Remote Sensing of Environment 328 (2025) 114839

Contents lists available at ScienceDirect

Remote Sensing of Environment

journal homepage: www.elsevier.com/locate/rse

Spectral properties and remote sensing of snow algal blooms in the Antarctic Peninsula☆

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ARTICLE INFO

Editor: Jing M. Chen

Keywords:
Snow algae
Algal bloom
Albedo
Remote sensing
Sentinel-2

ABSTRACT

Snow algae, microscopic organisms thriving in snow-covered environments, significantly affect snow albedo and broader climatic processes. This study introduces the Algae Presence Index (API), a novel spectral tool using Sentinel-2 multispectral imagery to detect and classify red and green algae on King George Island, Antarctica. From 2019 to 2023, we analyzed temporal and spatial variations in algae presence during austral summers and observed corresponding reductions in surface albedo, demonstrating how algal blooms influence snowmelt. Green algae showed a stronger albedo reduction (up to 8.46 %) compared to red algae (5.33 %), emphasizing their greater role in accelerating snowmelt. The API outperformed traditional indices, such as the red/green band ratio and Red-Green Normalized Difference. It eliminated spectral overlap and accurately distinguished algae types from algae-free snow. These findings underscore the critical role of snow algae in climate feedback mechanisms and highlight the importance of monitoring their growth during Antarctic warming. This methodology provides a robust framework for assessing algae impacts on the cryosphere, with important implications for climate models and conservation.

1. Introduction

Snow algae are microscopic organisms that thrive in snow-covered environments, significantly impacting the albedo and reflectance properties of the snow. These algae not only alter the spectral characteristics of snow but also play a crucial role in broader ecological and climatic processes. Antarctica is an isolated and largely unexplored area vital to the global climate system. Snow algal blooms in Antarctica were first documented during expeditions conducted in the 1950s and 1960s. A single snow algal bloom, covering areas of hundreds of square meters, positions snow algae as potentially one of the region's most significant photosynthetic primary producers. They also influence nutrient availability for downstream terrestrial and marine ecosystems (Gray et al., 2020). Furthermore, snow algae serve as a crucial food source for various microorganisms and invertebrates, creating a foundational element of the Antarctic food web and influencing the overall biodiversity in these extreme environments. These algal blooms contribute significantly to nutrient cycling by releasing organic carbon and other nutrients as they decompose. They are then utilized by other microorganisms and invertebrates, creating a dynamic and interconnected ecosystem (Convey, 2011; Convey et al., 2014).

Over the past 50 years, Antarctica has warmed significantly (Turner et al., 2005) and is one of the fastest-warming areas on Earth (Hansen et al., 2010; Steig et al., 2009; Vaughan et al., 2003). Warming in Antarctica has already exceeded 1.5 °C over pre-industrial temperatures (Turner et al., 2005), and current Intergovernmental Panel on Climate Change (IPCC) projections indicate further global increases (Masson-Delmotte et al., 2019). Due to current climate change, Antarctic warming has caused significant ice retreat and sea level rise, impacting both society and the global environment. These climatic changes influence the region's vegetation against natural decadal temperature variability (Convey, 2011; Convey et al., 2014). Due to this warming, the

☆ This article is part of a Special issue entitled: 'SDGSAT-1 for SDGs' published in Remote Sensing of Environment.

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https://doi.org/10.1016/j.rse.2025.114839
Received 14 March 2025; Received in revised form 5 May 2025; Accepted 24 May 2025
Available online 2 June 2025

available area for plant colonization in Antarctica will likely increase threefold (J. R. Lee et al., 2017). This rising temperature will likely increase snowmelt, potentially affecting red and green snow algal blooms, which are sensitive to light, water, and temperature (Hoham and Remias, 2020; Khan et al., 2021; Rivas et al., 2016). As temperatures rise, snow melts, providing the water necessary for algae to grow. These algae reduce the albedo by absorbing light, which in turn increases temperature and causes further snowmelt. This process creates a cyclic feedback mechanism. Accurate snow algae detection and mapping are essential for understanding their effects on snowmelt dynamics, climate feedback mechanisms, and their implications for Sustainable Development Goals (SDGs), particularly Goal 13 (Climate Action).

Remote sensing technologies, particularly high-resolution satellite imagery, have proven essential for accurately detecting and mapping snow algal blooms. These technologies allow scientists to monitor red and green snow algae growth and distribution throughout the Antarctic summer, providing essential data on their extent and biomass (Gray et al., 2021). Advancements in remote sensing technologies, especially with high-resolution Sentinel-2 multispectral imagery, have improved the ability to detect and classify snow algae and impurities, helping to better understand their spatial distribution and impact on snow albedo during the Antarctic summer (Huovinen et al., 2018). Additionally, recent studies, such as Di Mauro et al. (2024), have explored alternative indices for detecting snow algae, offering valuable insights into improving detection accuracy and differentiation between algae and other snow impurities. Furthermore, detailed spectral analysis has revealed that snow algae can be effectively identified and monitored by their unique spectral signatures in the visible and near-infrared regions, allowing for accurate differentiation between algal blooms and other surface features (Hashim et al., 2016). The remote sensing-based monitoring of snow algae aligns with SDG 13 (Climate Action) by improving our understanding of how biological processes in polar regions contribute to climate feedback mechanisms. The presence of chlorophyll and various accessory pigments, such as carotenoids in snow algae, contribute to their distinct spectral signatures, as these pigments absorb light in the blue and red regions while reflecting green light, facilitating their identification and monitoring through remote sensing techniques (Huovinen et al., 2018).

Due to their unique pigment compositions, red and green algae also exhibit distinct spectral reflectance properties. Green algae contain chlorophylls a and b, which reflect more in the green band, providing a higher reflectance. On the other hand, red algae contain phycobiliproteins such as phycoerythrin, which absorb light maximally at wavelengths around 495 nm, 539 nm, and 565 nm. This absorption leads to distinct spectral features, particularly lower reflectance around the 495 nm (blue-green) and 539–565 nm (green-yellow) regions and higher absorption in these bands compared to surrounding wavelengths (Bernard et al., 1992; Malairaj et al., 2016; Ulagesan et al., 2021). These properties can be captured by integrating the reflectance values from the blue, green, red, NIR, and SWIR bands, effectively highlighting the presence of algae based on their unique spectral signatures. Traditional indices like the Red/Green band ratio and RGND are limited by their reliance on narrow spectral ranges, leading to overlap between algae, snow, and other impurities such as vegetation or dust. They fail to capture key physical changes in the snowpack, such as moisture increase and grain size alteration, which affect reflectance in NIR and SWIR bands. These limitations reduce detection accuracy and hinder differentiation between algae types. The proposed API overcomes these challenges by integrating multiple spectral bands and normalization, providing more robust and precise algae detection under varying conditions.

This study aims to address the limitations of existing methods by providing a more precise spectral signature of algae presence in snow, accounting for variations in algae concentration and type. This innovative use of multi-spectral data will improve the accuracy of algae detection and differentiation, offering a clearer understanding of the distribution and impact of snow algae in Antarctica. The specific aims of this study are to (1) develop a novel Algae Presence Index (API) to accurately detect and differentiate between algal blooms and other snow-covered surfaces, (2) classify algae into two categories (red and green) based on their spectral differences, supported by field data, and (3) investigate the albedo response of different algae, specifically red and green algae. Understanding this process will help determine which type of algae absorbs more light, leading to increased temperatures and causing snowmelt. This study improves our understanding of snow algae dynamics and their impact on the Antarctic ecosystem, aiding broader climate change research and mitigation efforts.

1.1. Study area

King George Island (KGI) (Fig. 1), the largest of the South Shetland Islands (SSI), is located within the SSI archipelago at the northern tip of the Antarctic Peninsula (M. J. Lee et al., 2008). This island is a significant research site, hosting eight permanent research stations and numerous seasonal huts and camps. Approximately 90 % of the island's 1250 km^2 surface is glaciated, consisting of several interconnected ice caps with pronounced outlet glaciers (Rückamp et al., 2011). The highest point on the island exceeds 720 m at a central dome. The northern coast features gentle slopes, while the southern coast has steeper slopes and fjord-like inlets. Two smaller icefields, Warzawa and Krakow, with elevations up to 400 m, fringe the main ice cap. The climate on KGI varies significantly with the seasons. Air temperatures often rise above freezing in summer, and this trend can also occur in spring and autumn. However, surface melting is rare in winter. These temperature fluctuations greatly influence the glacial and snowpack dynamics on the island.

The field data used in this study were originally collected by Khan et al. (Khan et al., 2021) in January 2018 and later made available online. Field observations were conducted at two specific sites on KGI in January 2018. The first site was located near Fildes/Mx Bay, between the Chilean Prof. Julio Escudero Station and the Chinese Great Wall Station, approximately 200 m above mean high tide. This site experienced slightly less wildlife traffic than the second site. The second site was situated in Collins Bay, adjacent to Collins Glacier, approximately 100 m above mean high tide, and saw more frequent activity from seals, penguins, and other birds. Both sites were characterized by flat, low-sloping southeast-facing beaches. During the field observations, weather conditions varied between the two sites: Fildes/Mx Bay was uniformly cloudy, while Collins Bay had clear skies. For the spectral albedo data acquisition and snow algae sampling, optically thick snowpacks (greater than 30 cm) were prioritized to minimize the impact of the underlying ground on spectral albedo. Sampling locations were chosen based on relatively clean snow with no visible snow algae (control site), green snow algae, and red snow algae. At each site, duplicates of each snow type were measured using a spectrometer. All samples were collected around noon local Chilean time to ensure the seasonal snowpack received the most incoming solar radiation. Snow depth was measured at each observation site and reported to the nearest centimeter if less than one meter.

2. Materials and methods

2.1. Datasets

The research utilized Sentinel-2 Surface Reflectance data from the European Space Agency's Copernicus program, accessed through Google Earth Engine (GEE), to analyze and classify the presence of algae over KGI during the austral summer (October–March) for each year from 2019 to 2023. The dataset was filtered to include images that covered the study area and had less than 10 % cloud cover, ensuring high-quality observations. A cloud masking function was applied to each image to remove pixels affected by clouds and shadows, using the ‘QA60’ band,

