

Research papers

Retrieving snow water equivalent from GRACE/GRACE-FO terrestrial water storage anomalies using modified spectral combination theory

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ABSTRACT

Snow Water Equivalent (SWE) refers to the quantity of water contained within the snowpack, which is a critical component of the seasonal water cycle in cold regions, notably Canada. The Gravity Recovery and Climate Experiment (GRACE) mission primarily focuses on quantifying Terrestrial Water Storage Anomalies (TWSA), which is the sum of anomalies in groundwater, soil moisture, surface water, and snow/ice. Separating the individual components with high precision is a challenging task due to the complex interactions of these parameters and their uncertainties involved. This study proposes an enhanced estimator which is modified based on the spectral combination theory, to extract the SWE component from GRACE/GRACE-FO (Follow-On) TWS measurements. This estimator uses a hydrological model and its uncertainty to optimally extract the SWE component from the GRACE monthly models in spectral domain. The approach was applied in eight selected basins across Canada, covering a diverse range of climatic and geographical conditions. Different winter seasons of each basin were considered, including the peak accumulation and ablation phases of the snowpack, from January 2003 to the end of 2022. Among the basins examined, the Fraser-Lower Mainland and Ottawa basins exhibited the most pronounced seasonal variations in SWE, with maximum value of about 200 mm. In contrast, the Saint John-St basin demonstrated the lowest SWE variability, with maximum amount of 50 mm. All the studied basins across Canada except for Okanagan-Similkameen basin and Saint John-St basin displayed a positive trend in SWE. The results from the proposed approach were compared to the SWE component derived from Canadian Historical Snow Water Equivalent dataset (CanSWE), Canadian Meteorological Centre (CMC), and GlobSnow. Varying levels of agreement were found depending on the basins (correlations between $r = 0.40$ and $r = 0.83$, and RMSE between 10 mm and 55 mm). The best agreements were found with CMC and CanSWE products. The inclusion of streamflow component highlighted the relationship between maximum SWE and the peak flow. The results found indicate significant correlations between SWE derived from our modified spectral combination approach and peak flow in several basins (r varying from 0.42 to 0.80); thus emphasizing the critical role of snowmelt in influencing peak flows in the basins.

1. Introduction

Snowpack is one of the most important freshwater resources in high latitude regions. Snow water equivalent (SWE) is the equivalent quantity of liquid water stored within the snowpack. SWE is an essential climate variable (Pulliainen et al., 2020), with useful applications in different areas such as flood forecasting, water resources management,

hydropower production, climate change, wildlife habitats, and agriculture (Ryan, 2024; Schilling et al., 2024; Taheri and Mohammadian, 2022; Tsang et al., 2022; Yang et al., 2020). SWE has spatial and temporal variations, which depend on climate regime, topography, forest cover, landscape, and geology (Liljestrand et al., 2024; Zhong et al., 2021).

There are various approaches to estimate and analyze changes in

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SWE, each with distinct benefits and drawbacks. Ground-based measurements such as snow gauges, snow pillars, and snow cores have been widely used in meteorological and hydrological networks to provide direct SWE data (Ma et al., 2024; Stuefer et al., 2020). These instruments provide highly accurate SWE measurements at specific locations, however, they have drawbacks due to their limited spatial coverage, labor-intensive setup and restricted accessibility. In fact, these measurements are point-based and may not represent the variability of SWE across larger areas. Moreover, they require frequent maintenance and human intervention, especially in harsh environments (Stuefer et al., 2020). Additionally, ground-based observations may be sparse in remote or mountainous regions, limiting their effectiveness in large-scale snow assessments.

Hydrological and land surface models (e.g., GLDAS, FLDAS, WaterGAP) simulate SWE changes by incorporating snow accumulation, melting, and other snow dynamics using meteorological inputs like temperature, precipitation, and radiation (Sun et al., 2024; Dong, 2018). They can be used to predict future changes in SWE based on climate change projections, however, they have drawbacks due to model uncertainty and data dependency on input data quality (Bian et al., 2019). In fact, Models rely on assumptions and parameterizations, which may introduce significant uncertainties (Panchanathan et al., 2024). Furthermore, model calibration and validation remain challenging, particularly in data-scarce regions where independent validation datasets are unavailable (Smyth et al., 2020).

Remote sensing techniques utilize satellite-based instruments to estimate SWE at regional or global scales. Commonly used sensors include passive microwave radiometers (e.g., AMSR-E, SSM/I), radar (e.g., Sentinel-1), and lidar (e.g., ICESat-2) (Yang et al., 2022; Luo et al., 2021; Bair et al., 2019). While these techniques offer benefits such as wide spatial coverage and continuous temporal monitoring, they also have limitations, including moderate accuracy, coarse resolution, and reduced sensitivity to deep snowpacks (Rittger et al., 2021; Bair et al., 2018). Specifically, passive microwave sensors perform poorly in boreal forest regions and in areas where snowpacks are deep or wet (Niu et al., 2007). These limitations present significant challenges for SWE estimation when considering that a significant portion of the world's boreal zone lies in Canada (about 28 %), stretching from Newfoundland to the Yukon-Alaska border, with 75 % of Canada's forests and woodlands located in this zone. Given these factors, relying on passive microwave data for SWE estimation in our study area is not ideal (Bahrami et al., 2020).

