ASSESSING THE IMPACT OF BLACK CARBON IMPURITIES ON THE NORMALIZED DIFFERENCE SNOW INDEX

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ABSTRACT

The deposition of black carbon (BC) impurities in snow covers can have significant effects on a wide range of environmental processes. It can accelerate snow melting, affect the spectral quality of propagated light and reduce the landscape's albedo, just to name a few. These effects, in turn, can lead to alterations in fresh water supplies, vegetation patterns and radiative feedback loops linked to local and global climate changes. Although the normalized difference snow index (NDSI) has been extensively employed in the monitoring of snow covers, empirical studies about its sensitivity to the accumulation of BC impurities are still scarce in the related literature. In this work, we aim to address this pressing issue by employing a predictive *in silico* approach supported by measured data obtained from real snowpacks. More specifically, we systematically assess the impact that the deposition of realistic amounts of BC impurities can have on NDSI values calculated for dry and wet snow samples with distinct nivological characteristics. Our findings are expected to contribute to the reliable interpretation of NDSI values, particularly those obtained for snow covers located in regions concomitantly affected by increasing anthropogenic emissions and warming conditions.

Index Terms— snow, spectral index, black carbon.

1. INTRODUCTION

Snow has a strong influence on the planet's climate and ecological sustainability. Moreover, it represents a vital source of fresh water for human and animal populations inhabiting different geographical regions. Accordingly, the reliable monitoring, both *in situ* and remotely [1, 2], of this pivotal natural resource is essential for a wide range of environmental studies and applications [3, 4]. It generally involves the detection and analysis of variations in the morphology and composition of snow covers, and it is centred on the correct interpretation of snow spectral responses elicited by those variations.

The morphology and composition of snow covers can be affected by natural phenomena (*e.g.*, melting) and anthropogenic activities (*e.g.*, burning of biomass and fossil fuels). The latter have been receiving considerable attention in the last decades. The light-absorbing impurities originating from these activities can be wind transported far from their sources [2, 5, 6, 7]. Eventually, these aerosols (nanoparticles) may end up deposited in snow covers, altering their light attenuation mechanisms and, thus, contributing to the accentuation of a myriad of interconnected processes, from snowmelt [4, 8] and vegetation greening [9, 10] to radiative feedback loops [10, 11], with serious environmental ramifications. In this work, we focus on black carbon (BC) impurities (*e.g.*, motor vehicle aerosols) due to their strong light-absorbing capabilities and less episodic occurrence when compared to dust particles or brown carbon impurities (*e.g.*, wild fire aerosols).

The monitoring of snow covers often relies on reflectance readings obtained at the visible (VIS) and shortwave-infrared (SWIR) spectral domains [4, 12]. These readings can then be used to calculate spectral indices such as the normalized difference snow index (NDSI) [13, 14]. In the case of the NDSI, its formulation specifically considers high and low reflectance values of snow in the VIS and SWIR spectral domains, respectively, and produces values ranging from -1 to 1 [12].

The NDSI is extensively employed in the remote assessment of snow covers and in field campaigns to complement *in situ* observations of snowpacks' spatial and temporal variations [4, 15, 16]. Although relevant investigations have been carried out on its sensitivity to alterations in the morphology and composition of snowpacks (*e.g.*, [2, 14, 17, 18]), its sensitivity to the deposition of realistic amounts of BC impurities under dry and wet conditions, notably in regions where climate change effects are more accentuated (*e.g.*, the Arctic [3, 7]), remains to be comprehensively unveiled.

