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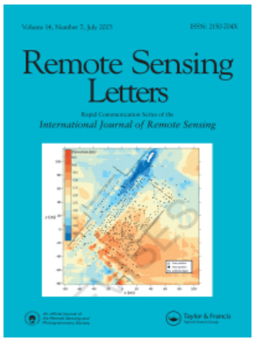
DOI
10.1080/2150704X.2024.2327084

Publication date
2024

Document Version
Final published version

Published in
Remote Sensing Letters



Remote Sensing Letters

ISSN: (Print) (Online) Journal homepage: www.tandfonline.com/journals/trsl20

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REMOTE SENSING LETTERS
2024, VOL. 15, NO. 4, 363–372
https://doi.org/10.1080/2150704X.2024.2327084

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ABSTRACT
Imagery acquired by the Moderate-resolution Imaging Spectroradiometer (MODIS) provides a global archive of dailyNormalized Difference Snow Index (NDSI) at 500 m nominal resolution since the year 2000. While Sentinel-2 (S2) NDSI provides an increased spatial resolution of 20 m since the year 2015, the temporal resolution amounts to only 5 days and thus lacks the high temporal resolution of MODIS. Efforts to combine NDSI datasets for an increased temporal and spatial resolution have so far focused on the deriving binary snow cover maps or combining data from other sensors. In contrast, we produce fine scale (20 m) fractional snow cover (FSC) by downscaling MODIS NDSI to S2 resolution. Random forest regression predicts S2 NDSI based on dynamic features (MODIS NDSI, day-of-year) and static, topographic features for an alpine study site. Subsequently, FSC is derived from S2 NDSI. Cross-validation results in R^2 of 0.795 and RMSE of 0.155 for FSC and outperforms common resampling methods. Multi-annual S2 NDSI metrics are able to slightly improve model accuracy. Our results suggest that combining topographical data and low-resolution NDSI allows to produce daily, high-resolution S2 NDSI and FSC and improve fine scale characterization of snow cover dynamics in mountain landscapes.

ARTICLE HISTORY
Received 25 August 2023
Accepted 28 February 2024

KEYWORDS
Fractional Snow Cover (FSC); downscaling; Normalized Difference Snow Index (NDSI); Sentinel-2 (S2); MODIS; machine learning

1. Introduction

Alpine ecosystems are characterized by rough topography and steep environmental gradients, generating a mosaic of habitats with very heterogeneous patterns of snow cover on small spatial scales. As a consequence, snowmelt in spring, which is crucial for the onset of plant development and vegetation differentiation (Körner 2021), also varies considerably at fine spatial resolution. Thus, fine-grain information on snow cover in both space and time is key for understanding and predicting alpine plant life, but also for estimating runoff and surface albedo (Immerzeel et al. 2009; Jonas et al. 2008; Li et al. 2018). Landsat and Sentinel-2

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(S2) snow cover monitoring provide such information at high spatial (30 m and 20 m, respectively, Gascoin et al. 2019), but relatively low temporal resolution (5 and 8 days). Moreover, S2 only covers the period from 2015 till today. In contrast, Moderate-resolution Imaging Spectroradiometer (MODIS) snow products (National Snow and Ice Data Center 2023) offer daily temporal resolution and cover the years from 2000 until today, but are characterized by a coarse (nominal) spatial resolution of 500 m. Combining the strengths of both products would thus allow a step forward in the representation of spatio-temporal snow cover dynamics relevant for many scientific domains like hydrology, ecology and climatology.

