

Aggregate Effects of Density and Black Carbon Content Variations on the Hyperspectral Reflectance of Snow under Natural Conditions

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ABSTRACT

The understanding and monitoring of snow cover alterations are essential for the effective management of a diverse array of ecosystems across the planet and the predictive assessment of local and global climate changes. Besides representing vital freshwater supplies, these snow deposits can significantly contribute to heat transfer exchanges affecting the sustainability of different biomes and influencing distinct weather patterns. Accordingly, variations in the morphology and composition of snow are of pivotal relevance for applied research conducted in a broad scope of fields, from hydrology and ecology to environmental remote sensing and climatology. Due to the technical challenges posed by the intrinsic complexities of this ubiquitous granular material, the sensitivity of its radiometric responses to variations in key nivological characteristics is still not completely understood. Density is arguably one the most relevant of these characteristics, being central in the estimation of snow water equivalent quantities and in the assessment of changes in soil and vegetation processes of snowy landscapes. However, the full extent of its effects on snow radiometric responses has been largely overlooked, notably in studies involving snowpack contamination by black carbon (BC) impurities. In this work, we systematically examine its impact on the reflectance of pure and BC-contaminated snow in the visible and near-infrared spectral domains. Our investigation was carried out through controlled *in silico* experiments supported by measured data obtained from natural snowpacks. It brings forward specific spectrally-dependent trends elicited by aggregate effects of density and BC content variations on snow reflectance. Thus, our findings are expected to strengthen the knowledge foundation required for the reliable interpretation of snow radiometric responses, both *in situ* and remotely. This aspect, in turn, is indispensable for the success of inverse modeling applications aimed at detecting environmental changes, notably those leading to significant fluctuations in the freshwater yield and vegetation productivity of regions markedly affected by accentuated warming conditions.

Keywords: snow, hyperspectral reflectance, density, black carbon, environmental changes, soil and vegetation processes, predictive simulations.

1. INTRODUCTION

Snow is one of the main drivers of the planet's climate and plays a central role in the ecological sustainability of a wide range of biomes. It not only provides critical thermal insulation for subnivean species inhabiting those biomes, but it also represents an essential source of freshwater for animal and human populations worldwide. Accordingly, it has been the object of extensive interdisciplinary investigations, both *in situ* and remotely.¹ Following the aggravation of global warming conditions verified in recent years, alterations in the characteristics of snow covers, particularly those found in high latitude and high altitude regions, are increasingly attracting the scientific community's attention due to their serious environmental ramifications.²⁻⁴

The aforementioned alterations can directly affect snow radiometric responses whose correct interpretation is instrumental for the effective monitoring and assessment of snowy landscapes. This aspect emphasizes the need of advancing the current understanding about the effects of distinct nivological characteristics on snow and light interactions. However, while the impact of certain characteristics (*e.g.*, grain size) on snow radiometric responses has been extensively examined, the impact of other key characteristics still remains unclear. Among the latter, one can underscore density,⁵ a snow characteristic of focal importance for a diverse array of environmental

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studies, from the investigation of snow cover alterations leading to significant changes in soil and vegetation processes³ to the estimation of snow water equivalent quantities associated with the timing and magnitude of snowmelt runoff.⁶

This knowledge gap has been attributed to the difficulty of conducting controlled *in situ* observations in which only a single characteristic is affected/modified at the time.⁵ Often in natural settings, changes in one characteristic due to metamorphic processes are accompanied by changes in other characteristics. For instance, a snowpack subjected to melting and settling may have its density altered, and this alteration may be accompanied by changes in its grains' size. The latter are known to mask the effects of other nivological characteristics on the radiometric responses of snow.⁵

Furthermore, a snowpack may not be in a pure state, *i.e.*, it may contain impurities, such as black carbon (BC) particles (*e.g.*, originating from the incomplete combustion of fossil fuels), that can also significantly affect its radiometric responses.⁷ The detection and analysis of the occurrence of these particles represents a notorious challenge for remote sensing technologies due the relative small amounts of these impurities deposited in natural snowpacks.⁸ Alternatively, controlled laboratory experiments may be conducted using artificially prepared snow samples. However, these may lack the morphological diversity of natural samples. Moreover, these experiments often consider unrealistically large amounts of BC impurities to facilitate the detection of BC effects.

