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Monitoring and estimation of aufeis area dynamic changes using remote sensing and machine learning in Erdenebulgan soum of Khuvsgul province in Mongolia

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ABSTRACT

Aufeis, or icings, are seasonal ice formations that occur when groundwater or surface water repeatedly freezes, forming layered ice sheets in cold climates. Monitoring aufeis dynamics is essential for understanding regional hydrology, permafrost processes, and the impacts of climate variability. This study analyzes the interannual variability of aufeis extent from 2018 to 2025 in Erdenebulgan soum, Khuvsgul province, Mongolia, using a combination of Sentinel-2 satellite imagery, UAV Phantom 4 RTK drone orthophotos, and a Random Forest (RF) machine learning classification model. Twelve input variables-including spectral bands, vegetation and snow indices, and topographic features-were tested for their contribution to classification accuracy. Feature importance analysis indicated that the Maximum Difference Ice Index (MDII), Topographic Position Index (TPI), and Sentinel-2 Band 12 were the most influential predictors. Aufeis area showed significant temporal variation during the study period, increasing from 149 ha in 2018 to a peak of 235 ha in 2022, then declining sharply to 105 ha by 2025. This decline may reflect changing precipitation, groundwater discharge, or warming trends affecting ice formation. The RF model was validated using high-resolution UAV data collected in 2025. The aufeis extent derived from Sentinel-2 imagery (32.47 ha) closely matched the UAV-based measurement (32.78 ha), demonstrating the method's high spatial accuracy. These results confirm that combining Sentinel-2 data with machine learning and UAV validation is an effective approach for long-term aufeis monitoring in mountainous, permafrost-affected regions.

KEYWORDS

Aufeis, Random forest, MDII, UAV Phantom 4 RTK, Sentinel-2

1. INTRODUCTION

Aufeis—also known as icings or naleds—are multi-layered ice formations created by the repeated overflow and freezing of groundwater or surface water during the cold season [6]. These features commonly develop in high-latitude and high-altitude environments where water continues to discharge beneath snow cover and freezes upon exposure to subzero temperatures [4]. Aufeis plays a crucial role in cold-region hydrological systems by modifying streamflow patterns, influencing groundwater recharge, and contributing to the thermal dynamics of permafrost [9]. As such, monitoring aufeis dynamics is essential for understanding the impacts of climate variability and anthropogenic influences on permafrost-associated water resources.

In Mongolia, particularly in regions such as Erdenebulgan soum of Khuvsgul province, aufeis forms a recurrent seasonal phenomenon. However, recent climatic changes—most notably increasing temperatures—pose significant threats to the stability and persistence of these ice bodies. A study by Walther et al. (2021) in north-central Mongolia found that the mean annual air temperature increased by 2.6 °C between 1969 and 2018, leading to a notable reduction in aufeis extent near Ulaanbaatar [7]. Furthermore, in urban and peri-urban areas, aufeis and its meltwater have been shown to damage infrastructure and contribute to environmental degradation, emphasizing the need for improved monitoring and management strategies.

Traditional field-based approaches to mapping aufeis are often hindered by limited accessibility, high operational costs, and safety concerns, particularly in remote and rugged permafrost terrain. Recent advancements in high-resolution remote sensing technologies—such as the Sentinel-2 satellite constellation and UAV-based imaging systems—have significantly improved the ability to monitor seasonal ice features with greater efficiency, accuracy, and spatial coverage. When combined with topographic information and advanced machine learning techniques, particularly the Random Forest (RF) algorithm, these datasets offer powerful capabilities for classifying and analyzing aufeis across large areas and multiple years.

In this study, we employ an RF-based classification framework to map annual aufeis extent from 2018 to 2025 in Erdenebulgan soum, Khuvsgul province, Mongolia, using Sentinel-2 surface reflectance imagery. High-resolution UAV orthophotos acquired in 2025 serve as ground-truth data for validating classification accuracy. Beyond temporal mapping, the analysis also investigates the relative influence of input variables—including spectral bands, ice-related indices, and terrain features—providing insight into the environmental drivers of aufeis formation and persistence in this permafrost-affected landscape.

2. RESEARCH METHODS

Sentinel-2 Level-2A surface reflectance imagery, acquired between March and April from 2018 to 2025, was used as the primary data source for aufeis detection. Topographic variables were derived from the ALOS PALSAR Digital Elevation Model (DEM) with a spatial resolution of 12.5 meters. High-resolution UAV imagery, captured on April 5, 2025, using a DJI Phantom 4 RTK drone, was used for validation purposes (Table 1)[5].