Recent technologies like satellite gravimetry have become invaluable tools for estimating SWE, offering distinct advantages over traditional methods. Unlike remote sensing techniques such as passive microwave or radar, which estimate SWE by inferring physical characteristics of snow like depth, reflectance, or emissivity, Gravity Recover and Climate Experiment (GRACE) uses a mass-based approach (Khorrami et al., 2023; Merkouriadi et al., 2021; Mortimer et al., 2020). This method bypasses the need for assumptions about snow density, a key factor that can introduce uncertainties in other techniques. GRACE is particularly well-suited for regional to continental-scale assessments, providing comprehensive insights into total snow mass across large areas, which is crucial for understanding water availability on a broad scale (Fatolazadeh and Goita, 2021; Tapley et al., 2019). Additionally, its ability to measure changes in SWE in remote and inaccessible areas without requiring ground-based data collection offers a significant advantage for researchers, making it a powerful tool in snow and water resource management (Cowherd et al., 2024; Faquseh and Grossi, 2024).

Despite these advancements, there remains a significant research gap in accurately estimating SWE using satellite gravimetry, particularly in regions with complex hydrological and topographical conditions. Previous studies have demonstrated the potential of GRACE for SWE estimation, but challenges remain in optimizing its retrieval methods, improving spatial resolution, and validating results against independent datasets.

Ramillien et al. (2005) used linear combinations of climate models to separate spherical harmonic coefficients of GRACE geoids and estimate SWE from GRACE observations, though the accuracy and reliability of the inversion method remained a challenge. Frappart et al. (2006) applied a similar approach to compute snow mass from GRACE, obtaining reliable results in high-latitude zones with significant snow accumulation, particularly in Northwest Canada. Niu et al. (2007) employed a more straightforward method to estimate snow storage by subtracting land surface model estimates of soil moisture storage, surface water, canopy water storage, and groundwater from GRACE-derived total terrestrial water storage (TWS), finding it more accurate than microwave retrievals in deep snow regions. Swenson (2010) compared GRACE TWS with accumulated precipitation in cold regions from satellite-gauge analyses, observing similarities in eastern Canada and along the Rocky Mountains, but significant differences in central Canada, which increased at higher latitudes. Seo et al. (2010) applied the same method in the Arctic, while Mudryk et al. (2015) examined spatial and temporal SWE variability across the Northern Hemisphere from 1981 to 2010, identifying a negative winter SWE trend and a strong correlation among SWE observations in boreal forests compared to Arctic and alpine regions.

Wang and Russell (2016), Wang et al. (2017) used a mass balance approach to estimate SWE from GRACE and peak river flow in the Mackenzie River basin, concluding that snow significantly influences peak flows in southern Canadian basins, with their snow estimates approximately 20 % higher than Global Land Data Assimilation System (GLDAS) data. Behrangi et al. (2017, 2018) applied a mass balance equation to estimate accumulated precipitation from GRACE in High Mountain Asia, finding high agreement with other products in summer but deviations in winter due to errors in the products. Trautmann et al. (2018) assessed the contribution of hydrological variables to GRACE TWS patterns in northern mid- to high-latitude humid regions, showing that seasonal TWS is dominated by snowpacks in winter, while soil moisture drives interannual TWS variations.

Robinson and Clark (2020) combined GRACE water balance data with evaporation and river discharge estimates, revealing that satellite microwave measurements overestimate snowfall in four large Arctic basins. Qian et al. (2020) found that snow cover accounts for a large proportion of TWS in winter in Northeast China, with strong consistency between GRACE and other data from December to March. In a recent study, Singh et al. (2022) explored the relationship between GRACE-derived snow cover variations and climate variables in a Himalayan catchment, demonstrating that snow cover is more sensitive to temperature changes than to precipitation. Colombo et al. (2022) analyzed long-term SWE variability in the Italian Alps, concluding that SWE trends are closely linked to precipitation variability, particularly in the southern Alpine region. Recently, Khorrami & Gündüz (2023) analyzed the spatio-temporal variations of hydrological dynamics of TWS and GWS over the basins of Türkiye and found that the SWE is significant over the eastern basins of the country.

Building upon these prior works, this study aims to enhance SWE estimation using a modified spectral combination approach (Sjöberg, 1980, 1981) with an improved estimator, addressing key limitations in previous methodologies. Specifically, we seek to (1) refine GRACE/GRACE-FO-derived SWE estimates by incorporating an advanced retrieval method, (2) assess SWE variations across different Canadian basins, and (3) investigate the relationship between SWE and stream-flow dynamics during snow cover seasons. By addressing these research gaps, this study provides new insights into the accuracy and applicability of gravimetric methods for SWE estimation in high-latitude regions.

2. Case study

SWE is of great importance in Canada, where extensive areas experience substantial snow accumulation (Fang and Pomeroy, 2023; Kouki

et al., 2022). Winter months in the Canadian southern regions typically span from December to February, whereas in northern and mountainous regions, winter conditions can begin as early as October and extend into May or June. Coastal regions, particularly along the Pacific coast, tend to have milder winters with more rain than snow (Lv et al., 2019). Canada is characterized by numerous drainage regions basins with distinct climatic and topographic settings that influence SWE accumulation and melt.

