Predicting Patagonian Landslides: Roles of Forest Cover and Wind Speed

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Key Points:

- Wind speed and crown openness of forests can aid landslide prediction in temperate rainforests of southern Chile;
- Volcanic disturbance appears to smooth out the role of wind speed;
- Distinguishing between landform types in a hierarchical model context improves the average performance of the landslide classification.

Abstract

Dense tree stands and high wind speeds characterize the dense temperate rainforests of southern Chilean Patagonia, where landslides frequently strip hillslopes of soils, rock, and biomass. Assuming that wind loads on trees promote slope instability, we explore the role of forest cover and wind speed in predicting mapped landslides with a robust Bayesian logistic regression. We find that more crown openness and higher wind speeds credibly predict higher probabilities of detecting landslides moderately well regardless of topographic location, though much better in low-order channels and on midslope locations than on open slopes. Wind speed has less predictive power in areas that were smothered by tephra fall from recent volcanic eruptions, while the influence of forest cover remains.

Plain Language Summary

Chilean Patagonia is home to not only some of Earth's largest swaths of temperate rainforests, but also to strong winds. Landslides commonly occur on steep hillslopes and remove, transport and deposit soil, rock and vegetation. To predict which areas are more likely fail compared to others, landslide models are needed. We developed a data-driven model that predicts from forest cover and wind speed the probability of detecting landslide terrain. Our findings indicate that both forest cover and wind speed play important, yet previously underappreciated, roles in predicting landslides in dense temperate rainforest. The model performance differs if distinguishing between landform types and previous volcanic disturbance, which may override the comparable modest control of wind on landsliding. Our study is the first of its kind in one of the windiest spots on Earth, and encourages a more discerning approach to landslide prediction.

1 Introduction

Many of Earth's steepest, wettest, and rapidly denuding landscapes are covered by dense temperate rainforests. The forests of southeast Alaska, southwest New Zealand, or Chilean Patagonia are amongst the most dense and biomass-rich biomes worldwide (DellaSala, 2011). These forests store large amounts of organic carbon (Luyssaert et al., 2008; Mohr et al., 2017) but also experience frequent disturbances (Johnstone et al., 2016) such as earthquakes, landslides, avalanches, windstorms, or volcanic eruptions (Buma et al., 2019; Korup et al., 2019; Sommerfeld et al., 2018; Veblen & Alaback, 1996) and thus high rates of erosion and biomass turnover (Hilton et al., 2008; Hilton et al., 2011). Landslides in particular have both a destructive and vital role in these forest ecosystems by regulating biomass erosion and deposition, nutrient cycling, and stand succession (Pawlik, 2013). Forest disturbances, in turn, alter landslide susceptibility (Buma & Johnson, 2015), and reported landslide densities in forest areas can be 50-90% lower than in open land, depending on forest type and health (Rickli & Graf, 2009). Studies of landsliding after deforestation revealed that the susceptibility to shallow landslides can increase because of limited root reinforcement (Sidle, 1991; Schwarz et al., 2010) and altered hydraulic conductivity (Mirus et al., 2017). But also biomass surcharge (O' Loughlin & Ziemer, 1982) or trees transferring dynamic wind forces to the soil can trigger slope instability (Buma & Johnson, 2015).

Among these possible controls on slope stability in forested mountains, forest cover and wind speed have been the least considered in landslide prediction; most research instead addressed the less dynamic factors of geology and topography (Reichenbach et al., 2018).

Despite numerous studies on forest disturbances (Baumann et al., 2014) enquiries into the role of wind on landslide initiation have been anecdotal with unclear indications of cause and effect

(Buma & Johnson, 2015; Schwab, 1983). We suspect that forest cover and wind speed have opposite effects on slope stability. Despite anchoring soils, trees transfer dynamic wind forces as turning moments (torque) to the soil mantle via the tree bole, causing tree fall or even triggering shallow slope failure (Buma & Johnson, 2015). The torque depends mostly on wind speed (squared) and to lesser degree on tree physiology such as height or diameter (Hale et al., 2015). Storm-induced tree throw also displaces soil and opens up pits for enhanced water infiltration and pore-water pressure in soils (Valtera & Schaetzl, 2017).

In this context, we investigate the role of wind in triggering shallow landslides in the temperate rainforests of Chilean Patagonia. This mountainous region is exposed to high westerly winds that bring large amounts of rain from the Pacific, but has been featured rarely in landslide studies (Korup et al., 2019; Sepúlveda et al., 2010; Somos-Valenzuela et al., 2020). Our objective is to explore the combined effects of forest cover and wind speed, grouped by different topographic positions, on predicting landslides in rainforests in three study areas of south-central Chile (**Figure 1**).

2. Study areas

The regional tectonic setting is characterized by active oblique subduction of the Nazca oceanic plate along the Southern Chile Trench and intra-arc dextral transpressional motion along the Liquiñe-Ofqui Fault zone in the southern Andes; Quaternary arc volcanism is active in the Southern Volcanic Zone (**Figure 1**). The western fringe of the Andes features steep mountainous terrain that was extensively glaciated (Singer, et al., 2004), and numerous cirques and small glaciers occupy headwaters today. The predominant soils are 1-2 m deep Andosols (Mohr et al.,

2017) on top of Pleistocene volcanic sediments covering a basement of Miocene granitoids and Paleozoic schists and gneisses (Piña-Gauthier et al., 2013).