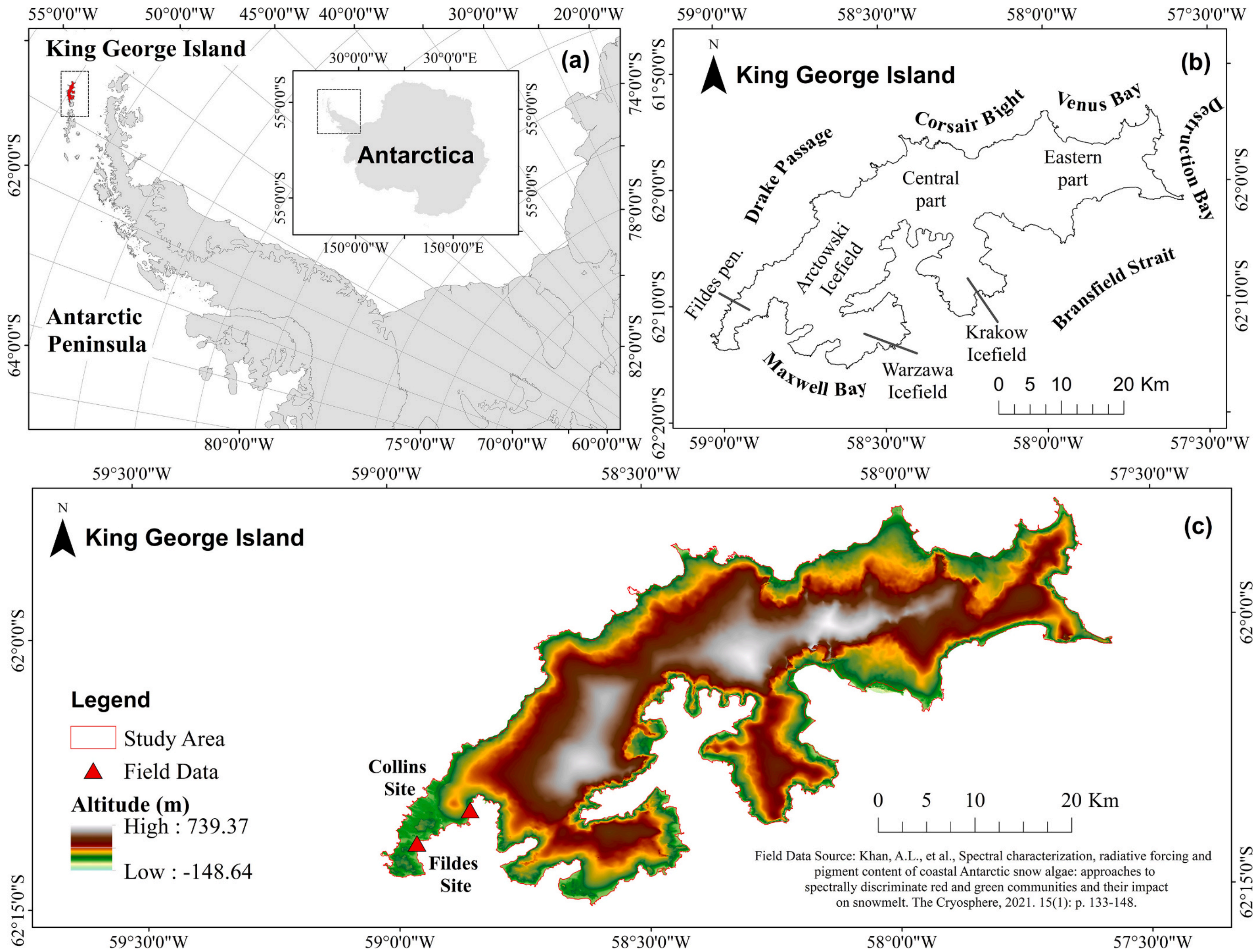

Fig. 1. Study area: King George Island, Antarctica. (a) Location within the Antarctic Peninsula. (b) Key geographical features. (c) Topography and field sites (Collins and Fildes).

which contains cloud and shadow information. The analysis focused on five spectral bands: blue (B2), green (B3), red (B4), near-infrared (B8), and shortwave Infrared 1 (B11) to create the API as displayed in Table 1, selected for their sensitivity to vegetation and algae characteristics. The inclusion of the red, near-infrared (NIR), and shortwave infrared (SWIR1) bands likely leverages algae's high chlorophyll absorption in the red spectrum and its influence on snow reflectance in the NIR range, which is typically elevated in clean snow but reduced in algae-affected areas (Painter et al., 2001). The SWIR1 band, sensitive to snowpack liquid content, captures changes induced by algae-related snowmelt, further distinguishing algae-covered from clean snow (Hannula and Pulliainen, 2019; Picard et al., 2022). Together, these bands enhance detection by emphasizing the contrast between algae and non-algae areas. On the other hand, the blue and green bands add sensitivity to chlorophyll and carotenoid absorption, which are prominent in algae and further aid in differentiating algae types based on their pigmentation (Khan et al., 2021). This targeted use of specific spectral ranges is critical for identifying algae presence and type reliably.

Table 1
Characteristics of the bands of Sentinel-2 used for calculating API, red/green band ratio, RGND, albedo, and NDVI.

Band number	Central λ (nm)	Resolution (m)	Characteristics
2	490	10	Blue
3	560	10	Green
4	665	10	Red
8	842	10	NIR
11	1610	20	SWIR1
12	2190	20	SWIR2

API was calculated for each image by combining these bands. This enhanced the spectral signals of algae and helped differentiate them from the surrounding environment. The filtered and masked images were processed to produce a median composite for the austral summers (October 1 – March 31) of 2019–2020, 2020–2021, 2021–2022, and 2022–2023, reducing temporal variability and enhancing the clarity of spatial patterns. Median composites were selected to minimize the impact of outliers, such as cloud contamination and sensor noise, which can distort the analysis. Unlike the mean, the median is more robust to extreme values, providing a more reliable representation of algae presence and albedo changes, especially in areas with frequent cloud cover. This approach leveraged GEE's capabilities for handling large-scale geospatial data efficiently, facilitating detailed and reliable analysis of the spectral information relevant to the study area (Ghosh et al., 2022). In KGI, the red/green (R/G) band ratio, algae presence index (API), red-green normalized difference (RGND), normalized difference vegetation index (NDVI), and albedo were calculated, with details provided in Table 2 below.

Table 2
Algorithms and satellite bands used to calculate API, R/G, NDVI, and albedo.

Index name(s)	Algorithm	Sentinel bands	Criteria	Refs
API	$\frac{(\text{Red} + \text{Swir1} + \text{NIR})-(\text{Blue} + \text{Green})}{(\text{Blue} + \text{Green} + \text{Red} + \text{Swir1} + \text{NIR})}$	B2, B3, B4, B8, B11	Red = $0.00 \leq \text{API} \leq 0.01$ Green = $0.05 \leq \text{API} \leq 0.07$	This study
R/G	$\frac{Red}{Green}$	B4, B3	R/G > 1.02 red algae	(Di Mauro et al., 2024; Takeuchi et al., 2006)
RGND	$\frac{(Red - Green)}{(Red + Green)}$	B4, B3	Not specified (empirical threshold needed)	(Di Mauro et al., 2015; Engstrom et al., 2022; Ganey et al., 2017; Huovinen et al., 2018)
NDVI	$\frac{(Nir - Red)}{(Nir + Red)}$	B4, B8	Scale 0–1	(Townshend and Justice, 1986)
Albedo	0.356 * Blue +0.130 * Red +0.373 * NIR + 0.085 * SWIR1 + 0.072 * SWIR2–0.0018	B2, B4, B8, B11, B12	Scale 0–1	(Guo et al., 2020)

2.2. Field data

The API, R/G band ratio, and RGND were applied to spectral data sourced from (Khan et al., 2021) research on spectral albedo, accessed via the US Antarctic Data Center (Dataset ID 601412, accessed 03 March 2024). In their study, Khan et al. collected surface spectra of red and green snow algae from two sites on King George Island and one on Nelson Island in January 2018. The research focused on optically thick snowpacks to minimize ground impact on spectral albedo. Sampling included control sites with clean snow and green, red, and mixed-phase algae areas. Spectral reflectance was measured using an ASD FieldSpec® 4 hyperspectral spectroradiometer, covering 350–2500 nm wavelengths. The measurements, taken in triplicate around noon to capture peak solar radiation, involved downwelling and upwelling planar irradiance. A total of 24 measurement sites across three locations were selected, avoiding areas with snowmelt ponding. The field data points, representing red algae, green algae, and algae-free snow, were utilized in this study.

2.3. Algae presence index (API) calculation

The API is a novel spectral index developed to detect and quantify the presence of algae on snow-covered surfaces using remote sensing data. This index enhances the contrast between clean snow and algae-infested snow by leveraging the distinct reflectance characteristics of snow and algae across various spectral bands. Snow algae contain chlorophyll and various accessory pigments, such as carotenoids, which contribute to their unique spectral signatures. These pigments absorb light primarily in the blue (430–450 nm) and red (640–680 nm) regions, leading to reduced reflectance in these bands for algae-covered snow. In green algae, chlorophylls a and b reflect more light in the green band (500–570 nm) since chlorophyll absorbs less green light, making green algae more detectable in this band. Conversely, red algae contain additional pigments, such as phycobiliproteins like phycoerythrin, which absorb light at wavelengths around 495 nm, 539 nm, and 565 nm. This absorption results in lower reflectance in the blue-green and green-yellow regions, creating distinct spectral features that enable the identification of red and green algae based on their unique spectral properties (Bernard et al., 1992; Gray et al., 2021; Huovinen et al., 2018; Ulagesan et al., 2021).

In addition to pigment absorption, the presence of algae induces physical changes in the snowpack that further impact reflectance across multiple spectral bands. Algae absorb sunlight, which accelerates snow melting and increases the snow's liquid water content. Since water absorbs more light in the near-infrared (NIR) and shortwave infrared (SWIR) regions, this increased moisture reduces reflectance in the NIR and SWIR bands. Furthermore, as snow melts, the snow grain size increases, causing less efficient light scattering, particularly in the NIR band, leading to a further decrease in reflectance. These physical changes, combined with the pigment-induced spectral signatures, result in an overall darker snow surface across multiple bands.

The API integrates reflectance values from the blue, green, red, NIR, and SWIR1 bands, effectively capturing the unique spectral characteristics of algae-covered snow. By combining both pigment absorption effects and the broader physical modifications caused by algae, the API provides a robust means of distinguishing algae-covered snow from clean snow and also helps in distinguishing green and red algae in remote sensing applications. The formula for the API is given by:

$$\mathbf{API} = \frac{(\text{RED} + \text{SWIR} + \text{NIR}) - (\text{BLUE} + \text{GREEN})}{(\text{BLUE} + \text{GREEN} + \text{RED} + \text{SWIR1} + \text{NIR})} \quad (1)$$

The formula comprises three key components: the combination of the red, near-infrared (NIR), and shortwave infrared (SWIR1) bands; the combination of the blue and green bands; and a normalization factor. Each component plays a specific role in enhancing the index's sensitivity to algae presence. The first component, represented by the combination of the red, NIR, and SWIR1 bands, captures the overall reduction in reflectance caused by algae (Fig. 2). The red band, which typically shows moderate reflectance for clean snow, is sensitive to chlorophyll in algae. Chlorophyll absorbs red light, resulting in a significant reduction in reflectance when algae are present. This makes the red band a critical indicator of algal presence. The NIR band generally exhibits high reflectance for clean snow due to snow crystals' strong light scattering. However, algae cause a reduction in NIR reflectance by changing the physical properties of the snow, such as increasing grain size and moisture content through algae-induced melting. The SWIR1 band is highly sensitive to the liquid water content in the snowpack. While clean snow generally reflects moderately in this band, algae-induced melting increases water content, causing a drop in SWIR1 reflectance. The combined use of these three bands allows the API to effectively measure the overall darkening of snow due to algae, providing a strong indicator of their presence across a broad spectral range.

The second component of the formula, which combines the blue and green bands, is important for differentiating between clean snow and algae-infested snow. In the blue band, clean snow reflects strongly due to efficient light scattering by snow crystals. The presence of algae significantly reduces reflectance in this band because pigments such as chlorophyll and carotenoids strongly absorb blue light. This reduction is one of the most sensitive indicators of algae presence. The green band adds further contrast because different types of algae exhibit varying reflectance behaviors in this band. Green algae, rich in chlorophyll, reflect more green light, whereas red algae, which contain more carotenoids like astaxanthin, absorb more green light. The combination of the blue and green bands captures these unique spectral characteristics and enhances the index's sensitivity to the presence of different types of algae. This differential behavior in the blue and green bands allows the API to better distinguish algae-covered snow from clean snow.

