

Influence of forest canopy cover on automated Avalanche Terrain Exposure Scale classification in the Pirin Mountains, Bulgaria

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Abstract

Backcountry skiing and touring have gained significant popularity in recent years, with numerous accidents occurring annually worldwide. Bulgaria's Pirin Mountains have experienced similar trends, highlighting the urgent need for tools that enhance public awareness of avalanche-prone terrain. The Avalanche Terrain Exposure Scale (ATES) offers a systematic approach to classifying terrain based on its potential avalanche exposure, relying exclusively on static terrain and vegetation characteristics. While early ATES maps were manually produced by experts, recent advancements, such as machine learning-based approaches, have enabled scalable and accurate automated ATES (AutoATES) mapping over larger areas. A critical component of AutoATES classification involves modelling the protective effect of forests, which requires information on forest structure. Recent applications have incorporated remote sensing-derived forest structural parameters, such as percent canopy cover (PCC), to approximate forest protective effects in AutoATES model chains. In this study, we applied a recently developed machine learning framework for AutoATES classification to generate ATES maps for a study area in the Pirin Mountains, focusing on the effect of different PCC datasets on final and intermediate results of the model chain. Specifically, we tested a few forest cover scenarios: (1) the Copernicus Tree Cover Density product as a baseline, (2) a treeless simulation with PCC set to 0%, and (3) two alternative PCC estimates derived from RapidEye satellite imagery and information from digital elevation models. Our findings indicate that forests significantly reduce avalanche terrain exposure in the study area and that variations in PCC estimation can substantially alter the extent and distribution of different ATES classes. Notably, the second investigated RapidEye-based PCC estimation approach

provided improved identification of forest gaps and dwarf mountain pine (*Pinus mugo* Turra) compared to the first, resulting in more accurate ATES maps in those respective areas.

Key words: Copernicus Tree Cover Density, machine learning, protective effect of forests, RapidEye, snow avalanches.

Introduction

Snow avalanches are estimated to cause approximately 250 fatalities worldwide each year (Acharya et al. 2023). Bulgaria has experienced a sharp rise in back-country recreation, accompanied by regular avalanche accidents (Panayotov et al. 2021).

Improving public and institutional awareness of avalanche-prone terrain is critical for mitigating avalanche risk and enhancing safety. One effective tool for this is the Avalanche Terrain Exposure Scale (ATES), which classifies terrain based on its potential exposure to avalanche hazards. ATES maps rely solely on static terrain and vegetation characteristics, and do not incorporate dynamic meteorological or snowpack conditions. Originally developed in Canada in 2006 (Statham et al. 2006), its first version categorised terrain into the following three classes – simple, challenging, and complex. A fourth class, extreme, was later added in the second version to account for high-consequence avalanche terrain, such as steep gullies, cliffs or vertical drop-offs (Statham and Campbell 2025).

Initial ATES maps were produced manually by avalanche professionals and relied on expert-based assessments of the local avalanche terrain (Campbell and Gould 2013, Gavalda et al. 2013). While effective, this process is labour-intensive and difficult to scale across large or remote areas. To address this limitation, au-

tomated approaches such as AutoATES versions 1.0 and 2.0 (Larsen et al. 2020, Toft et al. 2024) and their derivatives (Avis et al. 2023, Huber et al. 2023, Sykes et al. 2023, Markov and Panayotov 2024, Markov et al. 2024) have been developed. The most recent advancements include the use of machine learning approaches that combine multiple geospatial data layers to create ATES maps (Markov et al. 2025).

Regardless of the method used to generate ATES maps, accounting for the protective effect of forests is essential and results in improved accuracy (Schumacher et al. 2022). Forests are widely recognised as providing significant biological protection against avalanches. When assessing this protective role, it is important to differentiate between avalanche release areas and runout zones. In release areas, forests can mitigate the likelihood of avalanche release, although the degree of protection depends on multiple factors, including stem density, crown cover, forest gaps distribution, terrain ruggedness relative to snow depth, and other structural characteristics (Bebi et al. 2009). The influence of forests on avalanche runouts has also been extensively studied. Research indicates that the runout distances of small to medium avalanches are particularly affected by forest structure. In contrast, medium to large avalanches originating above treeline are generally less influenced by forest structure; however, their speed and energy often decreases upon entering forested terrain (Teich

et al. 2012). Beyond avalanches, forests also serve as effective natural barriers against other hazards such as rockfalls and landslides. Given their multifunctional role in hazard mitigation, understanding forest characteristics and quantifying their protective capacity are essential for comprehensive natural hazard risk assessments (Perzl et al. 2021). Usually, most existing approaches utilise remotely sensed forest structure information to assess the protective effects of forest vegetation. Among other metrics Percent Canopy Cover (PCC) can be estimated based on data from different remote sensing platforms and has been used to characterise the forest protective effect of forests against avalanches.

In this study, we adopted the machine learning framework developed by Markov et al. (2025) to create ATES maps for a part of the Pirin Mountains, Bulgaria. The main objective was to investigate how forest PCC layers derived from open source and easily accessible data sources affect the identification of potential avalanche release areas (PRAs), modelled avalanche runouts and intensities, and the resulting ATES classifications. In the first step, Copernicus Tree Cover Density data (Copernicus Land Monitoring Service 2018), as originally used by Markov et al.

(2025), was adopted. Next, we simulated a treeless landscape by setting PCC to 0 % across the region to observe the complete loss of protective effect. Finally, we tested two alternative methods for estimating forest PCC, inspired by the recent work of Panayotov et al. (2024), using RapidEye satellite imagery (European Space Agency 2025) and a combination of digital surface (DSM) and digital terrain models (DTM).