The regional climate is humid, with annual precipitation totals of 3000-3200 mm (Alvarez-Garreton et al., 2018; Mohr et al., 2017) and a mean annual temperature of 8 °C (Alvarez-Garreton et al., 2018).

Our study areas are largely covered by stands of Valdivian temperate rainforests, which are structurally complex with many endemic species (DellaSala, 2011). The living biomass is high (~370 tC/ha) and up to twice as much organic carbon may reside in floodplain forest soils around Chaitén (**Figure 1**; (Mohr et al., 2017). Broadleaf species dominate these rainforest, while conifers are rare. Prominent tree species include *Nothofagus nitida* (Phil.) Krasser (coïgue de Chiloé); *Podocarpus nibigens* Lindl. (Manio); *Drimys winterii* J.R.Forst and G.Forst (canelo); *Amomyrtus meli* (Phil.) D.Legrand and Krausel (meli); and *Luma apiculata* (DC.) Burret (Arrayán rojo). Rainforest stands around Chaitén are in various states of post-volcanic disturbance initiated by the 2008 eruption sequence of Chaitén Volcano (Lara, 2009). The eruption gave rise to pyroclastic density currents, small lateral blasts, lava-dome growth and collapse, lahars and widespread tephra (Alfano et al., 2011). Subsequent reworking of volcaniclastic sediments aggraded river channels and floodplain forests by up to 11 m, causing channel avulsions, bank erosion, and log jams (Major et al., 2016; Pierson et al., 2013; Swanson et al., 2013). Tephra damaged on hillslope forests triggered a pulsed and distinctly delayed increase in landslide activity several years after the eruption (Korup et al., 2019).

