

Climatic and Landform Effects on the Distribution of Fine-Textured Volcanic Ash in a Temperate Forest Ecosystem

OVERVIEW

Historical Background

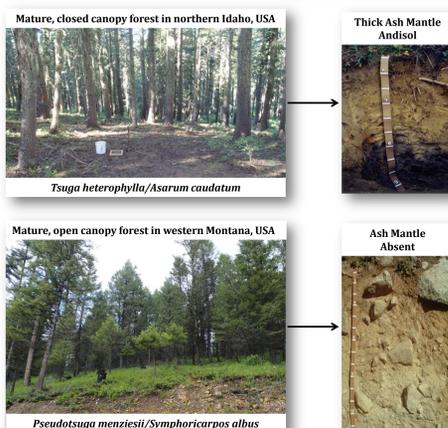
The epochal circular ring fissure eruption associated with Mount Mazama approximately 7,700 yr BP blanketed the Pacific Northwest, USA and western Canada with approximately 120 km³ of volcanic ash and pumice (Zdanowicz et al., 1999). Volcanic ash-influenced forest soils have lower soil bulk density, higher porosity, and higher water infiltration and retention than soil unaffected by ash (McDaniel et al., 2005). There is increasing awareness of the benefit of these properties by forest land use planners and a subsequent desire to spatially identify the distribution of these soils.

Problem Statement

Past volcanic ash modeling efforts primarily focused on landform effects upon ash distribution with varying degrees of success and failure. These modeling efforts did not attempt to define the role of climate (i.e. vegetation cover effects on ash retention). There is growing evidence that climate induced changes to vegetation communities (i.e., ash retention/erosion) may play as large a role in volcanic ash distribution as topography (Brown et al., 2012). Further, none have questioned the assumptions inherent to traditional ordinary least squares regression – specifically, stationarity of the parameter estimates.

Null Hypotheses

- 1) Inclusion of climatic variables does not significantly improve an ash distribution model.
- 2) Independent variable parameter estimates are stationary across the geographic extent of an ash distribution model.



ASH DISTRIBUTION MODEL DEVELOPMENT – Hypothesis 1

Variable Identification

Ash thickness point data ($n = 917$) was obtained from the USDA Natural Resources Conservation Service soil survey ID612 located in north central Idaho, USA (Fig. 1). Topographic variables were derived from a 10 m elevation grid using ArcGIS 10 Spatial Analyst. Climatic variables associated with each x,y coordinate pair were obtained from USDA Rocky Mountain Forest Sciences Laboratory thin plate climate splines (Table 1).

Sector	Code	Physiographic Feature
Ash Depth	adep	Thickness of ash mantle
Location	x	Latitude
	y	Longitude
Topography	elev	Elevation
	slp	Slope
	asp	Aspect
	plcv	Plan curvature
	prcv	Profile curvature
	flowdir	Flow direction
	flowacc	Flow accumulation
Temperature	cti	Compound topographic index
	mat	Mean annual temperature
	dd0	Degree-days <0 degrees C (based on mean monthly temperature)
	dd5	Degree-days >5 degrees C (based on mean monthly temperature)
	d100	Julian date the sum of degree-days >5 degrees C reaches 100
	gsdd5	Degree-days >5 degrees C accumulating within the frost-free period
	fday	Julian date of the first freezing date of autumn
	flp	Length of the frost-free period (days)
	mmax	Mean maximum temperature in the warmest month
	mmin	Mean minimum temperature in the coldest month
mcm	Mean temperature in the coldest month	
Precipitation	map	Mean annual precipitation
	gsp	Growing season precipitation, April to September
	smrsprpb	Summer/Spring precipitation balance: (jul+aug)/(apr+may)
	smrpb	Summer precipitation balance: (jul+aug+sep)/(apr+may+jun)
	smi	Summer moisture index
	pratio	Ratio of summer precipitation to total precipitation

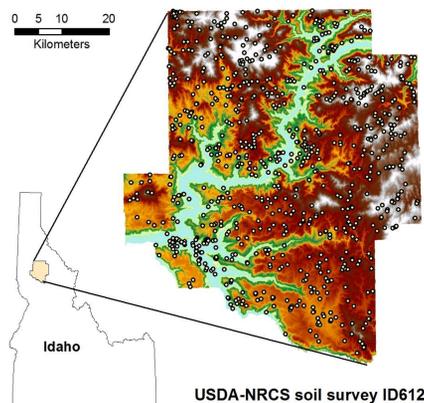


Fig. 1. Geographic location of USDA-NRCS ID612 and the spatial distribution of sampling points.

Variable Selection & Linear Regression Modeling

Multicollinearity between the explanatory variables was assessed through correlation and cluster analyses. Clustered variables showing high inter-correlation were trimmed to one variable showing the highest correlation with the dependent variable ash thickness (adep). Highlighted variables in Table 1 show the trimmed variables selected for modeling ash distribution.