This study focuses on eight distinct basins, each exhibiting unique hydrological characteristics influenced by topography, climate, and land use (Fig. 1). These basins were selected to represent a diverse range of hydro-climatic conditions across Canada, allowing for a comprehensive analysis of SWE variations in different geographic settings. The selection includes basins from coastal, interior, mountainous, and subarctic regions, ensuring that the findings are applicable to a wide range of environments. Additionally, these basins cover areas with varying degrees of SWE accumulation, snowmelt dynamics, and hydrological influences, making them ideal for evaluating the effectiveness of our SWE estimation approach. SWE has a direct impact on the hydrology of these Canadian basins, as the timing and volume of snowmelt significantly affect river flows, groundwater recharge, and water availability for both ecosystems and human use (Fontrodona-Bach et al., 2023; Dibike et al.,

2021). Information on the Canadian basins can be found in different sources, including for example MacKay and Pedersen, 2022. Below is an overview of how SWE influences the specific basins selected:

The Fraser-Lower Mainland Basin in British Columbia is shaped by a maritime climate with mild, wet winters and heavy snowfall at higher elevations. The coastal mountains dominate the landscape, with forested terrain, urban areas, and agricultural land. SWE accumulation in these mountains regulates river flows, supporting agriculture, municipal water supply, and hydropower.

In contrast, the Okanagan-Similkameen Basin, also in British Columbia, is situated in a semi-arid interior region with valley terrain surrounded by highlands. It experiences lower snowfall accumulation, but SWE remains a crucial water source for irrigation and drinking supplies. Snowmelt from the surrounding highlands dictates seasonal water availability, making it vital for local agriculture and water management.

The Columbia Basin, spanning British Columbia and Alberta, is a mountainous region dominated by the Rocky Mountains. It experiences a continental climate with cold, snowy winters and steep, rugged topography covered by dense forests and alpine tundra. SWE plays a crucial role in hydroelectric generation and water supply, as snowmelt from the high-altitude regions contributes significantly to river

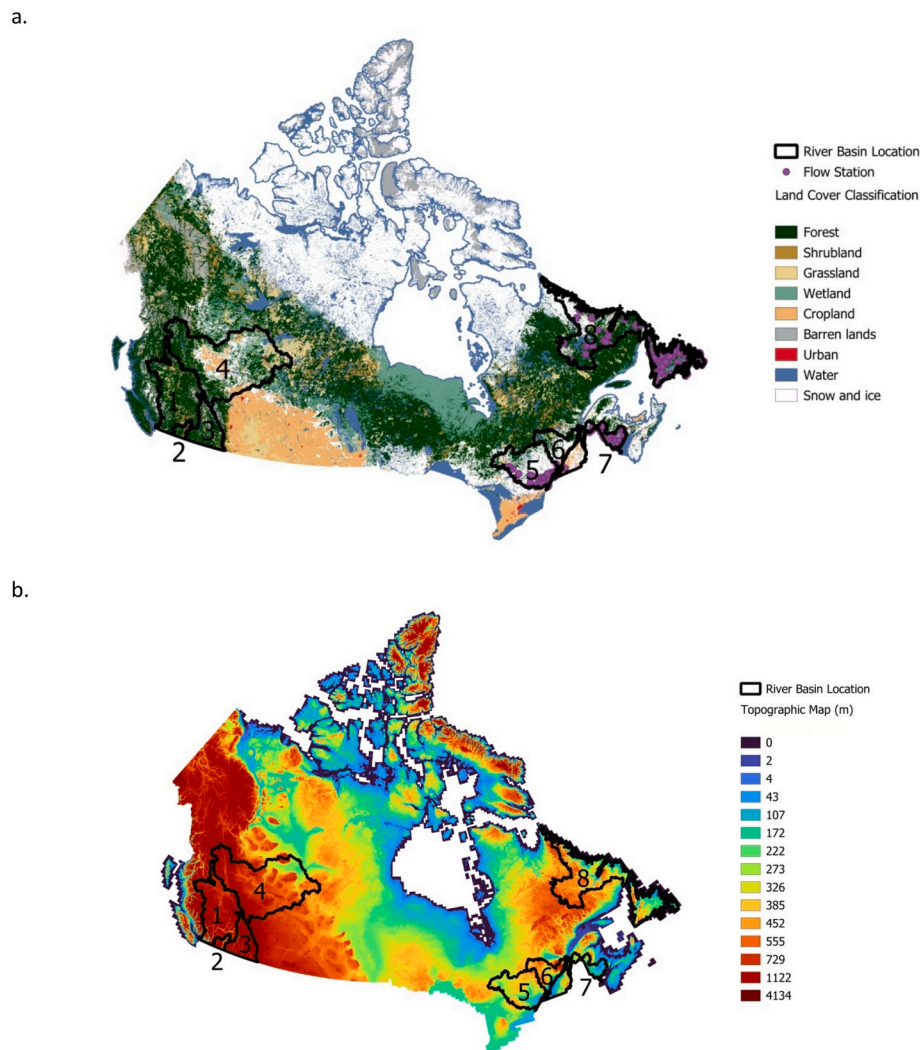


Fig. 1. A. the land cover map of the eight Canadian river basins (1: fraser-lower mainland, 2: okanagan-similkameen, 3: columbia, 4: peace-athabasca, 5: ottawa, 6: st. lawrence, 7: saint john-st. and 8: newfoundland-labrador). the red points show the in-situ flow used in this study. b. the topography map of the aforementioned eight Canadian river basins. (modified from data provided by the national resources Canada, containing information licensed under the open government licence –Canada.). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

discharge.

Further north, the Peace-Athabasca Basin, located in Alberta and the Northwest Territories, falls within a subarctic climate zone, experiencing long, cold winters and substantial snowfall. The basin's landscape consists of boreal forests, wetlands, and tundra, with a vast network of rivers and lakes. SWE-driven snowmelt sustains the Mackenzie River system, which is crucial for local ecosystems, Indigenous communities, and regional water balance.

