89916	-107.12836	3723
Ruby	38.89732	-107.12805	3833
Teocalli	38.89571	-106.89122	2776
Teocalli	38.90614	-106.88384	2868
Teocalli	38.92877	-106.87845	2948
Teocalli	38.94404	-106.88717	3047
Teocalli	38.94815	-106.89016	3157
Teocalli	38.94758	-106.88071	3275
Teocalli	38.94720	-106.87756	3351
Teocalli	38.95034	-106.87619	3443
Teocalli	38.95344	-106.87629	3553
Teocalli	38.95593	-106.87794	3667
Teocalli	38.95818	-106.87793	3771
Teocalli	38.95919	-106.88007	3879
Teocalli	38.96000	-106.88272	3954
Treasury	38.91862	-107.03628	2747
Treasury	38.93282	-107.04979	2795
Treasury	38.97258	-107.06186	2972
Treasury	38.96515	-107.05943	3038
Treasury	38.97073	-107.05871	3197
Treasury	38.97579	-107.05853	3257
Treasury	38.98617	-107.06182	3371
Treasury	38.98793	-107.06498	3418
Treasury	38.99574	-107.07463	3521
Treasury	39.00000	-107.08065	3598
Treasury	38.99993	-107.08430	3698
Treasury	39.00584	-107.09083	3815
Treasury	39.01131	-107.09565	4023

Table S2. There was significant spatial autocorrelation in five out of the six predictor variables. For each predictor, Moran's *I* estimates the amount of spatial autocorrelation for a given predictor, such that high values indicate high spatial autocorrelation. Each Moran's *I* is accompanied by a standard deviation estimate (*SD*) and a *p*-value.

Predictor	Moran's *I*	*SD*	*p*-value
Forb:grass	0.06548605	0.04408553	0.0674
Inverse Simpsons'	0.09267314	0.04680174	0.0212
Sine aspect	0.1270489	0.04701599	0.0025
Cosine aspect	0.1463025	0.04624237	0.0005
Soil depth	0.2016100	0.04644518	<0.0001
MAT	0.3085896	0.04684599	<.00001

Supplementary Methods S1- Climate interpolation detailed methodology and results
All code and data associated with this document are available upon request to Joshua Lynn (jslynn@unm.edu) or Jennifer Rudgers (jrudgers@unm.edu).

METHODS

Data compilation

We compiled climate data from 29 weather stations in Gunnison and Pitkin Counties, Colorado (Table S3, Fig. S1). Slope, elevation, and aspect for each station were obtained from USGS digital elevation models (DEMs; Dollison 2010), based on the station's reported latitude and longitude. Weather stations varied in the period of record, therefore, while the data are useful for interpolating climate means, we do not recommend using them to interpolate values for a given year, without investigating the level of basin-wide coverage in that time period. More recent years will have complete coverage.

Daily data are available in the file: `allclimatedata_oct2016.csv`

Climate yearly summaries

We gap-filled missing data only for days that were flanked on both sides by available data, and did so by taking the average of the single prior day and single subsequent day. We then calculated annual summaries of climate variables over each water year (1 Oct - 30 Sep). For the calculation of average summer temperature, we excluded four outlier observations <0C from Porphyry Creek (station 25) during 1989. The mean cumulative growing degree days (GDD) was determined over the period of 1 Jun - 30 Sep using a base temperature of 0°C (Frank and Hofmann 1989). GDD is particularly useful because it provides an integrated measure of temperature combined with the length of the growing season. Mean annual precipitation (MAP) and mean snow depth (MSD) were calculated for each water year over the full period of record of each weather station (Table S3). Because snow depth is highly locally variable, we urge caution in interpolating snow depth data to new sites.

Our process excluded data that may be compromised by missing observations due to temporary equipment failures. We used GDD and snow depth data from a station × water year combination only if <5% of days in a given water year were missing data. We used annual precipitation data only if <10% of days in a given water year were missing data, under the assumption that this decision could be less conservative than for temperature or snow depth because many days have zero precipitation, and MAP is a cumulative, rather than average, metric.