Published methods to downscale daily MODIS snow cover to S2 or Landsat resolution differ in the required input datasets, methodological formulations as well as target variables (e.g., fractional snow cover (FSC) and snow cover). These methods comprise probabilistic approaches (Revuelto et al. 2021), physically inspired, empirical methods (Cristea et al. 2017; Walters et al. 2014), as well as machine and deep learning models (Richiardi, Siniscalco, and Adamo 2023; Rittger et al. 2021; Yatheendradas and Kumar 2022). Revuelto et al. (2021) and Richiardi et al. (2023) target S2 data and resolution using a probabilistic and machine learning method, respectively, while Premier et al. (2021) employ both Landsat and S2 data. Eventually, Revuelto et al. (2021), Richiardi et al. (2023) and Premier et al. (2021) aim to produce a binary snow cover map. In contrast, Rittger et al. (2021) target downscaling to high-resolution Landsat FSC. While featuring a similar methodology to the presented study, Richiardi et al. (2023) do not quantify the accuracy of downscaling Normalized Difference Snow Index (NDSI), which they employ in an intermediate step before deriving snow cover. Further methods to downscale snow cover are based on climate model output and MODIS imagery (Matiu and Hanzer 2021) or observational datasets (Tryhorn and DeGaetano 2013). In summary, most methods are restricted by their spatial resolution (targeting Landsat rather than S2) and/or downscale directly to (fractional) snow cover. However, an approach downscaling NDSI to S2 resolution and evaluating derived FSC is still lacking.

In contrast to these methods, here we present a novel method for generating high-resolution NDSI and FSC. Our method downscales MODIS Terra Snow Cover (MOD10A1) on a daily basis, cloud cover permitting, and combines static features (elevation and derivatives thereof) with dynamic features (MODIS NDSI and day-of-year (DOY)) as input to a machine learning model, which is trained on S2 data to predict 20 m NDSI. Compared to the available methods, this allows (i) to increase the temporal resolution of present S2 FSC from several days to one day, by performing a temporal gap-filling, and (ii) to provide high spatial resolution FSC for the time prior to the launch of S2 by hindcasting daily S2 FSC based on MODIS imagery.

2. Study site and datasets

The study site encompasses around 25 km^2 in the Stubai Alps (Tyrol, Austria). It extends over an elevational gradient from ~1500 to ~3500 m.a.s.l. and covers the upper montane to nival vegetation belts. Land cover mainly consists of glaciers, bare rock, sparsely vegetated areas, semi-natural grasslands and coniferous forest (Figure 1, Copernicus Land Monitoring Service 2023a).

We use S2 A/B Level-2A (surface reflectance product) as obtained from ESA's Open Access Hub (European Space Agency 2023). Based on band 3 (green centred at 560 nm) and band 11 (short-wave infrared centred at 1610 nm), NDSI (Hall,