The subtraction of the blue and green bands from the red, NIR, and SWIR1 bands effectively amplifies the contrast between clean snow and algae-infested snow. The sum of the blue and green bands is typically high for clean snow due to high reflectance, while the sum of the red, NIR, and SWIR1 bands is moderate. This results in a lower API value. In

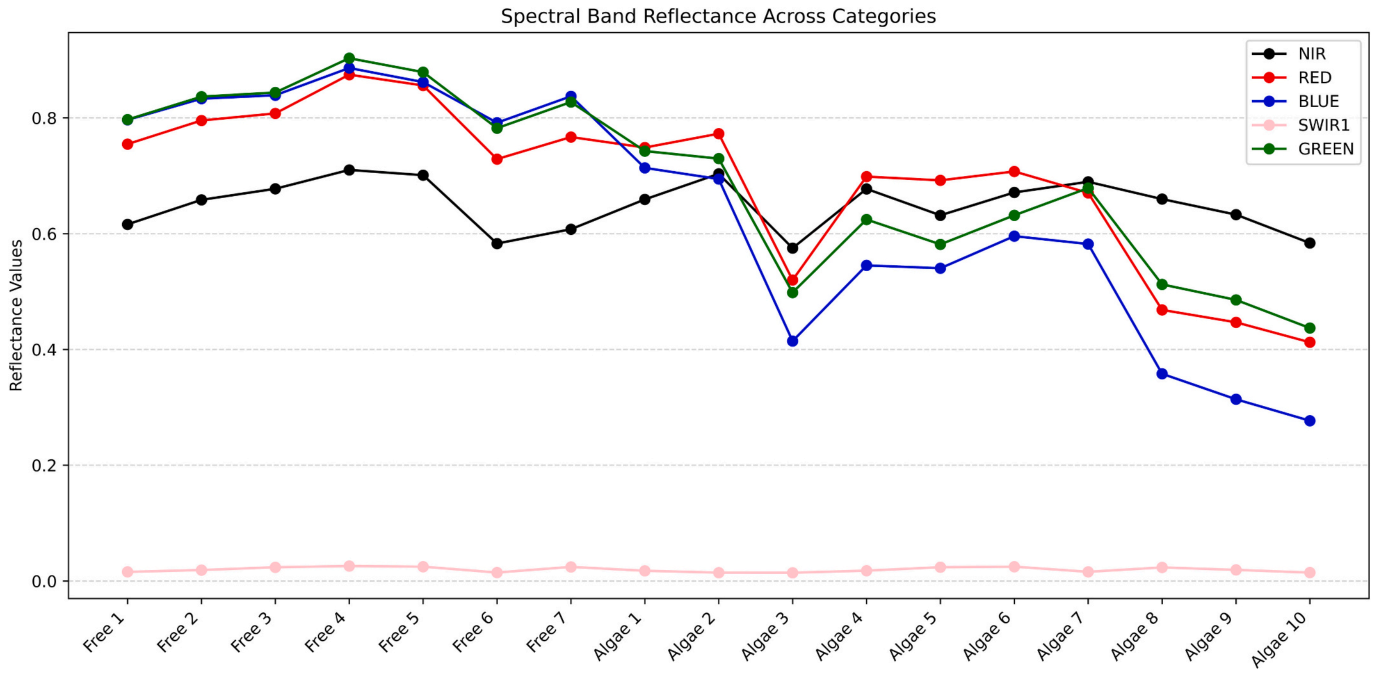

Fig. 2. Spectral reflectance for clean and algae-infested snow across NIR, RED, SWIR1, BLUE, and GREEN bands. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

contrast, for snow with algae, the sum of the blue and green bands is significantly lower due to reduced blue reflectance and variable green reflectance, while the sum of the red, NIR, and SWIR1 bands is also reduced but remains comparatively higher, leading to a higher API value. This differential allows for the effective distinction between algae and clean snow.

The normalization factor (third component) in the formula, represented by the sum of all five bands (blue, green, red, NIR, and SWIR1), ensures that the API accounts for overall variability in snow reflectance due to factors other than algae, such as snow cover, snow type, and environmental conditions. This normalization reduces the influence of these external factors, making the API robust and consistent across different snow types and settings. The API can be used for algae detection across various regions and periods by providing a standardized measure, enhancing its utility in remote sensing applications.

The API formula effectively utilizes the differential spectral behavior of snow and algae across visible and infrared bands to detect and quantify algae presence. By leveraging the contrasting reflectance properties and normalizing the index, the API provides a robust and reliable method for remote sensing applications in the environmental monitoring of snow-covered regions.

2.4. Algae classification

A threshold-based clustering approach, informed by field data, was used to classify green and red algae in satellite images. Field reflectance values for red and green algae were analyzed, identifying distinct spectral ranges for each algae type. Specifically, red algae API values were clustered between 0.0018 and 0.0169, while green algae were clustered within the range of 0.0596 to 0.0733. These thresholds were applied to satellite imagery, facilitating an accurate and efficient classification of algae types. Similar field-based approaches have been effectively used in remote sensing studies to map and classify snow impurities and biological communities. Takeuchi et al. (2006) utilized field reflectance data to derive a band ratio threshold, distinguishing red snow algae from clean snow on the Harding Icefield based on SPOT satellite imagery. Ganey et al. (2017) also employed spectral data to establish a normalized difference index for estimating microbial abundance, applying it to satellite data to map red algae on an Alaskan icefield. Additionally, Di Mauro et al. (2015) applied thresholds derived from ground-based spectral measurements to estimate the concentration of mineral dust in the European Alps, showing the utility of threshold-based clustering in remote sensing of snow-covered surfaces. These studies validate our use of empirically derived thresholds for algae classification, highlighting the robustness of threshold-based clustering in identifying snow algae.

2.5. Mann–Whitney U test analysis

To assess the statistical significance of differences in index values among the three snow surface conditions (Green Algae, Red Algae, and Algae-Free Snow), the Mann–Whitney *U* test was applied (Yang et al., 2022). This non-parametric test was chosen due to its robustness in comparing independent samples that may not follow a normal distribution. Pairwise comparisons were conducted for each index—RGND, Red/Green Band Ratio, and API—to determine whether the differences between groups were statistically significant. The significance levels were categorized as follows: $p < 0.05$ (*) and $p < 0.01$ (**), with non-significant results denoted as "n.s.". The test results are visualized using box plots to illustrate the distribution and variability of each index under different snow surface conditions.

2.6. Impact of green and red algae on albedo

Albedo, which represents the reflectivity of a surface, is affected by the presence of algae, as their unique spectral properties lead to lower reflectance (Cook et al., 2017a). Green algae, rich in chlorophyll, and red algae, which contain phycobiliproteins, influence the albedo in distinct ways due to their differential interaction with light. For this study, albedo was calculated based on reflectance values from a set of spectral bands: Blue (B2), Red (B4), Near-Infrared (B8), and Shortwave Infrared (B11, B12). The formula used for albedo calculation (Feng et al., 2023) was derived from the weighted combination of these bands, based on their relationship to the reflectance characteristics of snow-covered surfaces.

$$\text{Albedo} = 0.356^{*}\ \text{Blue} + 0.130^{*}\ \text{Red} + 0.373^{*}\ \text{NIR} + 0.085^{*}\ \text{SWIR1} + 0.072^{*}\ \text{SWIR2} – 0.0018 \tag{2}$$

The reflectance values for these bands were extracted from the satellite images corresponding to each study period (austral summers from 2019–2020 to 2022–2023). To reduce temporal variability caused by cloud cover and atmospheric conditions, median composites were generated for each year (Flood, 2013; White et al., 2014). This approach helped create more consistent and reliable albedo values for snow surfaces in the study region, ensuring that the results accurately represent surface reflectivity across different periods. The percentage difference in albedo between red and green algae was computed to quantify the differential impact of green and red algae on surface albedo. The calculation involved subtracting the mean albedo of green algae from the mean albedo of red algae, dividing the result by the mean albedo of red algae, and then multiplying by 100:

$$\textbf{Percentage Difference} = \left(\frac{\text{Mean Albedo}_{\text{red}} - \text{Mean Albedo}_{\text{Green}}}{\text{Mean Albedo}_{\text{red}}} \right) \times 100 \tag{3}$$

This approach provides a standardized metric for comparing the effects of different algae types on surface reflectance properties, enabling a clearer understanding of their influence on albedo reduction.

3. Results

3.1. Spectral analysis based on field data

Fig. 3 illustrates the Red/Green band ratio (left) and RGND (red-green normalized difference) (right) values for two snow conditions: ‘Algae’ and ‘Algae-free snow.’ The median Red/Green ratio for algae-containing snow is 0.993, compared to 0.951 for algae-free snow. The algae-containing snow group displays higher variability, with an interquartile range from 0.909 to 1.067 and whiskers extending from 0.842 to 1.194, indicating a broader distribution. Conversely, the algae-free snow exhibits a narrower interquartile range between 0.918 and 0.961, with whiskers from 0.927 to 0.969, reflecting more consistent values. Notably, there is overlap between 0.951 and 0.960, suggesting that the red/green ratio may not sufficiently distinguish between the two conditions, underscoring the need for more robust indices. The median RGND value for algae-free snow is −0.021, with an interquartile range from −0.027 to −0.017 and whiskers from −0.036 to −0.013, indicating a limited spread. In contrast, algae-containing snow has a median RGND value of 0.003, with an interquartile range from −0.037 to 0.033 and whiskers from −0.081 to 0.076, indicating greater variability. While the RGND values for algae-containing snow are more diverse, overlap between the two categories persists. This highlights the need for a more effective index, such as the newly developed API, which shows no overlap and provides better differentiation, as discussed in subsequent sections.

Fig. 4 (left) illustrates API values plotted against their index, with blue crosses indicating regular data points and red crosses representing outliers. The majority of the data points display a gradual upward trend; however, two outliers at higher indices, with precise values of 0.328 and 0.624, deviate significantly from the general pattern. These outliers were detected using the interquartile range (IQR) method, as they exceed 1.5 times the IQR from the quartiles, and were removed to prevent their influence from skewing subsequent analyses. Fig. 4 (right) shows the API values for ‘Algae-free snow’ and ‘Algae-containing snow,’ clearly distinguishing the two groups. The API values for algae-free snow are consistently negative, with a median of −0.121 and an interquartile range between −0.138 and − 0.116, indicating limited variability and short whiskers that show minimal deviation. In contrast, algae-containing snow exhibits a broader distribution, with a median API value of 0.022, an interquartile range from −0.038 to 0.063, and whiskers extending further, reflecting greater variability. This spread may correspond to differences in algae concentration or pigmentation across samples. The plot demonstrates a clear separation between the two conditions, with no overlap, highlighting the API's superior effectiveness in distinguishing between algae-containing and algae-free snow compared to the red/green ratio and RGND values.

The box plots presented in Fig. 5 illustrate the results of the Mann–Whitney *U* test, which assessed the statistical significance of differences in RGND, red/green ratio, and API values among different conditions: Green Algae, Algae-Free Snow, and Red Algae. For RGND values (a), the analysis reveals significant differences between Green Algae and both Algae-Free Snow and Red Algae conditions, with *p*-values less than 0.01 (**). However, no significant difference was observed between Red Algae and Algae-Free Snow (denoted by “n.s.” for not significant). In the Red/Green ratio (b), significant differences were observed between Green Algae and both Algae-Free Snow and Red Algae (p-value <0.01, **), but there was no significant difference between Red Algae and Algae-Free Snow. Despite containing chlorophyll, Green algae exhibit values lower than snow in both the RGND and red/green band ratio indices, similar to other vegetation that also contains chlorophyll. This similarity suggests that these indices may not effectively distinguish green algae from snow or other chlorophyll-containing impurities and vegetation, due to the broad spectral overlap.