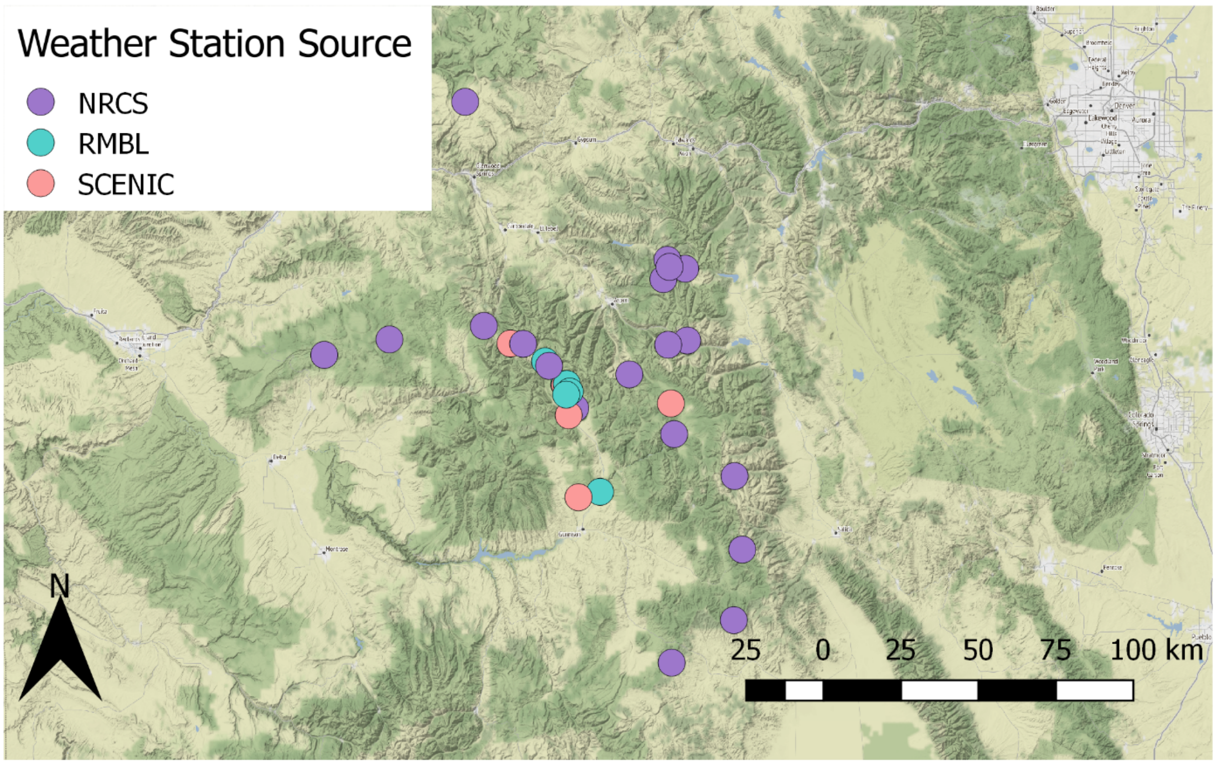
R script to create the yearly summaries: `GunnisonBasinYearlyMet.R`
Yearly data summary produced by this script: `GunnisonBasinYearlyMet.csv`

Slope, aspect, elevation from Digital Elevation Models

For each meteorological station and each site for which we wished to predict climate, we determined the median value of slope, aspect, and elevation from “The National Map” DEMs, provided by the USGS (Dollison 2010). All GIS analyses were performed in QGIS (QGIS Development Team 2017). DEMs were used to create layers containing slope and aspect data for the region (*r.slope.aspect*; GRASS Development Team 2017). Coordinates for the weather station were then given a circular buffer area with a radius of 10m (*Fixed distance buffer* tool; GRASS Development Team 2017). Slope, elevation and aspect values for each weather station were taken as the median for the buffer area, with aspect converted to radians.

DEM data for each weather station: `GunnisonBasinDEM.csv`

Fig. S1. Map of weather stations in Gunnison and Pitkin Counties, Colorado, used for climate interpolation.



Climate regression models

To determine coefficients to interpolate climate for locations of biological observations that lacked weather stations, we used model selection procedures based on the second order Akaike Information Criterion (*AICc*), following Anderson (2008) and Burnham and Anderson (2002). This method predicts each climate variable from the best combination of elevation, slope, and aspect according to the minimum *AICc*, which discounts for model complexity and corrects for bias due to sample size. Aspect was included in models as sine (aspect) + cosine (aspect) to account for the circularity in this metric. The sine of aspect represents the east-west gradient (1=east), and the cosine of aspect accounts for north-south variation (1=north). We initially tested each climate variable for significant nonlinearities against elevation, slope, and aspect, and detected none. We therefore used linear equations to interpolate climate for each location of biological data collection. We also examined models that included latitude and longitude; however, these predictors were weak, and should not have a directional influence at the small spatial scale of the Upper Gunnison Valley Basin (I. Rangwala, *pers. comm.*).

The set of eight candidate models included all predictors (1 model: elevation + slope + sin(aspect)+cos(aspect)), all sets of two predictors (3 models), single predictors alone (3 models), and the null model, which included only random effects. All linear mixed effect models included the random effects of station identity and water year to account for the lack of independence of observations from the same location or same time period (`lmer` function in `lme4` package, R Core Team 2016). We tested all models for assumptions of normality of residuals and homogeneity of variances, and used outlier exclusions (<9 observations per variable) to meet model assumptions rather than imposing transformations on the data that would alter interpretability.