This knowledge gap can be partially attributed to the problems posed by relatively small (*e.g.*, below 40 ng/g [2, 7, 19]), albeit radiometrically significant, BC concentrations typically found in natural snowpacks. Also, while field experiments can be hindered by a narrow BC content variability and the difficulty of controlling other nivological parameters [16], laboratory experiments usually rely on artificially prepared snow samples whose morphological and structural characteristics may markedly differ from those normally observed in natural snow samples [20]. Although computational (*in silico*) experiments represent a viable alter-

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native to address these limitations, their predictive capabilities are bound by the level of abstraction employed to represent a complex granular material like snow [2]. Moreover, both laboratory and *in silico* experiments are often conducted considering BC concentrations substantially larger (*e.g.*, up to 1000 ng/g [18, 20]) than those found in natural snowpacks.

In this paper, we systematically investigate the impact that the deposition of realistic amounts of BC impurities can have on NDSI values calculated for representative snow samples with distinct nivological characteristics and under different water saturation states. To overcome the limitations mentioned earlier, we employ an *in silico* approach supported by measured data obtained from natural snowpacks [21]. Our investigation is carried out using a first-principles model for light interactions with snow, known as SPLITSnow (*SP*ectral *LI*ght *T*ransport in *Snow*), that explicitly accounts for its particulate nature in order to output high-fidelity radiometric data for different experimental scenarios [22]. Moreover, its original ray-optics formulation has been expanded [23] to predictively simulate light attenuation effects prompted by the deposition of carbon-based impurities in dry and wet snow samples through suspension and sedimentation processes [24].

2. INVESTIGATION FRAMEWORK

2.1. Materials

In our investigation, we considered four distinct virtual snow samples, henceforth referred to as samples I, II, III and IV. Their characterizations were based on actual snow samples from Arctic snowpacks with negligible amounts of liquid water. These samples' nivological descriptions were made available through the SISpec (Snow and Ice Spectral) library along with their respective measured reflectance curves [21]. More precisely, these samples, identified as SISpec S6, S158, S195 and S197, were respectively employed to guide the selection of plausible values (Table 1) for the parameters used in the characterization of the virtual samples I, II, III and IV. For conciseness, more detailed information about the selection of these values is provided elsewhere [9, 23].

Regarding the parameters listed in Table 1, we note that snow grains are described as prolate spheroids, with a semi-major axis equal to b and a semi-minor axis related to b by their sphericity, which varies from 0 to 1 (perfectly spherical) [22]. It has been recommended [1, 23] that the size of a snow grain should correspond to its greatest extension. Thus, we considered the size of a grain to correspond to $2b$. The grains' facetness also varies from 0 (perfectly smooth) to 1 [22].

We also remark that BC impurities can be found in the ice grains (through a sedimentation process) and/or in the samples' pore space (through a suspension process) [24]. In our simulations, we considered a BC sedimentation factor equal to 1. Furthermore, we elected to set the BC mass absorption efficiency, reference wavelength and Angstrom exponent to 16.619 m^2g^{-1}, 880 nm and 1, respectively [23].

Table 1. Parameter values employed in the characterization of the virtual snow samples considered in this investigation.

	Samples			
Parameters	**I**	**II**	**III**	**IV**
Grain size range (μm)	200–300	150–450	150–800	400–1000
Temperature ($^\circ C$)	-8	-5	-3	-1
Thickness (cm)	18	11	10	19
Density (kg/m^3)	360	385	340	300
Facetness range	0.05–0.25	0.01–0.23	0.1–0.4	0.2-0.4
Facetness mean	0.15	0.1	0.3	0.25
Facetness std. deviation	0.075	0.05	0.1	0.1
Sphericity range	0.7–0.9	0.6–0.95	0.9–0.97	0.6–0.95
Sphericity mean	0.8	0.9	0.935	0.8
Sphericity std. deviation	0.1	0.1	0.05	0.07
BC content (ng/g)	0	3	0	6