In this work, we aim to advance the knowledge in this area by systematically examining the impact of density and BC content variations on the hyperspectral reflectance of representative snow samples. To overcome the difficulties cited above, we conducted controlled *in silico* (computational) experiments considering realistic ranges for these variations. These ranges correspond to density values^{1,5,9} and BC contents^{8,10–12} reported for natural snowpacks. Our experiments were carried out using a first-principles model for light interactions with snow, known as SPLITSnow (*S*Pectral *L*ight *T*ransport in *S*now),¹³ and employing measured radiometric data obtained for real snow samples¹⁴ as baseline references. This stochastic model explicitly accounts for the particulate nature of snow in order to output reliable radiometric data for different experimental scenarios. In addition, its original ray-optics formulation has been expanded^{15,16} to predictively simulate light attenuation effects elicited by the presence of carbon-based impurities deposited in dry and wet snow samples through suspension and sedimentation processes.

2. MATERIALS AND METHODS

2.1 Snow Characterization Data

We considered two representative virtual snow samples, henceforth referred to as samples A and B, in this investigation. Their characterizations were based on two typical snow samples (from real snowpacks formed on the Norwegian Svalbard archipelago in the Arctic) whose descriptions and corresponding measured radiometric datasets were provided by Salvatori *et al.*¹⁴ and made available through the SISpec (Snow and Ice Spectral) library. More specifically, the SISpec samples S158 and S197 served as references to guide the selection of appropriate values (presented in Table 1) for the parameters employed in the characterization of the virtual samples A and B, respectively. For conciseness, more details about the selection of parameter values are provided elsewhere.^{15,16}

In our simulations, the snow grains are represented by prolate spheroids with a semi-major axis b and a semi-minor axis related to b by the grains' sphericity ($\Psi \in [0..1]$, with Ψ equal to 1 yielding perfectly spherical grains).¹³ This parameter is associated with a random variable with a probability distribution previously employed for particulate materials.¹³ It has been recommended¹ that the size of a snow grain should correspond to its greatest extension. Thus, in our simulations, the size of a grain corresponds to $2b$, with b represented by a random variable with a uniform probability that allows for a configurable range. Similarly, the grains' facetness ($f \in [0..1]$), with f equal to zero yielding perfectly smooth grains) is associated with a random variable with a normal probability distribution.¹³

The virtual samples, like their real counterparts, are assumed to be in a dry state. Accordingly, their water saturation (fraction of the samples' pore space occupied by liquid water) was set to zero. It is also worth mentioning that the polar location of the real samples was susceptible to a relatively low BC contamination. This aspect

was taken into account in the selection of default values for their BC contents, along with BC concentration ranges reported for snowpacks located in high latitude regions.^{8,11} Furthermore, we note that BC impurities can be found in the ice grains (through a sedimentation process) and/or in the pore space (through a suspension process).^{11,16} In our simulations, we considered a BC sedimentation factor equal to 1. Lastly, we elected to set the BC mass absorption efficiency, reference wavelength and Angstrom exponent to $16.619 \text{ m}^2\text{g}^{-1}$, 888 nm and 1, respectively.^{15,16}

Table 1: Parameter values employed in the characterization of the virtual snow samples A and B.

Snow Parameters	Samples	
	A	B
Grain size range (μm)	150–450	400–1000
Temperature ($^{\circ}\text{C}$)	-5	-1
Thickness (cm)	11	19
Density (kg/m^3)	385	300
Facetness range	0.01–0.23	0.2–0.4
Facetness mean	0.1	0.3
Facetness standard deviation	0.05	0.1
Sphericity range	0.6–0.95	0.6–0.95
Sphericity mean	0.9	0.8
Sphericity standard deviation	0.1	0.07
Black carbon content (ng/g)	3	6

2.2 In Silico Experimental Setup

Our controlled *in silico* experiments consisted primarily in the computation of directional-hemispherical reflectance curves for the selected snow samples using the SPLITSnow model,¹³ with its formulation expanded to account for the presence of carbon-based impurities.^{15,16} These curves were computed considering a spectral resolution of 5 nm , with 10^6 incident rays per sampled λ . This number of rays was selected to ensure asymptotically convergent radiometric readings with a confidence of 0.1% as indicated by the exponential Chebyshev inequality.¹⁷ Regarding the light incidence geometry, we considered a normal angle of incidence of 0° (with respect to the samples' normal vector). As briefly described below, this choice took into account the measured conditions in which the reference radiometric datasets were obtained.