A PROC GLM statement in SAS 9.2 tested the first null hypothesis with the following full model statement and ANOVA:

$$adep = \beta_0 + \beta_1(elev) + \beta_2(pratio) + \beta_3(dd5) + \beta_4(plcv) + \beta_5(cti)$$

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	5	127779.79	25555.96	156.25	<.0001
Error	912	149163.40	163.56		
Corrected Total	917	276943.19			

Parameter	Estimate	Standard Error	t Value	Pr > t
Intercept	104.5862933	12.53719282	8.34	<.0001
ELEV	0.0192036	0.00532831	3.60	0.0003
PRATIO	-248.4597761	15.35444414	-16.18	<.0001
DD5	-0.0050572	0.00412656	-1.23	0.2207
PLCV	0.3910278	0.46817868	0.84	0.4038
CTI	0.2955029	0.18623956	1.59	0.1129

Linear Model Reduction

Full model ANOVA results indicate that elevation (ELEV) and the ratio of summer precipitation to total precipitation (PRATIO) are the primary factors influencing volcanic ash depth. It is surprising that topographic features such as curvature and deposition zones are insignificant in the model, thereby suggesting that 1) variation structure in the independent variables is not being adequately captured by standard linear regression, and/or 2) topography does not play as large a role as previously expected. It does indicate that landscapes receiving the bulk of annual precipitation outside the summer months have thicker ash mantles. This condition would correlate with plant communities dominated by dense coniferous forests at higher elevations.

A reduced model ANOVA is shown here for comparison with the full model ANOVA:

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	2	127116.79	63558.40	388.16	<.0001
Error	915	149826.40	163.74		
Corrected Total	917	276943.19			

Parameter	Estimate	Standard Error	t Value	Pr > t
Intercept	94.7962415	6.48771602	14.61	<.0001
ELEV	0.0251868	0.00190635	13.21	<.0001
PRATIO	-253.9385170	15.06904989	-16.85	<.0001

ASH DISTRIBUTION MODEL DEVELOPMENT – Hypothesis 2

Point and Attribute Clustering Analysis

Linear regression analysis suggests that topographic features do not significantly influence the distribution of volcanic ash. However, standard linear regression cannot capture variance structure in the independent variables due to any spatial autocorrelation in the dataset. To test for spatial autocorrelation, we used a transformed Ripley's K function to identify point clustering (Fig. 2) and a global Moran's Index function to identify ash thickness clustering (Fig. 3).

Spatial autocorrelation findings:

- 1) Peak point clustering occurred between 2000 and 7000 m indicating that soil survey sampling was not random, but was focused in distinct physiographic zones
- 2) Within this point cluster band, ash thickness was also found to be highly clustered with a Moran's I of 0.66, a z-score of 4.77 and p-value of <.0001. Peak Euclidean distance for ash depth clustering was 6643 m.

Test for Parameter Estimate Stationarity

Clustered data can suggest distinct relationships between independent variables and the dependent variable as clusters vary across geographic space. Consequently, the assumption that independent variable influence does not change with space needs to be investigated.

A Monte Carlo spatial variability significance test was used to test whether parameter estimates varied across space. The peak Euclidean distance of 6643 m was used as the neighborhood search bandwidth.

Parameter estimates were generated for each of the trimmed physiographic variables listed in Table 1 as a function of each point location and the number of points located within the bandwidth area. A moving window function then created parameter estimates at each point location, which were then extrapolated spatially using an Inverse Distance Weighting algorithm (Fig. 4).

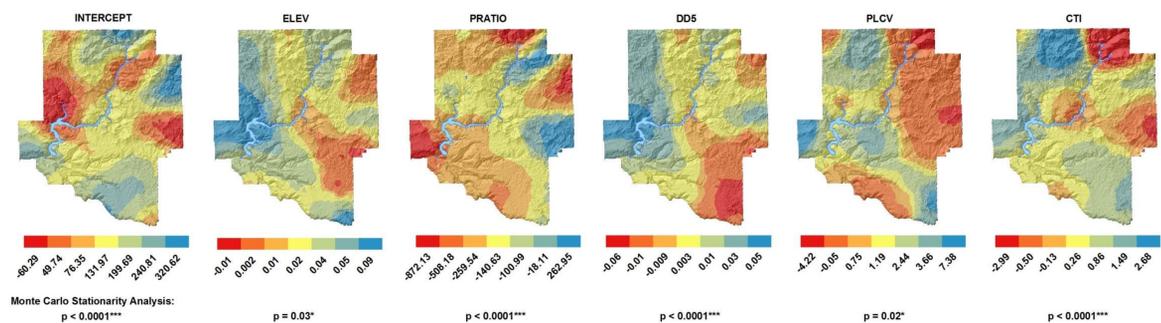


Fig. 4. Parameter estimate spatial variability for the trimmed physiographic features across soil survey ID612 in north Idaho (* = significant at 5% level, *** at 0.1%).