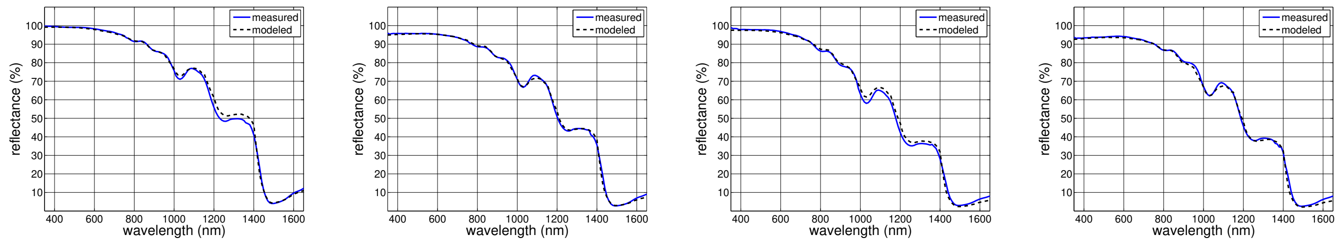
2.2. Methods

Our *in silico* experiments involved primarily the computation of reflectance curves for the selected snow samples using the SPLITSnow model [22], with its formulation expanded to account for the presence of carbon-based impurities [23]. These curves were computed considering a spectral resolution of 5 nm, with 10^6 incident rays per sampled λ and an angle of incidence equal to $0°$.

While the specified number of rays was selected to ensure asymptotically convergent reflectance values with a confidence of 0.1% [23], the angle of incidence was selected for consistency with measurement setups described in the literature. For instance, the measured reflectance curves used as references in our investigation correspond to reflectance factors calculated considering a hemispherical incidence geometry, with the acquisition sensor positioned directly above the snowpack [21]. The modeled curves, on the other hand, correspond to directional-hemispherical reflectances. We note that, in experiments involving materials characterized by a near-Lambertian reflective behaviour, such as snow irradiated from an angle of incidence of $0°$, directional-hemispherical reflectance and hemispherical-directional reflectance factor quantities can be used interchangeably [23].

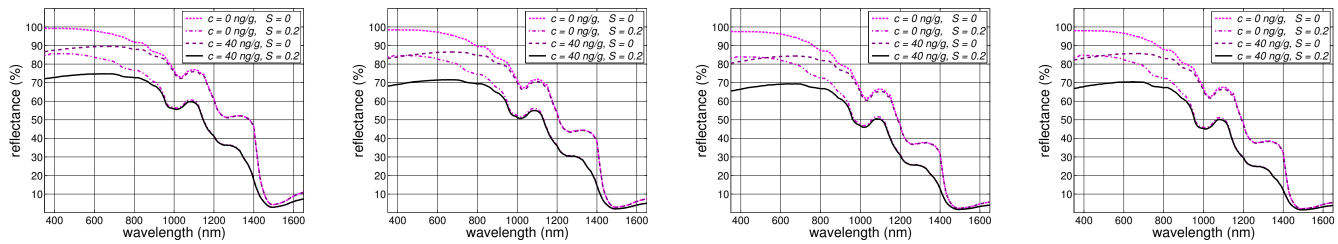
Initially, we computed the reflectance curves for the virtual samples (using the parameter values listed in Table 1) and compared them with measured radiometric data obtained for the (reference) SISpec samples [21]. This enabled us to verify the plausibility of the snow characterization datasets and to establish reliable baselines for our subsequent simulations.

These simulations were conducted to obtain the samples' reflectances as we varied their BC content and water saturation ($S \in [0..1]$ representing the fraction of the samples' pore space occupied by liquid water). More specifically, we considered BC concentrations (c) varying from 0 to 40 ng/g as reported for natural snowpacks [2, 7, 19, 24, 25], and S equal to 0 (dry state) and 0.2 (wet state) [1, 23].



(a) Sample I. (b) Sample II. (c) Sample III. (d) Sample IV.

Fig. 1. Modeled and measured reflectance curves obtained for the snow samples considered in this investigation.



(a) Sample I. (b) Sample II. (c) Sample III. (d) Sample IV.