When the best model included multiple predictors, we examined correlations among the predictors and tested for possible multicollinearity using the `vif` function in `car`; we found no violation of multicollinearity. When models were similar in *AICc* (delta < 2) we selected the model with more predictors and higher R^2 to increase resolution of the prediction. We obtained marginal and conditional likelihood R^2 for the best candidate models using the `sem.model.fits` function in the `piecewiseSEM` package implemented in R (Lefcheck 2015; Nakagawa and Schielzeth 2013, R Core Team 2016). Marginal R^2 describes the proportion of variance explained by the fixed factors alone, whereas conditional R^2 describes the proportion of variance explained by both the fixed and random factors. We used likelihood ratio X^2 tests to evaluate the statistical significance of individual predictors within the best model.

R script to build regression models: `GunnisonBasinInterpolation.R`

Climate interpolation

To predict average yearly climate variables for a new set of sites, we used the `predict` function in R stats package. For each climate variable, we generated two prediction models. The first included the random effects of site and year to account for non-independence of observations at those scales and generate year-specific predictions (p1). The second returns the average predicted value, without random effects in the model (p2). Standard errors of predictions are not easily computed because of the difficulty in incorporating uncertainty in the variance parameters, and we have not tackled the uncertainty issue.

R script for prediction is at the end of: `GunnisonBasinInterpolation.R`

RESULTS

Coefficients from the best model for each climate variable appear in Table S4. Datasets differed in coverage over the range of elevation, slope, and aspect (Table S3). Even though predictions were linear, we caution predicting outside of this range, especially at the highest elevations, where weather station data were most limited.

Temperature variables strongly declined with elevation, with a marginally positive influence of slope. Mean yearly minimum temperature was not explained by any predictors; the null model had the lowest *AICc*. Thus, minimum temperatures should not be interpolated using this dataset. Minimum temperatures in Gunnison, CO (2420 m) are often lower than those at higher elevation, which may explain the lack of influence of elevation for this variable.

Precipitation variables consistently increased with elevation, but some also had relationships with slope and aspect. Mean annual precipitation was primarily influenced by elevation, with equivalently weak influences of both north-south and east-west axes of aspect. This pattern was likely driven by the higher snow depths in west-facing sites and the higher summer precipitation in south-facing sites.

Mean snow depth increased with elevation, and west-facing slopes had deeper snow, with no significant influence of the north-south gradient of aspect. Slope had no meaningful influence on mean snow depth, but because of the location of weather station sites, coverage did not include slopes > 30. Given the local-scale variability of snow depth, we suggest using caution when interpolating that variable, despite the relatively high marginal R^2.

Mean summer precipitation increased with elevation, slope, and in south-facing sites [cosine (aspect)]. However, the low marginal R^2 (Table S4) and high variability suggests using caution when interpolating this variable to other sites using our models.

Significant contributors (for Acknowledgements):

If you use these data or their products, please acknowledge:

Melanie Kazenel acquired and gap-filled the climate dataset and constructed initial models. Joshua Lynn and Jennifer Rudgers conducted statistical analyses in consultation with Imitaz Rangwala (University of Colorado, Boulder) and Shannon Sprott (Rocky Mountain Biological Laboratory). This work was funded by NSF DEB#1354972.

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R Core Team. 2016. R: A Language and Environment for Statistical Computing. R Foundation for Statistical Computing, Vienna, Austria.

Table S3. Locality information of weather stations from which climate data were aggregated, along with data collection period of record and data source (RMBL = Rocky Mountain Biological Laboratory, NRCS = USDA Natural Resources Conservation Service, SCENIC = Southwest Climate and Environmental Information Collaborative). Elevation is given in m. Slope and aspect data were not available for Bison Lake; it was excluded from analyses.

Station Name	Number	Elevation	Latitude	Longitude	Record	Source
Billy Barr	1	2917	38.9631	-106.9933	2011-2015	RMBL
Bison Lake	11	3316	39.7649	-107.3568	1987-2015	NRCS
Brumley	12	3231	39.0877	-106.5417	1981-2015	NRCS
Butte	13	3097	38.8943	-106.9530	1982-2015	NRCS
Chapman Tunnel	14	3082	39.2622	-106.6293	2008-2015	NRCS
Cochetopa Pass	15	3054	38.1628	-106.5988	2005-2015	NRCS
Crested Butte	6	2702	38.8739	-106.9769	1981-2015	SCENIC
Crested Butte 6.2N	7	2928	38.9603	-106.9908	2006-2015	SCENIC
Gunnison 6.6N	8	2420	38.6391	-106.9408	2010-2015	SCENIC
Independence Pass	16	3231	39.0754	-106.6117	1982-2015	NRCS
Ivanhoe	17	3170	39.2920	-106.5492	1993-2015	NRCS
Judd Falls	2	3004	38.9636	-106.9836	2010-2015	RMBL
Kettle Ponds	3	2860	38.9417	-106.9731	2010-2015	RMBL
Kiln	18	2926	39.3172	-106.6145	1981-2015	NRCS
Marble 0.5NNW	9	2565	39.0791	-107.1906	2011-2015	SCENIC
McClure Pass	19	2896	39.1290	-107.2881	1981-2015	NRCS
Mexican Cut	4	3412	39.0283	-107.0636	2010-2015	RMBL
Nast Lake	20	2652	39.2972	-106.6069	1987-2015	NRCS
North Lost Trail	21	2804	39.0781	-107.1439	1986-2015	NRCS
Overland Reservoir	22	2999	39.0906	-107.6347	1990-2015	NRCS
Park Cone	23	2926	38.8200	-106.5897	1981-2015	NRCS
Park Reservoir	24	3036	39.0464	-107.8741	1981-2015	NRCS
Porphyry Creek	25	3280	38.4888	-106.3397	1981-2015	NRCS
Saint Elmo	26	3213	38.6998	-106.3680	2008-2015	NRCS
Sargents Mesa	27	3514	38.2856	-106.3707	2010-2015	NRCS
Schofield Pass	28	3261	39.0152	-107.0488	1986-2015	NRCS
Snodgrass	5	3396	38.9331	-106.9861	2010-2015	RMBL
Taylor Park Colorado	10	3173	38.9078	-106.6017	1989-2015	SCENIC
Upper Taylor	29	3243	38.9908	-106.7542	2010-2015	NRCS