Through this investigation, we aimed to address two main research questions:

1. Do forests in the study region significantly mitigate avalanche hazard through their protective effect?

2. How do different estimates of PCC created from easily accessible data sources influence resulting ATES map quality compared to maps produced with the Copernicus Tree Cover Density product as a proxy for PCC?

Materials

Our study focused on an area around Bansko Ski Resort and the neighbouring Bunderitsa and Demyanitsa Valleys, located just to the south of the town of Bansko (Fig. 1). These valleys are representative of the entire northern part of the

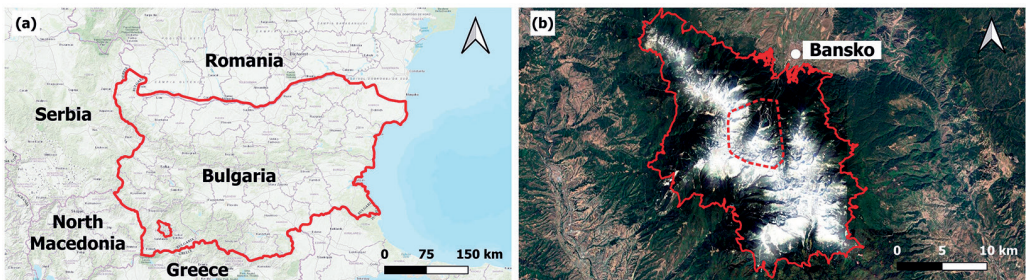


Fig. 1. Location of the study area: (a) location of Pirin National Park in southwestern Bulgaria; (b) study area shown as a dashed red line within Pirin National Park (solid red line).

Pirin Mountain range and contain sharp peaks with steep slopes and numerous avalanche couloirs and tracks below them. Some of these avalanche paths run through forests and avalanches have occurred there in the past (Panayotov et al. 2023, Panayotov and Tsvetanov 2024). The lower sections of the valley slopes (up to approx. 2200 m a.s.l.) are predominantly covered by Macedonian pine (*Pinus peuce* Griseb.)-dominated forests, while in extensive areas of the middle and upper parts of the valleys, up to approximately 2500 m a.s.l., dwarf mountain pine (*Pinus mugo* Turra) dominates the landscape. The mountain tops are free of high vegetation and are covered mostly by bare rocks, low juniper bushes (*Juniperus communis* L. var. *nana* Rehder) and grasses, located on steep to very steep slopes, sometimes with sections of vertical cliffs.

In this study, our analysis primarily concentrated on ATES classifications within forested regions and areas dominated by dwarf mountain pine, which constitute a large portion of the study area and exhibit the most pronounced differences across the various methods used to estimate the PCC.

The input data requirements for this study closely align with those used in previous studies (Larsen et al. 2020, Toft et al. 2024). The two primary datasets needed are a DTM and a forest structure layer. In many studies PCC has been used to approximate forest structure in terms of forest density. The DTM used for most of the study area had a resolution of 5 m and was provided by Pirin National Park (2022). Additionally, a higher-resolution 2 m DTM from the private geospatial provider GEO Polymorphic Cloud (2025) was used for a limited portion of the study area. To ensure consistency with previous

AutoATES studies, both DTMs were combined and resampled to a resolution of 10 m. This resolution has been found to provide a good balance between processing time, amount of noise in the data (arising from terrain irregularities such as small isolated rocks or microtopographic features), and the level of geographical detail required to capture major terrain features.

For the representation of forest structure, we investigated different data sources describing PCC in our study area. The first approach utilised the readily available 10 m resolution Copernicus Tree Cover Density product (Copernicus Land Monitoring Service 2018), hereafter referred to as Copernicus PCC for consistency with previous AutoATES related studies. In addition, we also investigated two approaches for custom PCC estimation, which were inspired by the work of Sykes et al. (2022) and Panayotov et al. (2024). These approaches made use of RapidEye satellite imagery (European Space Agency 2025), with a resolution of 5 m, which provides five spectral bands: blue, green, red, red edge, and near-infrared. A DSM obtained from the Bulgarian Ministry of Agriculture and Food, with a resolution of 4 m, was also employed for the second approach.

All datasets were reprojected to the WGS 1984 UTM Zone 35N coordinate reference system. For the two custom PCC estimation approaches, the pixel size was resampled to match the highest native resolution among the input data layers used in each case – 5 m for the first approach and 4 m for the second. The resulting PCC layers were subsequently resampled to a 10 m resolution to ensure consistency with the DTM before further processing. All resampling was performed using bilinear interpolation in ArcGIS Pro. Spatial alignment between layers was ensured using the Extract by Mask tool.

Methods

General methodology

The methodology used to generate the ATES maps followed the machine learning approach described by Markov et al. (2025), closely resembling the general structure adopted in previous AutoATES model chains (Larsen et al. 2020, Huber et al. 2023, Panayotov et al. 2024, Toft et al. 2024). The standard modelling workflow consists of three main steps: (1) identification of PRAs, (2) delineation of potential avalanche runouts from those PRAs, and (3) a final avalanche terrain classification step, often referred to as the AutoATES classifier (Toft et al. 2024). All basic steps and parameter settings were replicated exactly from the study by Markov et al. (2025). The remainder of this section provides a summary of this approach.