The measured reflectance curves¹⁴ correspond to reflectance factors calculated considering a hemispherical incidence geometry, with an acquisition sensor positioned directly above the target snowpacks. The modeled reflectance curves, on the other hand, correspond to directional-hemispherical reflectances. We note that in studies involving the radiometric responses of materials characterized by a near-Lambertian behaviour, such as snow irradiated from an angle of incidence of 0° ,¹⁸ for practical purposes directional-hemispherical reflectance and hemispherical-directional reflectance factor can be used interchangeably.¹⁹

Initially, we compared the modeled reflectance curves computed for samples A and B (considering the default parameter values provided in Table 1) with measured radiometric data obtained for the SISpec samples.¹⁴ This enabled us to verify the plausibility of the snow characterization datasets and to establish reliable baselines for our *in silico* experiments.

Subsequently, we conducted simulations to assess the aggregated effects of density and BC content (concentration) variations on the reflectance of the selected samples under natural conditions. To represent these conditions, we considered densities^{1,5,9} (D equal to 150, 300 and $450 \text{ kg}/\text{m}^3$) and BC concentrations^{8,10–12} (c equal to 0, 10, 20 and $30 \text{ ng}/\text{g}$) reported for natural snowpacks in the corresponding cited works.

Finally, we note that the predictive capabilities of the SPLITSnow model employed in our experiments have been extensively evaluated through quantitative and qualitative comparisons with actual measured data and observations reported in the related literature.^{13,16,20} Also, the degree of fidelity²¹ of its predictions is further illustrated in our baseline experiments (Section 3). As for the reproducibility of our findings, we also note that

we made SPLITSnow accessible for online use (Fig. 1) through our model distribution system.^{22,23} Furthermore, all supporting datasets, such as the spectral refractive indices for water and ice, employed in this work are openly available in a dedicated data repository.²⁴

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SPLITSnow

Spectral Light Transport Model for Snow

(Spectrometric Mode*)

The SPLITSnow model employs a Monte Carlo formulation to simulate light interaction with snow. Light propagated within the medium is scattered or absorbed by particles along its path which are generated on-the-fly during the simulation process and are subsequently discarded. For more details about this model, please refer to our related publication (2021).

The default parameters (on the right) correspond to measured and estimated values for the representative snow sample measured by Dumont (2010). The spectral input data files for ice considered by the online SPLITSnow model are available here. BRDF outputs can be obtained using the model's gonimetric mode of this website.

Additional Notes

- In lieu of measured data for snow grain sphericity that may be employed to restrict inputs to valid ranges, we have elected to allow a wide range of input values for snow grain sphericity. Please note that some combinations of sphericity parameters may produce unexpected results.
- The density of ice is dependent upon ice temperature. The sample density and ice density are then used compute the porosity of the sample. The porosity, in turn, is employed in the computation of the snow grain spacing. For more details and references, please refer to our related publication (2021).
- Note that the water saturation parameter represents a fraction of the pore space, and not a fraction of the total volume or total mass.

The code for this version was last updated and compiled on February 2020.

Run SPLITSnow Online

Enter your email address: petri.varsa@gmail.com

(used to send the results)

Model Parameter

Value

Number of samples

100000

Spectral interval

10nm

Wavelength range

400-2500nm

Angle of incidence

0°

Sample Properties

Grain size

300-750µm

Temperature

-1°C

Thickness

12cm

Water saturation

0.05

Density

275kg/m³

Black (Inorganic) Carbon Properties

Mass Absorption Efficiency

16.619m²/g

Reference Wavelength

880nm

Angstrom Exponent

1

Content

0ng/g

Sedimentation Fraction

1

Brown (Organic) Carbon Properties

Mass Absorption Efficiency

16.619m²/g

Reference Wavelength

880nm

Angstrom Exponent

2

Content

0ng/g

Sedimentation Fraction

1

Grain Facetness

Facetness range

0.2-0.4

Mean

0.3

Standard deviation

0.072

Grain Sphericity

Sphericity range

0.6-0.95

Mean

0.798

Standard deviation

0.064

Submit Query

Logout

Logging out will take you back to this model's sign-in page, where you will have the opportunity to request access to more models.