Table S4. Coefficients for regressions of climate variables on elevation, slope, and aspect.

	Intercept		Elevation				Slope				sin(Aspect)				cos(Aspect)				Model		Observed Range			N	Elevation Range	Slope Range	Aspect Range
Climate variable	Est.	*s.e.*	β	*s.e.*	X^2	P	β	*s.e.*	X^2	P	β	*s.e.*	X^2	P	β	*s.e.*	X^2	P	mR^2	cR^2	*min*	*mean*	*max*				
Temperature (C)																											
Mean Annual Temperature	12.28	2.56	-0.0038	0.0009	20.05	**<0.0001**	0.0444	0.0285	2.43	0.1188	----	----	----	----	----	----	----	----	0.21	0.88	-6.61	1.05	6.28	517	2659 - 3501	2.2 - 30.1	----
Average Summer Temperature	26.10	2.26	-0.0050	0.0007	44.75	**<0.0001**	0.0423	0.0250	2.86	0.0907	----	----	----	----	----	----	----	----	0.43	0.94	5.94	11.314	16.01	489	2659 - 3501	2.2 - 30.1	----
Growing Degree Days	2966.24	291.22	-0.5430	0.0970	19.87	**<0.0001**	5.0200	3.2100	2.33	0.1272	----	----	----	----	----	----	----	----	0.37	0.91	724.6	1373.1	2047.3	481	2659 - 3501	2.2 - 30.1	----
Precipitation (mm)																											
Mean Annual Precipitation	-405.96	457.20	0.3804	0.1509	6.35	**0.0117**	----	----	----	----	-75.17	54.03	1.94	0.1641	-76.34	60.48	1.59	0.2069	0.19	0.90	105.9	778.8	1814.0	567	2420 - 3501	0.8 - 26.9	0.15 - 6.32
Mean Snow Depth	-626.78	403.37	0.3367	0.1313	6.57	**0.0103**	----	----	----	----	-108.07	41.79	6.69	**0.0097**	26.62	46.51	0.33	0.5671	0.30	0.90	30.0	419.2	1237.3	188	2659 - 3501	2.2 - 30.1	0.15 - 6.32
Summer Precipitation	-88.53	87.97	0.0895	0.0295	9.19	**0.0024**	4.7048	1.8763	6.29	**0.0122**	17.26	10.57	2.67	0.1024	-28.69	11.65	6.07	**0.0138**	0.12	0.63	50.0	203.7	472.0	536	2420 - 3501	0.8 - 14.8	0.15 - 6.32

Visualizations

Fig. S2. Growing degree days (GDD) decrease with elevation. Partial regression plot of the full model described above.

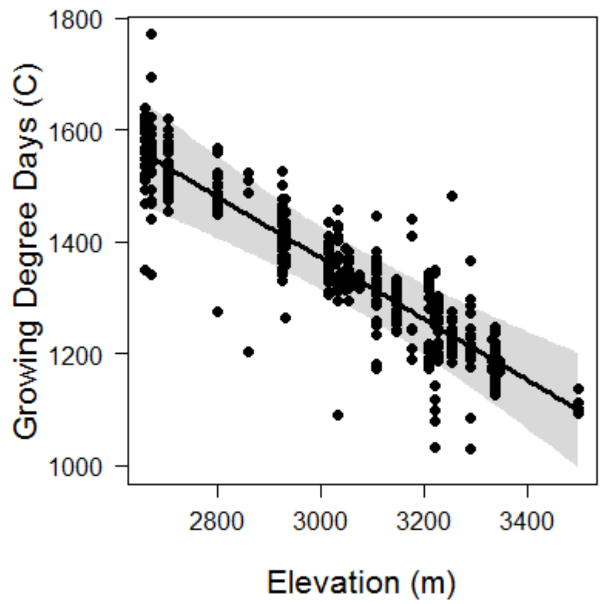

Fig. S3. GDD decreases with the slope and elevation of the weather station interactively.