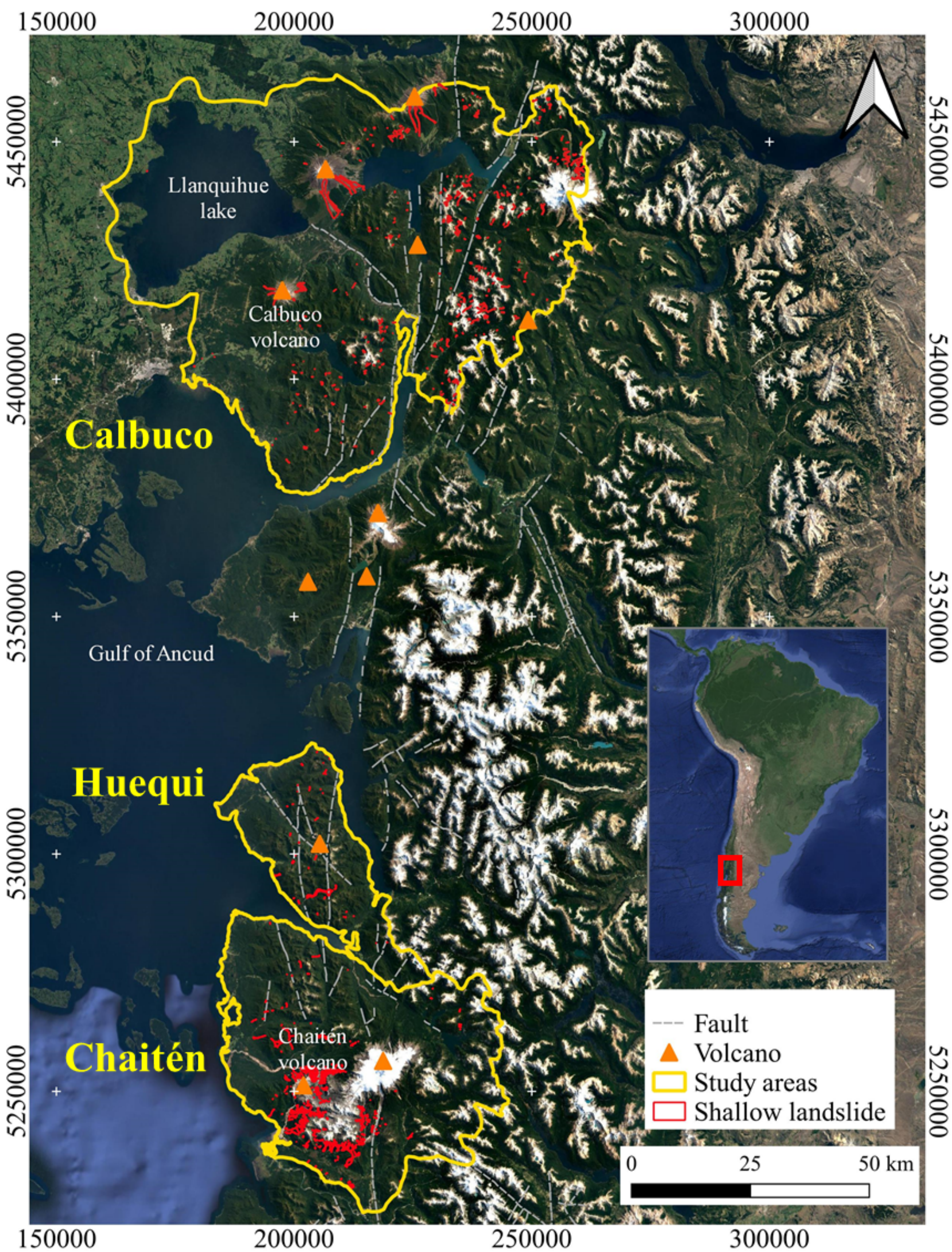


Figure 1. Distribution of landslides mapped from 2001 to 2019 in the three study areas (yellow borders) in south-central Chile: Calbuco (5880 km^2), Huequi (897 km^2) and Chaitén (2413 km^2). Faults are part of the greater active Liquiñe-Ofqui Fault Zone. Hydrographic data are from the Dirección General de Aguas de Chile (DGA); geological data are from the National Geology and Mining Service of Chile (SERNAGEOMIN). Coordinate system is UTM 19S; satellite imagery is from Google Earth®.

3 Methods

3.1 Data

We compiled inventories of landslides that occurred in our study areas between 2001 and 2019 by mapping from Google Earth® imagery and carrying out several local ground checks between 2014 and 2019. We mapped landslides using diagnostic features such as distinct, elongate, and contrast-rich forest gaps with bare scarps showing displaced soil, and rock together with transport zones and runout lobes (Fiorucci et al., 2011). We mapped polygons approximating the total affected area for each landslide, estimating the date of each landslide with approximately annual precision that we obtained from the difference in timestamps of the images showing the latest undisturbed conditions and the earliest landslide occurrence. The triggers of these landslides remain unknown, though we can largely exclude seismic effects: the *M*7.6 Chiloé earthquake in 2016 (43.406°S, 73.941°W) was the largest recent near our study areas, though triggered 5% of the landslides in our study areas at the most. We mapped a total of 411 landslides in Calbuco, 38 in Huequi, and 616 in Chaitén, covering 0.6%, 0.4% and 0.8% of each study area.

We used forest-cover information from the Global Forest Change inventory (Version 1.7) (Hansen, 2013) as a proxy of tree canopy cover in 2000, thus giving an indication about forest stands prior to all landslides that we mapped. Tree cover is defined as the fraction of canopy closure for >5 m high vegetation classified from time series of Landsat images at 30-m resolution (https://earthenginepartners.appspot.com/science-2013-global-forest/download_v1.7.html). Given the mostly high (>80%) crown closure in most of our study area, we used a log1p-transformation of tree cover to reduce the strong negative skew in its distribution; we thus obtain a complementary metric of crown openness.

Regional data on wind speed have become widely available given the rising interest in the potential for clean and renewable power generation. We used wind speed (m/s) estimates from the Worldclim dataset (Fick & Hijmans, 2017), available as monthly averages for the period 1970-2000. These data were generated based on weather station data interpolated with elevation, distance from the coast, and mean MODIS cloud cover as covariates at 1-km grid resolution. We aggregated these data to mean annual wind speeds (Figure S1, Supporting Information).

To characterize topographic position, we used SAGA GIS 2.3.2 and its landform classification tool by Weiss (2001) to derive a multi-scale Topographic Position Index (TPI) from 30-m elevation data from the Shuttle Radar Topography Mission (SRTM). The TPI compares the elevation of each pixel in a digital elevation model (DEM) to the mean elevation of a circular neighborhood around the pixel. To find a compromise between local landform detail and the wind-data resolution, we classified landform types by averaging over two neighborhoods of 100 m and 1000 m.

