



Supplement of

Tracking the slopes: a spatio-temporal prediction model for backcountry skiing activity in the Swiss Alps using user-generated content

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Supplement to ‘Tracking the slopes: A spatio-temporal prediction model for backcountry skiing activity in the Swiss Alps using user-generated content’

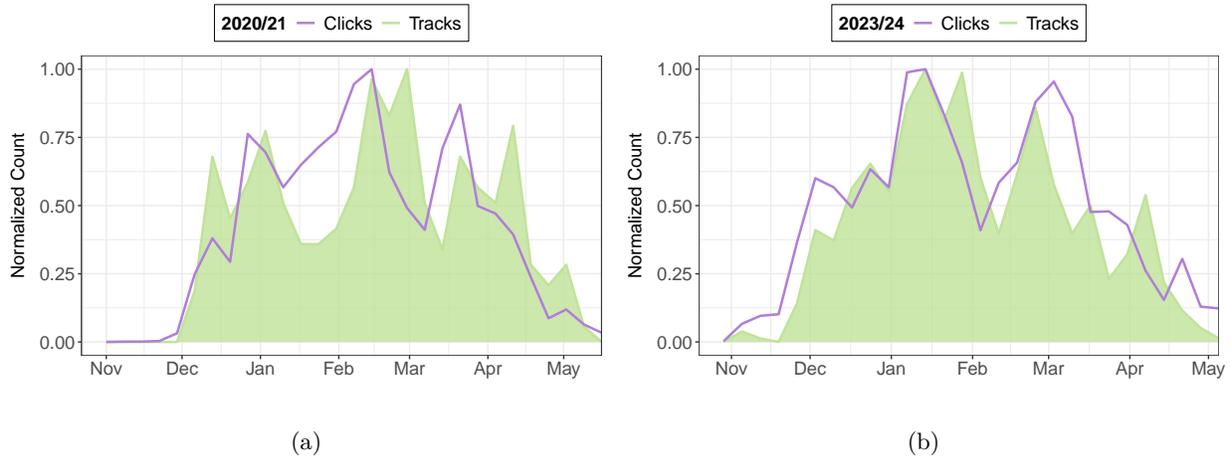


Figure S1: Normalized and weekly aggregated click and track counts for (a) 2020/21 and (b) 2023/24 season. Clicks and tracks are aggregated over the whole study area

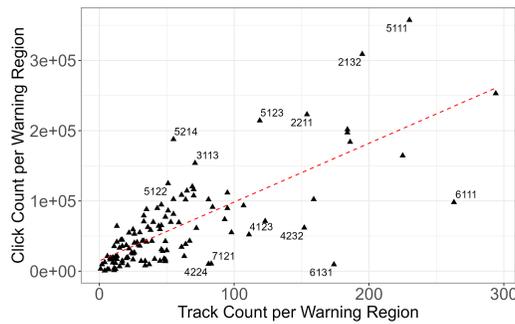


Figure S2: Correlation of total track count and total click count per warning region. Each point is labelled with the warning region code. Both axes are log-transformed to enhance readability. The red line represents the linear trend line.

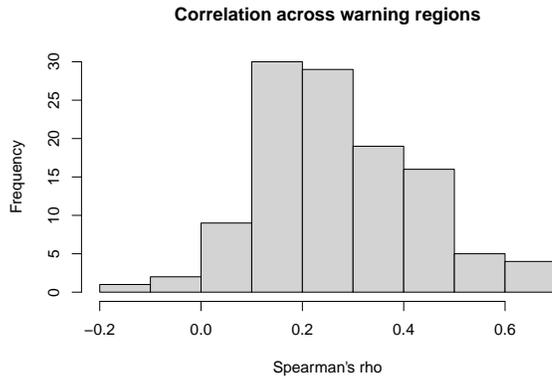


Figure S3: Histogram of correlation between click and track counts per warning region. Correlations range from 0 to 0.66. In total, 21% of regions have $\rho > 0.4$.