The Ottawa Basin, covering parts of Ontario and Quebec, is influenced by a humid continental climate with cold winters and moderate to high snowfall. Its landscape includes rolling hills, river valleys, mixed forests, urban centres, and agricultural land. The seasonal SWE accumulation plays a key role in spring snowmelt, contributing to flood risks and water management strategies in the region.

The St. Lawrence Basin, extending from Quebec to Atlantic Canada, has a maritime-continental transition climate with moderate snowfall. The basin consists of forested regions, wetlands, and urbanized areas, with lowland plains and river corridors shaping the terrain. SWE accumulation influences seasonal river discharge, affecting fisheries, shipping, and regional hydrology.

The Saint John-St. Croix Basin in New Brunswick is characterized by a humid maritime climate, with moderate snowfall and rolling hills influenced by coastal weather patterns. Land cover includes mixed forests, agricultural land, and urban areas. Snowmelt impacts river levels, flood management, and overall water resources, making SWE an important factor in seasonal water availability.

Lastly, the Newfoundland-Labrador Basin experiences a subarctic-maritime climate, with heavy snowfall in northern regions and variable accumulation elsewhere. The landscape consists of boreal forests, tundra, and wetlands, with a rugged coastline and interior plateaus. SWE accumulation and subsequent snowmelt significantly influence river discharge, hydrology, and water resource availability across the region.

3. Data and data processing

In this study, we utilized the GRACE/GRACE-FO monthly gravity estimates, specifically the spherical harmonic coefficients up to degree and order 60 (RL-06), which were released by the University of Texas Center for Space Research (UTCSR) (Ince et al., 2019). The monthly temporal resolution of the data was used in this study. Moreover, the original spatial resolution of data is 3 degrees, however, it could be increased based on maximum degree of spherical harmonic coefficient used in calculation. As our interest was to derive SWE variations at finer scales, we downsampled the data to 0.25 degrees based on the spectral combination approach elaborated in Fatolazadeh et al. (2022). The focus was on the snow cover seasons, spanning from 2003 to end of 2022. To ensure the reliability of the data, we performed various pre-processing. These steps included replacing degrees 1 and 2, addressing leakage errors, accounting for the glacial isostatic adjustment (GIA) effect, and correcting the de-stripping error. The purpose of these pre-processing steps was to obtain refined TWS data, which were subsequently used in our analysis. For more detailed information on pre-processing, please refer to the study by Fatolazadeh and Goïta (2022).

Hydrological variables including soil moisture storage (SMS), SWE, canopy water storage (CWS), groundwater Storage (GWS), and TWS were derived from the Catchment Land Surface Model (CLSM) L4 daily $0.25^\circ \times 0.25^\circ$ (GLDAS_CLSM025_DA1_D 2.2) dataset. These variables were obtained from the latest version of the Global Land Data Assimilation System (GLDAS) (Rodell et al., 2004). The same winter months and period as the GRACE/GRACE-FO data were considered for consistency. Among the available GLDAS models, the Catchment L4 V2.2 was chosen because it provides both the groundwater storage (GWS) component, which contributes significantly to the total water storage, and the TWS component (Ali et al., 2023; Li et al., 2019). The daily

components from the GLDAS dataset were resampled to monthly averages to match the temporal resolution of the GRACE/GRACE-FO data.

In order to find the snow cover seasons, we utilized data of Freeze/Thaw Earth System Data Record (FT-ESDR), spanning from 2003 to 2020. This record was primarily derived using similar calibrated overlapping daily [morning (AM) and afternoon (PM) overpass] radiometric brightness temperature (Tb) measurements at 37 GHz (V-pol) frequency from the Scanning 3 Multichannel Microwave Radiometer (SMMR), the Advanced Microwave Scanning Radiometer for EOS (AMSR-E), the Advanced Microwave Scanning Radiometer 2 (AMSR2), Special Sensor Microwave Imager (SSM/I), and SSM/I Sounder (SSMIS) sensor series (Kim et al., 2023). Satellite ascending and descending orbital data time series are processed separately to produce information on morning (AM), afternoon (PM) and composite daily FT conditions (CO). Additional variables distinguished by the FT-ESDR include transitional (AM frozen and PM thawed) or inverse transitional (AM thawed and PM frozen) conditions. We used the latest version (V5.1) which effectively replaces earlier product releases (Kim et al., 2023). The Version 5.1 FT-ESDR release is developed by merging SMMR and SSM/I(S) 37 GHz vertically (V) polarized Tb records, and applying similar protocols used to construct earlier FTESDR product versions (Kim et al., 2023; Kim et al., 2021; Kim et al., 2017). The geographical range of the FT-ESDR product is global, extending from -179.99 degrees to 179.99 degrees' longitude and from -86.7167 degrees to 86.7167 degrees' latitude. The FT-ESDR data are available for public access via FTP download through the FT-ESDR project web site (<https://freezethaw.nts.gov.umt.edu>) and NTSG HTTP Data Service (https://files.nts.gov.umt.edu/data/FT_ESDR/), and through the NASA DAAC at the National Snow and Ice Data Center (<http://nsidc.org/data/nsidc-0477.html>).

Monthly mean in-situ flow hydrometric data were obtained from the Water Survey of Canada's HYDAT database. These data provide information on river flow rates at various monitoring stations across 4 basins. Approximately 433 active flow hydrometric observations were used from the same months as the previous data sources, spanning from January 2003 to July 2020. However, it is worth noting that there were some gaps in the available flow data for certain months. To address this issue, a linear interpolation method was employed to fill in the missing values and ensure a more complete dataset (Niedzielski and Halicki, 2023). As the gaps are assumed to be linear and short-term, the interpolation was performed in the temporal domain, filling in missing monthly flow data over time.