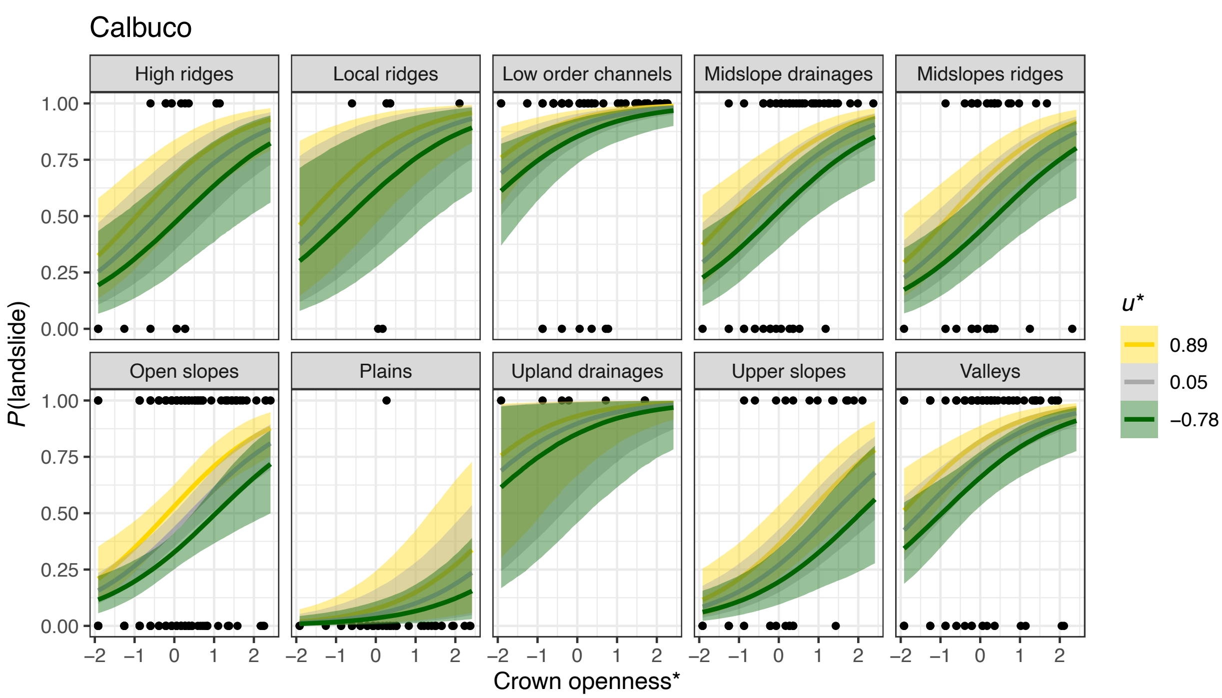
3.2 Bayesian multilevel model

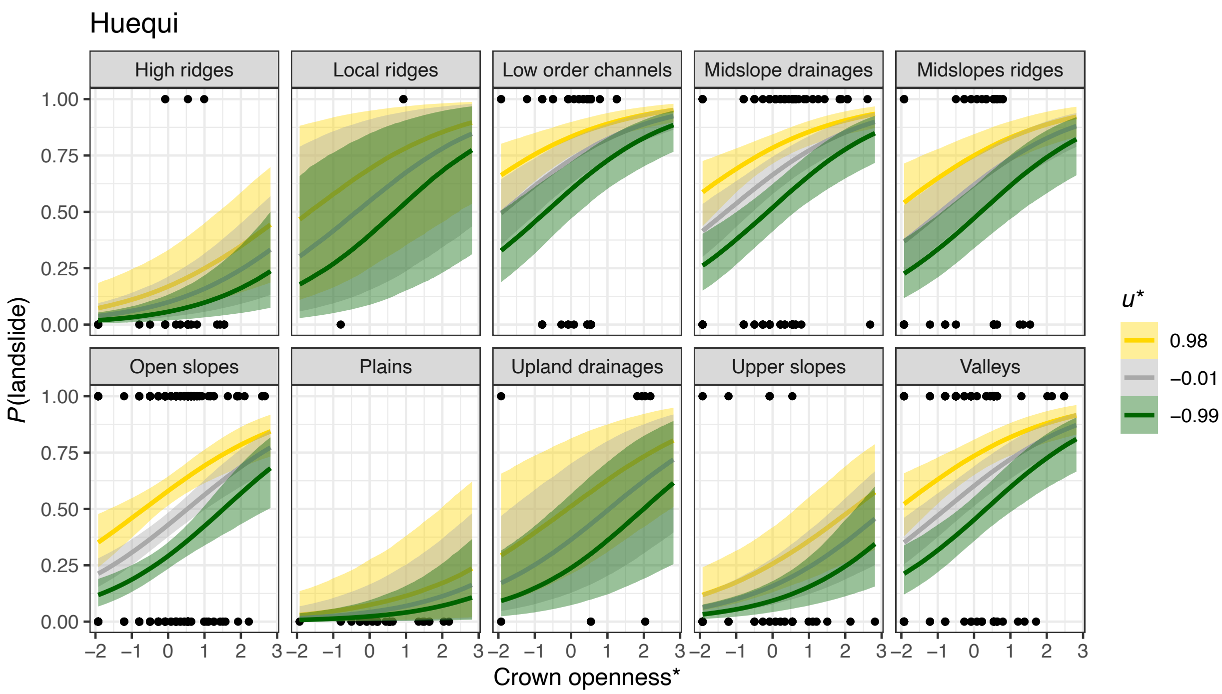
To analyze the role of crown openness and wind speed on the occurrence of shallow landslides we used logistic regression. This method has been used widely for landslide susceptibility studies due to its simplicity and ease of interpreting parameters (Das et al., 2012). We chose a Bayesian variant of logistic regression that admits prior knowledge about the parameters and explicitly handles uncertainties and sparse, imbalanced data (Bürkner, 2017; van de Schoot et al., 2021). We chose a hierarchical model (Kruschke & Vanpaemel, 2015) because we surmise that landslide occurrence, crown openness, and wind speed vary with landform type, hence acknowledging structure in our data. The model predicts the probability of classifying a given location (pixel) as part of a mapped landslide P(L) as a function of crown openness and wind speed for each landform type and the average of all data. The hierarchical structure of the model learns from the data one pooled (or population-level) parameter estimate for all the data, and individual parameters estimates that express deviations (or group-level effects) from this average for each landform type (see Supporting Information). We chose a varying intercept model, in which the weights of crown openness and wind speed remain unchanged across all landform types, though with differing average landslide probability. During the learning process, parameter estimates can inform each other across groups, thus reducing the potential for overconfident and unduly high or low coefficient values (Kruschke, 2014).