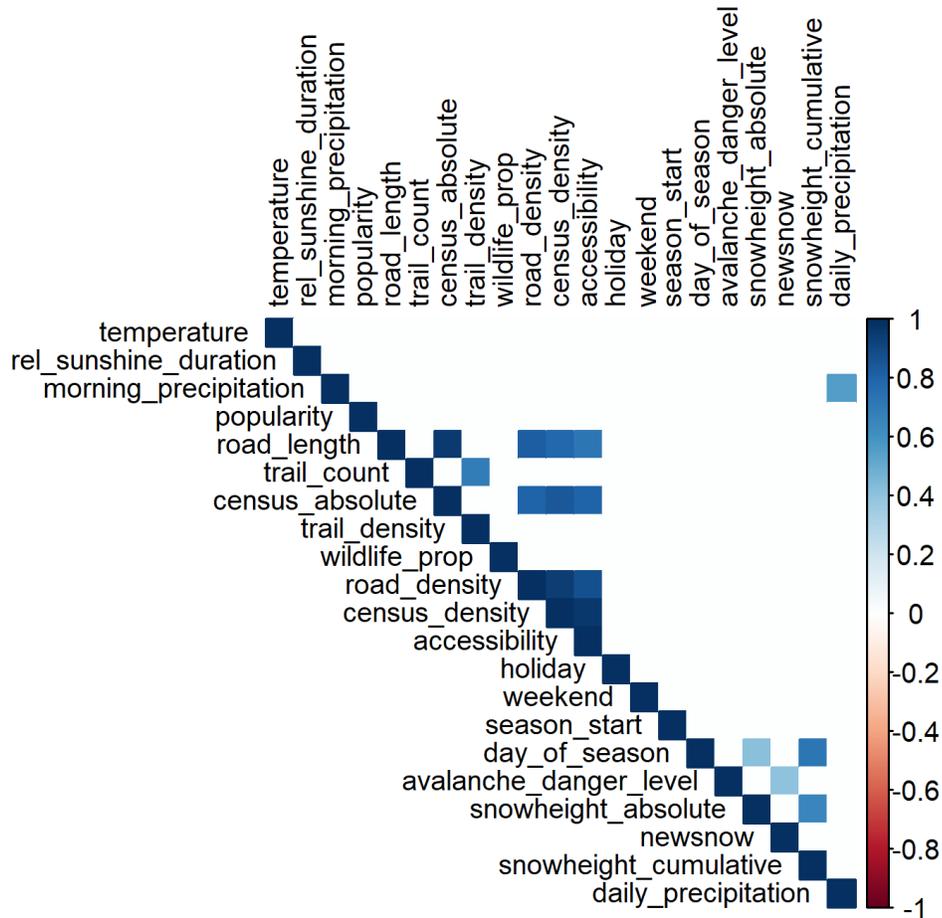


Figure S4: Correlation matrix of all initial variables for track data, only significant variable correlation are coloured. Plots were created using the 'corrplot' R package

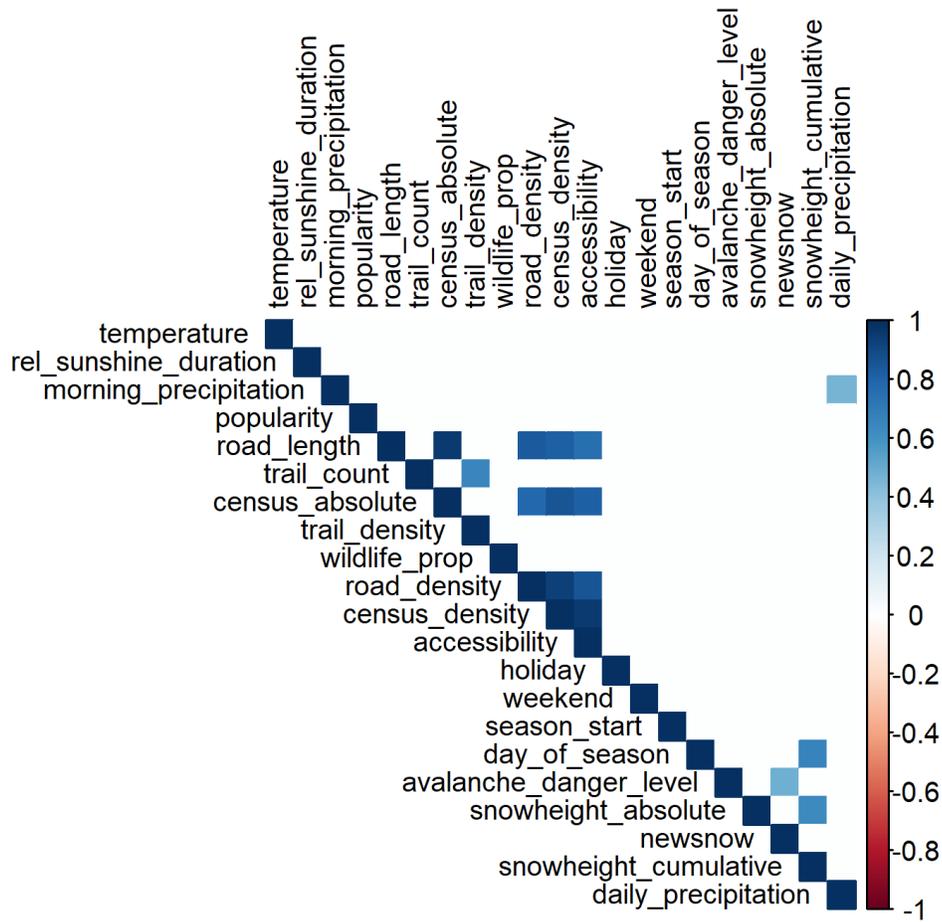


Figure S5: Correlation matrix of all initial variables for click data, only significant variable correlation are coloured. Plots were created using the ‘corrplot’ R package