Created using [proud](#)

Figure 1: Screenshot of the web interface deployed to enable the use of SPLITSnow model in simulations of light interactions with snow samples that may contain carbon-based impurities.²³

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3. RESULTS AND DISCUSSION

As it can be observed in Fig. 2, the reflectance curves computed for the snow samples considered in this investigation showed a close agreement with their measured counterparts. Also, the root-mean-square errors calculated for the modeled curves obtained for samples A (Fig. 2a) and B (Fig. 2b) were equal to 0.0128 (or 1.28%) and 0.0112 (or 1.12%), respectively. These aspects reiterated the plausibility of the snow characterization datasets (Table 1) used in our simulations and provided a high-fidelity basis for our subsequent *in silico* experiments.

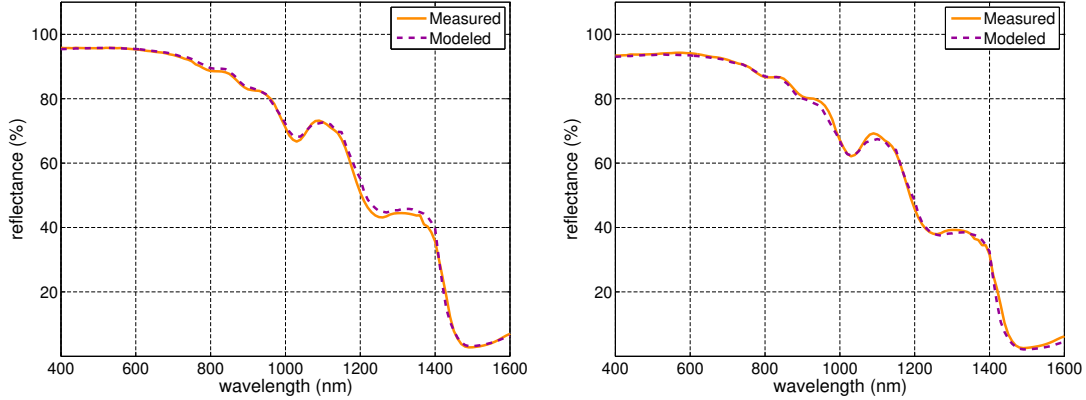


Figure 2: Comparison of measured and modeled reflectance curves obtained for samples A (left) and B (right).

In Fig. 3, we present the reflectance curves obtained for the selected samples considering variations in their densities and the absence of BC impurities. As indicated in these curves, the density increase resulted in higher reflectance values in the visible domain (from 400 to 700 nm) and lower values in the near-infrared domain (from 700 to 1400 nm). Beyond 1400 nm, the differences among the reflectance curves associated with the distinct densities were negligible.

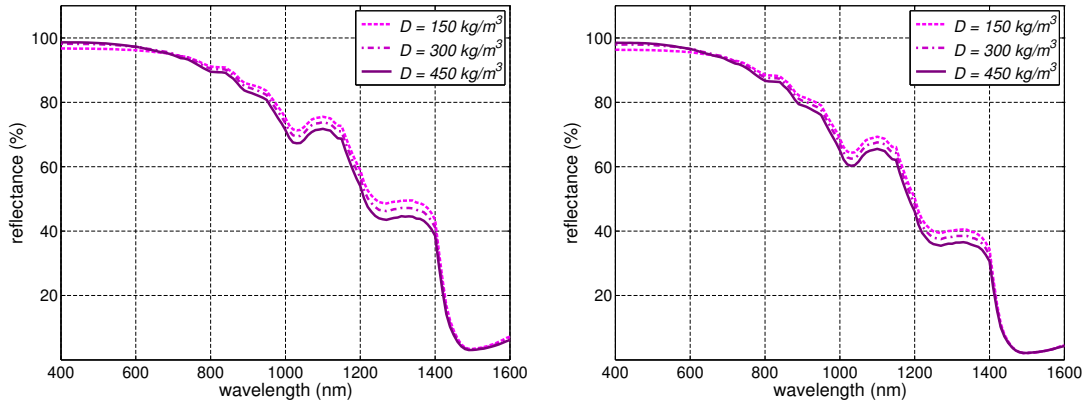


Figure 3: Reflectance curves computed for samples A (left) and B (right) considering increasing densities (D) and no black carbon content.

These trends are consistent with empirical observations made by Bohren and Beschta⁹ indicating that the average reflectance (across the visible and infrared domains) of an “old”, high-density snowpack (D varying from 300 to 450 kg/m^3) was lower than that of a “new”, low-density snowpack (D varying from 50 to 200 kg/m^3). As pointed out by Perovich,⁵ such *in situ* observations may be biased by accompanying alterations of other snow characteristics such as grain size. We remark that the samples’ distinct grain sizes were kept fixed in our *in silico* experiments.