We use a weakly informative, but robust, Student-*t* prior distribution for both crown openness and wind speed, and for the (population-level) intercept; for the standard deviation of group-level (landform) effects we chose a standard exponential prior, assuming that a lower variance of P(L) between landforms is more likely than a higher one. We standardized all predictors to zero means and unit standard deviations and sampled from the numerically approximated posterior distribution given training data with a balanced number of landslide and unaffected terrain samples. We used the NUTS sampling scheme implemented in the STAN probabilistic programming language (Carpenter et al., 2017) to draw samples from the joint posterior distribution via the **R** package `brms` (Bürkner, 2017). We ran four independent Hamiltonian Monte Carlo chains based on 2000 iterations including 500 warm-up samples and checked each chain for convergence. We assessed the performance of this classifier based on its posterior predictive distribution and recorded the fraction of correct classifications compared to the observed frequency of landslides in all study areas and for all landform types.

4 Results

In all three study areas, the posterior distributions show that different landform types have credibly different model intercepts and thus log-odds ratios of classifying landslides (Figure S2). For an average crown openness and wind speed, the posterior probability of classifying a location as part of a landslide is highest in midslope locations and low-order channels and their adjacent hillslopes, and lowest on upper slopes and (mostly flood and coastal) plains (Figure 2).





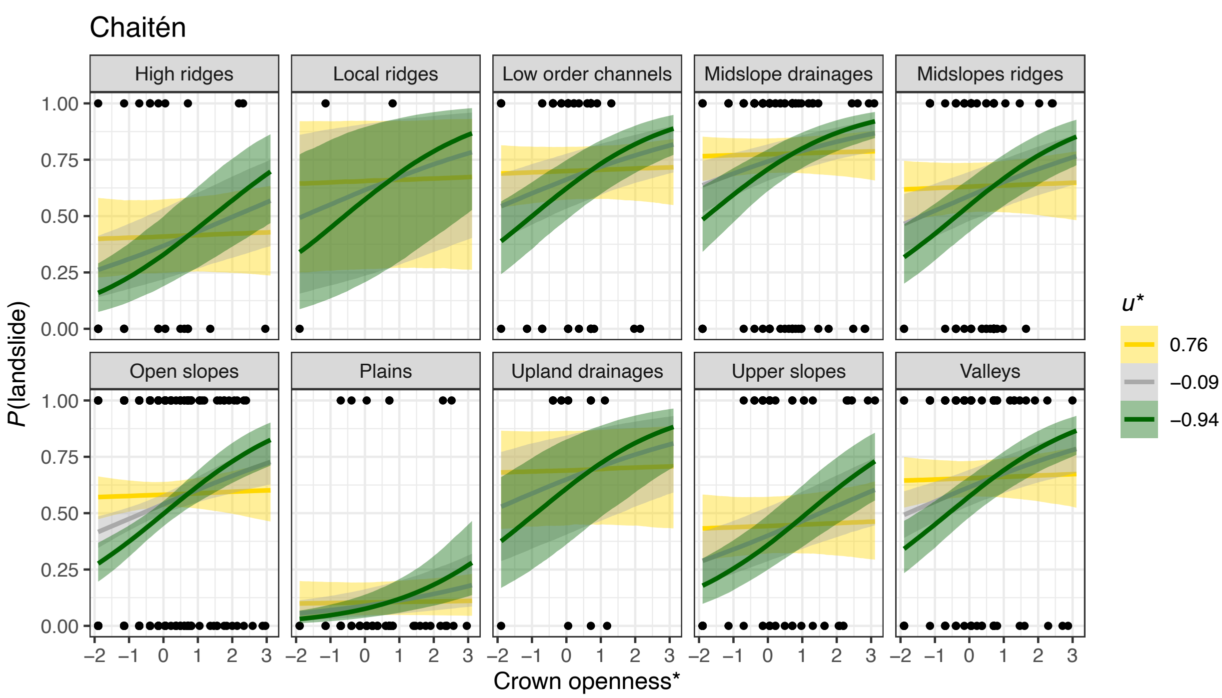


Figure 2. Posterior estimates of the probability of classifying a landslide based on standardized predictors crown openness and wind speed u^* in our three study areas (Figure 1). Thick lines are posterior medians, and shaded areas enclose the 95% highest density intervals for mean wind

speed (grey), and roughly one standard deviation above (gold) and below (green). Black dots are observed data.

Both crown openness and wind speed have positive credible and similar weights around Calbuco and Huequi, but roughly half their weight around Chaitén (**Figure 3**). The probability of classifying landslide terrain *P*(L) increases with crown openness and wind speed in all areas. For a fixed crown openness, *P*(L) changes with wind speed, except for the Chaitén area, which is the only area with a credible negative interaction between these two predictors. There, *P*(L) is nearly unchanged at high wind speeds regardless of forest cover (**Figure 2**). While the model predicts that *P*(L) increases with increasing wind speed in more dense forests around Chaitén, this relationship is reversed and lower wind speeds raise *P*(L) in more open forest stands.