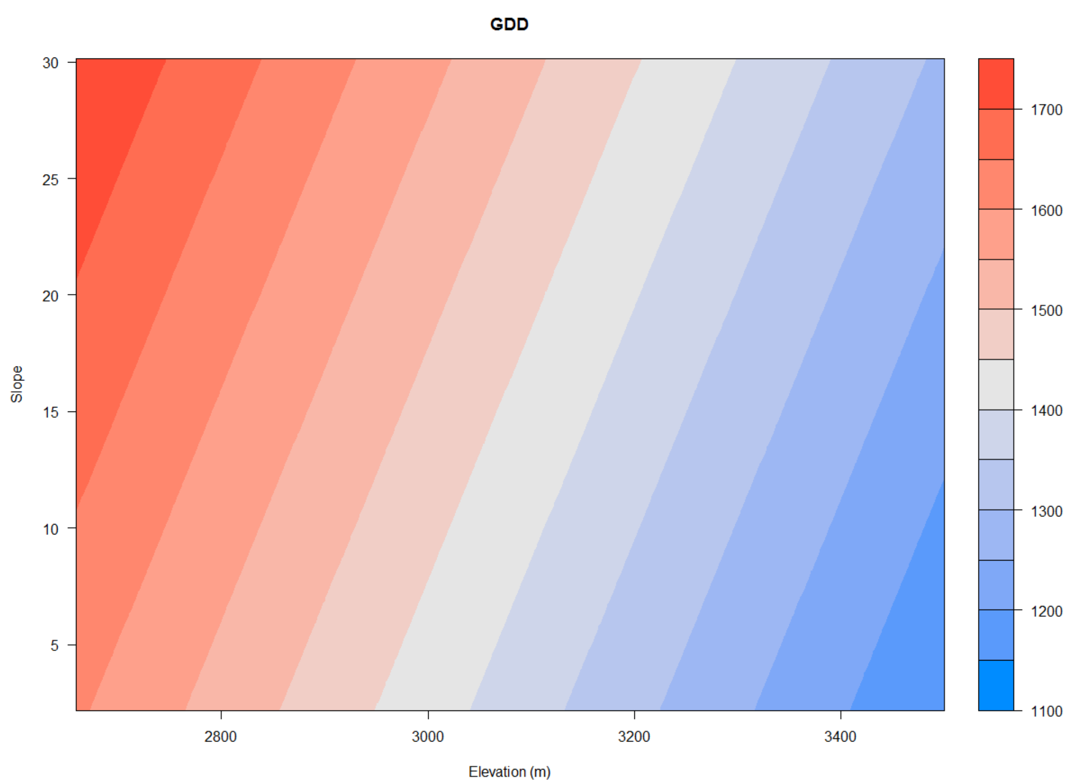

Fig. S4. Mean annual temperature decreases with elevation of the weather station.

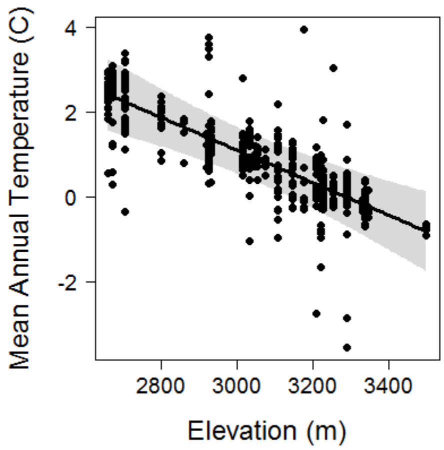

Fig. S5. MAT decrease with slope and elevation of the weather stations, interactively.

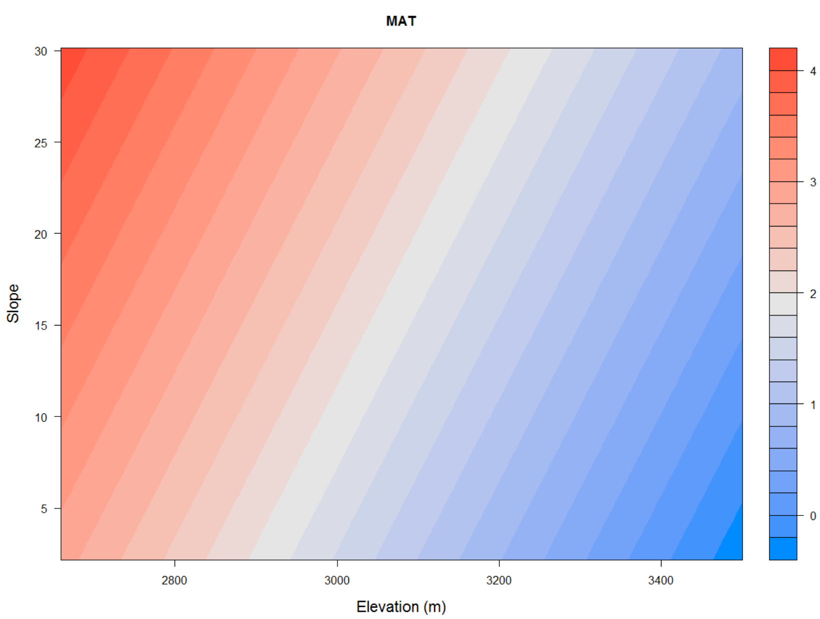

Fig. S6. Mean summer temperature (MSuT) decreases with elevation of the weather station.