SWE data considered in this study come from different sources. We used multiple sources of SWE data to ensure a robust and comprehensive validation of our proposed approach. Each dataset offers unique strengths that complement one another. First, we used in-situ pan-Canadian measurements of SWE from the Canadian historical SWE dataset (CanSWE) to validate the results obtained from both the theoretical and mass balance parts of our research. The CanSWE dataset is a compilation of SWE measurements from 15 different sources and provides information on SWE across all provinces and territories in Canada (Vionnet et al., 2021). These measurements were obtained from around 100 different locations across 8 basins in Canada, and they cover the same snow cover period mentioned earlier, from January 2003 to July 2020. However, similar to the flow hydrometric data, some gaps exist in CanSWE data for certain months. The same linear interpolation was performed to be consistent with other datasets.

The second source of SWE data used in the comparison/validation of our proposed approach is the Canadian Meteorological Centre (CMC) SWE product, which can be accessed through the National Snow and Ice Data Center (NSIDC) website. CMC SWE data is derived by combining ground-based observations, remote sensing techniques, numerical weather prediction models, and model simulations (Verseghy and MacKay, 2017; Brown and Brasnett, 2010). We used Version 01.2 monthly data from January 2003 to end of 2020 at spatial resolution of 0.25 degrees, to be consistent with the other datasets considered.

Finally, GlobSnow SWE, a well-know satellite-based product was

also used. This product was developed through assimilation of in-situ measurements from weather stations and other sources in a physically-based passive microwave emission model (Pulliainen et al., 2020). GlobSnow data are publicly available on various platforms. We extracted monthly aggregated SWE (V3.0, L3B) from NSIDC website. These data cover the period from 2003 to mid-2018, at a spatial resolution of 0.25 degrees.

4. Methods

The methodological approach of this study follows a step-by-step process that is summarized in Fig. 2. First, we determined the snow cover seasons to identify months where SWE estimation is meaningful. Next, we enhanced the SWE estimator by modifying the spectral combination of GRACE and GLDAS data while incorporating uncertainty quantification. Next, we estimated the uncertainty for each hydrological parameter, including SWE, and integrated these uncertainties to improve SWE estimation and downscaling. The approach was then validated using three independent SWE datasets. Finally, we investigated a mass balance approach to analyze the relationship between SWE and streamflow during winter seasons.

4.1. Modified spectral combination estimator for downscaling and separation of SWE from the GRACE/GRACE-FO models

We can enhance a SWE estimator in spectral domain to extract the SWE height from TWS estimated from the GRACE/GRACE-FO gravity estimates. By minimizing the mean-squares error of the estimator, the

spectral coefficients of the estimator are estimated. Let us write this estimator in the following form:

$$T_n^{SWE,G} = \sum_{n=0}^N (a_n k_n + b_n) \bar{T}_n^{TWS,G} = \sum_{n=0}^N (a_n k_n + b_n) \sum_{m=-n}^n \bar{T}_{nm}^{TWS,G} Y_{nm}(\theta, \lambda) \quad (1)$$

where a_n and b_n are respectively, the degree-scale and degree-shift spectral coefficients, $\bar{T}_{nm}^{TWS,G}$ is the spherical harmonic coefficients of degree n and order m of the TWS estimated from the monthly GRACE models, $Y_{nm}(\theta, \lambda)$ is the spherical harmonic functions with arguments of co-latitude and longitude. k_n is the convertor or the spectrum of the ratio of the monthly SWE and monthly TWS of hydrological models like GLDAS $k_n = \left(\frac{T_n^{SWE,H}}{T_n^{TWS,H}} \right)_n$. In order to have the estimator unbiased to $T_n^{SWE,G}$, the following constraint should be applied.

$$b_n = (1 - a_n) k_n \quad (2)$$

In order to estimate the spectra coefficients, the RMS of Eq. (1) should be minimized. By taking the derivative with respect to a_n we obtain:

$$\frac{\partial RMS}{\partial a_n} = ((2a_n - 1) k_n^2 (c_n^{TWS,G} + \sigma_n^G) + a_n \sigma_n^k c_n^{TWS,G}) = 0 \quad (3)$$

Solution of Eq. (3) for a_n is:

$$a_n = \frac{k_n^2 (c_n^{TWS,G} + \sigma_n^G)}{2k_n^2 (c_n^{TWS,G} + \sigma_n^G) + \sigma_n^k c_n^{TWS,G}} \quad (4)$$

and by inserting it in Eq. (2), we obtain:

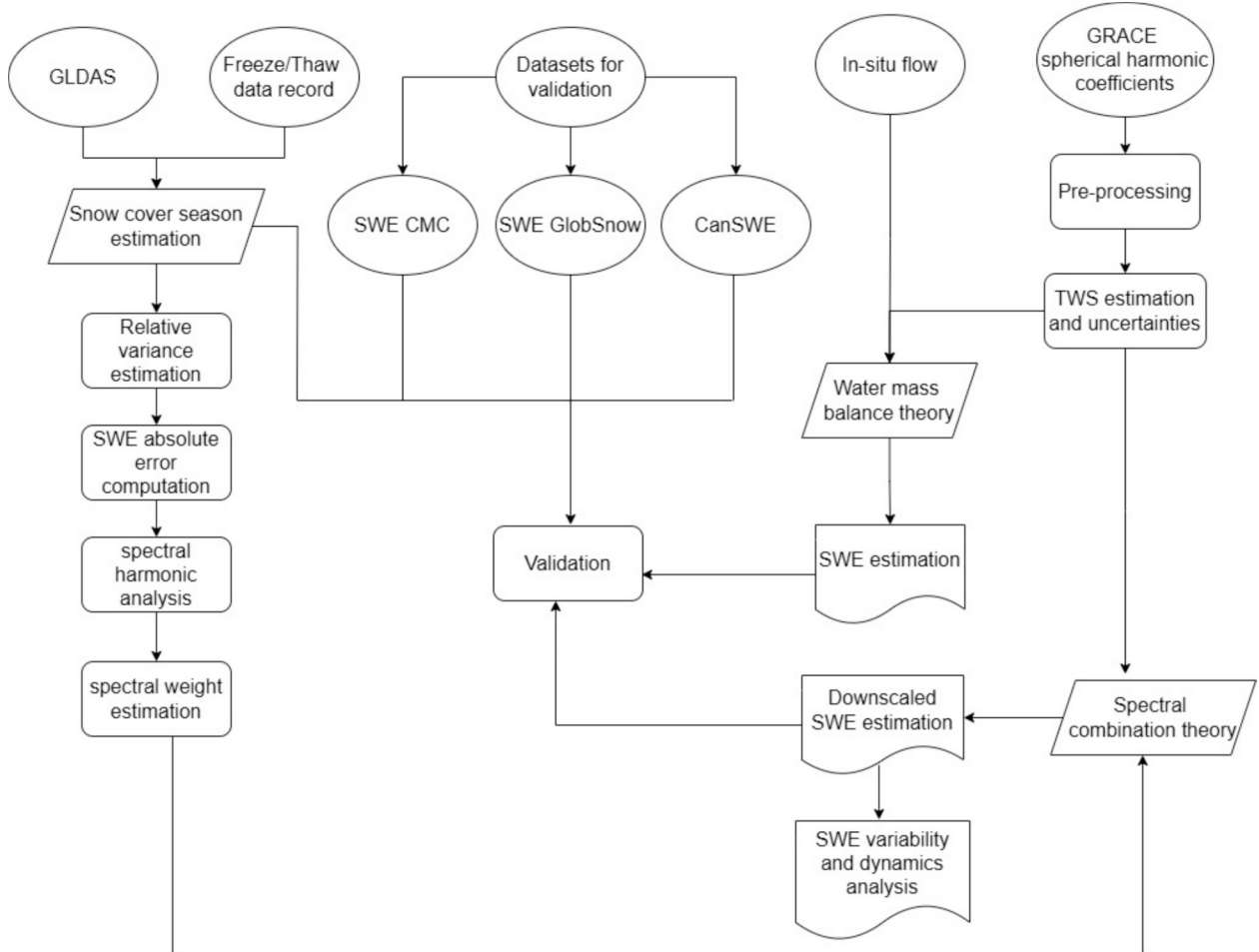


Fig. 2. Technical flowchart of this study.

$$b_n = \left(1 - \frac{k_n^2 (c_n^{TWS,G} + \sigma_n^G)}{2k_n^2 (c_n^{TWS,G} + \sigma_n^G) + \sigma_n^k c_n^{TWS,G}} \right) k_n \quad (5)$$

where $c_n^{TWS,G} = M\{\bar{T}_n^{TWS,G} \bar{T}_n^{TWS,G}\}$, and $\sigma_n^G = M\{\varepsilon_n^G \varepsilon_n^G\}$ and $\sigma_n^k = M\{\varepsilon_n \varepsilon_n\}$ with

$$M\{\cdot\} = \frac{1}{4\pi} \iint_{\Omega} E\{\cdot\} d\Omega \quad (6)$$

Ω stands for the unit sphere and $d\Omega$ the surface integration element, $E\{\cdot\}$ stands for statistical expectations, and ε_n and ε_n^G are the error spectra of k_n and $\bar{T}_n^{TWS,G}$, respectively. The challenging practice is to estimate σ_n^k . We rewrite k_n formula in the following form:

$$k_n = \frac{T_n^{SWE}}{\bar{T}_n^{TWS}} \quad (7)$$

According to the error propagation law of the random errors the variance of k_n is:

$$\sigma_n^k = \sum_i \left(\frac{\partial k}{\partial T_n^i} \right)^2 \sigma_{T_n^i}^2 \quad (8)$$

$i = \text{SWE, SMS, CWS, Surface Water (SW) and GWS.}$

In the case of taking derivative with respect to T_n^{SWE} , the solution of would be:

$$\sigma_n^k = \left(\frac{\bar{T}_n^{TWS,H} - T_n^{SWE}}{(\bar{T}_n^{TWS,H})^2} \right)^2 \sigma_{T_n^{SWE}}^2 + \sum_i \left(\frac{-T_n^i}{n(\bar{T}_n^{TWS,H})^2} \right)^2 \sigma_{T_n^i}^2 \approx \frac{\sigma_{T_n^{SWE}}^2}{|\bar{T}_n^{TWS,H}|} \quad (9)$$

In Eq. (9), $\sigma_{T_n^{SWE}}^2$ represents the variance of SWE, which is estimated using the methodology proposed by Eshagh et al. (2023). This method focuses on quantifying the uncertainties of hydrological parameters involved in the spectral combination of the GLDAS and GRACE/GRACE-FO models. Precisely, we applied the water balance equation as a condition adjustment model, and later estimating the uncertainty of each hydrological parameter, including SWE, relative to their magnitude. Specifically, the variance equation is used as an additional condition for estimating the relative error of each parameter (Eshagh et al., 2023). By considering the magnitudes or weights of these parameters, the method provides a more reliable estimation of the absolute uncertainties, resulting in more accurate and realistic results.

$$T^{SMS} + T^{SWE} + T^{CWS} + T^{GWS} + T^{SW} - T^{TWS} = c \quad (10)$$

T^{SMS} , T^{SWE} , T^{CWS} , T^{GWS} , T^{SW} , and T^{TWS} represent the observation vectors for SMS, SWE, CWS, GWS, SW, TWS, respectively, while c denotes a constant value.