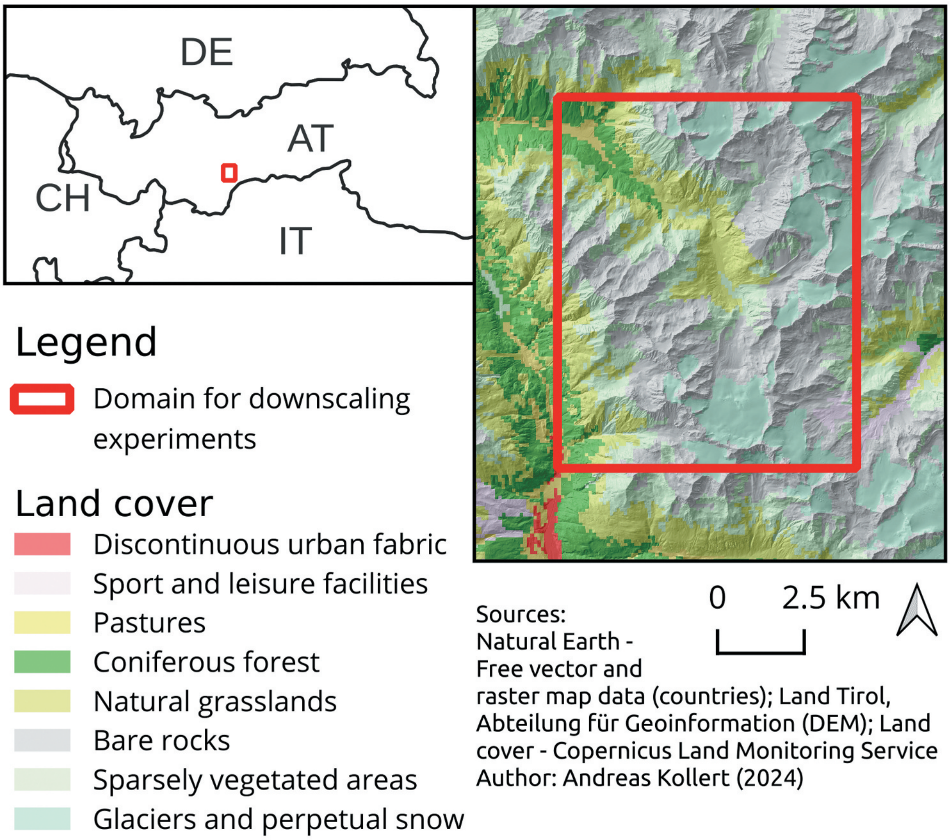

Figure 1. Location and Corine land cover 2018 (Copernicus Land Monitoring Service 2023a) of the study site in the Stubai Alps, Austria.

Riggs, and Salomonson 1995) is calculated at 20 m resolution (referred to as $NDSI_{S2}$). Furthermore, S2 multi-annual (2018–2021) mean of summer Normalized Difference Vegetation Index ($NDVI_{avg}$) (Rouse et al. 1974) is calculated as a proxy for fractional vegetation cover and surface characteristics. As the primary feature of low-resolution snow cover data, we use MODIS Terra Snow Cover Daily (MOD10A1 collection 6.1) obtained from National Snow and Ice Data Center (2023). This product includes the raw NDSI calculated from MODIS bands (referred to as $NDSI_{MODIS}$) at a nominal resolution of 500 m as well as quality layers which are used to mask out clouds. Bilinear interpolation is used to resample MODIS NDSI to the S2 grid. For evaluation of the proposed method, imagery covering four full years (2018–2021) is considered, a period where both S2-A and S2-B are fully operational. The only other dynamic feature is DOY, which acts as a proxy for seasonality (Rittger et al. 2021). A digital terrain model (DTM) with a resolution of 1 m, obtained from the Department of Geoinformation, State of Tyrol, Austria (2023), is resampled to 20 m resolution to compute slope, aspect and maximum curvature using the tool r.param.scale in GRASS GIS (Neteler et al. 2012). We furthermore derive diurnal anisotropic heating (DAH) in SAGA GIS (Conrad et al.

2015). Most of these features have already been used in the context of downscaling snow cover, mainly motivated by the assumption that they are connected to snow accumulation and ablation (Cristea et al. 2017; Rittger et al. 2021; Walters et al. 2014). To include texture information, which was shown to potentially improve model performance (de Roda Husman et al. 2021), we use Google Earth Engine (Gorelick et al. 2017) to calculate metrics from the Gray-Level Co-Occurrence Matrix based on the DTM. Based on a correlation analysis, three variables (variance, correlation and cluster shade) are manually selected due to their relatively low correlation for neighbourhoods of 3 and 15 pixels, to limit the total amount of features (referred to as 'texture'). Inspired by the S2 snow probability described in Revuelto et al. (2021), we also use the multi-annual mean, 5th and 95th percentile of S2 NDSI (these three are referred to as '$\mathrm{NDSI}_{\text{multi-annual}}$').

3. Methodology

3.1. Machine learning algorithm

We use random forest regression (RF, Breiman 2001) as the main statistical modelling tool to predict high-resolution S2 NDSI. The hyperparameters (i.e., number of trees, number of features considered for a split, maximum tree depth and minimum number of samples for a leaf node in a tree) are optimized in a nested cross-validation embedded into the training stage. Based on the datasets described in Section 2, we fit three models:

- $\mathrm{Model}_{\text{base}}$: $\mathrm{NDSI}_{\mathrm{S2}} = f(\mathrm{NDSI}_{\mathrm{MODIS}}$, DOY, elevation, slope, aspect, curvature, DAH, $\mathrm{NDVI}_{\text{avg}})$
- $\mathrm{Model}_{\text{base+NDSI}}$: $\mathrm{NDSI}_{\mathrm{S2}} = f(\mathrm{NDSI}_{\mathrm{MODIS}}$, DOY, elevation, slope, aspect, curvature, DAH, $\mathrm{NDVI}_{\text{avg}}$, $\mathrm{NDSI}_{\text{multi-annual}})$
- $\mathrm{Model}_{\text{base+NDSI+texture}}$: $\mathrm{NDSI}_{\mathrm{S2}} = f(\mathrm{NDSI}_{\mathrm{MODIS}}$, DOY, elevation, slope, aspect, curvature, DAH, $\mathrm{NDVI}_{\text{avg}}$, $\mathrm{NDSI}_{\text{multi-annual}}$, texture)

3.2. Derivation of snow cover and FSC

After downscaling by the RF model, the NDSI is transformed to FSC using Equation. 1 developed for S2 products by Gascoin et al. (2020):

$$\mathrm{FSC} = 0.5 \times \tanh(2.65 \times \mathrm{NDSI} - 1.42) + 0.5 \quad (1)$$

For comparison with the resampled MODIS product, we apply both Equation 1 and equation 'FRA6T' from Salomonson and Appel (2006), which was specifically developed for MODIS Terra products. As errors are lower, we only present results derived from Equation (1). We use the NDSI threshold of 0.4 (Hall, Riggs, and Salomonson 1995) for deriving binary snow cover from (downscaled) NDSI as this is a commonly chosen value.

3.3. Evaluation

FSC and snow cover are evaluated against simultaneous, cloud-free S2 observations of the same variable. Since DOY is included as a feature, a cross-validation is set up in which each year of the dataset from 2018 to 2021 is used as a separate test set and the remaining three years are used for model training, which results in a four-fold cross-validation. Model goodness of fit and accuracy of the FSC are assessed by the metrics R^2, root mean square error (RMSE), mean absolute error and mean error. Snow cover is evaluated by the overall accuracy and F1-score. Error metrics are calculated as the average of the four cross-validation runs. Similar to Revuelto et al. (2021), we include datasets derived by common resampling methods as a model baseline, since any new method should be superior in terms of accuracy compared to common image resampling, which does not take any further information into account. To this end, we resample MODIS NDSI to S2 resolution using nearest neighbour and bilinear resampling. Furthermore, errors are analysed with respect to three selected features (slope, aspect and month) and five dominating CORINE land cover classes (Copernicus Land Monitoring Service 2023a) to increase the understanding of error sources. In order to remove a positive bias in no-snow scenarios, we only consider cases of FSC > 1% for calculation of error metrics, similar to Rittger et al. (2021). A cross-comparison is also conducted with the official Copernicus FSC product (Copernicus Land Monitoring Service 2023b).

4. Results

The proposed downscaling method outperforms both commonly used resampling methods for all error metrics (Table 1). RMSE, mean absolute error and R^2 are improved from 0.256–0.155, 0.178–0.085 and 0.81–0.21, respectively, compared to the resampling methods. The overall accuracy and F1-score for snow cover are improved from 0.853–0.942 to 0.863–0.946, respectively. The best performance for all error metrics was achieved with $\text{Model}_{\text{base+NDSI+texture}}$, but differences in the mean error metrics among the three RF models are small (<0.01, cf. Table 1). Supplying $\text{Model}_{\text{base}}$ with $\text{NDSI}_{\text{multi-annual}}$ led to a stronger improvement than further adding texture as a feature. The training time differed by <5 minutes among the models.

Glaciers and perpetual snow show the smallest median RMSE while coniferous forest shows the highest (Figure 2). Considering the median RMSE, bare rocks, sparsely vegetated areas and natural grassland take intermediate positions. Figure 3(a) shows increasing RMSE with increasing slope. Especially steep (>40º), south-facing areas are prone to higher than average errors, while areas characterized by a slope of <20º show a lower RMSE, especially those facing north. Regarding time of the year, RMSE peaks in May, June and October (Figure 3(b)).

Table 1. Error metrics for FSC and snow cover for the three models used in this study and two commonly used resampling methods. Errors are averaged after four-fold cross-validation. Best performance is highlighted bold for each metric.