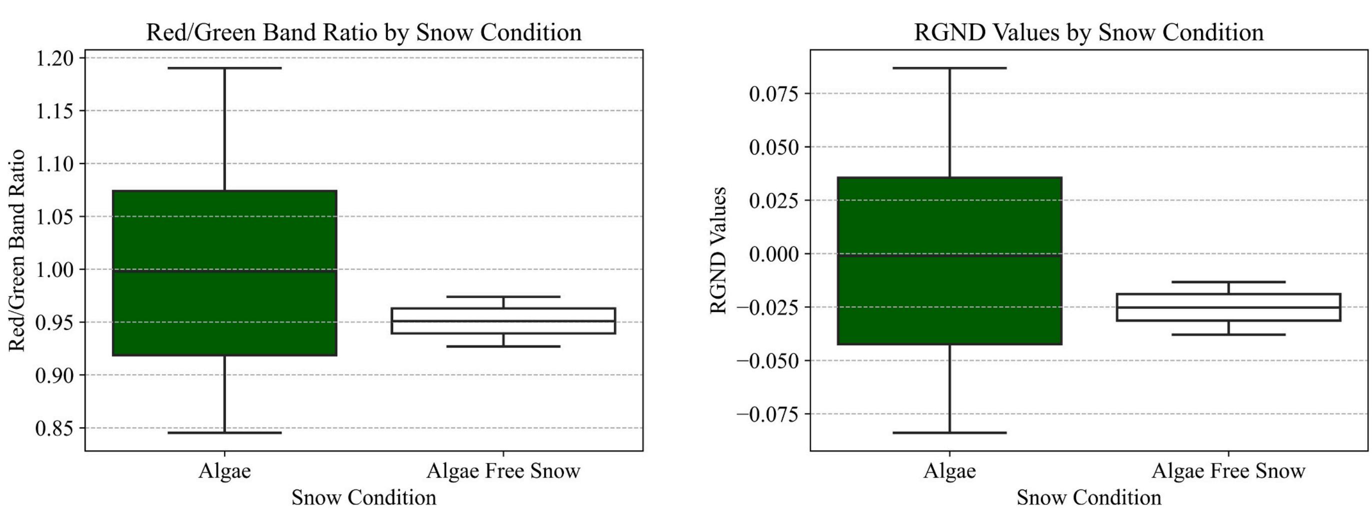

Fig. 3. Red/Green band ratio (left) and RGND values (right) by snow condition. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

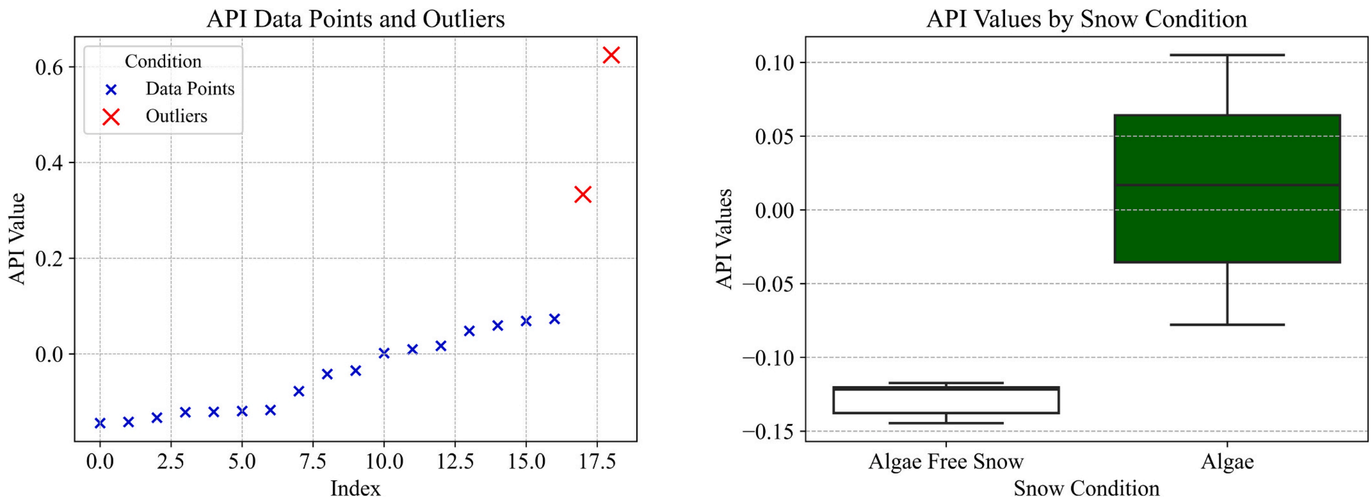

Fig. 4. API data points with outliers (left) and API values for algae and algae-free snow conditions (right).

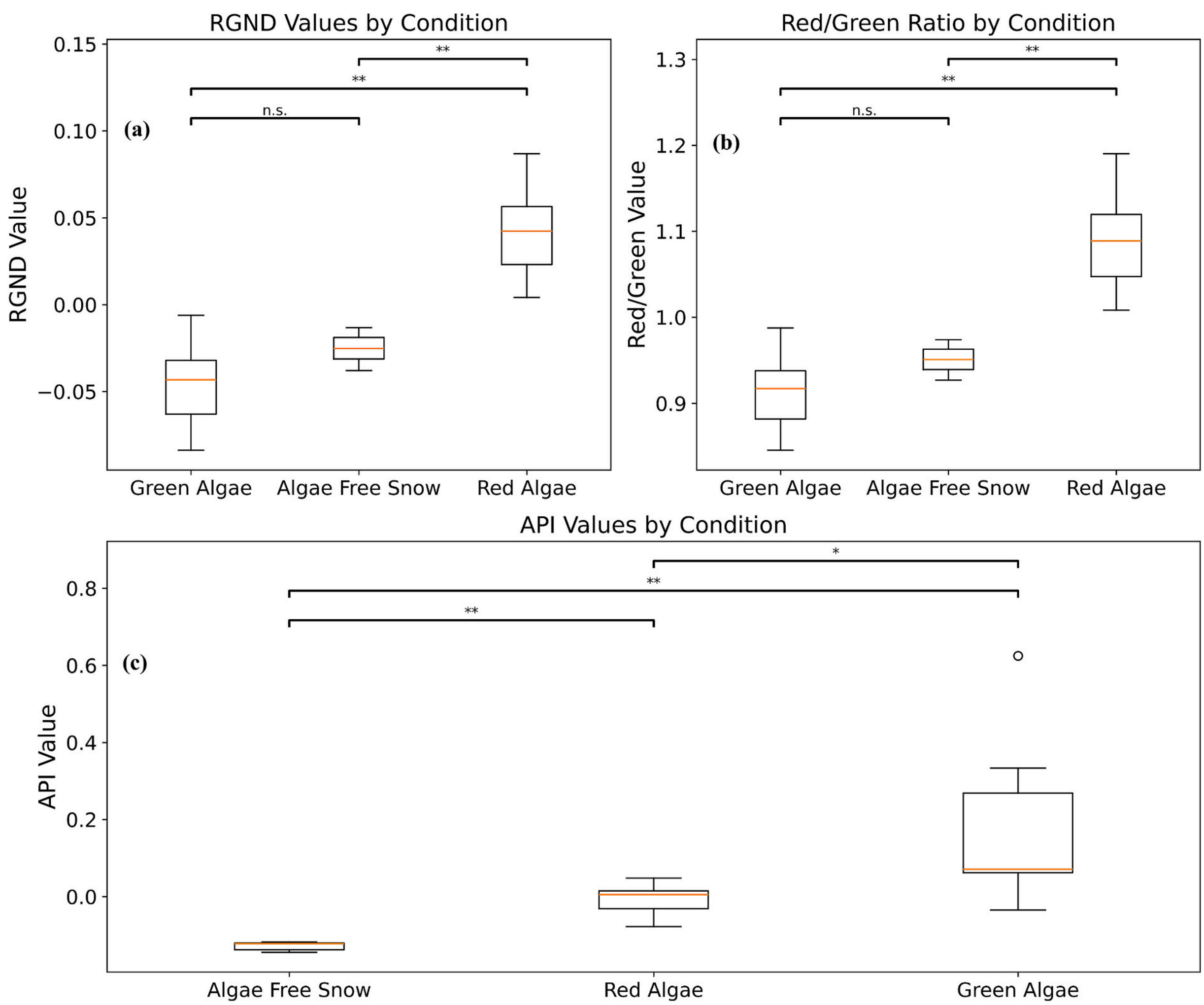

Fig. 5. Boxplot distributions of RGND, Red/Green Band Ratio, and API values for green algae, red algae, and algae-free snow. (a) RGND, (b) Red/Green Band Ratio, and (c) API values. Statistical significance is indicated by ** ($p < 0.01$), * ($p < 0.05$), and n.s. (not significant). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

For the API values (c), a significant difference was found between Algae-Free Snow and both Red Algae and Green Algae, with p-values less than 0.01 (**). Additionally, a significant difference was observed between Red Algae and Green Algae, with a p-value less than 0.05 (*). These results suggest that the API index is highly effective in distinguishing between the three conditions, highlighting its potential as a reliable tool for differentiating between algae and algae-free snow in remote sensing applications. Specifically, the API is capable of clearly separating Green Algae and Red Algae from Algae-Free Snow, and it also reveals differences between the two types of algae, providing a finer level of detail for snow algae detection.

3.2. Spatial and temporal analysis of snow algae and albedo dynamics

The API across the four austral summer seasons (2019–2023) shows significant temporal and spatial variations in snow algae presence (Fig. 6). During the austral summer of 2019–2020, widespread and relatively uniform algae coverage with high API values indicated favorable environmental conditions for algae growth, likely linked to higher temperatures and sufficient snowmelt. In contrast, the 2020–2021 season exhibited a patchier distribution of algae, with high API values confined to specific areas. This uneven distribution is due to masked out pixels caused by cloud cover, leading to the mapping of algae only over the available pixels. The 2021–2022 season showed a notable decline in overall algae presence, as evidenced by predominantly lower API values, possibly due to less favorable climatic conditions, such as lower temperatures or reduced snowmelt. The 2022–2023 season demonstrated a partial recovery in algae presence; however, the maximum API values remained lower than in previous years, suggesting that environmental conditions had improved compared to the prior season but were still less favorable than during 2019–2020. Multiple environmental factors, including temperature changes, snowmelt dynamics, and nutrient availability, likely drive these temporal variations in algae presence.