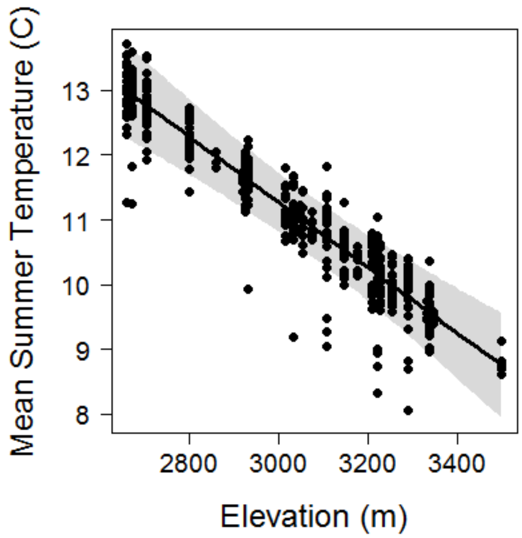

Fig. S7. Mean summer temperature decreases the slope and elevation of the weather station, interactively.

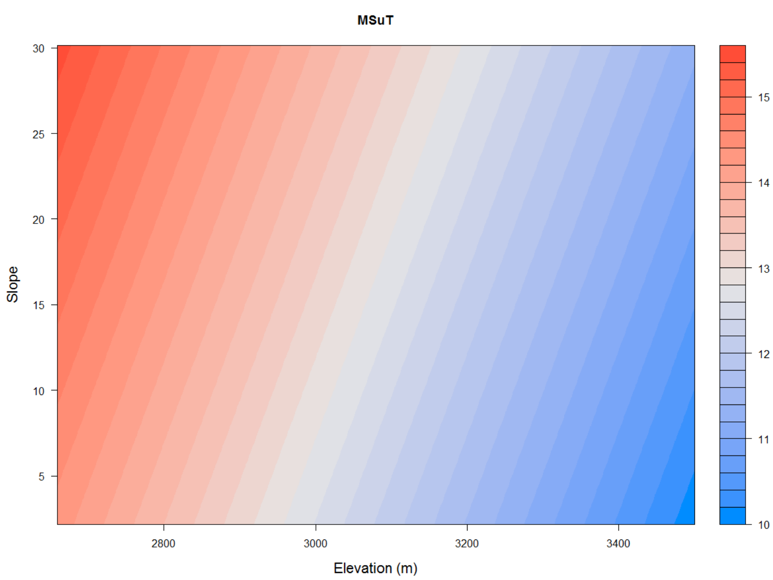

Fig. S8. Mean annual precipitation increases with elevation the weather station.

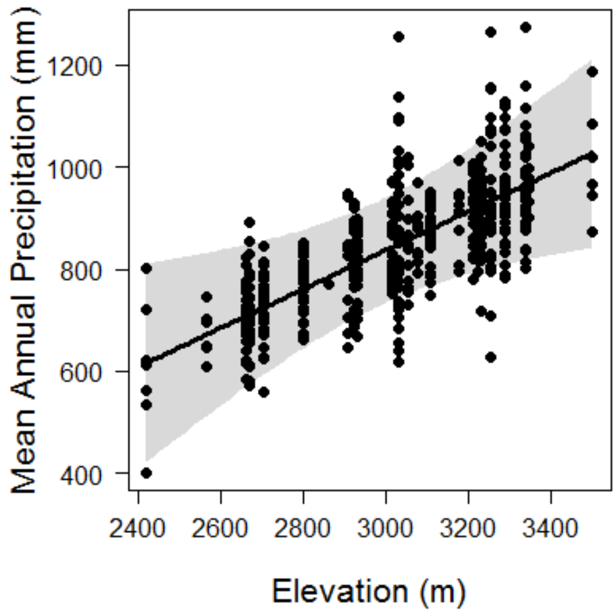

Fig. S9. Summer precipitation increases with weather station elevation. Stations with a slope>25 were excluded.