	FSC				Snow cover	
Method	R^2	RMSE	Mean absolute error	Mean error	Overall accuracy	F1-score
$\text{Model}_{\text{base}}$	0.769	0.166	0.093	0.023	0.937	0.942
$\text{Model}_{\text{base+NDSI}}$	0.792	0.157	**0.085**	**0.021**	0.941	**0.946**
$\text{Model}_{\text{base+NDSI+texture}}$	**0.795**	**0.155**	**0.085**	**0.021**	**0.942**	**0.946**
Bilinear resampling	0.470	0.256	0.178	0.081	0.853	0.863
Nearest neighbour resampling	0.449	0.261	0.180	0.079	0.848	0.858

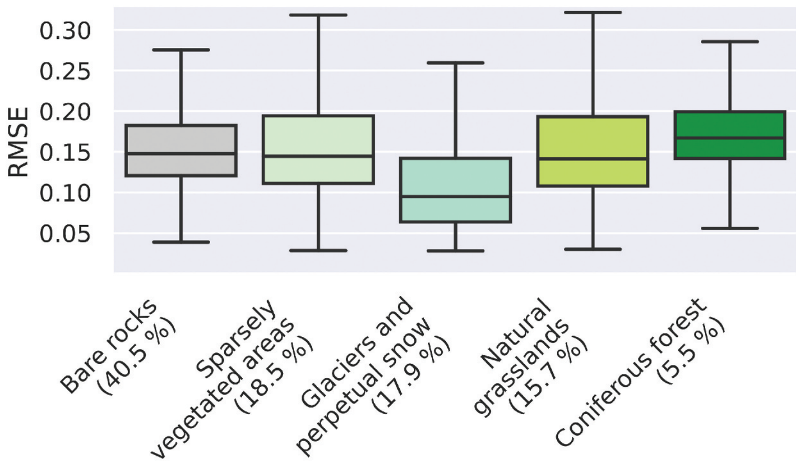

Figure 2. RMSE of downscaled FSC compared among dominating CORINE land cover classes (Copernicus Land Monitoring Service 2023a) for Model$_{base+NDSI+texture}$. Values in brackets refer to the proportional coverage of each class on the study site. Classes covering <5% of the study site are excluded.

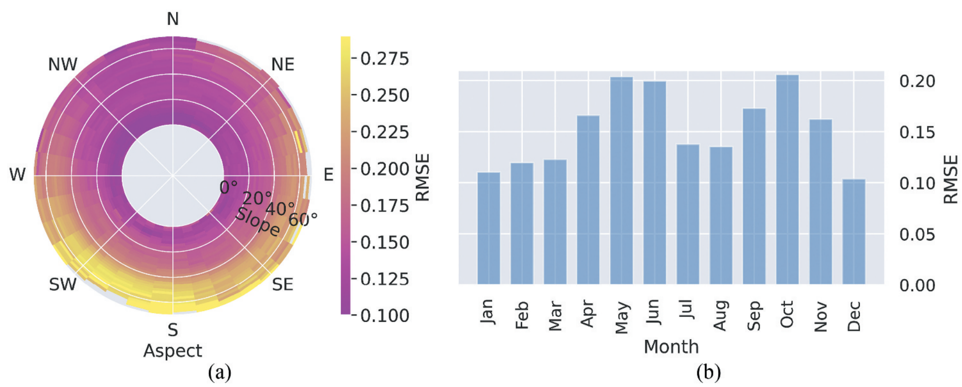

Figure 3. RMSE of downscaled FSC by slope and aspect (a) as well as aggregated monthly by averaging (b) for the model that includes all features.

A comparison of the downscaled FSC with the Copernicus FSC product (Copernicus Land Monitoring Service 2023b) resulted in a relatively good agreement throughout most of the study site, except for areas within cast shadows from mountains. However, these differences are already present for the primary S2 NDSI and FSC, which is used to train the RF model in the first place. The overall accuracy and F1-score for Model$_{base+NDSI+texture}$ amount to 0.942 and 0.946, respectively. Model$_{base}$ has an overall accuracy of 0.937 and an F1-score of 0.942, respectively.