The methodology for identifying PRAs originates from the approach proposed by Veitinger et al. (2016) and used the input layers slope, wind shelter (both calculated from the DTM), and PCC, converting them to the interval of 0 to 1 using fuzzy logic. These input layers are then combined and weighted by a fuzzy logic approach into a single continuous PRA value, representing the likelihood of avalanche release from 0 to 1. The resulting continuous PRA layer was subsequently converted into binary format using a threshold value of 0.3, consistent with previous studies (Huber et al. 2023, Panayotov et al. 2024, Toft et al. 2024, Markov et al. 2025). In this binary layer, a value of 1 indicates that avalanche release is possible at a given location ($PRA > 0.3$), while a value of 0 indicates that it is not.

To model potential avalanche runouts, the simulation tool com4FlowPy with its forest friction module was used (D'Am-

boise et al. 2022, Huber et al. 2024). The binary PRA layer from the previous step served as the potential release area input, along with the same DTM used in that calculation. The forest structure index (FSI) input into the software was derived by linearly scaling the PCC, which originally ranges from 0 % to 100 %, to the interval 0 to 1. The FSI represents the degree to which a forest with a given structure is capable of decelerating avalanches, where a value of 1 indicates an optimal forest structure for protection and 0 indicates the absence of forest. The com4FlowPy outputs used in this study were the local travel angle (γ), cell counts, $z_{\max}^{\delta}$, and the sum of routed flux ($\sum_{\text{routFlux}}$). Local travel angle provides a measure of the proximity of a location to the nearest PRA. Cell counts represents how many potential PRA cells may affect a given location. The $z_{\max}^{\delta}$ layer indicates the maximum avalanche intensity at a given cell (which can be converted to velocity), while $\sum_{\text{routFlux}}$ represents the sum of all modelled flux values. $\sum_{\text{routFlux}}$ can be interpreted more intuitively as potential flow thickness at a certain point along an avalanche path. Consequently, higher modelled flux values are observed in gullies or locations where multiple avalanche paths may converge.

The final ATES classification step combines outputs from the previous steps of the model chain and maps them to the four ATES classes. This final classification step was performed using the best performing Random Forest model (model RF 2) from the study by Markov et al. (2025).

Study-specific methodology

This study specifically focused on evaluating the influence of different PCC representations on the PRA outputs and the final ATES classification. It is important

to note that each PCC implementation used in this study was applied consistently across all components of the model chain – including the PRA calculation, avalanche runout and intensity modelling with com4FlowPy, and the final classification step. This consistency allowed us to investigate the influence of each PCC layer on all intermediate data layers as well as on the final ATES map.

The baseline scenario replicated the entire setup from Markov et al. (2025), using Copernicus PCC and the best-performing Random Forest model from that study (model RF2). In the first analysed scenario we replaced the PCC layer with a synthetic raster containing zero values across the entire domain. This analysis was conducted to address Research Question 1 by modelling the avalanche terrain exposure in our study area in the absence of forest cover. We refer to this scenario as the NoForest scenario.

In the next step we investigated two alternative methods to derive custom PCC layers and assessed how they impact both PRA detection and final ATES outputs. The first approach followed a method outlined by Sykes et al. (2022), using supervised machine learning classification and RapidEye imagery. We manually created training polygons for forest and non-forest classes by visual inspection of high-resolution orthophoto imagery and converted them to a raster layer (with 0 representing forest and 1 representing non-forest), splitting them at random (50/50) into a train/test set partition. We used the five spectral bands of the RapidEye imagery along with three derived indices – the Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI), and Normalized Difference Red Edge Index (NDRE) as input features for the classification, as

described in Sykes et al. (2022). NDVI helps distinguish healthy vegetation from bare soil or rock, while NDWI detects water bodies. NDRE highlights chlorophyll content for assessing subtle vegetation health. All three indices provide valuable information for forest vs non-forest classification and supplying them to a machine learning model leverages the unique strengths of each. A Random Forest classifier was trained to distinguish between the forest and non-forest classes using a hyperparameter grid identical to that of the Random Forest models in Markov et al. (2025), with 500 random combinations evaluated via 3-fold cross-validation. The resulting model was then applied on the held-out test set and on the remainder of the study area to classify them into forest and non-forest classes. This approach is hereby referred to as the RapidEye approach.

The second approach from RapidEye imagery shares the same methodology as the first, but was extended by incorporating an additional feature into the classification – the difference between a DSM and a DTM. The applied methodology is also described in Panayotov et al. (2024). The DSM-minus-DTM feature was used as an additional input to better distinguish forested areas from regions dominated by dwarf mountain pine – a known area of confusion. Dwarf mountain pines and higher conifer tree species are spectrally similar, leading to frequent misclassifications using the RapidEye approach. However, dwarf mountain pine, while dense, is much shorter than typical trees and frequently becomes entirely buried under snow in winter, thus losing its protective effect against avalanches. Correctly identifying and separating it from taller forest vegetation is therefore of high importance. Large differences between the DSM and

the DTM suggest forested areas, while dwarf mountain pine is significantly shorter than trees, resulting in a small difference there. This approach is hereby referred to as the RapidEye Enhanced approach.

We made a brief comparison of the binary forest vs non-forest classification performance of both custom approaches by using the held-out test set, which was not seen at all during training procedures. We used the commonly applied statistical measures precision, recall, and F1 score for each class, as well as the corresponding precision-recall curves. Precision quantifies the proportion of correctly classified instances among all instances predicted as belonging to a given class. Recall, on the other hand, measures the proportion of actual instances of a class that were correctly identified by the model. The F1 score is a measure of a model's accuracy that combines precision and recall and is especially useful in the case of class imbalances. The precision-recall curve illustrates the trade-off between precision and recall across different decision thresholds, with better-performing models producing curves that stay close to the top-right corner.