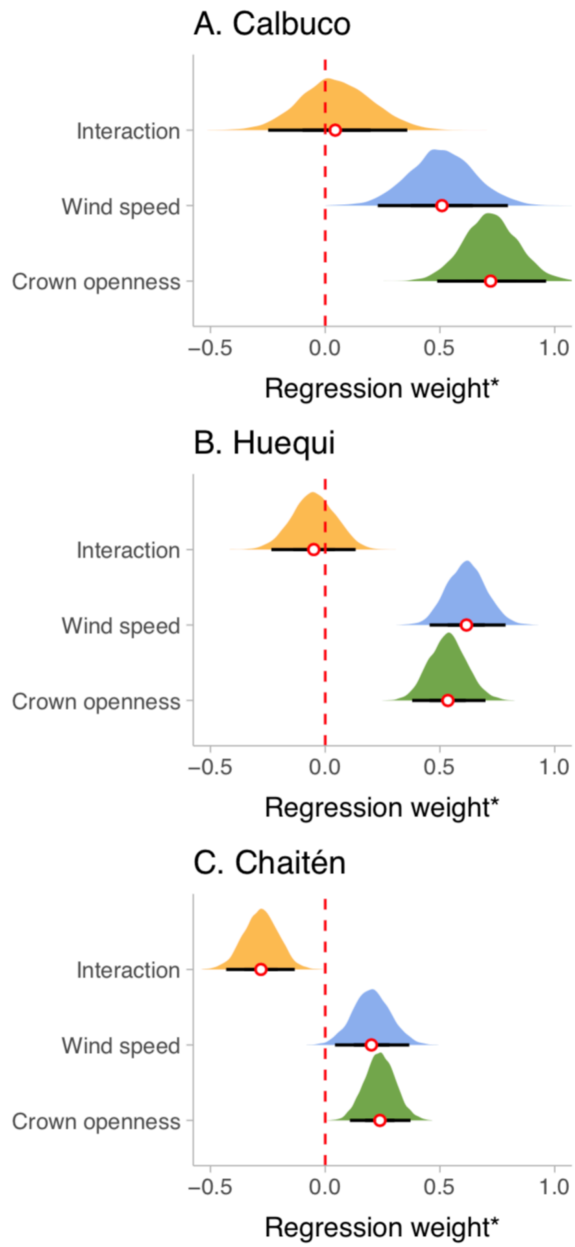


Figure 3. Posterior regression weights of standardised crown openness, wind speed, and their interaction. Black horizontal lines are 95% highest density intervals, and white circles are posterior means. Interaction between crown openness and wind speed is credibly non-zero only in the Chaitén area.

The model performance at the level of each study area is moderate: the true positive rates are 0.75 on average, and mostly higher than the average true negative rates, which are 0.52 on average (Figure S3). We note that models trained for Calbuco and Huequi have less average predictive skill for the volcanically disturbed Chaitén area, where 97% of mapped landslides and 96% of the total landslide area occurred after the 2008 eruption sequence (Korup et al., 2019). However, the model trained for this particular area predicts landslides in the less or undisturbed study areas much better (though absence of landslides much worse). The average performance of all models improves substantially to true positive rates >0.8 if considering individual landform types in the hierarchical model (**¡Error! No se encuentra el origen de la referencia.**). This improvement holds for most landforms except for high and local ridges and upper slopes, for which the model predicts true negative rates (landslide absence) better.