The maps (Fig. 7) illustrate the spatial distribution of red and green algae on King George Island, Antarctic Peninsula, over four austral summer seasons: 2019–2020, 2020–2021, 2021–2022, and 2022–2023. During the 2019–2020 season, red algae exhibited widespread coverage, particularly in the central and southern regions, while green algae were mainly concentrated in the southern areas of KGI. During the

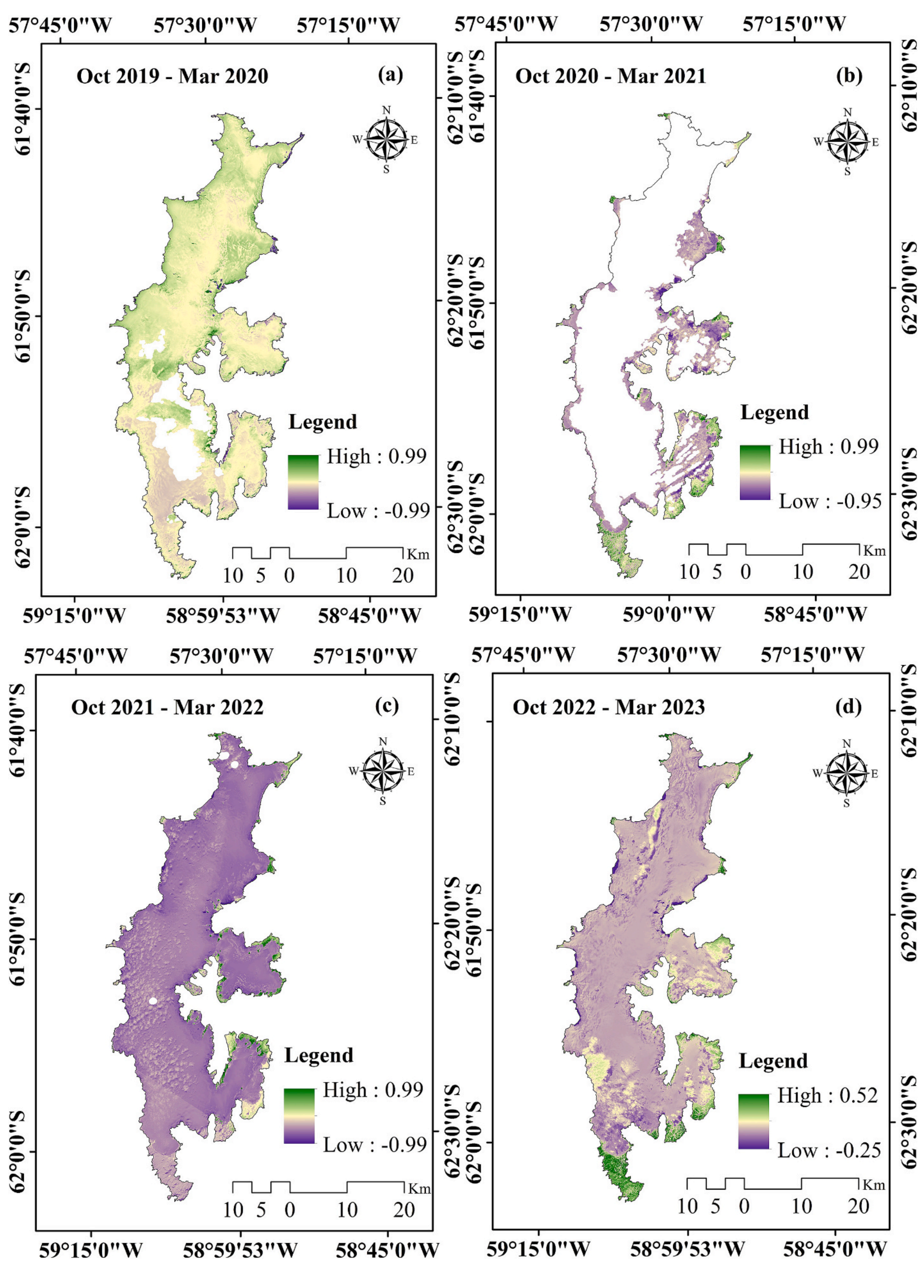

Fig. 6. Spatio-temporal variations in API across King George Island from October 2019 to March 2023, showing changes in API distribution and intensity. (a) Oct 2019–Mar 2020, (b) Oct 2020–Mar 2021, (c) Oct 2021–Mar 2022, and (d) Oct 2022–Mar 2023.

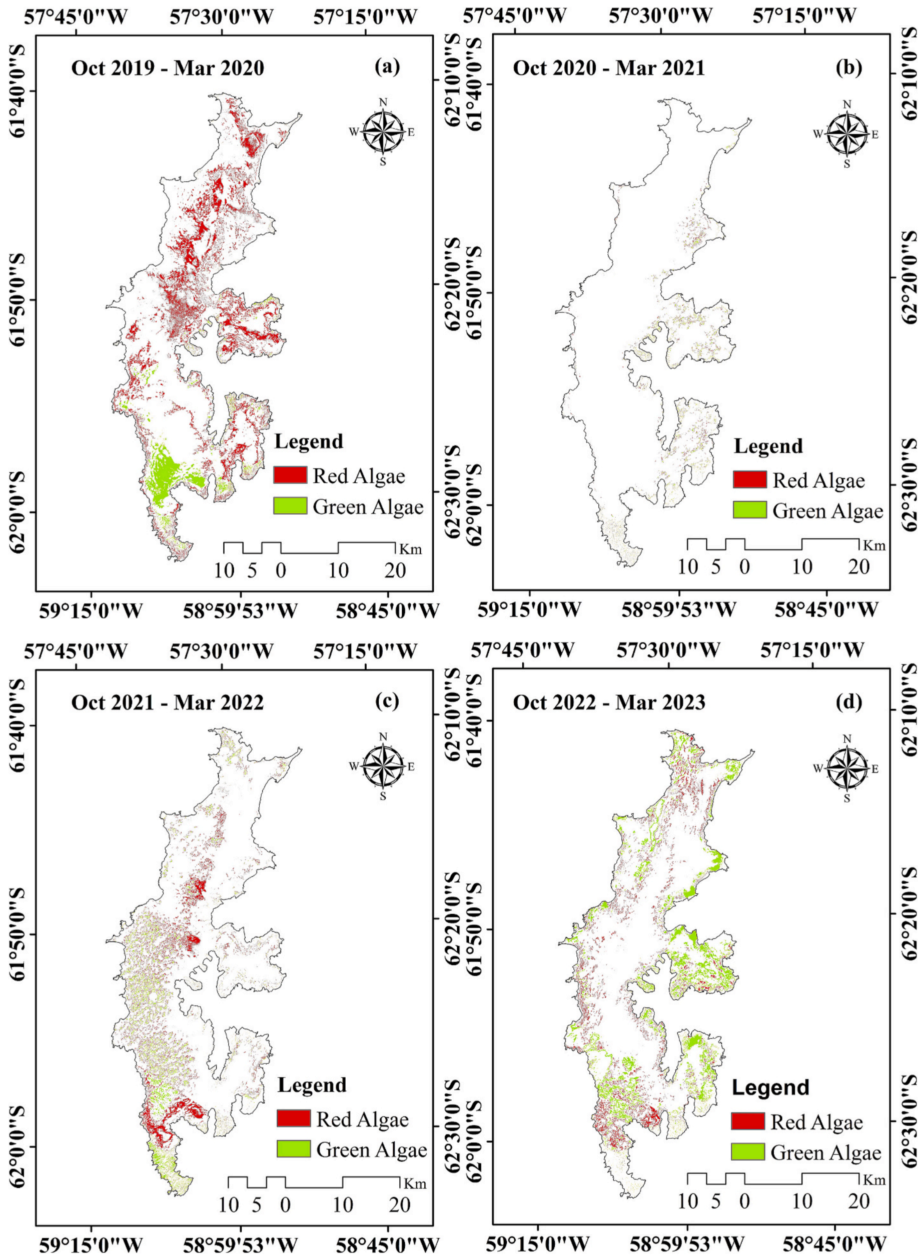

Fig. 7. Spatial distribution of red and green algae on King George Island, Antarctic Peninsula, during four austral summer seasons: (a) 2019–2020, (b) 2020–2021, (c) 2021–2022, and (d) 2022–2023. The maps highlight interannual variations in the extent of red and green algal cover. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

2020–2021 season, red and green algae were mainly observed along the borders, as many pixels were masked due to cloud cover. This resulted in mapping algae only within the available cloud-free areas. The 2021–2022 season showed a notable decline in overall algae presence as compared to 2019–2020, with red algae forming smaller clusters and green algae becoming more dispersed. By the 2022–2023 season, green algae coverage expanded significantly, suggesting a recovery and more favorable growth conditions, while red algae remained confined to a few isolated areas. These results highlight the substantial interannual variability in snow algae distribution. The year-to-year changes emphasize the sensitivity of snow algae to climatic conditions and their role as indicators of ecosystem health in polar regions.

Fig. 8 illustrates albedo changes over four distinct periods from 2019 to 2023. During the first period (Oct 2019 – Mar 2020), the albedo map highlights high values throughout most of the study area, with the classified algae map (Fig. 7) revealing widespread distribution of red and green algae. The southern region, in particular, showed a notable presence of algae, which coincided with areas of reduced albedo, indicating that algae significantly impacted the lowering of snow surface reflectance. In the second period (Oct 2020 – Mar 2021), the data coverage was limited, as cloud cover masked most pixels. This limitation made it challenging to analyze algae presence and albedo variations effectively, resulting in less detailed observations during this period. The third period (Oct 2021 – Mar 2022) shows a recovery of algae, with substantial red and green algae coverage across the southern and central regions. This increase in algae presence corresponds to marked reductions in albedo values, supporting the idea that algae contribute to decreased surface reflectance and potentially accelerated snowmelt in these areas. In the final period (Oct 2022 – Mar 2023), the maps show a decrease in the extent of red algae, while green algae maintained a significant presence. This reduction in red algae coverage is accompanied by a partial recovery of high albedo regions. However, low albedo

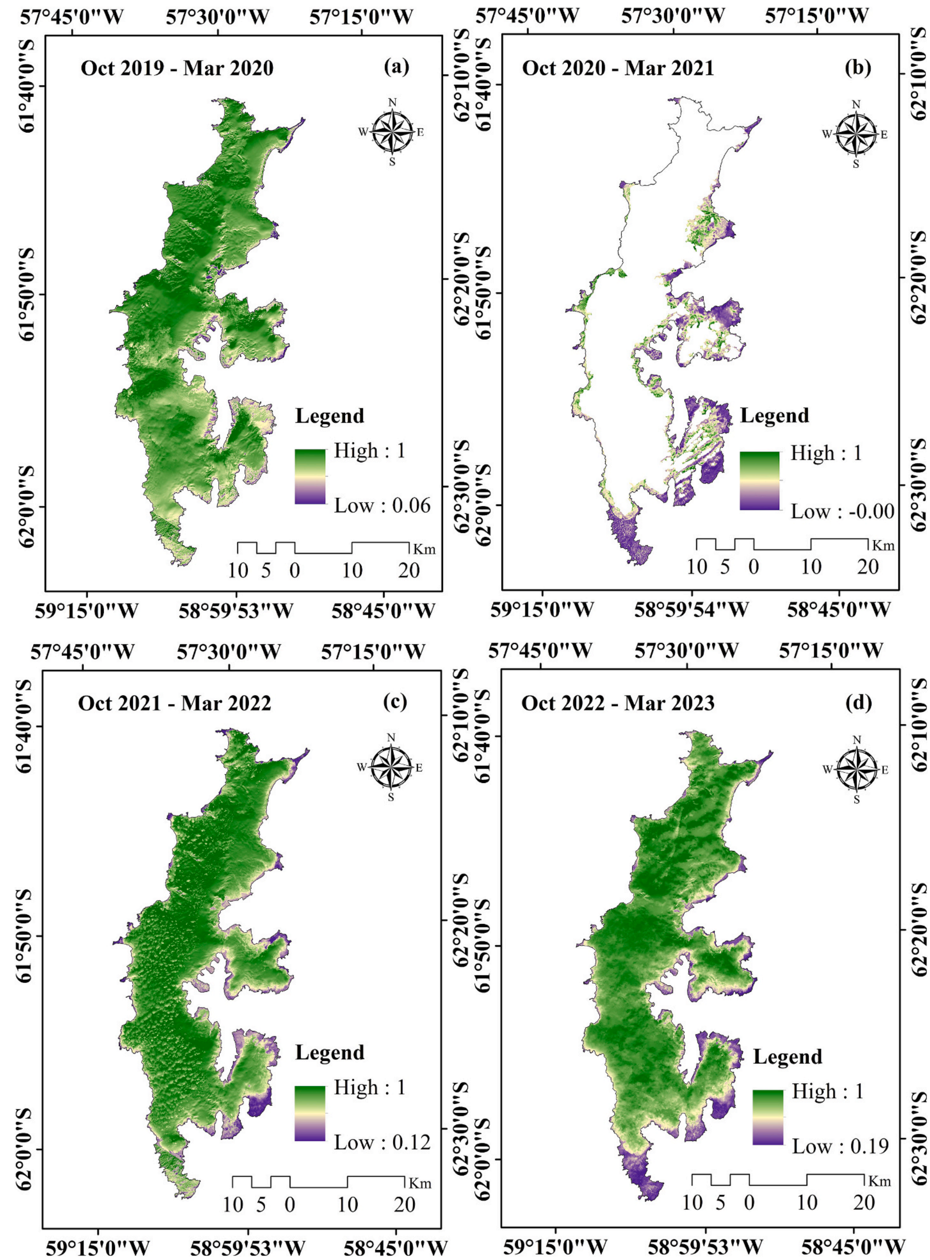

Fig. 8. Spatial distribution of albedo on King George Island, Antarctic Peninsula, during four austral summer seasons: (a) 2019–2020, (b) 2020–2021, (c) 2021–2022, and (d) 2022–2023. The maps highlight interannual variations in albedo distribution and intensity.