Table 1. Remote Sensing Data Sources

Sentinel-2 data
S2B_MSIL2A_20180320T041539_N0500_R090_T47UPR_20230913T084450
S2A_MSIL2A_20190330T041551_N0500_R090_T47UPR_20221111T053845
S2A_MSIL2A_20200403T041551_N0500_R090_T47UPR_20230531T164802
S2B_MSIL2A_20210304T041659_N0500_R090_T47UPR_20230607T172802
S2A_MSIL2A_20220403T041551_N0510_R090_T47UPR_20240521T053549
S2A_MSIL2A_20230329T041551_N0509_R090_T47UPR_20230329T082758
S2A_MSIL2A_20240402T041551_N0510_R090_T47UPR_20240402T080348
S2C_MSIL2A_20250407T041611_N0511_R090_T47UPR_20250407T093316
ALOS PALSAR DEM
AP_13195_FBD_F0990_RT1

Sentinel-2 imagery was preprocessed using ESA's SNAP Desktop software, where cloud masking and atmospheric correction were applied to obtain surface reflectance values. All spectral bands utilized in the analysis were resampled to a consistent spatial resolution of 20 meters and clipped to the boundaries of the study area. UAV imagery was processed into high-resolution orthomosaics and precisely georeferenced using RTK GPS data within Agisoft Metashape.

Eleven features were utilized for the Random Forest classification, comprising six spectral bands (B2, B3, B4, B8, B11, and B12), three spectral indices—the Normalized Difference Vegetation Index (NDVI), the Normalized Difference Snow Index (NDSI), and the Modified Difference Ice Index (MDII)—and two terrain variables, elevation and the Topographic Position Index (TPI), derived from a Digital Elevation Model (DEM). A Random Forest classifier with 100 decision trees was trained on manually labeled samples using Python. Based on this model, annual aufeis distribution maps were produced for the period 2018 to 2025 [1][2].

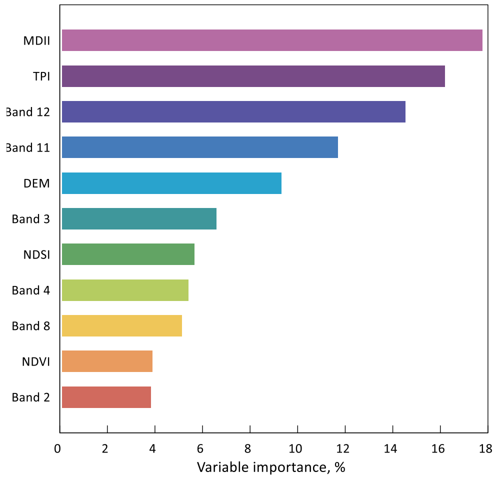

Figure 1. Variable importance in RF model for aufeis detection.

The relative contribution of each input feature was assessed using the internal feature importance metric of the Random Forest model, based on the mean decrease in Gini impurity. The results revealed that the Maximum Difference Ice Index (MDII), the Topographic Position Index (TPI), and Band 12 (SWIR2) were the most influential variables for identifying aufeis zones (Figure 1).

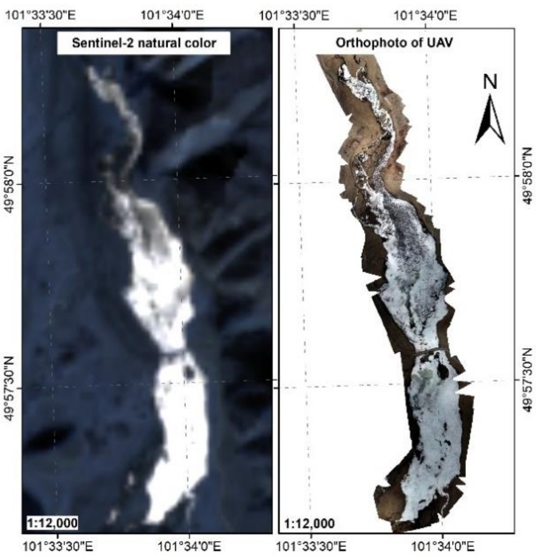

Figure 2. Comparison between Sentinel-2 and UVA images

To evaluate the model's performance, the aufeis area derived from the 2025 Sentinel-2 imagery (32.47 ha) was compared with the UAV-based measurement (32.78 ha), yielding a minimal difference of 0.31 ha (Figure 2). This close agreement highlights the effectiveness of the Sentinel-2 and Random Forest-based approach for accurately mapping aufeis in permafrost landscapes.

3. RESULT AND DISCUSSION

The annual aufeis extent in Erdenebulgan soum, Khuvsgul province, exhibited substantial interannual variability between 2018 and 2025 (Figure 3). The maximum extent was recorded in 2022 (235.13 ha), followed by 2019 (221.72 ha), while the minimum was observed in 2025 (104.94 ha). These fluctuations indicate that aufeis formation and persistence are strongly influenced by environmental conditions. Accuracy assessments of the classification results demonstrated consistently high performance, with overall accuracy values ranging from 0.981 to 0.996 (Table 1), confirming the robustness of the Random Forest (RF) model used in this study. Comparison with manually digitized reference areas revealed minimal differences, with the largest discrepancy being only 1.08 ha in 2018.

Variable importance analysis (Figure 1) revealed that the Maximum Difference Ice Index (MDII), Topographic Position Index (TPI), and Sentinel-2 Band 12 (SWIR) were the most influential features for detecting aufeis. These variables likely capture critical hydrological and thermal conditions associated with aufeis presence, including water-saturated areas, terrain-driven cold air pooling, and spectral signatures characteristic of ice surfaces. These findings are consistent with previous studies that highlight the importance of combining spectral and topographic information for effective cryospheric feature mapping [3][8].