Fig. 2. Modeled reflectance curves computed for the virtual samples using the selected boundary values for their BC concentration (c) and water saturation (S).

The computed reflectances were then employed to calculate the NDSI values (associated with each *in silico* experimental instance) using the following formula [13]:

$$\text{NDSI} = \frac{\rho(560) - \rho(1650)}{\rho(560) + \rho(1650)}, \quad (1)$$

where $\rho(\lambda)$ denotes the reflectance readings obtained at the wavelength λ (in nm). It is worth mentioning that different versions of this formula can be found in the related literature. However, as pointed out by Riggs *et al.* [12], the selection of bands for calculating NDSI values is guided by the sensor(s) being used in a given investigation, and these values are relatively insensitive to the exact location of the sampled wavelengths within the VIS and SWIR bands of interest.

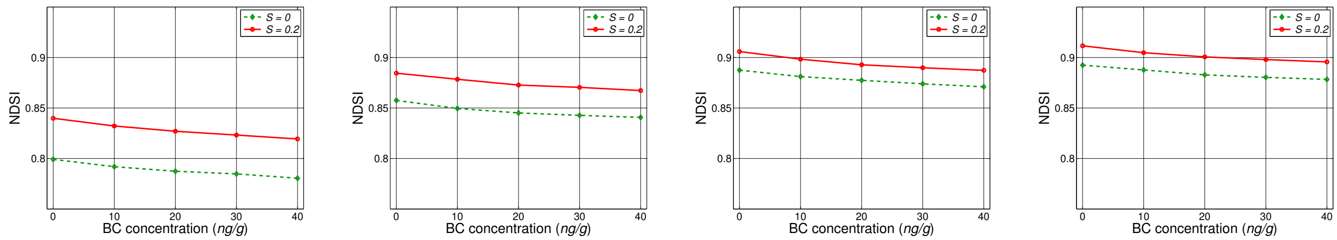
Lastly, we note that the predictive capabilities of the SPLITSnow model have been extensively evaluated through quantitative and qualitative comparisons with actual measured data and observations reported in the related literature [9, 17, 22]. The degree of fidelity of its predictions is further illustrated by the outcomes of our baseline experiments presented in the next section. As for the reproducibility of our findings, we note that the SPLITSnow model is accessible for online use [26], and all supporting datasets employed in this work are openly available in a dedicated data repository [27].

3. RESULTS AND DISCUSSION

In Fig. 1, we present quantitative comparisons between modeled reflectance curves (computed using the default parameter values listed in Table 1) with measured reflectance curves obtained for the SISpec samples [21] employed as references. One can observe a close agreement between the modeled and measured curves. This aspect is also highlighted by the relatively low root-mean-square errors calculated for the modeled curves with respect to their measured counterparts in the 350 to 1650 nm spectral region: 0.0165, 0.0095, 0.0169 and 0.0116 for samples I, II, III and IV, respectively. This level of fidelity provided a sound basis for our *in silico* experiments.

In Fig. 2, we present the graphs depicting the reflectance curves obtained for the virtual samples considering the boundary cases of our investigation, namely BC concentrations equal to 0 ng/g and 40 ng/g, and water saturations equal to 0 (dry state) and 0.2 (wet state). It can be observed that the presence of BC impurities led to a reflectance decrease in the VIS domain, and this decrease was markedly nonuniform, *i.e.*, it was less prominent for larger wavelengths within that spectral domain. On the other hand, the presence of liquid water in the samples' pore space led to a reflectance decrease in both the VIS and SWIR domains, and this decrease was relatively uniform. These observations are consistent with related analyses provided in the literature with respect to the impact of BC contamination [14, 19] and water saturation [28] on snow reflectance. We note that this aspect further strengthened the physical basis of our investigation.

In Fig. 3, we present the graphs showing the NDSI values calculated for the virtual samples considering distinct BC concentrations and water saturation states. As it can be noticed in these graphs, there was a nonlinear decrease in the NDSI values as we increased the samples' BC contents. Al-



(a) Sample I. (b) Sample II. (c) Sample III. (d) Sample IV.