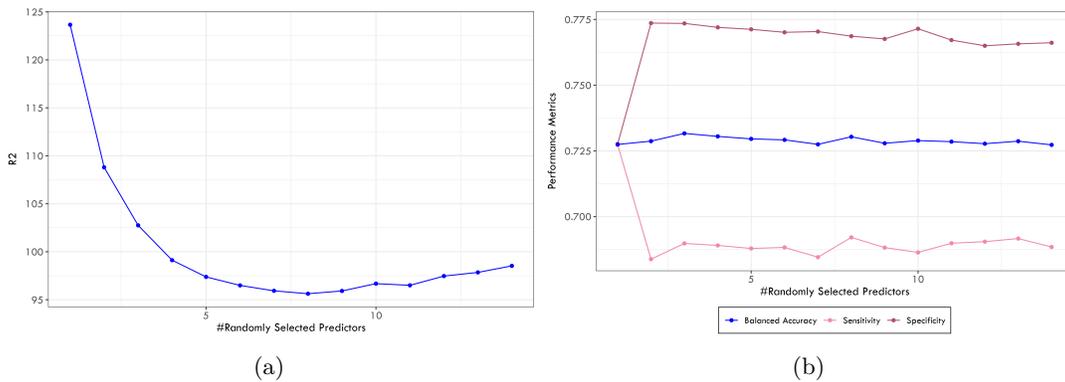


Figure S6: MTRY (number randomly selected predictors at each node) tuning for (a) tracks and (b) clicks. MTRY was chosen based on minimum RMSE (maximum balanced accuracy) for clicks (tracks). For the track model, the tuning of mtry did not show any major variations of the balanced accuracy, therefore we left it to the default value (mtry = 3). For the click model, mtry = 8 was chosen.

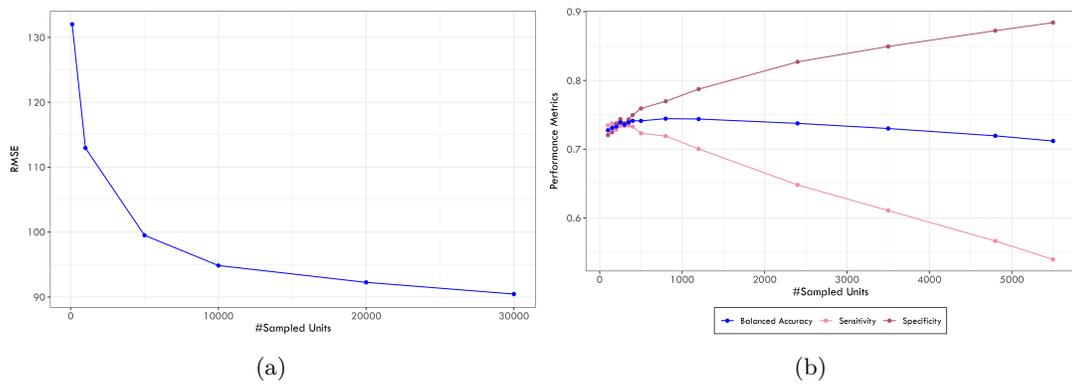


Figure S7: sampsize (number of samples used to train each tree) tuning for (a) tracks and (b) clicks. sampsize was chosen based on minimum RMSE (maximum balanced accuracy) for clicks (tracks). For the track model, 300 was chosen, even though balanced accuracy is maximized for sampsize = 800. The reason for this is that sensitivity and specificity drift apart after sampsize = 300, which leads to unequal performance in the two classes. For sampsize = 300, performance is approximately equal in both classes and balanced accuracy is only marginally smaller than for the maximized value of 800