Next, it was necessary to convert the resulting binary forest vs non-forest classification from both custom approaches into a PCC layer representing forest density, ranging from 0 % to 100 %, just like the Copernicus PCC. This was done using a 3×3 pixel sliding window method, as described by Sykes et al. (2022). The sliding window method counts the number of pixels classified as forest within each sliding window and assigns the resulting proportion (expressed as a percentage) to the central pixel. After the conversion from a binary layer to PCC, the FSI again was derived by linearly scaling this PCC to the interval 0 to 1, as was done with the base-

line Copernicus PCC approach.

After obtaining the PCC from both RapidEye approaches and using it to calculate the PRAs and avalanche runouts using com4FlowPy, the final step was to integrate all features into the final ATES map. For this stage, we utilised the best-performing Random Forest model identified by Markov et al. (2025), hereafter referred to as RF2. This model incorporates a range of input features – slope, PCC, a continuous raster representing the potential release areas (PRA), and the previously described outputs from the com4FlowPy model. We retrained the model using feature values generated from our two alternative RapidEye PCC datasets specific to this study. Each retraining was conducted using the same training set and an identical hyperparameter grid search space, with 10,000 randomly sampled combinations, consistent with the original methodology described in Markov et al. (2025). For the NoForest scenario, we did not retrain the model – instead, we applied the pre-trained RF2 model from Markov et al. (2025) directly, as this scenario was intended solely to test a hypothetical situation in which no forest cover is present.

We formally compared the results for the final ATES classification stemming from Copernicus PCC (Markov et al. 2025), the NoForest scenario, and from our two alternative RapidEye PCC approaches (RapidEye, RapidEye Enhanced) by calculating the precision, recall, and F1 score for each ATES class and analysing corresponding precision-recall curves in the held-out test set. This set was identical to the one used in the study by Markov et al. (2025) and was kept the same for each approach in our study to ensure consistency and comparability of the results.

In addition, we conducted a visual in-

spection of the PRA and final ATES results for selected regions of interest to evaluate how the classifiers based on the different PCC layers perform beyond the test set.

Results

Forest classification and PRAs

Figure 2 illustrates the test set performance for the forest vs non-forest classification step in both custom PCC approaches. The DSM-minus-DTM feature in the RapidEye Enhanced approach emerged as an influential variable, leading to a notable improvement in classification performance on the test set. This enhancement is reflected in the precision-recall curves for each class (Fig. 2a), as well as in the overall precision, recall, and F1 scores (Fig. 2b) – all of which show significant improvements with the enhanced method. In Figure 2a it can be seen how the

precision-recall curves for the RapidEye Enhanced approach are very close to the ideal curve, indicating that the classifier is highly confident in its classification on the test set. These improvements in forest classification are subsequently reflected in the more accurate results observed in the downstream ATES classification (Fig. 4c).

Figure 3 presents the PRAs as a binary layer, focusing on a region encompassing the western slope of Todorka Peak and the Echmishte area, located centrally within Bansko Ski Resort. This region covers a heterogeneous landscape consisting of forest openings and gaps, ski trails, couloirs, and extensive cover of dwarf mountain pine. Figure 3a displays the PRA results based on the baseline approach using Copernicus PCC. Figures 3b and 3c show the results using the RapidEye approach and the RapidEye Enhanced approach, respectively. Figure 3d illustrates the hypothetical scenario in

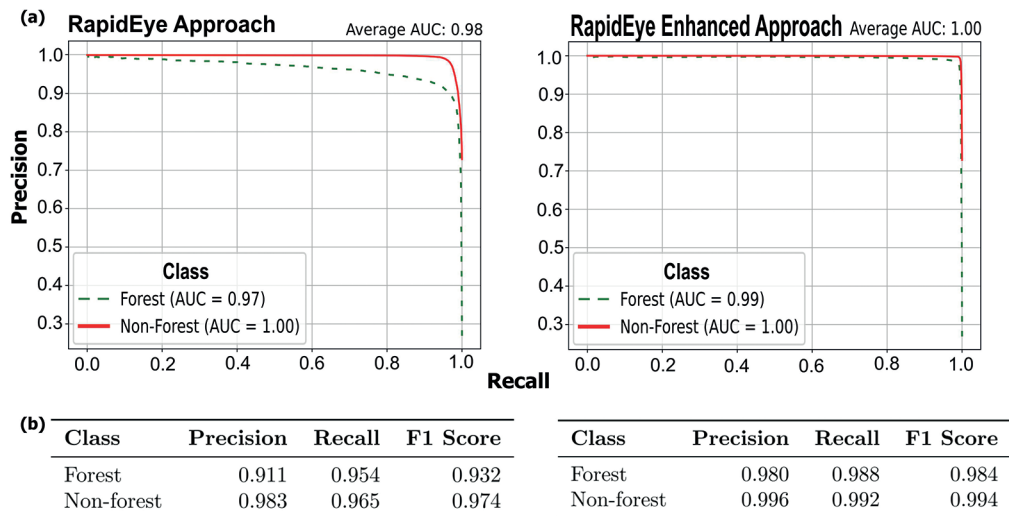


Fig. 2. Test set performance for forest/non-forest classification using the RapidEye and RapidEye Enhanced approaches: (a) precision–recall curves; (b) precision, recall, and F1 scores for both classes.

Note: AUC denotes the area under the curve.

