SPATIAL MODELLING OF PYROCLASTIC COVER DEPOSIT THICKNESS WITH REMOTE SENSING DATA AND GROUND MEASUREMENTS: A FORECASTING COMBINATION APPROACH

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ABSTRACT: Thickness of pyroclastic deposits governs various geomorphological and hydrological processes, but studies on the areas characterized by pyroclastic soil coverage are limited in the literature worldwide and the existing models predict thickness mainly based on morphological features of the slope. In this paper, additional variables are also derived from Digital Elevation Model (DEM) and satellite multispectral images to propose a spatial model for forecasting the thickness of pyroclastic deposits. For the prediction model, a two-step procedure is adopted: (1) the best subset of variables is selected; and (2) the predictions from different schemes are combined for deriving the final model. Predictive accuracy tests verify that the combination procedure provides a statistically significant improvement in predictions.

KEYWORDS: ensemble forecasting, remote sensing, environmental science, spatial modelling

1 Introduction

In an eruptive event, volcanic ash disperses in the atmosphere and deposits on the ground surface based on wind speed and direction. Because the geotechnical and hydraulic properties of the unconsolidated pyroclastic ash-fall deposits usually differ from bedrock, the spatial variation of their thickness significantly influences geomorphological and hydrological processes such as landscape evolution, hillslope hydrology, erosion, and landslides. Estimating the spatial distribution of thickness of pyroclastic ash-fall deposits is challenging because there might be more than one eruptive event, changes in wind characteristics during a single eruption can enhance complexity of the ash-dispersal pattern, and soil-forming and geomorphological processes continuously influence the expected spatial thickness.

In the literature, estimating thickness was mainly carried out for the areas covered by residual regolith (e.g., Saulnier et al., 1997; Saco et al., 2006; Tesfa et al., 2009; Segoni et al., 2013) and the approaches developed based on independent variables and applied to a specific site or in limited areas had a better performance (Del Soldato et al., 2018). There is, however, limited information on the thickness of pyroclastic ash-fall deposits under the influence of hillslope processes (De Vita et al., 2006).

Our paper proposes a new approach that considers additional variables for modelling and forecasting the thickness of pyroclastic ash-fall deposits. Combining the results provides more accurate forecasts, which are validated in terms of field measurements and compared with those obtained from three previously developed approaches: (1) Slope Angle Pyroclastic Thickness (SAPT; De Vita et al., 2006); (2) Geomorphological Pyroclastic Thickness (GPT; Del Soldato et al., 2016); and (3) Slope Exponential Pyroclastic Thickness (SEPT; Del Soldato et al., 2018). We apply the predictions for the area around Somma-Vesuvius, Phlegrean Fields and Roccamonfina volcanoes in southern Italy to evaluate the possibility of mapping thickness for a territory with complex geology and geomorphology.

2 Data and methodology

The literature on the tephra-producing eruptions of Somma-Vesuvius, Phlegrean Fields and Roccamonfina volcanoes was studied to prepare a database and compute the distance from eruptive vents along with the cumulative thickness of the ash layer deposited on the ground surface. The existing models like SAPT, GEPT and SEPT predict thickness mainly on the basis of morphological features of the slope. In this paper, we consider additional variables derived from Digital Elevation Model (DEM) and LANDSAT satellite multispectral images.

The following terrain features were then obtained from the DEM (resolution: 10×10m): altitude, slope degree, slope aspect, curvature, profile curvature, plan curvature, flow direction, flow accumulation, stream power index, stream transport index and topographic wetness index. Distance from the hydrographic network was also computed. The imageries of LANDSAT 8 Operational Land Imager (acquired in August 2017 and 2019), Collection 1 Level-1, were finally implemented to obtain four additional variables, i.e. Normalized Difference Vegetation Index (NDVI), Modified Secondary Soil-Adjusted Vegetation Index ($MSAVI_2$) and Normalized Clay Index (NCI) as proposed in the literature.

Following splitting a dataset of 7000 units (70% for training and 30% for testing), a stepwise regression (STPW) is applied to the training dataset for choosing the best subset of variables and for estimating the coefficients of the predictive model. Then, we use the resulting model for forecasting the thickness in the testing dataset.

The final forecasting model is obtained by combining the predictions of the GPT ($\hat{y}_{i,GPT}$), the SAPT ($\hat{y}_{i,SAPT}$), the SEPT ($\hat{y}_{i,SEPT}$) and the STPW ($\hat{y}_{i,STPW}$) approaches:

$$\hat{y}_i = w_1\, \hat{y}_{i,GPT} + w_2\, \hat{y}_{i,SAPT} + w_3\, \hat{y}_{i,SEPT} + w_4\, \hat{y}_{i,STPW} \tag{1}$$

where w_1, w_2, w_3, w_4 are the combination weights. We choose combination weights by evaluating the performance of five different schemes in out-of-sample. The first one is the Sample Average (SA) combination scheme. The second criterion is the Minimum Variance (MV, Hsiao and Wang, 2014):

$$w\colon \min_{w} w'\Sigma w \tag{2}$$

where $w = (w_1, w_2, w_3, w_4)'$ refers to the vector of unknown weights and Σ is the covariance matrix between forecasts of alternative models. The third scheme considers the inverse ranking (InvRank, Ailofi and Timmermann, 2006) of the alternative forecasting models in terms of Root Mean Square Error (RMSE):

$$w_k = Rank_k^{-1} / \sum Rank_k^{-1} \tag{3}$$

where k=1,2,3,4 is the index associated with the k-th forecasting model and $Rank_k^{-1}$ is the inverse ranking of the models in terms of RMSE. The last two considered combination schemes are the Ordinary Least Squares (OLS, Granger and Ramanathan, 1989) and the shrinkage approach (Shrink) of Bodnar et al. (2019).

3 Main results and final remarks

Tab. 1 shows results of the single forecasting models and the combination procedures. The GPT model is the best approach available in the literature, but the stepwise approach provides lower RMSE and MAE values (84.58 and 60.53, respectively). It indicates that including additional data derived from DEM and satellite imageries improves the accuracy of thickness predictions.

Tab. 1: Forecasting accuracy results

Category	Models	RMSE	MAE	Best performance
Single F~~f~~orecasting model	GPT	94.21843	62.64876	
	SEPT	110.2305	72.32251	
	SAPT	167.8572	141.7064	
	STPW	84.57994	60.52539	*
Combination procedure	SA	91.45242	67.57764	
	MV	84.56758	60.51947	
	InvRank	83.48263	60.24573	*
	OLS	84.54387	60.45999	
	Shrink	84.56749	60.92980	

In the next step, the predictions of single models are combined and it is revealed that performance of most combination approaches is better. The Inverse Ranking presents the best weighing system because the RMSE and MAE of the predicted thickness values are the lowest. Thus, we obtain a more representative pyroclastic cover thickness distribution map for the areas affected by natural hazards such as landslides and floods.

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