areas persisted, suggesting that even lower algae densities can continue to affect snow surface properties. Overall, these observations underscore an inverse relationship between algae coverage and surface albedo: periods with extensive algae presence align with noticeable decreases in albedo, impacting the region's snowmelt dynamics. Table 3 further illustrates the year-to-year variations in algae coverage and proportions, highlighting the temporal changes in the abundance of red and green algae on King George Island from 2019 to 2023.

Table 3
Annual coverage (sq km) and percentage of red and green algae on King George Island from 2019 to 2023, showing variations in total algal extent and individual contributions of red and green algae over the years.

Year	Red Algae (sq. km)	Green Algae (sq. km)	Total Algae (sq. km)	Red Algae (%)	Green Algae (%)
2019–2020	289.99	94.89	384.88	12.36	4.04
2020–2021	14.12	15.00	29.12	0.60	0.63
2021–2022	130.00	65.92	195.92	5.54	2.81
2022–2023	101.9575762	186.8267976	288.77	4.34	7.96

Based on the observations, the analysis of the relationship between algae presence and albedo reveals distinct patterns across different periods. During the 2019–2020 period, the mean albedo of surfaces covered by green algae was approximately 8.46 % lower than those covered by red algae, indicating that green algae have a more pronounced effect on reducing surface reflectance. This difference is likely due to the higher absorption properties of green algae, which can contribute to accelerated snowmelt in regions with significant green algae coverage. In the 2021–2022 period, the mean albedo values show a similar trend, where green algae-covered surfaces exhibit a mean albedo approximately 5.33 % lower than red algae. This reduction in albedo is consistent with the algae presence observed in this period, suggesting that extensive algal growth can significantly alter the snow surface energy balance and influence the rate of snowmelt. However, the

2022–2023 period shows a smaller difference between the mean albedo values of red and green algae, with green algae only 2.18 % lower than red algae. This observation could indicate a change in algae dynamics or environmental conditions that limited the influence of green algae on surface reflectance. Overall, the results highlight the varying impact of different algae types on albedo and suggest that monitoring algae presence is crucial for understanding snowmelt and energy balance in snow-covered regions.

3.3. Visual comparison of algae and vegetation

It is also important to highlight that the API also demonstrated an effective ability to distinguish between algae and vegetation, as evident in Fig. 9. The visual analysis of algae and vegetation maps for four austral summer seasons confirms that algae pixels (in green) do not overlap with vegetation pixels (in pink), which were identified using NDVI values greater than 0.01. This verification underscores the effectiveness of the API in accurately distinguishing algae from vegetation. This differentiation is crucial for more accurate ecological and environmental assessments, particularly when analyzing seasonal and inter-annual variability in snow-algae presence.

4. Discussion

This study introduces the Algae Presence Index (API), which enhances the understanding of snow algae dynamics on King George Island, Antarctica. The findings contribute to SDG 13 (Climate Action) by emphasizing the critical role that biological factors, such as snow algae, play in influencing snowmelt and the surface energy balance in the Antarctic Peninsula. The API provides a significant improvement over traditional methods like the red/green band ratio and RGND in detecting and classifying both red and green snow algae. By integrating spectral bands sensitive to algae-specific pigments and snow moisture content, the API offers a more accurate and reliable classification of algae. Unlike

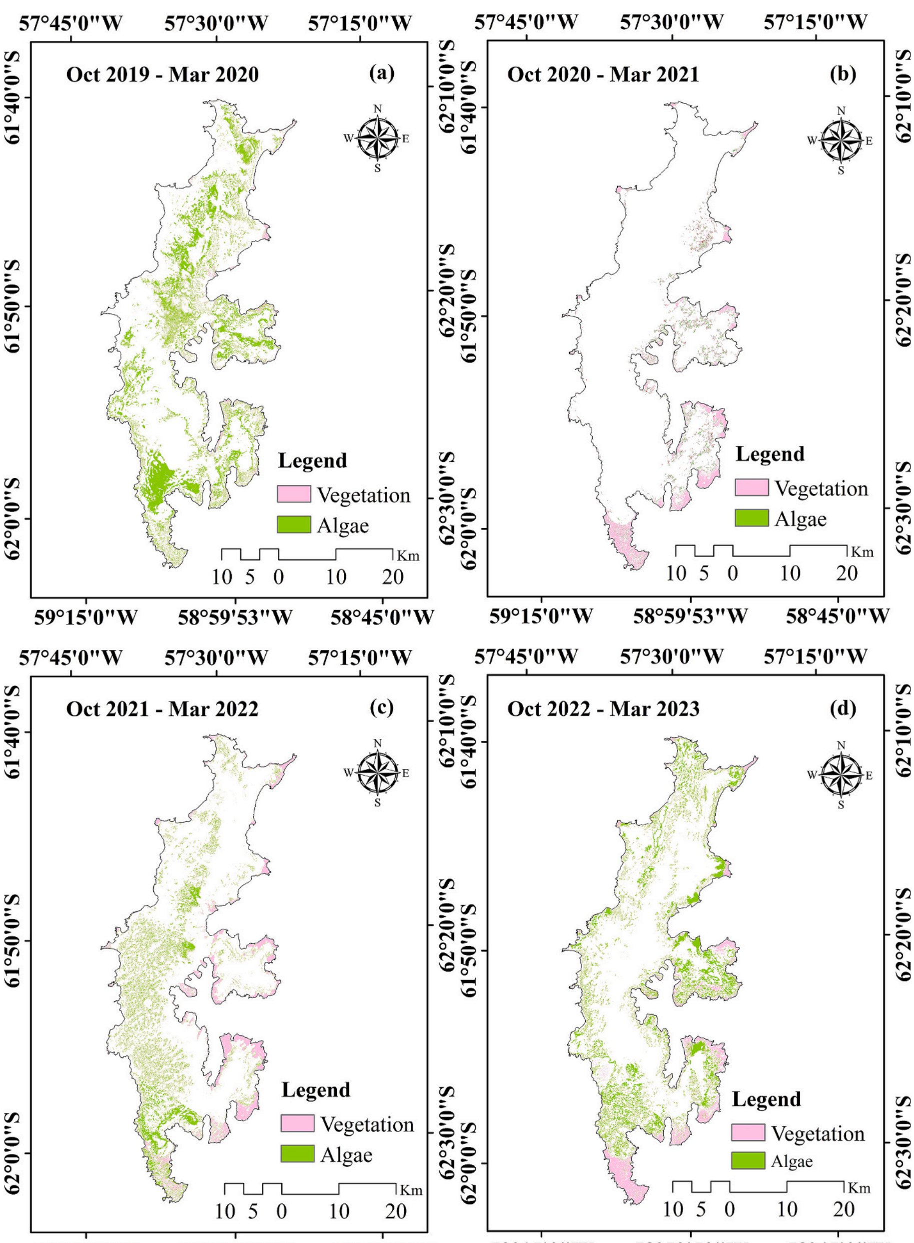

Fig. 9. Spatial distribution of algae (green) and vegetation (pink) on King George Island during four austral summer seasons: (a) 2019–2020, (b) 2020–2021, (c) 2021–2022, and (d) 2022–2023. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

the red/green band ratio and RGND, which rely solely on the reflectance difference between the red and green bands, the API also incorporates near-infrared (NIR) and shortwave infrared (SWIR1) bands. These additional bands enhance the detection capability of the API by capturing variations in chlorophyll content, algal pigmentation, and snow moisture factors essential for distinguishing algae from other impurities in the snow (Di Mauro et al., 2015; Ganey et al., 2017; Ouma et al., 2020). The red/green ratio and RGND are limited by their narrow spectral focus, which restricts their ability to capture the full variability in algae pigmentation and concentration, thus increasing the likelihood of misclassification, particularly when distinguishing green algae from algae-free snow. This study demonstrates that the API, with its broader spectral range, reduces this overlap and improves algae classification accuracy. In contrast, the API's advanced formula integrates multiple spectral bands and applies normalization, enhancing its capacity to maximize contrast and accurately differentiate algae from clean snow. This approach minimizes the impact of external factors like snow grain size, moisture content, or mixed impurities, which can skew simpler indices like the red/green ratio and RGND. Snow grain size and associated snowpack properties significantly influence snow albedo by modifying the snow surface reflectivity. Flanner et al. (2007) illustrated that increased snow grain sizes reduce albedo due to enhanced absorption, particularly within the near-infrared spectrum. Similarly, Skiles et al. (2018) emphasized that albedo reduction is amplified by a grain-size feedback mechanism, whereby the presence of light-absorbing particles accelerates grain growth, indirectly enhancing snow surface darkening. These findings highlight the challenge of differentiating biological factors, like snow algae, from physical factors affecting snow reflectance. This complexity underscores the advantage of the API's broader spectral approach over traditional indices, which are more prone to confounding factors. By improving snow algae monitoring, the API supports SDG 15, aiding the conservation of polar ecosystems.

Spectral data analysis from Sentinel-2 satellite imagery has revealed detailed patterns in the spatial distribution and intensity of snow algae blooms, along with their significant impact on surface albedo across multiple austral summer seasons. Previous studies (Khan et al., 2021) have shown that snow algae are highly sensitive to environmental factors such as light, moisture, and temperature. They become active as snow begins to melt, releasing essential nutrients. The results demonstrate that snow algae, particularly green algae, significantly reduce snow surface reflectance, thereby accelerating snowmelt. Consistently higher API values for green algae compared to red algae indicate their greater absorption of solar radiation, leading to a more substantial impact on albedo reduction.

Green algae reduce albedo more significantly than red algae, primarily due to their pigment composition and light absorption efficiency. Green algae are rich in chlorophylls a and b, which are highly effective in absorbing light, particularly in the blue (430–450 nm) and red (640–680 nm) regions of the spectrum enabling them to play a more prominent role in energy dynamics (Pereira, 2018). This enhanced pigment efficiency results in stronger absorption of solar radiation, leading to a greater reduction in snow surface reflectance compared to red algae. In contrast, red algae contain pigments like astaxanthin, which absorb light primarily in the green and yellow wavelengths, making them less efficient at absorbing light in the blue and red regions. As a result, red algae have a comparatively lower impact on snow darkening, as their absorption spectrum is narrower compared to green algae.