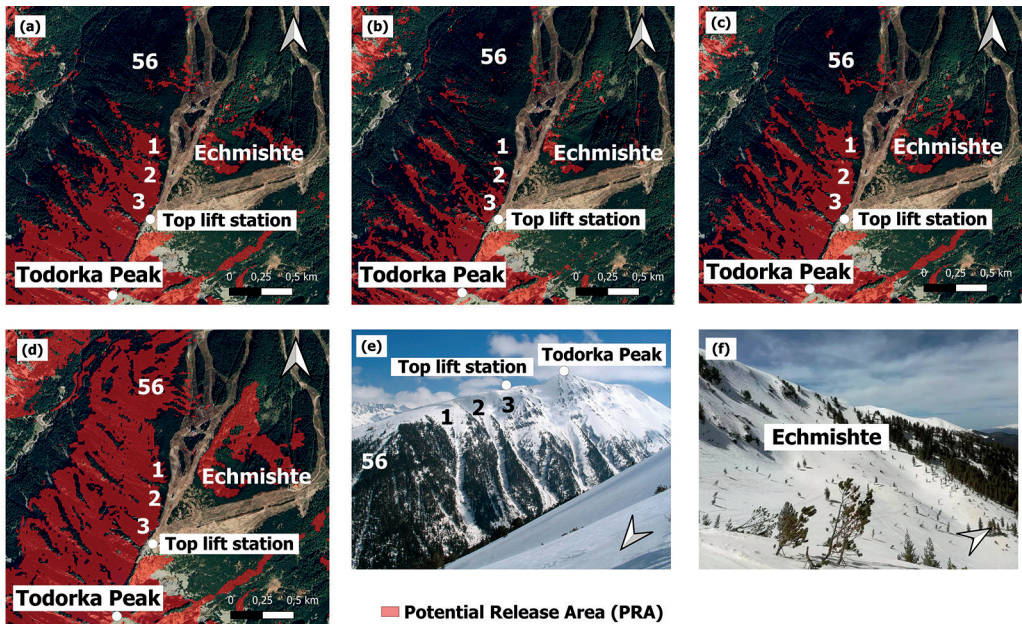


Fig. 3. Potential release areas (PRAs) calculated under different forest PCC scenarios: (a) Copernicus PCC; (b) RapidEye; (c) RapidEye Enhanced; (d) NoForest (0% PCC).

Note: Panel (e) shows a wintertime photo of the western face of Todorka Peak, panel (f) – a wintertime photo of the Echmishte region within Bansko Ski Resort. Numbers indicate corresponding locations in panels (a)–(e).

which forest cover is entirely absent (the NoForest scenario). For visual reference, figures 3e and 3f include real-world photographs of the region.

The figure highlights that, in the absence of forest cover (NoForest scenario) a significant portion of the area would be classified as PRAs (Fig. 3d, red colours). Additionally, the standard RapidEye approach (Fig. 3b) fails to correctly identify areas dominated by dwarf mountain pine – such as Echmishte and the top sections of couloirs 1, 2, and 3 on the western slope of Todorka Peak – misclassifying them as forest. Consequently, large parts of these areas are excluded from PRAs, which does not reflect observed local conditions. In contrast, the RapidEye Enhanced approach (Fig. 3c) is more successful in

distinguishing dwarf mountain pines from areas covered by taller forest vegetation. The resulting PRAs closely correspond to those derived with the baseline Copernicus PCC result (Fig. 3a).

Final ATES classification

Figure 4 displays the final ATES maps for the same region, with panel labels corresponding to those in Figure 3. In the NoForest scenario (Fig. 4d), a substantial portion of the terrain is classified as complex, in contrast to the simple or challenging classifications produced by the other approaches. The standard RapidEye approach (Fig. 4b), due to its misclassification of extensive areas of dwarf mountain pine as forest, erroneously la-

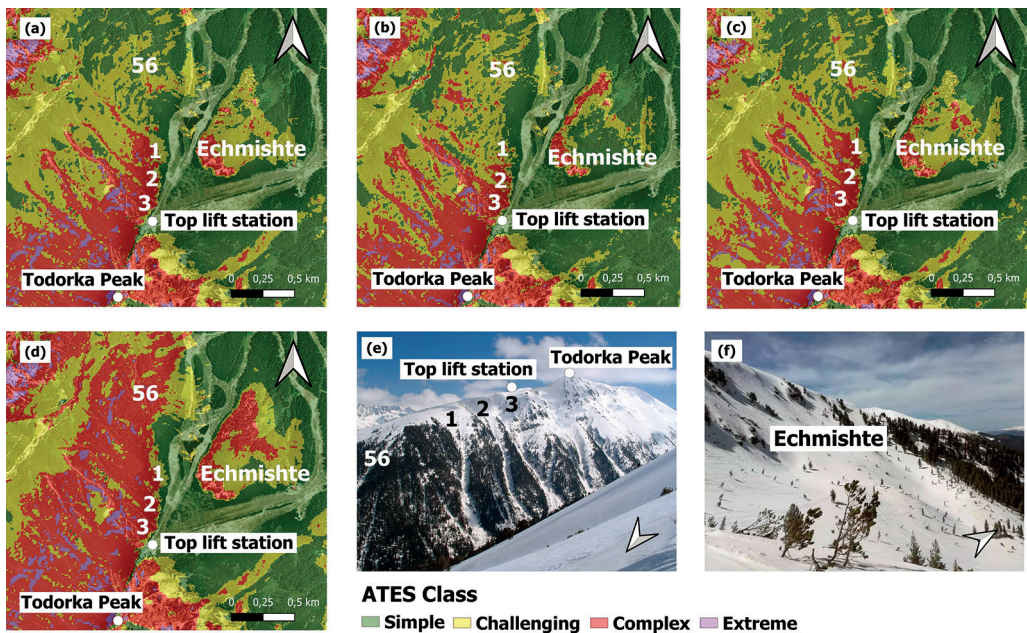


Fig. 4. ATES maps calculated under different forest PCC scenarios: (a) Copernicus PCC; (b) RapidEye; (c) RapidEye Enhanced; (d) NoForest (0% PCC).