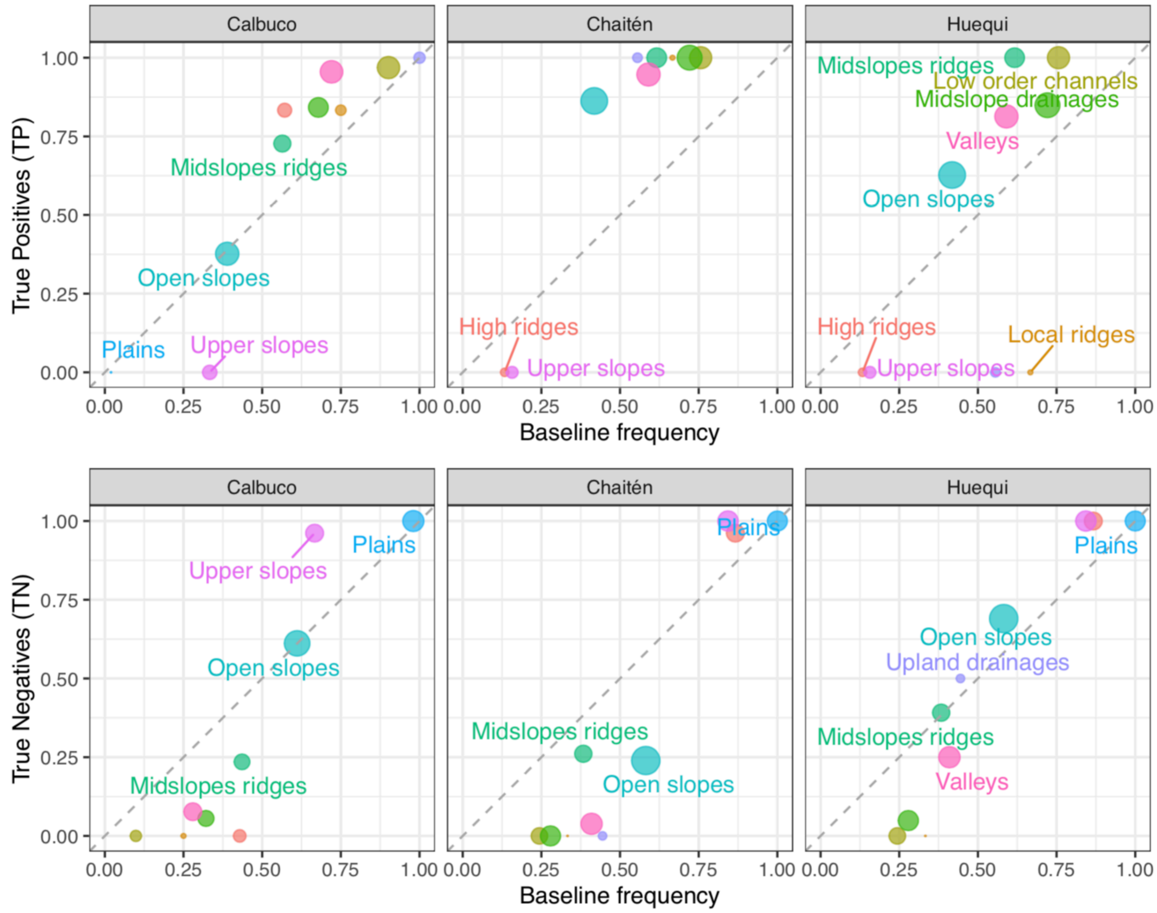


Figure 4. Model performance expressed as the true positive and true negative rates versus empirically observed frequencies of landslide per landform type (colour-coded). Dashed grey lines mark the baseline frequency of landslides (or their absence) and thus a purely random classifier. Bubbles are scaled by observed landslides per landforms. Bubbles above (below) the grey lines are posterior estimates that are better (worse) than the baseline.

5 Discussion

We explored the roles of forest cover and wind speed in predicting shallow landslides that occurred in Chilean Patagonia between 2001 and 2019. Our statistical approach is based on the assumption that the satellite-derived forest cover (Hansen, 2013) is sufficiently well resolved and accurate and representative of ecologically intact forest structure at the regional scale. Our balanced sample of landslide and unaffected terrain pixels is large enough to outweigh the role of possible outliers (such as local pixel noise or sensor artifacts) that we cater to by choosing a robust logistic regression. We acknowledge that the wind speed data are interpolated averages over at least three decades prior to the landslides that we mapped, and that more refined models could use synoptic data of wind fields and their variability as predictors. Averaged monthly wind speed may poorly reflect effects of gusts or windstorms. We therefore consider our estimates of the wind effects on landslides as conservative. Nonetheless, elevation is one foundation of these regionally interpolated wind speed estimates, and we expect that the data are consistent in this regard, collapsing effects of elevation and distance from the ocean (Fick & Hijmans, 2017). Measurements of wind directions in our study area highlight the role of wind exposure (Letelier et al., 2011) (Figure S4). An alternative model, however, in which the coefficients of crown openness and wind speed were allowed to vary across landforms revealed that neither predictor had weights that deviated credibly from the pooled average.

Another source of uncertainty and potential source of model misclassification is linked to the landslide inventory. Our mapping may underestimate the occurrence of smaller failures under forest cover mostly due to image resolution and shadow effects (Brardinoni et al., 2003). Yet we mapped landslides that happened since 2001, thus avoiding older imager with lower resolution. Several images taken after the eruption of the Chaitén volcano (2008) have artifact noise in tephra-covered areas and may under-represent landslide numbers. Some of the mapped landslides may have had failure surfaces too deep-seated to be affected by high wind loads, and we may have misclassified these deep-seated failures as shallow landslides. During our field surveys, we observed that root networks often spread laterally above the soil-bedrock interface, with only few smaller roots penetrating several to tens of centimeters into bedrock cracks. Hence some of the landslides that we mapped and that our model misclassified may have involved more fractions of rock debris than mechanical stresses transferred by tree roots alone could mobilize.

Keeping these caveats in mind, our results support the notion that denser tree cover reduces the probability of classifying landslide terrain in a Bayesian framework. We find that wind speed has a comparable weight (Figure 3) with higher wind speeds predicting higher probabilities of classifying landslides. We also observe that the Chaitén area shows the largest differences in the weights and interaction of these predictors. There, the probability of classifying landslides in areas of high wind speed hardly changes with forest cover (Figure 2). We attribute this conspicuous difference to the 2008 eruptions of Chaitén volcano, which buried >150 km^2 of temperate rainforest under tephra (Korup et al., 2019), causing die-back of tree cohorts due to toxic fallout, stomata plugging, and local loads, causing hundreds of shallow landslides that dominate our inventory in this study area. The defoliation of disturbed tree cohorts may have reduced the surface area exposed to wind loads and thus lowered the effects of high winds (Swanson et al., 2013). In contrast, less windy areas with low or disturbed tree cover are more likely to feature landslides under our model. Such low-wind speed areas may have favored deposition of tephra and hence accumulated thicker layers that promote the decay of dead roots, thus decreasing root cohesion (Sidle, 1991) particularly on wind-protected sites. We emphasize that the Calbuco area was also impacted by a volcanic eruption in 2015, but to a much lesser extent with smaller areas of forest dieback and fewer post-eruptive landslides. We attribute only 19% of the mapped landslides (or 10% of the total area) to the Calbuco eruption.