In Fig. 4, we present the graphs depicting the reflectance curves obtained for the selected samples considering variations in their densities and BC contents. As expected,⁸ the increasing BC presence resulted in lower reflectance curves in the visible domain. Interestingly, as it can also be observed in these graphs, the accompanying density increases markedly contributed to further decrease the reflectance values in the visible domain, with the differences among the reflectance curves associated with distinct densities increasing as larger BC contents were considered. These trends are consistent with the stronger light absorption properties of BC impurities in this spectral domain.⁷

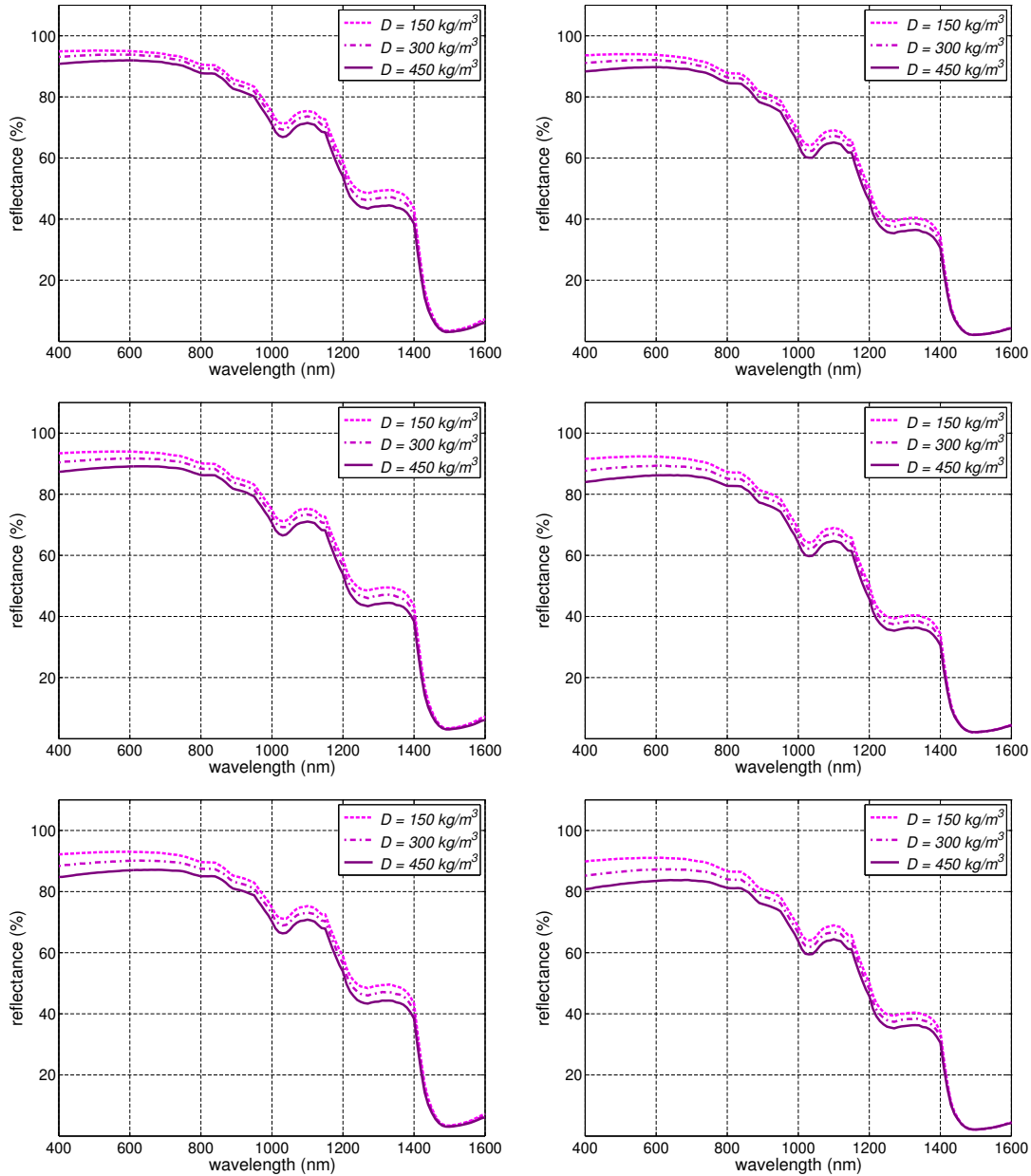


Figure 4: Reflectance curves computed for samples A (left column) and B (right column) considering increasing densities (D) and varying black carbon concentrations: 10 ng/g (top row), 20 ng/g (middle row) and 30 ng/g (bottom row).