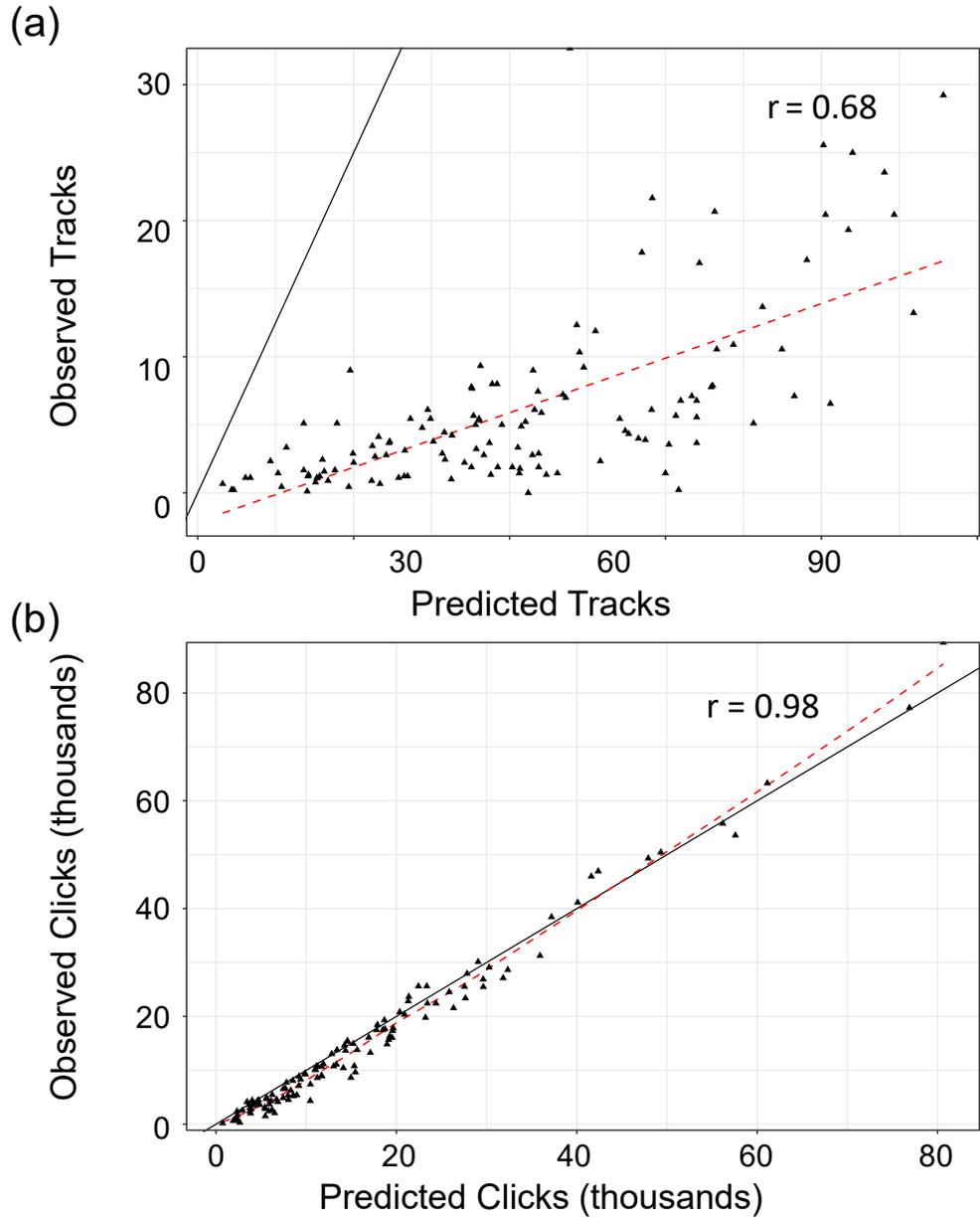


Figure S8: Temporally aggregated predicted versus observed counts for (a) tracks and (b) clicks. The black line indicates the 1:1 reference, and the red line shows the fitted linear trend. r denotes Pearson's correlation.