5. Discussion

Our results show that machine learning methods such as RF are capable of modelling high-resolution S2 FSC based on low-resolution MODIS NDSI together with additional features much better than common image resampling. Adding $NDSI_{multi\text{-}annual}$ and texture slightly enhances model performance further. Low values for mean error indicate that over- and underestimation of FSC are balanced with little systematic errors, for both resampling methods and even more for the RF downscaling.

5.1. Performance related to land cover and topography

The variability of snow cover plays an important role in the performance of the RF downscaling. The lowest RMSE occurs during periods when snow cover is homogeneous over large areas (i.e., snow cover from December to March or no snow cover from July to September). Likewise, the north-facing areas of the study site show lower RMSE compared to south-facing ones. Temporally, we observe peaks in RMSE in spring and autumn, when changes between snow-covered and snow-free conditions are (more) frequent. RF downscaling performs best for glacier and perpetual snow, while the largest errors are found for coniferous forest. Empirically, we observe high mean S2 NDSI coupled with a low standard deviation of S2 NDSI in the temporal domain for glacier and perpetual snow. Since both of these variables are moderately correlated with $NDVI_{avg}$ and elevation, we hypothesize that this is the reason for the particularly high performance in these areas. In contrast, detecting snow below the canopy of trees is challenging (Muhuri et al. 2021; Rittger et al. 2020), since MODIS resolution cannot resolve any structural forest characteristics and the model was also not supplied with such information on a high resolution. This likely explains the low model performance for coniferous forests.

5.2. Comparison to existing approaches and datasets

We are not aware of other studies that target downscaling of FSC based on S2 imagery. Rittger et al. (2021), who focus on downscaling FSC based on Landsat imagery, report an average RMSE of 0.25 and 0.34 for FSC for two dates. RMSE values as a function of topography reported in the same study are in the same range as our results (RMSE ~0.1 to ~0.3). These authors also found that models perform better on gentle slopes or in flat terrain. In addition, we find that performance also depends on aspect (north vs. south) for slopes of more than 40º (Figure 3), which was not apparent in Rittger et al. (2021).

Richiardi et al. (2023), who rely on a similar method as our study, but without texture and snow prior as features, report an overall accuracy of 0.936 for binary snow cover. By adding texture and a snow prior to the model, the overall accuracy is improved from 0.937 to 0.942 in our study. After converting FSC into snow cover, Rittger et al. (2021) report F1-scores and overall accuracy which are slightly higher for two scenes on the selected dates compared to our study.

Since some differences between the Copernicus FSC and our product are already present in the primary products, they are likely the result of different preprocessing methods rather than the downscaling procedure itself. Cast shadows from mountains, where we observe the strongest differences, tend to result in very low reflectance values and need to be treated with care in any case. For ideal results, a model for temporal gap-filling of Copernicus FSC should thus also be trained using Copernicus FSC and likewise for any other dataset.

6. Conclusion

The combined use of two remote sensing datasets (S2 and MODIS imagery) and topographic data for producing daily FSC at 20 m resolution using RF has been investigated. The method downscales NDSI from MODIS (nominal resolution of 500 m) to S2 20 m spatial resolution with an average RMSE of 0.155 and R^2 of 0.795 for derived FSC. Relatively speaking, RMSE increases with an increase in slope inclination in southern sectors and is highest in the months of May, June and October. This suggests that errors are related to the spatio-temporal variability in snow cover, as this can be expected to be higher during transitional months between summer and winter. Derived maps of binary snow cover at 20 m resolution show an overall accuracy of around 94%. We found that an increase in accuracy is achieved using a snow prior and texture as additional features for both FSC and snow cover. Overall, the presented method provides the means to downscale NDSI and obtain FSC at 20 m resolution with an error that is lower compared to common resampling methods. Therefore, we recommend employing our method for obtaining daily S2 FSC over image resampling, if feasible, since it allows for an increased accuracy of gap-filled and hindcasted data.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Funding

This work was supported by the European Research Council under [Grant No. 883669].

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