For the near-infrared domain and beyond, the general trend depicted in Fig. 4 was the same as the trend verified for the absence of BC impurities (Fig. 3), *i.e.*, the density increase also resulted in lower reflectance values. Furthermore, up to ≈ 1000 nm, the differences among the reflectance curves associated with distinct densities became more pronounced as larger BC contents were considered, while the differences remained practically the same beyond that point. These trends are consistent with the progressively weaker light absorption properties of BC impurities in the near-infrared domain.⁷

In our previous controlled *in silico* experiments, whose outcomes are presented in Fig. 4, we incrementally increased the densities and BC contents of the selected samples. For illustrative purposes, we present in Fig. 5 reflectance curves that correspond to asymmetric combinations of these characteristics (*e.g.*, lower density and higher BC concentration) that may be brought about by episodic events such a snow fall in a region more susceptible to the deposition of aeolian-transported BC particles. As it can be observed in these curves, although the presence of BC impurities contributes to maintain the same density and reflectance dependence in the visible and near-infrared domains reported earlier, the decrease in reflectance prompted by the density increase may also occur even when accompanied by a decrease in the BC content. This behaviour highlights the need of taking into account the aggregated effects of these two nivological variables when interpreting changes in snow reflectance responses elicited by them.

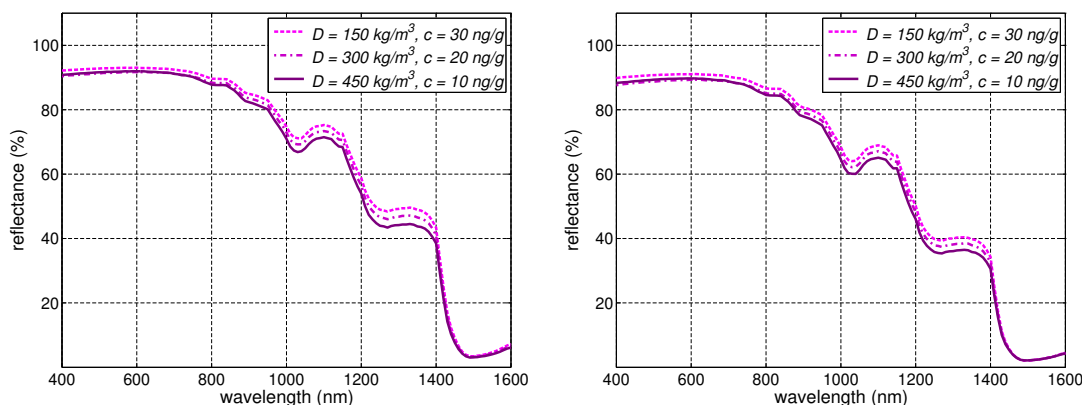


Figure 5: Reflectance curves computed for samples A (left) and B (right) considering distinct combinations of densities (D) and black carbon concentrations (c).

4. CONCLUDING REMARKS

Several factors, such as adverse warming conditions and anthropogenic activities (*e.g.*, burning of fossil fuels), are affecting snow covers of critical importance for the planet's environmental sustainability. To reliably address this situation, notably with the use of remote sensing technologies, it is necessary to correctly detect and analyze snow hyperspectral responses to changes in its morphology and composition that may be elicited by those factors. Such changes include the focal point of our investigation, combined variations in snow density and BC content, which have been largely overlooked in the related literature to date.

Employing an *in silico* experimental framework supported by measured data, we were able to overcome technical limitations in this area. This, in turn, enabled us to unveil qualitative and quantitative trends with respect to the effects of these variations on snow reflectance in visible and near-infrared spectral domains. As future work, we intend to extend the scope of our investigation. More specifically, we plan to study the impact of these combined density and BC content variations on the light penetration depth (LPD) of dry and wet snow covers. We note that the detailed assessment of LPD alterations can enhance the efficacy of applied research initiatives with relevant ecological and economical implications. These initiatives can range from the analysis of subnivean vegetation development patterns²⁰ to the prediction of avalanche conditions.²⁵

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