SPATIAL MODELING OF VOLCANIC ASH DISTRIBUTION

Geographically Weighted Regression in ArcGIS

Parameter estimates not only varied within space, but also switched signs. Overall, thick ash mantles were associated with cool/moist climates at higher elevations, divergent landscape positions and in zones of increasing deposition. These findings suggest that volcanic ash is stabilized by lush vegetation communities associated with cool/moist environments and is less susceptible to gravitational movement on divergent topography.

Based on these analyses, we created a predicted ash depth grid (Fig. 5) by multiplying parameter estimate grids by their respective physiographic raster using the following regression equation within the ArcGIS raster calculator:

$$adep = \beta_{0i} + \beta_{1i}(elev_i) + \beta_{2i}(pratio_i) + \beta_{3i}(dd5_i) + \beta_{4i}(plcv_i) + \beta_{5i}(cti_i)$$

Where, $\beta_{(1-n)_i}$ is the parameter estimate associated with each respective 10m grid cell at point i .

Final GWR model ANOVA:

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F	R-Square
OLS Residuals	6.0	135878.2				
GWR Improvement	62.4	28950.8	463.7			
GWR Residuals	756.6	106927.4	141.3	3.28	0.01	0.57

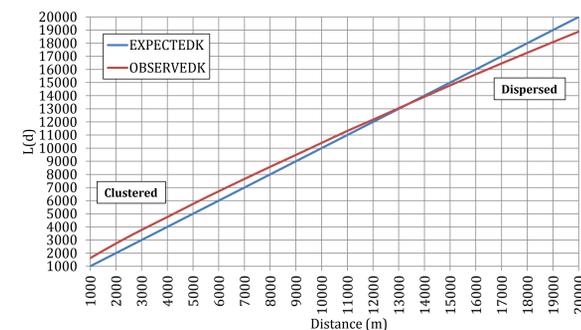


Fig. 2. Spatial autocorrelation of point locations across soil survey ID612 in north Idaho.

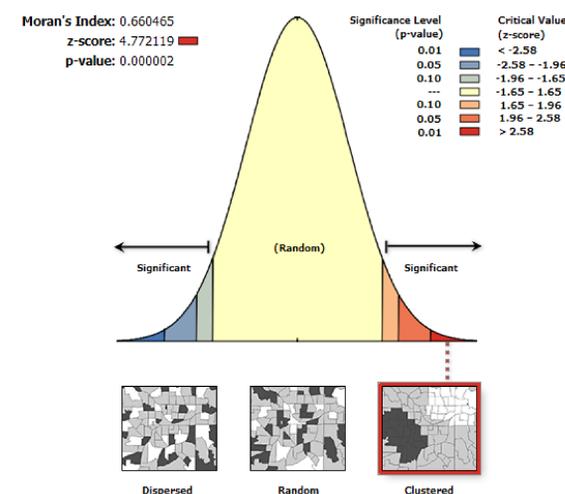


Fig. 3. Spatial autocorrelation of ash depth across soil survey ID612 in north Idaho.

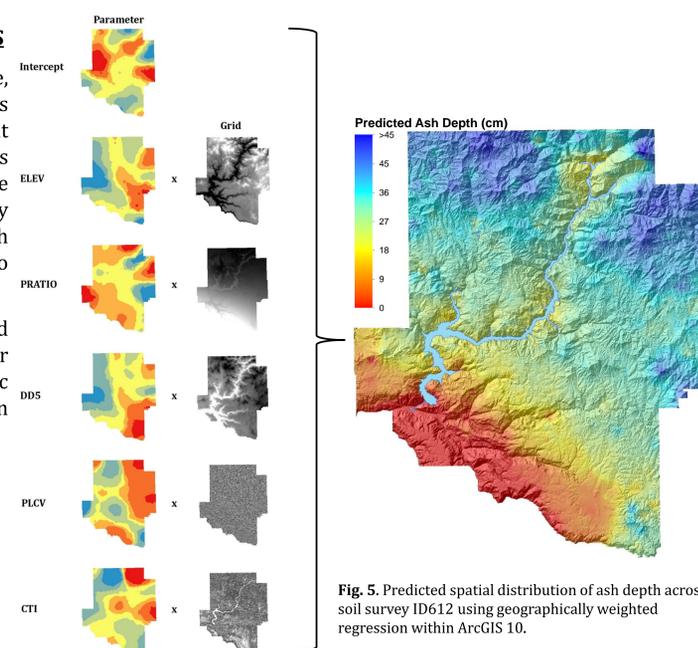


Fig. 5. Predicted spatial distribution of ash depth across soil survey ID612 using geographically weighted regression within ArcGIS 10.