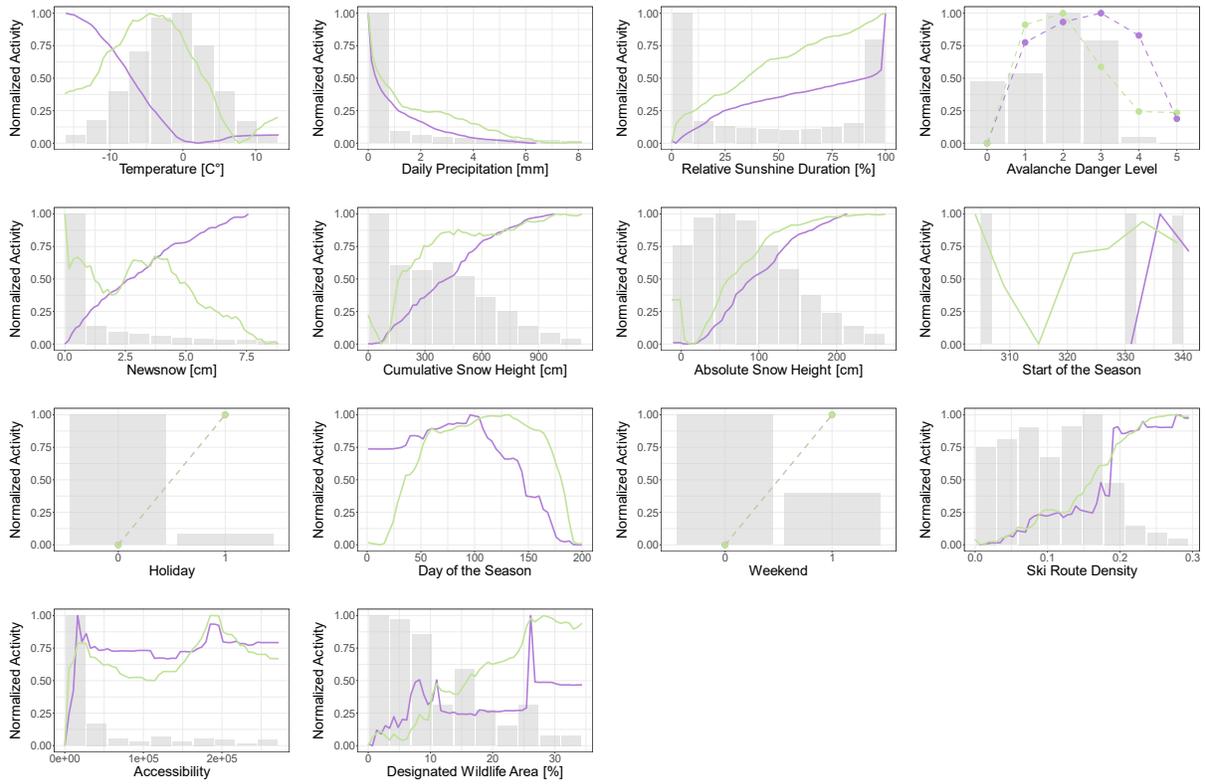


Figure S9: Partial dependence describe the marginal effect an independent variable has on the response variable. Plots were generated using the `pdp::partial()` function, where the different values of an independent variable is on the x-axis and the effect is has on the response is on the y-axis. A higher effect (higher \hat{y}) indicates higher skiing activity. \hat{y} is min-max normalized for each plot and curve separately.

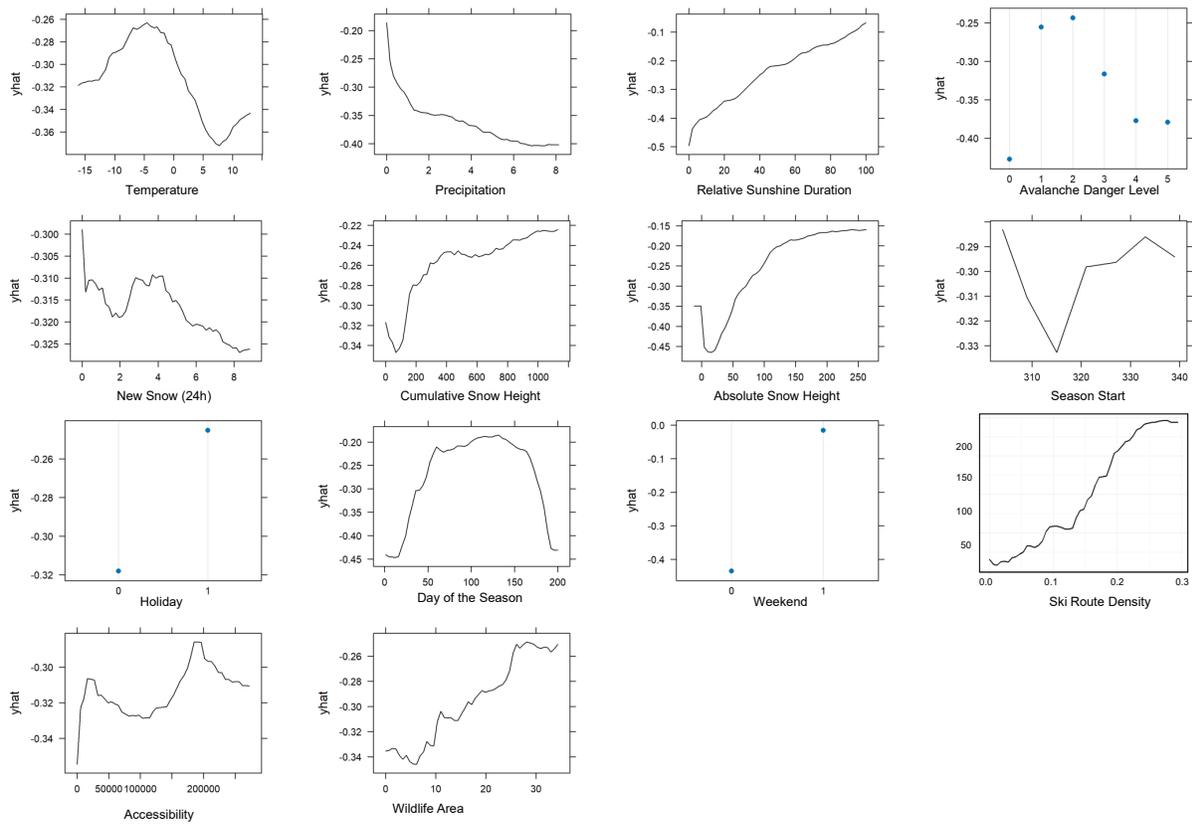


Figure S10: Non-normalized (ie., absolute value) partial dependence plots for tracks.