This finding is consistent with previous studies showing that the chlorophyll content in green algae absorbs solar energy more efficiently than the pigments in red algae, such as phycoerythrin, as measured in laboratory-based absorption spectra (Lutz et al., 2016; Takeuchi et al., 2006). Red algae adapt to low-light environments by modifying their phycobilisome composition, which enhances light-harvesting efficiency in specific spectral regions, particularly within mesophotic zones where light is scarce (Voerman et al., 2022). However, despite these adaptations, red algae are still less efficient in utilizing the full range of available sunlight compared to green algae.

Additionally, green algae often form dense blooms with high cell concentrations, which enhances their collective capacity to absorb solar radiation and reduce surface reflectance. This higher biomass density contributes to a more substantial decrease in snow albedo compared to red algae, which typically exhibit lower biomass densities. Thus, while the primary factor for green algae is their superior pigment efficiency, their denser blooms further amplify their ability to reduce albedo.

The spatial and temporal analysis reveals an inverse relationship between algae presence and albedo, with extensive algae coverage, such as during the 2019–2020 austral summer, leading to significantly reduced albedo on King George Island (Fig. 10). Green algae, with higher absorption properties, have a greater impact on surface reflectance than red algae and algae-free snow. This albedo reduction enhances solar radiation absorption, accelerating snowmelt and creating conditions that support further algae growth, reinforcing the cycle. These findings align with previous studies linking albedo reduction to enhanced solar energy absorption, such as Healy and Khan (2023), who observed the significant role of snow algae blooms in accelerating snowmelt in other regions, with broader implications for accelerating the loss of ice cover as the Antarctic Peninsula continues to warm. The observed albedo differences (5–8 %) between algae types underscore the critical role of algae composition in snowmelt dynamics and emphasize the importance of monitoring algal blooms to better understand their impact on the cryosphere. Remote sensing-based detection and classification of snow algae enhance our understanding of cryosphere dynamics and support SDG 13 by providing data to improve climate models and inform mitigation strategies.

Our findings align with studies highlighting the impact of biological factors, such as algae, on snow albedo and snowmelt dynamics (Almela et al., 2023; Engstrom and Quarmby, 2023). While this study provides valuable insights into snow algae dynamics on King George Island, the temporal range of 2019–2023 may limit the detection of long-term trends. Although previous research has highlighted the seasonal impact of snow algae on albedo reduction (e.g., Lutz et al., 2016; Takeuchi et al., 2006), extending the temporal scope of the API analysis would provide a more comprehensive understanding of algae dynamics over multiple years, capturing interannual variability and offering insights into the long-term effects of algae on snowmelt and albedo reduction under changing climatic conditions.

Algae further contribute to the planet's equilibrium through carbon sequestration (Onyeaka et al., 2021). During photosynthesis, they absorb atmospheric CO^2 and incorporate it into their biomass, which can remain stored if buried by snow, ice, or submerged in water (Ushasri et al., 2023). This natural carbon sink helps reduce greenhouse gas concentrations, aiding in global temperature regulation. By modifying surface reflectivity and acting as carbon sinks, algae exemplify how nature balances its systems—mitigating warming effects while supporting essential biological cycles. However, their activities also interact with the albedo feedback loop, where reduced albedo accelerates snowmelt, exposing darker surfaces and amplifying warming in polar and high-altitude regions, with consequences for global sea-level rise (Niu et al., 2020; Williamson et al., 2020). This intricate interplay highlights algae's dual role in sustaining ecological processes while influencing local and global climate patterns. As highlighted by (Cook et al., 2017b), snow algae accelerate snowmelt through bio-albedo effects and contribute to complex feedbacks involving snowpack properties and light-absorbing impurities. These direct and indirect interactions emphasize the need to integrate biological-cryospheric processes into climate models to better represent their impact on regional melt dynamics and cryosphere-climate feedbacks.

Furthermore, the API's potential for improving the understanding of snow algae dynamics presents an opportunity to address broader climate action goals. To strengthen the practical applications and SDG 13

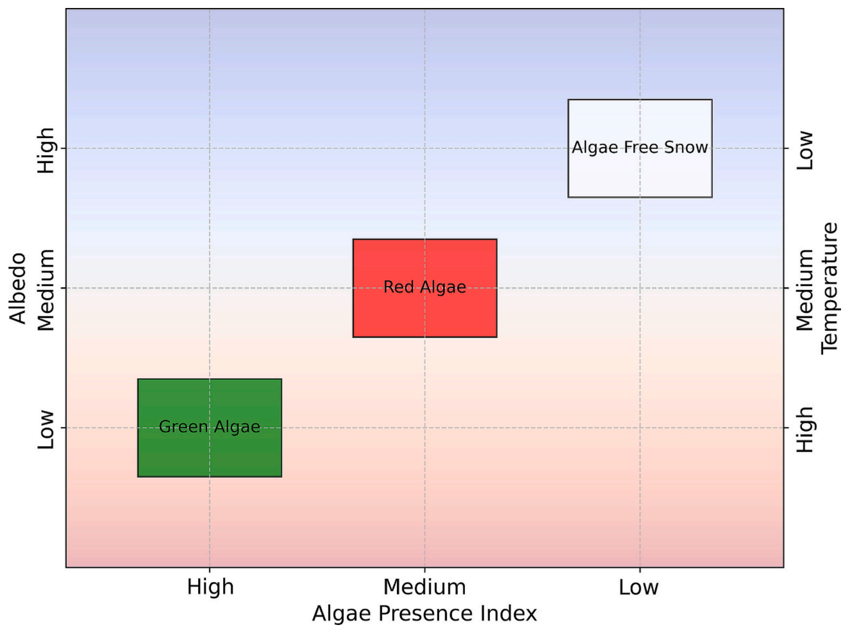

Fig. 10. Feedback between algae presence, albedo, and temperature. Green and red algae reduce albedo, increasing temperature and snowmelt, while algae-free snow retains higher albedo. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

(Climate Action) linkages, we propose integrating the Algae Presence Index (API) into a standardized Antarctic monitoring framework. This framework could be adopted by international initiatives such as the Antarctic Treaty Consultative Meeting (ATCM) or the International Polar Year (IPY) to systematically track algal blooms and their climatic impacts. By leveraging Sentinel-2's frequent revisit cycle, the API could provide near-real-time maps of algal distribution, enabling policymakers to prioritize regions for conservation and assess compliance with environmental protocols under the Antarctic Treaty System. Such data would also enhance the Climate Change Response Work Programme of the Committee for Environmental Protection (CEP), offering actionable insights into how algal-driven albedo reductions accelerate ice retreat—a critical input for refining IPCC climate projections.

4.1. Limitations and future outlook

The spatial resolution of Sentinel-2 imagery limits the detection of small algae patches. Atmospheric corrections may introduce uncertainties, especially in variable weather conditions. While the cloud-masking algorithm effectively removes most cloud-contaminated pixels, some residual cloud effects may remain, particularly in areas with frequent cloud cover. Moreover, the API thresholds in this study were derived from field data collected in January 2018, which may not capture spectral variability across years or regions. Future work should include multi-season and multi-site field campaigns to improve the robustness and generalizability of algae classification. Additionally, this study did not assess the uncertainty associated with API performance under varying sensor conditions and atmospheric influences, which should be addressed in future work. Additionally, while the API effectively distinguishes algae from clean snow and vegetation, its ability to separate algae from other darkening agents like dust or black carbon was not explicitly addressed. Integrating additional field spectra or hyperspectral data could enhance discrimination between biological and non-biological snow impurities. While this study focused on threshold-based classification due to limited field data, future work should consider machine learning approaches to capture a broader range of algae types based on their distinct spectral signatures and compare their performance to the API using metrics such as overall accuracy, Kappa coefficient, confusion matrices, and ROC curves, once sufficient labeled data are available. While this study qualitatively explored the impact of algae on snow albedo, future research should integrate snow physics data, including snow density, grain size, and liquid water content, to establish quantitative relationships between these parameters and the API. Regression models and sensitivity tests can be used to explore these connections. Moreover, radiative transfer models (e.g., SNICAR) could be applied to simulate the impacts of algae on snow albedo more precisely and validate the observed relationships.

5. Conclusion

This study builds on past research by providing new insights into the spectral differences in Antarctic snow impacted by red and green algae. A novel Algae Presence Index (API) was developed and applied to map the Antarctic Peninsula's red and green snow algae. Monitoring and mapping these albedo-reducing algae are particularly challenging due to the region's cloud cover. Despite this, the API enabled precise detection and classification of snow algae on King George Island using Sentinel-2 satellite imagery. Across four austral summers (2019–2023), spatial analysis revealed that green algae consistently had a stronger impact on reducing albedo than red algae. For instance, during the 2019–2020 season, green algae reduced albedo by 8.46 %, while red algae caused a 5.33 % reduction. Over the study period, algae coverage varied, peaking in 2022–2023 at 288.77 km^2.

As temperatures in the Antarctic Peninsula continue to rise, the growth of snow algae is likely to increase, which in turn could further reduce surface albedo, amplifying snowmelt through a positive feedback loop. Warmer conditions create favorable environments for more extensive algae blooms, leading to greater absorption of solar radiation and accelerating melt rates. This feedback mechanism should be considered in climate models, as it could significantly influence snowmelt dynamics and contribute to ice edge retreat in coastal Antarctic regions. Additionally, an extended algae bloom season may already be occurring due to persistent warmer temperatures, further enhancing the impact of algae on the cryosphere. These findings enhance the understanding of snow algae's role in the Antarctic and point to the importance of continuous monitoring and refined detection methods, particularly in light of future warming scenarios. Future research should explore snow algae's broader ecological and carbon cycling implications, with potential links to net primary productivity (NPP) and biogeochemical processes. The API developed here could also be adapted for algorithms that track algae blooms' spatial and temporal variability, contributing valuable data to global climate models and helping to predict changes in the Antarctic cryosphere under ongoing climate change. Future studies could leverage data from SDGSAT-1 to enhance the accuracy and temporal resolution of snow algae monitoring, further supporting the achievement of SDG targets related to climate change and environmental protection.

CRediT authorship contribution statement

Barjeece Bashir: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Dong Liang:** Writing – original draft, Supervision, Resources, Project administration, Funding acquisition, Conceptualization. **Rong Cai:** Writing – review & editing, Validation, Resources, Data curation, Conceptualization. **Faisal Mumtaz:** Writing – review & editing, Writing – original draft, Investigation. **Lingyi Kong:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Investigation. **Yahui Zou:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Formal analysis, Data curation.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used ChatGPT to enhance the language and readability of the manuscript. The authors reviewed and edited the content to ensure its accuracy and integrity and take full responsibility for the final content of the publication.

Declaration of competing interest

Dong Liang reports financial support was provided by the National Natural Science Foundation of China. Dong Liang reports financial support was provided by the Joint HKU-CAS Laboratory for iEarth. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

This work was supported by the National Natural Science Foundation of China (grant number 42376246) and Joint HKU-CAS Laboratory for iEarth (313GJHZ2022074MI, E4F3050300).

Data availability

The Sentinel-2 Surface Reflectance data used in this study are publicly available through Google Earth Engine.

References

Almela, P., Elser, J.J., Giersch, J.J., Hotaling, S., Hamilton, T.L., 2023. Brief communication: influence of snow cover on albedo reduction by snow algae. EGUsphere 2023, 1–11.