Table 2. Aufeis Area Accuracy Assessment Based on Pixel and Manual Estimations (2018–2025)

Year	Area	Pixel area	Area error	Accuracy
2018	149.16	150.24	±1.08	0.981
2019	221.72	222.48	±0.76	0.982
2020	157.73	157.56	±0.17	0.996
2021	195.90	195.64	±0.26	0.988
2022	235.13	234.28	±0.85	0.987
2023	149.24	149.32	±0.08	0.996
2024	180.93	180.84	±0.09	0.996
2025	104.94	105.4	±0.46	0.992

A comparison between annual aufeis extent and precipitation (Figure 3) revealed a partial correlation. Years with higher precipitation, such as 2022 and

2024, generally exhibited more extensive aufeis coverage. However, notable anomalies were observed—for instance, despite high precipitation in 2024, aufeis extent was only moderate. This suggests that precipitation alone does not fully explain aufeis dynamics. Additional influencing factors likely include sub-surface water discharge, timing and intensity of thawing conditions, and spatial variability in permafrost characteristics.

In 2025, UAV-derived orthophoto analysis estimated the aufeis area at 32.78 ha, closely matching the Sentinel-2-based estimate of 32.47 ha—a difference of only 0.31 ha. This high level of agreement confirms the reliability of the classification model and underscores the value of integrating high-resolution UAV data with medium-resolution satellite imagery for validating remote sensing-based classifications in cryospheric research.

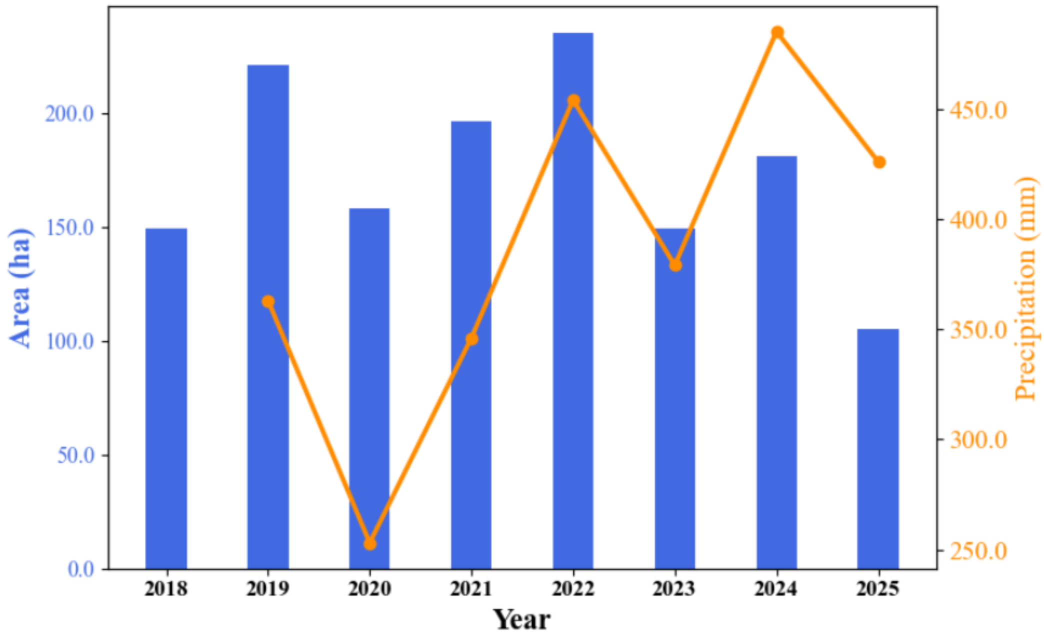

Figure 3. Aufeis area and annual precipitation changes

4. CONCLUSION

This study demonstrated the effectiveness of using Sentinel-2 imagery and a Random Forest (RF) machine learning approach to monitor annual aufeis area dynamics in Erdenebulgan soum, Khuvsgul province, Mongolia, from 2018 to 2025. By incorporating spectral indices, topographic parameters, and UAV-based validation data, we achieved high classification accuracy (above 0.98 each year). The feature importance analysis highlighted MDII, TPI, and Band 12 as the most critical predictors of aufeis presence.

Interannual variations in aufeis extent were evident, with a maximum area in 2022 (235.13 ha) and a minimum in 2025 (104.94 ha), reflecting the influence of climatic and hydrological variability. While precipitation was a contributing factor to aufeis formation, the spatial extent also depended on terrain conditions, sub-surface water discharge, and seasonal temperature trends. The close match between UAV-derived and Sentinel-2-based aufeis measurements in 2025 (difference of only 0.31 ha) further supports the accuracy and practical applicability of the RF classification method.

These findings contribute to a better understanding of aufeis behavior under changing environmental conditions and underscore the value of integrating satellite and UAV data for cryospheric monitoring. Future studies should explore additional environmental drivers such as soil moisture and groundwater flow to enhance predictive modeling of aufeis formation in alpine and permafrost regions.

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