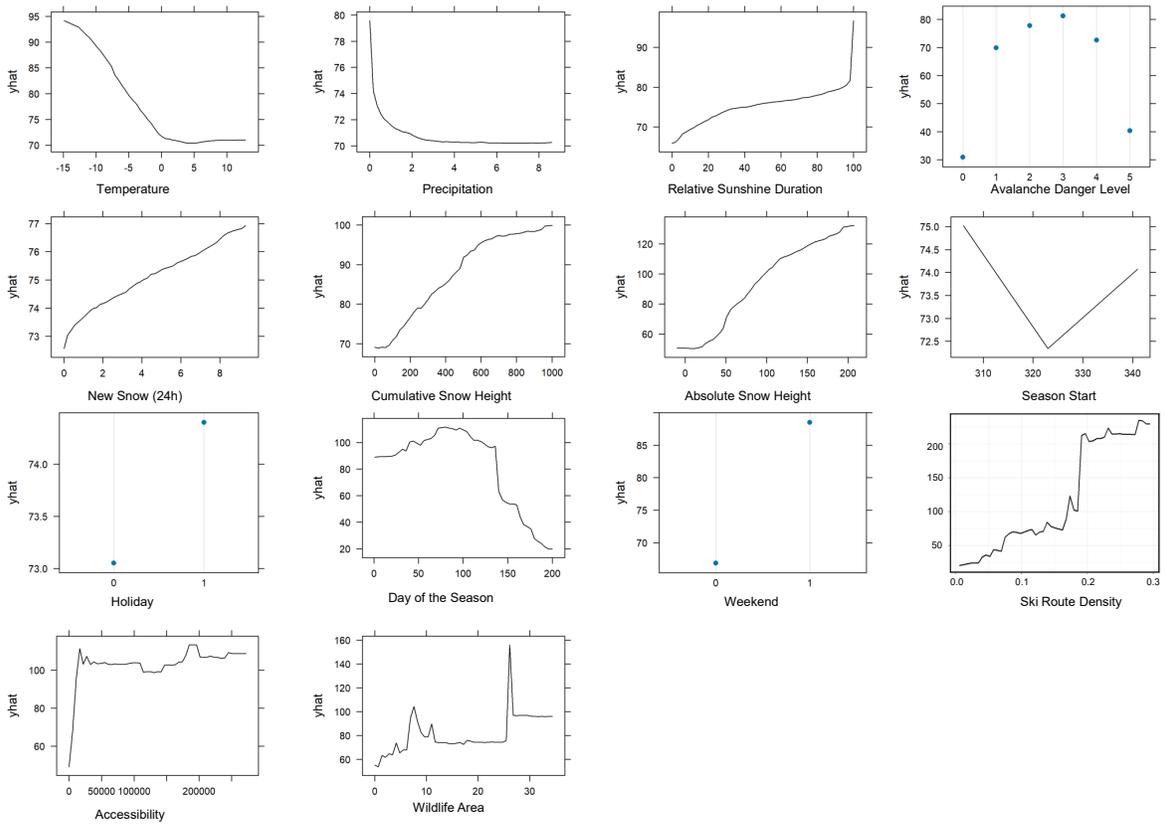


Figure S11: Non-normalized (ie., absolute value) partial dependence plots for clicks.