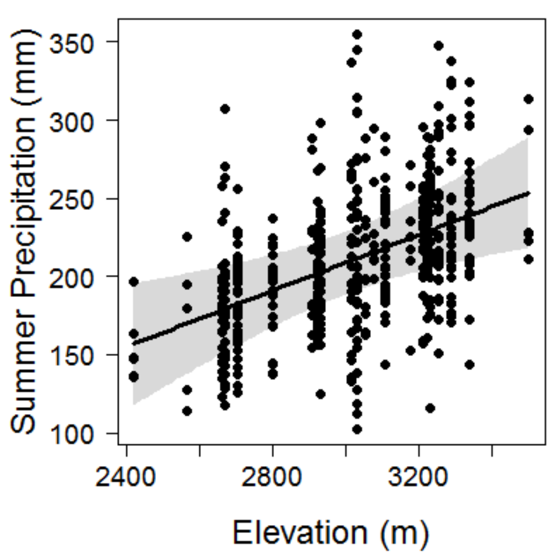

Fig. S10. Summer precipitation increased with slope and sin of the aspect (eastern facing slopes) of the weather stations, but decreased with the cosine of aspect (northern facing slopes).

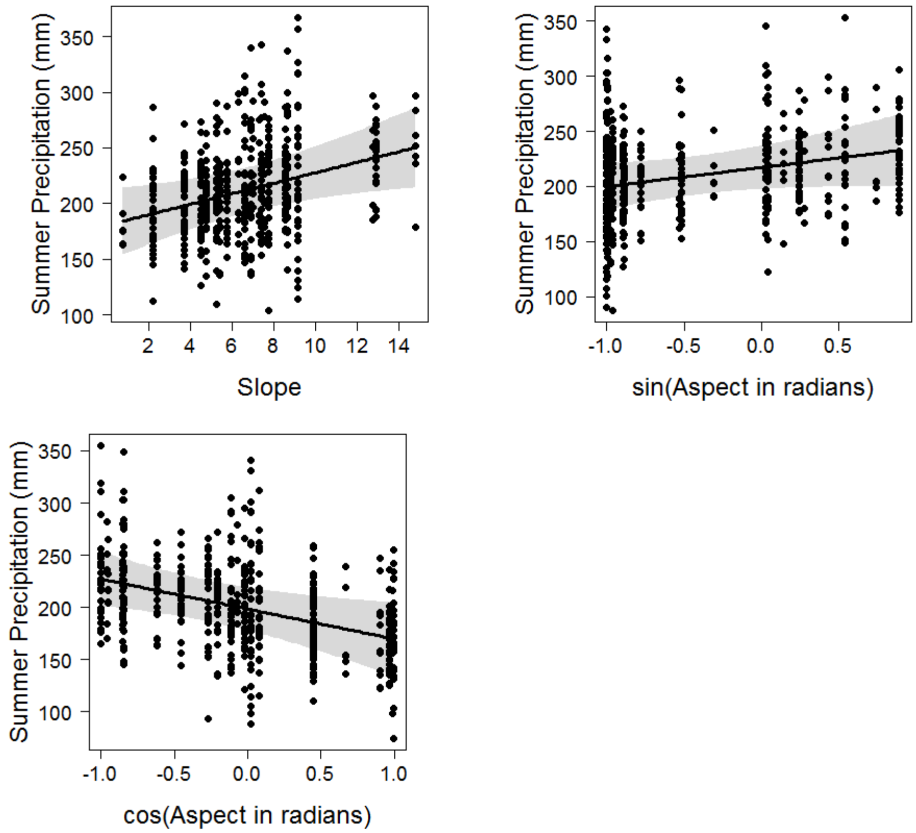

Fig. S11. Summer precipitation increased with the slope and elevation of the weather stations, interactively.

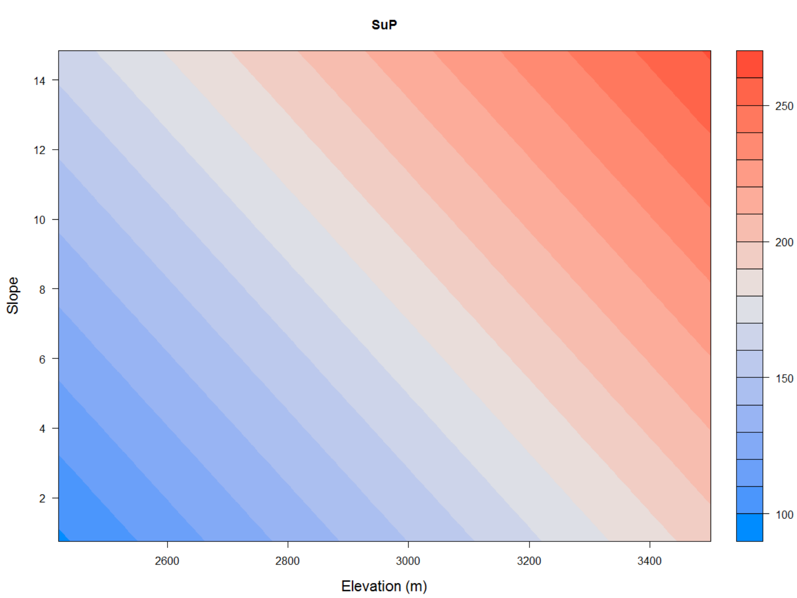

Fig. S12. Summer precipitation increased with elevation and southern facing slopes (negative cosine of aspect), interactively.