Overall, our findings about the role of wind speed are in line with those by Buma & Johnson (2015), who identified wind exposure as an important control for landslide initiation in the temperate rainforests of southeast Alaska. There, wind sheltered areas were devoid of evidence of major storms in the past 1000 years (Nowacki & Kramer, 1998), whereas wind-exposed slopes were disturbed by shallow landslides frequently (Kramer et al., 2001). Our model shows that wind speed without any information on direction can be an important predictor. While we would prefer wind speed squared u^2 as the physically more meaningful predictor, our data are monthly means, so that squaring them would yield underestimates, as $(E(u))^2 < E(u^2)$, where E is the expectation value.

In essence, our results demonstrate the advantage of using a hierarchical model admitting landform types over several ones that simply average over all landforms in a given study area (**Figure 4**). The predictive performance increases notably for some landforms, though at the cost of underpredicting landslides on other landforms. Upper hillslopes and high ridges seem the most problematic areas for our model in terms of negligible skill, whereas it can predict landslides in low-order channels, midslope ridges or valleys confidently in regions outside of the training areas. One reason for the less skilled predictions may be that our model ignores the structure or edge effects of forest patches (Ruck et al., 2012) that can locally modify wind patterns and speed (Pawlik, 2013). Such edge effects may emphasize the gradual expansion of landslide-affected areas by either the retrogressive erosion of scarps or the downslope migration of deposit lobes by reworking. While our random sampling scheme to obtain training data minimizes spatial autocorrelation in the predictors, the spatial association of topography, forest structure, and wind speed distribution may indeed drive more slope instability than our model detects.

Our model intentionally excludes the role of rainfall as one of the most plausible triggers of landslides in southern Chile. The high annual rainfall totals that can exceed 3,000 m in our study areas make precipitation rarely a limiting factor on landslides (Buma & Johnson, 2015). We suspect that wind speed correlates with precipitation metrics (Rulli et al., 2007), and that wind speed thus reflects to some degree also hydrological drivers of slope instability beyond the mechanical control of wind load. The high landslide counts that we observed in mostly low-order channels and their neighbouring hillslopes (79% of all landslides in Calbuco, 63% in Huequi, and 43% in Chaitén) also point to hydrological triggers. While these topographic depressions collect more water, they also favor denser tree cover and funnel winds, however. We stress that our model prediction is also independent of local slope inclination, which is the dominant predictor of slope instability in comparable landslide susceptibility models (Reichenbach et al., 2018). Local elevation differences define the topographic position index, on which our landform classification is based. Yet these landforms are groups instead of predictors in our model. Moreover, the linear correlation between wind speed and local slope inclination ($0.28 < r < 0.40$) in our study areas is too low to attribute the role of wind speed to effects of hillslope steepness alone.

In summary, we see two immediate benefits from our hierarchical modeling approach. First, it helps to improve model performance by structuring the data into topographic positions that are intuitive and objectively different from each other, whereas the popular alternative of using instead more predictors is more prone to the risk of overfitting and collinearity. Second, grouping the model by landforms opens the way for more customized and optimized landslide prediction catered to specific topographic locations even if the bulk average prediction for a study area is low. The hierarchical structure also helps to identify more objectively those portions of the landscape, for which we need better data constraints for landslide prediction.

6 Conclusions

Our Bayesian hierarchical logistic regression shows that more crown openness of forests and higher wind speeds credibly raise the chance to detect landslide terrain in three mountainous areas sustaining temperate rainforest areas in southern Chile. Volcanic disturbance appears to smooth out the role of high wind speeds by making denser forest stands more prone to landslides, and more open stands less prone. Trees cohorts buried or suffocated by tephra are areas where altered rates of soil water infiltration and root decay may be more dominant drivers of slope instability than wind loads alone. In any case, distinguishing between landforms in a hierarchical model context substantially improves an otherwise moderate average performance of the classification, but also highlights topographic locations for which the prediction needs to be refined. Our model also encourages further enquiry into the rarely investigated role of wind speed in promoting slope instability in southern Chile and dense forested mountain regions elsewhere, especially with weather and wind extremes being on a projected rise in a warming world (Jung & Schindler, 2019; Rosende et al., 2019).

Acknowledgments, Samples, and Data

E.P. acknowledges funding by the Agencia Nacional de Investigación y Desarrollo, Chile (ANID) and the German Academic Exchange Service, Germany (DAAD). E.P. and O.K. and collected and analysed the data; all authors contributed equally to writing the manuscript.

We are going to upload a **R** notebook containing the full code and data for the Bayesian logistic regression to a public repository, pending the final decision on this manuscript.

The SRTM DEM data are available at: https://www.earthexplorer.usgs.gov

The wind speed data are available at: https://www.worldclim.org/data/worldclim21.html

The forest-cover data are available at: https://earthenginepartners.appspot.com/science-2013-global-forest

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