In theory, $c = 0$, however, it is not 0 due to presence of error. Let us write Eq. (10) in the following matrix form:

$$\mathbf{B}(\mathbf{L} + \mathbf{v}) = \mathbf{w} \quad E\{\mathbf{v}\} = 0 \quad \text{and}$$

$$E\{\mathbf{v}\mathbf{v}^T\} = \sigma_0^2 \mathbf{Q} = \sigma_0^2 \text{diag}(\sigma_{T^{SMS}}^2, \sigma_{T^{SWE}}^2, \sigma_{T^{CWS}}^2, \sigma_{T^{GWS}}^2, \sigma_{T^{SW}}^2, \sigma_{T^{TWS}}^2) \quad (11)$$

where σ shows the errors of each parameter.

$$\mathbf{B} = \begin{bmatrix} 1 & 1 & 1 & 1 & 1 & -1 \end{bmatrix}, \quad \mathbf{L} = \begin{bmatrix} T^{SMS} & T^{SWE} & T^{CWS} & T^{GWS} \\ T^{SW} & T^{TWS} \end{bmatrix}^T \quad \text{and}$$

$$\mathbf{w} = c - \mathbf{B}\mathbf{L} \quad (12)$$

The posteriori variance factor is:

$$\hat{\sigma}_0^2 = \mathbf{w}^T (\mathbf{B}\mathbf{Q}\mathbf{B}^T)^{-1} \mathbf{w} \quad (13)$$

We rearrange the Eq. (13) with the relative uncertainties of each

parameter:

$$\begin{aligned} & \bar{\sigma}_{T^{SMS}}^2 (T^{SMS})^2 + \bar{\sigma}_{T^{SWE}}^2 (T^{SWE})^2 + \bar{\sigma}_{T^{CWS}}^2 (T^{CWS})^2 + \bar{\sigma}_{T^{GWS}}^2 (T^{GWS})^2 + \bar{\sigma}_{T^{SW}}^2 (T^{SW})^2 \\ & + \bar{\sigma}_{T^{TWS}}^2 (T^{TWS})^2 = \frac{w^2}{\hat{\sigma}_0^2} \end{aligned} \quad (14)$$

This is a new system of equations with the relative uncertainties as the unknowns. Note that the vector $\mathbf{w}$ has only one element, therefore, we can simply use the variable w . We use least-squares method to solve Eq. (14) as a matrix form:

$$\sigma_{T^i} = \frac{(T^i)^2 |w|}{\hat{\sigma}_0 \sqrt{\sum_{i=1}^6 (T^i)^4}}, \quad i = \text{SMS, SWE, CWS, GWS, SW and TWS} \quad (15)$$

which σ_{T^i} is the estimated uncertainty for each hydrological parameter, based on its magnitude and misclosure w .

4.2. Validation of the approach

SWE variations that were acquired from various in-situ CanSWE observations, located in all the eight basins, were used to validate the results of SWE variations that were extracted from TWS GRACE using the proposed procedure. The observations in the CanSWE that were considered are provided on a daily basis. However, they were converted to monthly means to make them comparable with other data that were used in the study. Due to unavailability of CanSWE up to present, validation was done for the period between 2003 and mid-2020. For the validation of the results that were obtained, we considered various statistical metrics, including the Pearson product-moment correlation coefficient (r), Root-Mean-Square Error (RMSE), and Mean Absolute Error (MAE).

Moreover, we performed additional comparisons with two other data references to illustrate the success of the proposed approach. Hence, we compared the estimated monthly SWE variations to respectively monthly CMC, and GlobSnow over the period from 2003 to mid-2020 to be consistent with other validation dataset. Furthermore, given the non-stationary behaviour of the time series data, we applied the Cross Wavelet Transform (XWT) to assess their relationships. Unlike traditional approaches such as Fourier analysis, XWT provides insights into both the magnitude of correlation and phase differences between two time series, while also identifying periods of shared power within the time-frequency domain. The Cross Wavelet Transform (XWT) of two time series $x(t)$ and $y(t)$ is defined as:

$$W_n^{xy}(s) = W_n^x(s) \cdot (W_n^y(s))^* \quad (16)$$

where $W_n^x(s)$ and $W_n^y(s)$ are the continuous wavelet transforms of $x(t)$ and $y(t)$, respectively, s is the scale (related to frequency), n is the time index, and $*$ denotes the complex conjugate. The cross wavelet power is given by $|W_n^{xy}(s)|$, representing the shared power between the time series.