Note: Panel (e) shows a wintertime photo of the western face of Todorka Peak, panel (f) – a wintertime photo of the Echmishte region within Bansko Ski Resort. Numbers indicate corresponding locations in panels (a)–(e).

bels larger sections of the Echmishte region as simple terrain. It also assigns less severe terrain classifications to the upper parts of couloirs 1 and 2 on the western slope of Todorka Peak - areas that are steep, frequently serve as avalanche start zones, and should be classified as complex terrain, as accomplished by the other approaches. In contrast, the ATES maps generated using Copernicus PCC (Fig. 4a) and the RapidEye Enhanced approaches (Fig. 4c) are both accurate and very similar, with the latter offering slightly improved delineation of narrower forested corridors in some areas.

Figure 5 displays the feature importance derived from training the Random Forest models for final ATES classification using the Copernicus PCC (as in Markov et al. 2025), the RapidEye approach PCC

and the RapidEye Enhanced approach PCC. The PCC feature ranks lowest in importance in all approaches, indicating that it was used in a very small proportion of splits in the trained models. In contrast, the continuous PRA feature and all com4FlowPy outputs, which are directly influenced by the PCC, exhibit significantly higher importance in all three models. Slope and the sum of routed flux are identified as the two most important features in all models. The continuous PRA layer, the local travel angle (γ), and cell counts are identified as the next most important features (albeit in varying order across the three models), being used in approximately 5–15 % of splits for both models.

Figure 6a shows the precision-recall curves on the test set for final ATES classification using the Copernicus PCC and

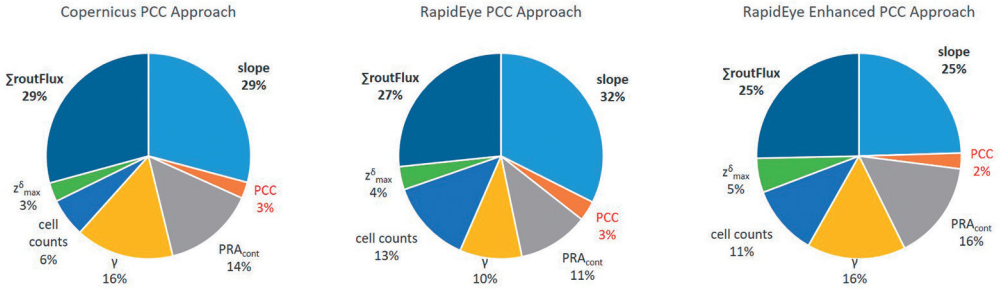


Fig. 5. Feature importance derived from training the Random Forest models for final ATES classification, using input features obtained from the Copernicus and the two RapidEye imagery-based approaches for PCC calculation.

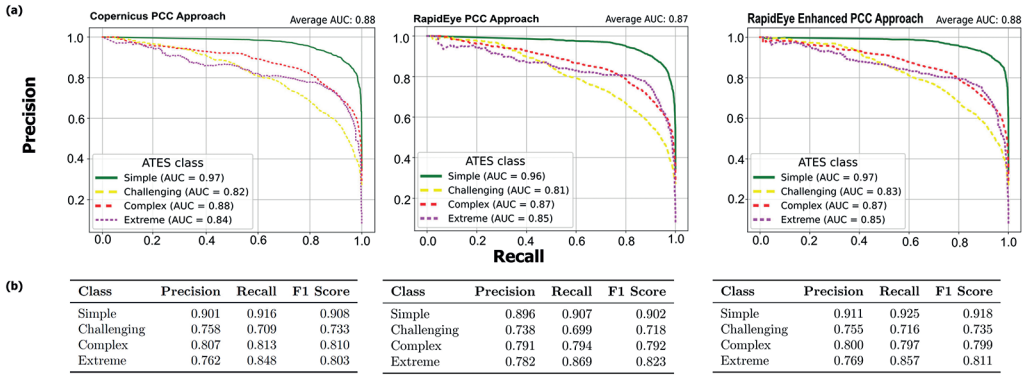


Fig. 6. Test set performance for the final ATES classification with Copernicus PCC and PCC obtained using the RapidEye approach and the RapidEye Enhanced approach: (a) precision–recall curves; (b) actual values of precision, recall, and F1 score for all ATES classes.

the two custom PCC approaches. We observe that performance is slightly lower for the RapidEye approach for PCC across most classes when compared to the RapidEye Enhanced PCC approach. Performance of the RapidEye Enhanced approach and the Copernicus baseline approach (Markov et al. 2025) is similar on the test set. Figure 6b presents the per-class precision, recall, and F1 scores for the models using Copernicus PCC and using the custom RapidEye approaches PCC. The RapidEye Enhanced approach yields a modest improvement in test set

performance compared to the RapidEye approach across all ATES classes except for the extreme class, where a slight decline is observed. This misclassification becomes evident from the confusion matrices for the two custom PCC models (tables 1 and 2). For each of the four ATES classes, the confusion matrices display how many samples were correctly classified and how many were misclassified into each of the other classes, allowing assessment of classification accuracy and error patterns. The numbers along the diagonal reveal correct classifications

Table 1. Confusion matrix for the final ATES classification using PCC obtained with the RapidEye approach.