Fig. 3. NDSI values calculated for the virtual samples as their BC concentration are incrementally increased and their water saturation state varied from dry ($S = 0$) to wet ($S = 0.2$).

though this reduction was observed for the samples in the dry and wet states, the NSDI values calculated for the samples in the wet state were higher than those obtained for the samples in the dry state. This observation may seem, at a first glance, counterintuitive since the reflectance values obtained for the samples in the dry state at 560 nm and 1650 nm were higher than those obtained for the samples in the wet state (Fig. 2). However, it is consistent with the nature of the normalized difference expressed in Eq 1.

Additionally, it can be verified in the graphs presented in Fig. 3 that the magnitudes of the calculated NDSI values were also correlated with the samples' grain size ranges. We remark that samples I, II, III and IV are characterized by increasingly larger grains, and their remaining nivological parameters do not follow a similar monotonic pattern (Table 1). The NDSI values calculated for each sample were lower than those calculated for the samples with larger grains considering the same BC concentration and water saturation state.

Although this connection with the samples' grain size is consistent with the strong influence of this parameter on snow spectral reflectance [29], our *in silico* results indicate that this aspect can be itself affected by variations in other nivological conditions. For instance, the NDSI values computed for sample III in a wet state (Fig. 3c) were higher than those computed for sample IV (characterized by the larger grains on average) in the dry state (Fig. 3d) considering the same level of BC contamination in both samples.

Our findings align with previous studies [14, 18] indicating that NDSI variations associated with changes in the BC concentrations of snow covers can be masked by alterations in other nivological characteristics such as grain size [14]. We note, however, that our findings also suggest that these NDSI variations can be potentially used to support differential analyses of phenomenological trends, notably those associated with processes affecting a given snowy region over a specific period of time. For instance, metamorphic processes affecting such a region would prompt a nonlinear increase in the corresponding NDSI values, while an accentuation of BC deposition would prompt a nonlinear decrease of those values (Fig. 3). Moreover, we remark that both trends remain invariant with an increase in snow water saturation, with NDSI values for wet snow being higher than those calculated for dry snow in both scenarios.

4. CONCLUSION

As it has been acknowledged in previous works, it is necessary to further the current understanding about the relationships between NDSI and environmental factors. This is essential for effectively enhancing the interpretation of data obtained from snow monitoring technologies, including ground, airborne and satellite-based platforms. Such an enhancement, in turn, can lead to more reliable predictions about the effects of BC impurities on the acceleration of ecological and climate changes tied to snow cover alterations.

In this paper, we aimed to contribute to these efforts by investigating the impact of snow-deposited BC impurities on the NDSI. The employed *in silico* approach allowed us to carry out controlled experiments considering snow samples with distinct nivological characteristics and containing typical amounts of BC impurities detected in natural settings.

More specifically, we selected BC concentrations within physically-valid ranges reported for natural snowpacks in the related literature, notably for those located in high latitude and high altitude regions more susceptible to global warming conditions. Furthermore, to increase our scope of observations, we also considered the virtual snow samples subject to dry and wet conditions. Our *in silico* findings indicated that the NDSI values decrease as (realistically) larger amounts of BC impurities are deposited in snow, and this decrease follows a nonlinear trend. Moreover, although the presence of water in the snow's pore space has a negligible effect on this qualitative trend, it increases the NDSI values' magnitude.

As future work, we intend to expand our research to other types of impurities, such as brown carbon and dust, and closely examine the effects of their distinct deposition mechanisms on the spectral responses of contaminated snow. However, we note that, although these and similar initiatives can provide valuable insights, new transformative advances in this area will greatly benefit from campaigns to increase the availability of high quality measured data, particularly considering broader ranges of deposited impurity amounts.

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