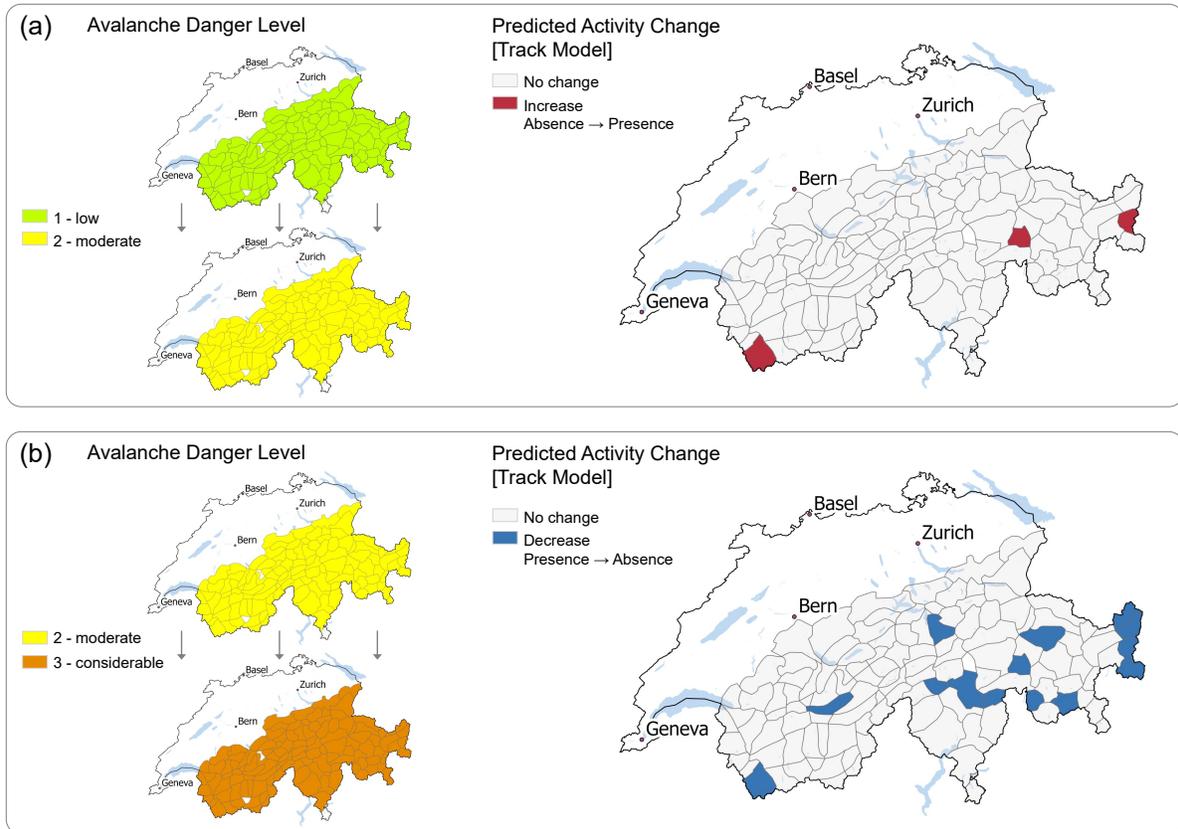


Figure S12: This figure shows the same scenarios as Fig. 8 in the manuscript, but for track model predictions. Here binary activity increases from avalanche danger levels 1 to 2 and decreases from levels 2 to 3. However, sparseness of the training data means that spatial variation is rare and the track data are not well suited to modelling at these spatial granularities.