Actual ATES class, m ²	Predicted ATES class			
	Simple	Challenging	Complex	Extreme
Simple	408,300 (90.67 %)	37,700 (8.37 %)	4200 (0.93 %)	100 (0.02 %)
Challenging	43,200 (12.09 %)	249,700 (69.89 %)	62,200 (17.41 %)	2200 (0.62 %)
Complex	3700 (0.96 %)	50,900 (13.25 %)	304,900 (79.38 %)	24,600 (6.40 %)
Extreme	300 (0.27 %)	0 (0.00 %)	14,200 (12.82 %)	96,300 (86.91 %)

Note: Grey diagonal cells represent correctly classified areas (values given in m²; dividing by 100 yields the number of pixels), while off-diagonal entries indicate misclassifications.

Table 2. Confusion matrix for the final ATES classification using PCC obtained with the RapidEye Enhanced approach.

Actual ATES class, m ²	Predicted ATES Class			
	Simple	Challenging	Complex	Extreme
Simple	416,500 (92.49 %)	32,800 (7.28 %)	1000 (0.22 %)	0 (0.00 %)
Challenging	38,500 (10.78 %)	255,900 (71.62 %)	60,600 (16.96 %)	2300 (0.64 %)
Complex	1900 (0.49 %)	49,700 (12.94 %)	306,300 (79.74 %)	26,200 (6.82 %)
Extreme	300 (0.27 %)	700 (0.63 %)	14,800 (13.36 %)	95,000 (85.74 %)

Note: Grey diagonal cells represent correctly classified areas (values given in m²; dividing by 100 yields the number of pixels), while off-diagonal entries indicate misclassifications.

(where the actual and predicted ATES classes match). The matrices reveal that for the RapidEye approach, 12.82 % of the actual extreme terrain pixels were misclassified as complex, while for the RapidEye Enhanced approach, this percentage increased slightly to 13.36 %. However, when visually evaluating model generalisation over larger spatial extents (Fig. 4), the RapidEye Enhanced approach demonstrates substantially improved accuracy compared to the RapidEye approach, closely aligning with the baseline Copernicus PCC model and even surpassing it in certain aspects – particularly in the detection and delineation of narrower forest openings. The performance metrics (precision, recall, and F1 score) of the Copernicus PCC model and the RapidEye Enhanced PCC model are also very similar, with slight improvements for

the simple and extreme terrain classes in the latter.

Discussion

The results of this study provide clear evidence in support of the research questions outlined at the beginning of the paper. Figures 3a, 3d and 4a, 4d illustrate the substantial protective effect of the forest cover in the study area and its critical role in mitigating avalanche hazard. As shown in Figure 3d, the extent of PRAs would be considerably larger in the absence of the forest cover (NoForest scenario). This finding aligns with established knowledge, as sufficiently dense forest cover is known to exert a stabilising influence on the snowpack, thereby inhibiting the release of avalanches in forests (Bebi et al. 2009,

Bebi et al. 2021). The PRAs, together with the FSI – defined as the scaled PCC – serve as inputs to com4FlowPy, directly influencing modelled avalanche runouts and intensities.

In Figure 4, this influence on ATES classes becomes evident: in the NoForest scenario (Fig. 4d), a large portion of the terrain is classified as complex, whereas with existing forest cover (Fig. 4a, 4b, 4c), much of the same area is more accurately identified as simple or challenging terrain (challenging being the areas that are very steep). These findings align with the earlier PRA results and are consistent with the known role of dense forests in reducing avalanche hazard (Bebi et al. 2009, Teich et al. 2012, Perzl et al. 2021). Generally, densely forested terrain is considered low-risk and classified as simple terrain, unless it includes steep slopes with forest gaps and openings, in which case it is appropriately labelled as challenging, which is consistent with Figure 4a, 4b, 4c.

The results of this study also allow us to examine the impact of different PCC estimation methods on modelled PRAs and the final ATES maps. As shown in Figure 2, the RapidEye Enhanced approach significantly improves the initial forest vs non-forest classification performance compared to the base RapidEye approach. This aligns with the findings of Panayotov et al. (2024), where incorporating the DSM-DTM difference led to more accurate delineation of forested and non-forested terrain. The DSM-minus-DTM feature emerged as the most important variable during the model training, which is expected, as areas without tall forest vegetation – such as dwarf mountain pine zones, open alpine terrain, and forest openings – tend to have low DSM-minus-DTM values, whereas tall trees produce high differences, making this fea-

ture particularly discriminative.

Figures 3b, 3c and 4b, 4c illustrate how errors in the initial forest classification propagate downstream to PRA detection and ATES terrain classification. In particular, the omission of the DSM-minus-DTM feature in the original RapidEye approach results in widespread misclassification of dwarf mountain pine as dense forest. Consequently, extensive areas in the upper sections of couloirs 1, 2, and 3 on the west face of Todorka, as well as in the Echmishte region are excluded from PRA maps and assigned a simple or challenging ATES classification. While such classification would be appropriate if these areas were indeed densely forested, in reality they are highly avalanche-prone and should be classified as complex. This visual comparison highlights that the RapidEye PCC approach produces lower-quality PRA and ATES maps compared to the Copernicus PCC baseline (figs 3a and 4a), which correctly identifies these regions as complex.