Bernard, C., Thomas, J., Mazel, D., Mousseau, A., Castets, A., Tandeau de Marsac, N., Dubacq, J., 1992. Characterization of the genes encoding phycoerythrin in the red alga Rhodella violacea: evidence for a splitting of the rpeB gene by an intron. Proc. Natl. Acad. Sci. 89 (20), 9564–9568.

Convey, P., 2011. Antarctic terrestrial biodiversity in a changing world. Polar Biol. 34, 1629–1641.

Convey, P., Chown, S.L., Clarke, A., Barnes, D.K., Bokhorst, S., Cummings, V., et al., 2014. The spatial structure of Antarctic biodiversity. Ecological monographs 84 (2), 203–244.

Cook, J.M., Hodson, A.J., Gardner, A.S., Flanner, M., Tedstone, A.J., Williamson, C., et al., 2017a. Quantifying bioalbedo: a new physically based model and discussion of empirical methods for characterising biological influence on ice and snow albedo. Cryosphere 11 (6), 2611–2632.

Cook, J., Hodson, A.J., Taggart, A., Mernild, S.H., Tranter, M., 2017b. A predictive model for the spectral "bioalbedo" of snow. J. Geophys. Res. Earth 122 (1), 434–454.

Di Mauro, B., Fava, F., Ferrero, L., Garzonio, R., Baccolo, G., Delmonte, B., Colombo, R., 2015. Mineral dust impact on snow radiative properties in the European Alps combining ground, UAV, and satellite observations. J. Geophys. Res. Atmos. 120 (12), 6080–6097.

Di Mauro, B., Garzonio, R., Ravasio, C., Orlandi, V., Baccolo, G., Gilardoni, S., et al., 2024. Combined effect of algae and dust on snow spectral and broadband albedo. J. Quant. Spectrosc. Radiat. Transf. 316, 108906.

Engstrom, C.B., Quarmby, L.M., 2023. Satellite mapping of red snow on north American glaciers. Science Advances 9 (47), eadi3268.

Engstrom, C.B., Williamson, S.N., Gamon, J.A., Quarmby, L.M., 2022. Seasonal development and radiative forcing of red snow algal blooms on two glaciers in British Columbia, Canada, summer 2020. Remote Sens. Environ. 280, 113164.

Feng, S., Cook, J.M., Anesio, A.M., Benning, L.G., Tranter, M., 2023. Long time series (1984–2020) of albedo variations on the Greenland ice sheet from harmonized Landsat and sentinel 2 imagery. J. Glaciol. 69 (277), 1225–1240.

Flanner, M.G., Zender, C.S., Randerson, J.T., Rasch, P.J., 2007. Present-day climate forcing and response from black carbon in snow. J. Geophys. Res. Atmos. 112 (D11).

Flood, N., 2013. Seasonal composite Landsat TM/ETM+ images using the medoid (a multi-dimensional median). Remote Sens. (Basel) 5 (12), 6481–6500.

Ganey, G.Q., Loso, M.G., Burgess, A.B., Dial, R.J., 2017. The role of microbes in snowmelt and radiative forcing on an Alaskan icefield. Nat. Geosci. 10 (10), 754–759.

Ghosh, S., Kumar, D., Kumari, R., 2022. Cloud-based large-scale data retrieval, mapping, and analysis for land monitoring applications with google earth engine (GEE). Environmental Challenges 9, 100605.

Gray, A., Krolikowski, M., Fretwell, P., Convey, P., Peck, L.S., Mendelova, M., Davey, M. P., 2020. Remote sensing reveals Antarctic green snow algae as important terrestrial carbon sink. Nat. Commun. 11 (1), 2527.

Gray, A., Krolikowski, M., Fretwell, P., Convey, P., Peck, L.S., Mendelova, M., Davey, M. P., 2021. Remote sensing phenology of Antarctic green and red snow algae using WorldView satellites. Front. Plant Sci. 12, 671981.

Guo, B., Zang, W., Luo, W., Wen, Y., Yang, F., Han, B., et al., 2020. Detection model of soil salinization information in the Yellow River Delta based on feature space models with typical surface parameters derived from Landsat8 OLI image. Geomat. Nat. Haz. Risk 11 (1), 288–300.

Hannula, H.-R., Pulliainen, J., 2019. Spectral reflectance behavior of different boreal snow types. Journal of Glaciology 65 (254), 926–939.

Hansen, J., Ruedy, R., Sato, M., Lo, K., 2010. Global surface temperature change. Rev. Geophys. 48 (4).

Hashim, M., Misbari, S., Reba, N.M., Abdul-Wahab, M., Pour, A.B., Said, M., Soeed, K., 2016. Mapping snow-algae in Antarctic Peninsula with multi-temporal satellite remote sensing data. Paper presented at the 2016 IEEE International Geoscience and Remote Sensing Symposium (IGARSS).

Healy, S.M., Khan, A.L., 2023. Albedo change from snow algae blooms can contribute substantially to snow melt in the north cascades, USA. Communications Earth & Environment 4 (1), 142.

Hoham, R.W., Remias, D., 2020. Snow and glacial algae: a review1. J. Phycol. 56 (2), 264–282.

Huovinen, P., Ramírez, J., Gómez, I., 2018. Remote sensing of albedo-reducing snow algae and impurities in the maritime Antarctica. ISPRS J. Photogramm. Remote Sens. 146, 507–517.

Khan, A.L., Dierssen, H.M., Scambos, T.A., Höfer, J., Cordero, R.R., 2021. Spectral characterization, radiative forcing and pigment content of coastal Antarctic snow algae: approaches to spectrally discriminate red and green communities and their impact on snowmelt. The Cryosphere 15 (1), 133–148.

Lee, M.J., Lee, J.I., Choe, W.H., Park, C.-H., 2008. Trace element and isotopic evidence for temporal changes of the mantle sources in the South Shetland Islands, Antarctica. Geochemical Journal 42 (2), 207–219.

Lee, J.R., Raymond, B., Bracegirdle, T.J., Chadès, I., Fuller, R.A., Shaw, J.D., Terauds, A., 2017. Climate change drives expansion of Antarctic ice-free habitat. Nature 547 (7661), 49–54.

Lutz, S., Anesio, A.M., Raiswell, R., Edwards, A., Newton, R.J., Gill, F., Benning, L.G., 2016. The biogeography of red snow microbiomes and their role in melting arctic glaciers. Nat. Commun. 7 (1), 11968.

Malairaj, S., Muthu, S., Gopal, V.B., Perumal, P., Ramasamy, R., 2016. Qualitative and quantitative determination of R-phycoerythrin from Halymenia floresia (Clemente) C. Agardh by polyacrylamide gel using electrophoretic elution technique. J. Chromatogr. A 1454, 120–126.

Masson-Delmotte, V., Zhai, P., Pörtner, H.-O., Roberts, D., Skea, J., Shukla, P.R., et al., 2019. Global warming of 1.5 C. An IPCC Special Report on the impacts of global warming of, 1, pp. 93–174.

Niu, H., Kang, S., Wang, H., Du, J., Pu, T., Zhang, G., et al., 2020. Light-absorbing impurities accelerating glacial melting in southeastern Tibetan plateau. Environ. Pollut. 257, 113541.

Onyeaka, H., Miri, T., Obileke, K., Hart, A., Anumudu, C., Al-Sharify, Z.T., 2021. Minimizing carbon footprint via microalgae as a biological capture. Carbon Capture Science & Technology 1, 100007.

Ouma, Y.O., Noor, K., Herbert, K., 2020. Modelling reservoir chlorophyll-a, TSS, and turbidity using sentinel-2A MSI and Landsat-8 OLI satellite sensors with empirical multivariate regression. J Sens 2020 (1), 8858408.

Painter, T.H., Duval, B., Thomas, W.H., Mendez, M., Heintzelman, S., Dozier, J., 2001. Detection and quantification of snow algae with an airborne imaging spectrometer. Appl. Environ. Microbiol. 67 (11), 5267–5272.
Pereira, L., 2018. Biological and therapeutic properties of the seaweed polysaccharides. International Biology Review 2 (2).
Picard, G., Leduc-Leballeur, M., Banwell, A.F., Brucker, L., Macelloni, G., 2022. The sensitivity of satellite microwave observations to liquid water in the Antarctic snowpack. The Cryosphere 16 (12), 5061–5083.
Rivas, C., Navarro, N., Huovinen, P., Gómez, I., 2016. Photosynthetic UV stress tolerance of the Antarctic snow alga Chlorella sp. modified by enhanced temperature? Rev. Chil. Hist. Nat. 89, 1–9.
Rückamp, M., Braun, M., Suckro, S., Blindow, N., 2011. Observed glacial changes on the King George Island ice cap, Antarctica, in the last decade. Global Planet. Change 79 (1–2), 99–109.
Skiles, S.M., Flanner, M., Cook, J.M., Dumont, M., Painter, T.H., 2018. Radiative forcing by light-absorbing particles in snow. Nat. Clim. Chang. 8 (11), 964–971.
Steig, E.J., Schneider, D.P., Rutherford, S.D., Mann, M.E., Comiso, J.C., Shindell, D.T., 2009. Warming of the Antarctic ice-sheet surface since the 1957 international geophysical year. Nature 457 (7228), 459–462.
Takeuchi, N., Dial, R., Kohshima, S., Segawa, T., Uetake, J., 2006. Spatial distribution and abundance of red snow algae on the Harding icefield, Alaska derived from a satellite image. Geophys. Res. Lett. 33 (21).
Townshend, J.R., Justice, C., 1986. Analysis of the dynamics of African vegetation using the normalized difference vegetation index. Int. J. Remote Sens. 7 (11), 1435–1445.
Turner, J., Colwell, S.R., Marshall, G.J., Lachlan-Cope, T.A., Carleton, A.M., Jones, P.D., et al., 2005. Antarctic climate change during the last 50 years. Int. J. Climatol. 25 (3), 279–294.
Ulagesan, S., Nam, T.-J., Choi, Y.-H., 2021. Extraction and purification of R-phycoerythrin alpha subunit from the marine red algae pyropia yezoensis and its biological activities. Molecules 26 (21), 6479.
Ushasri, R., Charumathi, G., Saseendran, S., 2023. Microbes in the recycling of carbon in the Arctic regions: a short review. Current Status of Marine Water Microbiology 27–31.
Vaughan, D.G., Marshall, G.J., Connolley, W.M., Parkinson, C., Mulvaney, R., Hodgson, D.A., et al., 2003. Recent rapid regional climate warming on the Antarctic peninsula. Clim. Change 60, 243–274.
Voerman, S.E., Ruseckas, A., Turnbull, G.A., Samuel, I.D., Burdett, H.L., 2022. Red algae acclimate to low light by modifying phycobilisome composition to maintain efficient light harvesting. BMC Biol. 20 (1), 291.
White, J.C., Wulder, M., Hobart, G., Luther, J., Hermosilla, T., Griffiths, P., et al., 2014. Pixel-based image compositing for large-area dense time series applications and science. Can. J. Remote. Sens. 40 (3), 192–212.
Williamson, C.J., Cook, J., Tedstone, A., Yallop, M., McCutcheon, J., Poniecka, E., et al., 2020. Algal photophysiology drives darkening and melt of the Greenland ice sheet. Proc. Natl. Acad. Sci. 117 (11), 5694–5705.
Yang, J., He, Q., Liu, Y., 2022. Winter–spring prediction of snow avalanche susceptibility using optimisation multi-source heterogeneous factors in the Western Tianshan Mountains, China. Remote Sensing 14 (6), 1340.