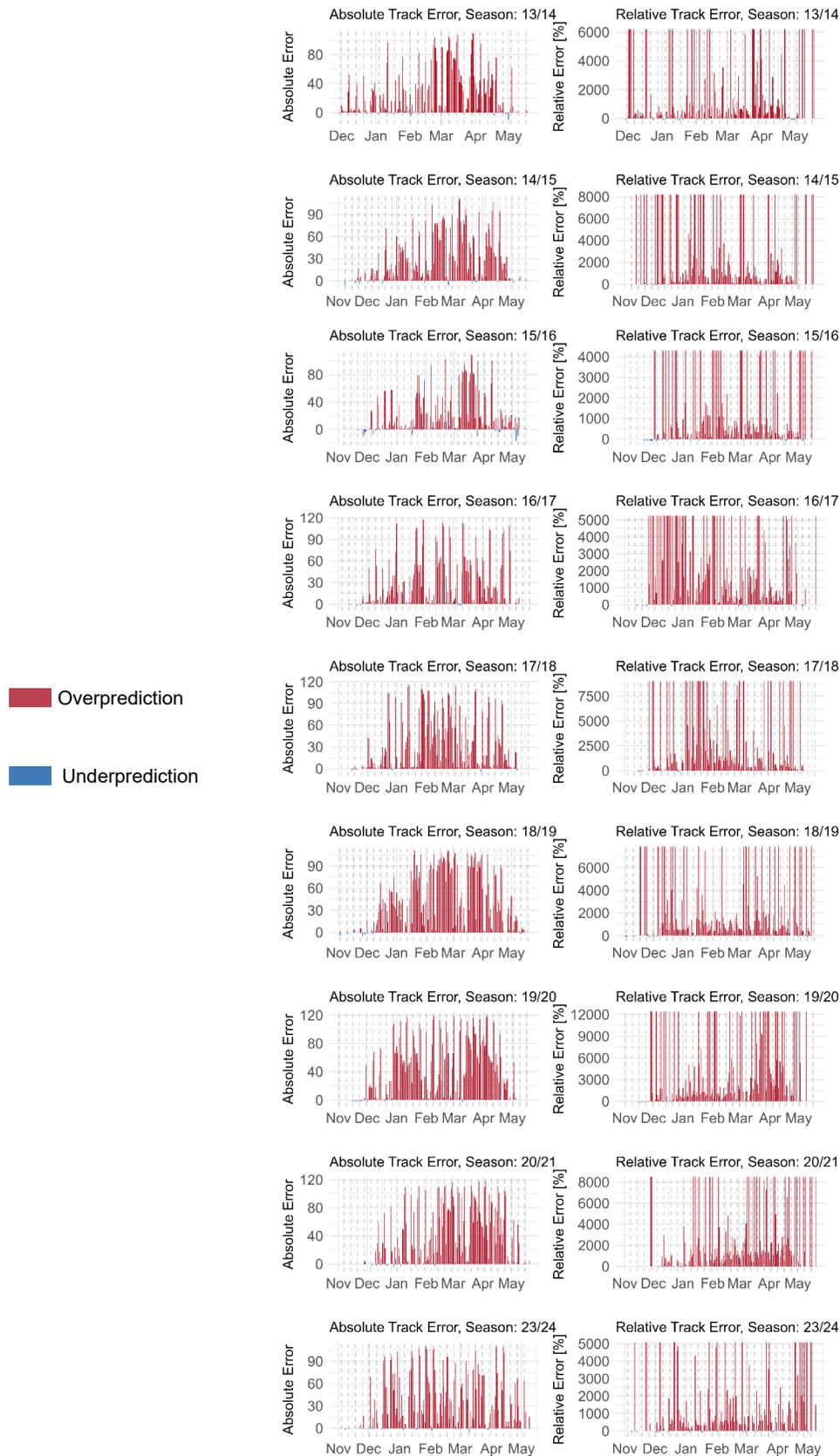


Figure S13: Relative and absolute prediction error of the track model for every season.

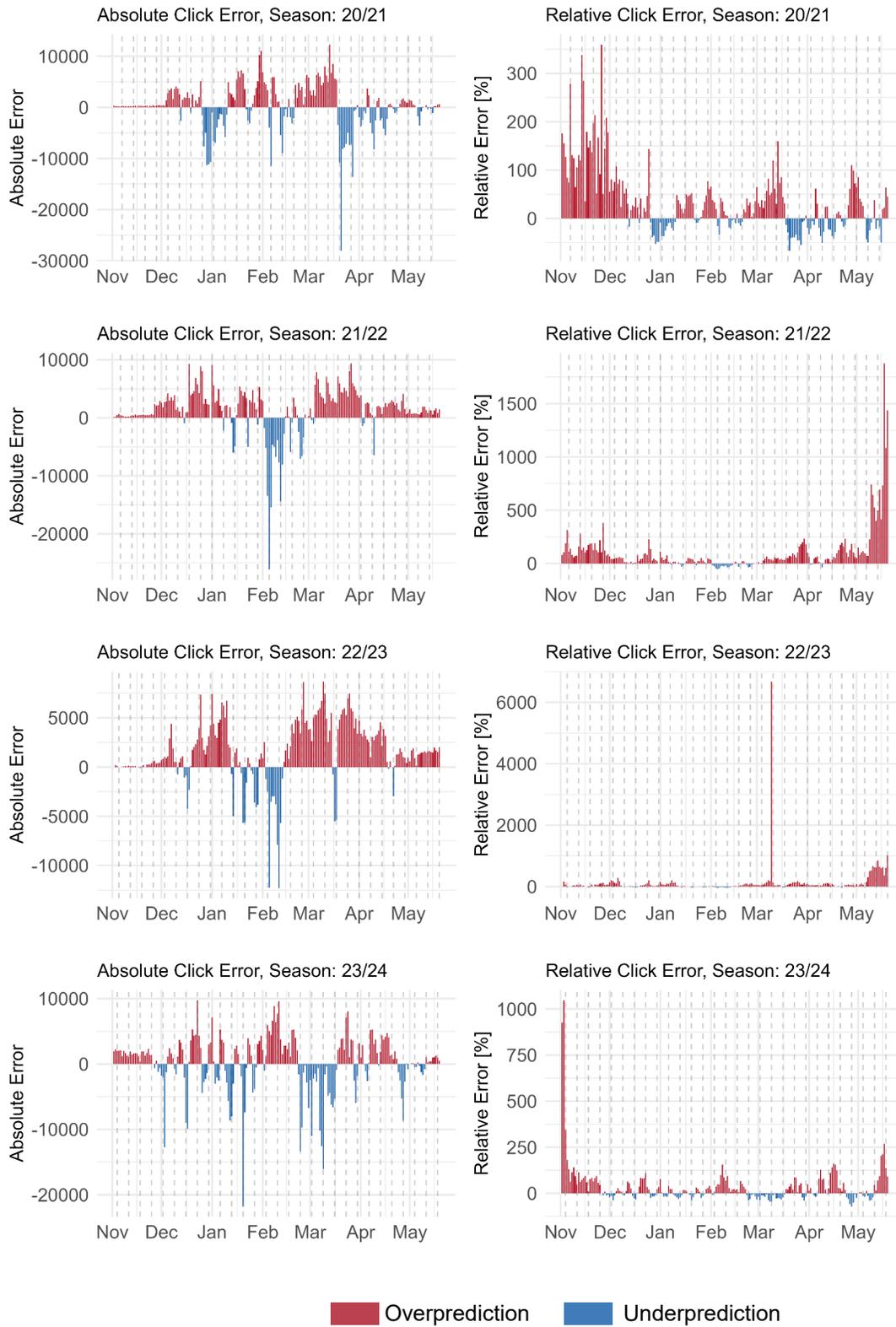


Figure S14: Relative and absolute prediction error of the click model for every season.