The RapidEye Enhanced PCC approach (figs 3c and 4c) provides a solution to the above-mentioned problem, correctly classifying dwarf mountain pine regions and producing results that closely match those of the Copernicus PCC baseline (figs 3a and 4a), in some cases even surpassing them. Although the overall maps are similar, the RapidEye Enhanced method better captures narrow forest couloirs and small forest gaps – such as the couloir 1 and gap 56 – thanks to its original use of higher-resolution input (5 m DTM, 4 m DSM) and the inclusion of the DSM-minus-DTM feature when calculating the PCC. These advantages help to better delineate small open-terrain features within forests and track them downslope, something that Copernicus PCC (with its coarser 10 m resolution) struggles with. It

is important to note that the subsequent resampling of the PCC layer in the RapidEye Enhanced approach to 10 m resolution before the further processing likely resulted in a minor loss of detail. Despite this, figures 3c and 4c show that the resulting PRA and ATES maps still reflect the advantages gained from initially using the finer-resolution data.

In open, alpine areas above the treeline and above the dwarf mountain pine regions, ATES classification is very similar across all investigated methods, as all PCC approaches produce the same value of 0% PCC in most locations in these areas.

Feature importance analysis for the final ATES classification Random Forest models (Fig. 5) further confirms findings from Markov et al. (2025) – slope and the sum of routed flux are consistently the most important features, while the PCC layer ranks as the least important. This strengthens the conclusion from that study that, since PCC is already used in defining PRAs and influences all com4FlowPy outputs, which are subsequently used in the final ATES classification step, it may be redundant to include it as a separate feature at that stage. In this study, regardless of the source, that PCC layer consistently showed very low importance, offering further support for its exclusion from this step.

Furthermore, formal model comparisons for the final ATES classification (Fig. 6) show that the RapidEye Enhanced approach for PCC on average outperforms the original RapidEye approach on the test set, though the improvement is modest (approximately 1–2 % on average). However, there is a slight decrease in performance in the RapidEye Enhanced approach for the extreme ATES terrain class. The decrease may stem from the

fact that the DSM and DTM may not be of as high quality over extreme terrain (very steep slopes and cliffs) and may thus exhibit large differences in those areas. This may have misled the model, and a small portion of this extreme terrain could have been incorrectly labelled as forested during the PCC stage of the processing chain, thereby being assigned a lower final ATES class. As shown in the confusion matrices in tables 1 and 2, the proportion of underclassified extreme terrain pixels was 13.09 % (with most being misclassified as complex) in the RapidEye approach, while in the RapidEye Enhanced approach, the proportion of underclassifications for the extreme class was 14.26 %, again with most errors falling in the complex class. This increase in misclassifications is relatively minor, considering the improvements in classification across all three other ATES classes.

The comparison between the RapidEye Enhanced approach and the Copernicus PCC-based method used in Markov et al. (2025) demonstrates very similar performance across all statistical metrics. This result is encouraging, as it provides mutual validation of both methodologies and supports their reliability. In contrast, a discrepancy between the two would have raised concerns regarding the accuracy of one or both approaches. Moreover, the RapidEye Enhanced approach is comparatively simpler, utilising eight input features derived from one input image (plus the DSM-minus-DTM feature from digital elevation models), whereas the Copernicus PCC method relies on spectral features extracted from multi-temporal imagery and employs a complex model chain, with several post-processing steps (Copernicus Land Monitoring Service 2018). Despite this difference in methodological complexity, our RapidEye Enhanced approach achieves

comparable results. Both approaches yield an average area under the precision-recall curve (AUC) of 0.88 for the final ATES classification, with per-class AUC values either identical or differing by no more than 1 %. These findings indicate that the RapidEye Enhanced method offers a reliable alternative to the Copernicus PCC dataset as input for ATES classification and can be applied in regions where Copernicus PCC is not openly available, such as outside Europe. Furthermore, as previously noted, our visual inspection suggests that the RapidEye Enhanced PCC-based ATES classification may outperform the Copernicus PCC-derived map in certain areas (such as forest gaps), although formal statistical validation is required to confirm this observation.

Conclusion and future work

This study demonstrates that forests in our study area in the Pirin Mountains (southwestern Bulgaria) have a notable protective effect against snow avalanches. The extent of the potential release areas would be significantly larger in the absence of forest cover, and a greater portion of the terrain would be assigned the complex ATES class.

We also find that alternative methods for estimating PCC using RapidEye satellite imagery, DEMs, and Random Forest models can provide a viable alternative to the Copernicus PCC as input for ATES classification, particularly in regions where Copernicus PCC is unavailable, such as areas outside Europe. Although the initial RapidEye approach often fails to distinguish dwarf mountain pine from taller forest, thereby reducing ATES classification performance, our RapidEye Enhanced method effectively utilises available DSMs and DTMs to resolve this issue,

producing final ATES results that closely match those derived from the Copernicus PCC baseline. In some cases, the RapidEye Enhanced approach even appeared to outperform the Copernicus PCC approach in identifying and tracking narrow forest openings.

While this study provides valuable insights, several opportunities for future work remain. The test set used to evaluate the final ATES classification, sourced from Markov et al. (2025), is representative of the overall terrain but was not specifically designed to target forested areas or regions dominated by dwarf mountain pine. Creating a test set that more directly focuses on these vegetation types could improve the ability to detect subtle differences between PCC estimation methods and better align visual observations with quantitative metrics.

Additionally, this study applied existing methods for PCC estimation rather than developing new ones. Future research could explore innovative approaches for generating forest PCC layers, potentially allowing more precise identification of forest openings, gaps, and couloirs – key elements for improving PRA detection and refining ATES terrain classification in complex environments.

Finally, rather than resampling the PCC outputs derived from higher-resolution layers to 10 m, as was done in both the RapidEye approach and the RapidEye Enhanced approaches, future work could consider retaining the original resolution throughout the processing chain to preserve the full level of spatial detail.

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