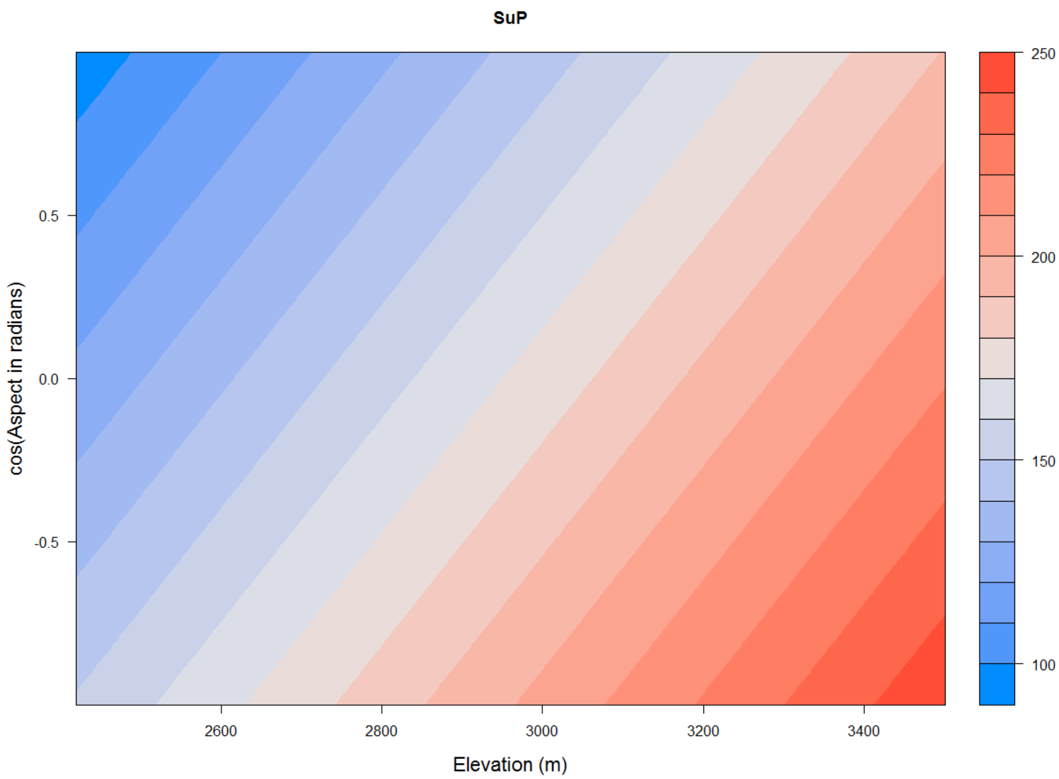

Fig. S12. Snow depth increases with elevation of the weather station and decreases towards eastern facing slope (positive sine of aspect).

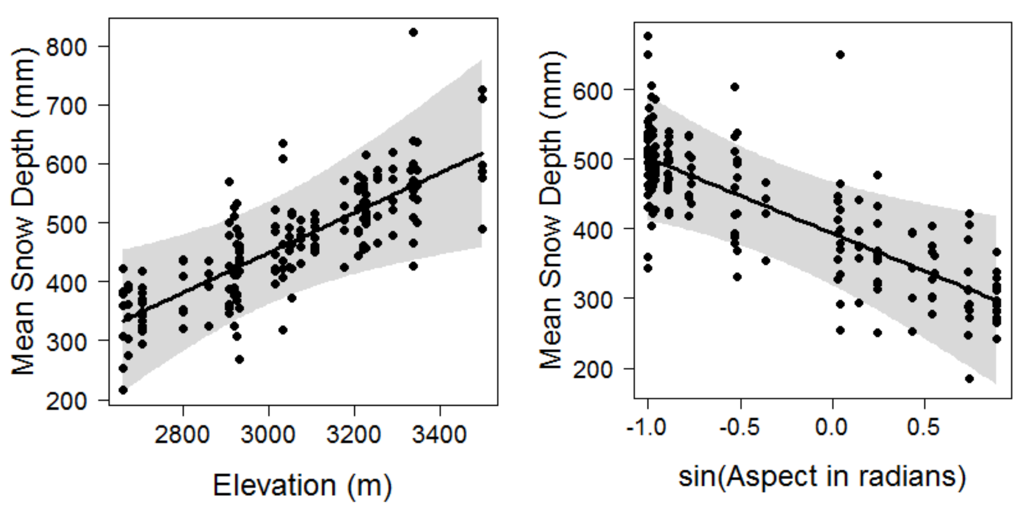

Fig. S13. Snow depth at a weather station decreases with elevation and towards eastern facing slopes, interactively.