To further explore localized correlation and interaction, we employed Wavelet Coherence (WTC), which measures the normalized correlation between two time series in the time-frequency domain. It is defined as:

$$R_n^2(s) = \frac{|S(s^{-1} W_n^{xy}(s))|^2}{S(s^{-1} |W_n^x(s)|^2) \cdot S(s^{-1} |W_n^y(s)|^2)} \quad (17)$$

where S denotes a smoothing operator in both time and scale. The resulting coherence values range from 0 to 1, indicating the strength of correlation, with values closer to 1 representing a stronger relationship.

For this analysis, the Morlet wavelet was selected due to its well-balanced resolution in both time and frequency (Grinsted et al.,

2004). All wavelet analyses were conducted at a 5% significance level to ensure statistical robustness.

4.3. Analysis of SWE variability and dynamics

In this section, we present a comprehensive analysis and a detailed assessment of the robustness of SWE variations, following validation the estimator using independent datasets. First, we computed the signal-to-noise ratio (SNR) of SWE changes, which allows for the identification of areas where the estimated SWE changes are statistically significant and distinguishable from background variability. By focusing on regions with a high SNR, we ensure that the observed changes reflect meaningful variations in SWE, aiding in the identification of critical regions for hydrological and climate-related impacts. Then, Annual variations in SWE were analyzed to capture year-to-year changes in snowpack across different basins. This aspect of the analysis is vital for understanding the interannual variability of snow storage and its influence on hydrological systems, water availability, and snowmelt-driven processes. By examining the year-to-year dynamics, we can better understand how snowpack responds to climatic shifts and provide insights into potential changes in seasonal water supply. Finally, beyond annual variability, a more granular analysis was conducted to investigate seasonal, interannual, and long-term trends in SWE across the selected basins. By combining these analytical approaches, we not only validate the robustness of the spectral combination method for SWE estimation but also provide a detailed understanding of SWE dynamics across multiple time scales and regions.

4.4. Mass balance approach to find a linkage with SWE

For a watershed in winter, the relationship between SWE, streamflow, and TWS follows the mass balance of (Wang et al., 2017):

$$\text{SWE} = \text{TWS} + \text{Streamflow} \quad (18)$$

This mass conservation approach assumes the land surface is covered fully by snow so there is no water loss through soil evaporation. Note that SWE is the net snow accumulation resulted from precipitation in the snow form and snow sublimation. When soil surface is present, soil evaporation would lead to the underestimation of SWE. Fortunately, soil surface at high latitude in winter is usually frozen and soil evaporation is very low. In vast part of Canada, the mid-winter soil evaporation is mostly under a few millimeters per month (Wang et al., 2013). Also, in winter, when snow cover and frozen soil dominate, plant transpiration is significantly reduced and can be considered negligible. While transpiration is not exactly zero, it is minimal due to the dormancy of vegetation and limited water availability (Liu et al., 2023).

Streamflow is the only hydroclimate variable that can be truly measured to represent a region. The other variables such as weather from stations, groundwater from wells, remote sensing SWE or snow tracks are generally localized and cannot give a clear portrait of a region without some mathematical generalizations. With the high accuracy of streamflow measurements (about 95 %), the mass balance approach theoretically should be a much more reliable method for accurately retrieving SWE (Cui et al., 2023; Levin et al., 2023; Wang et al., 2021).

4.5. Snow cover season estimation

To accurately estimate SWE variations across different basins in Canada, it is essential to determine the snow cover season for each basin. The snow season defines the period during which snow accumulation and melt occur. Given the diverse geographical locations of the basins, their snow seasons may vary significantly. Establishing a reliable method to define the snow season ensures that SWE changes are evaluated during the appropriate period, minimizing errors due to irrelevant or non-snow-related data.

To do so, we employed a combination of two approaches to estimate

the snow cover season: the freeze-thaw (FT) status from the FT-ESDR dataset and the continuity of SWE data from the GLDAS model. The FT-ESDR dataset provides freeze-thaw information at each pixel, classified into four distinct conditions: frozen (both AM and PM satellite overpasses are frozen), thawed/non-frozen (both AM and PM overpasses are thawed), transitional (AM is frozen and PM is thawed), and inverse transitional (AM is thawed and PM is frozen). Our primary focus was on the frozen condition, as it indicates the likelihood of snow accumulation.

However, the transitional states present a challenge, as they indicate periods where soil may be partially frozen, but snow cover may not be consistently present. To address this, we performed an additional analysis based on the SWE data from GLDAS to refine the identification of snow seasons. Specifically, the snow season was determined by when the SWE values from GLDAS remained consistently above zero. Normally, SWE is zero during non-snow seasons and positive during winter months, but there can be exceptions, such as in winter months with frozen soil but without significant snow accumulation.

To further refine the determination of snow seasons, we implemented a threshold-based approach. We established that a month could be considered part of the snow season if the SWE value remained above 10 mm for more than 14 consecutive days within the month. This threshold ensures that transient or minimal snow events do not incorrectly classify a month as part of the snow season. It also accounts for the stability of snow cover, as the presence of snow for a sustained period likely correlates with a frozen ground state, providing a more reliable indicator of the snow season.

5. Results

5.1. Results of snow season determination

In estimating the snow cover season for each basin, we noted that due to different climate and landscape conditions across Canada, snow cover season extents may vary from basin to basin. Therefore, we proposed a methodology (See Section 4.5) to determine the number of snow season months for each basin between 2003 and end of 2022 (period of 240 months in total). The results are summarized in Table 1. As it can be seen, the basins have variable number of snow months, from a maximum of 159 in Newfoundland-Labrador basin to a minimum of 76 in Ottawa basin.

5.2. Results of SWE estimation using the modified spectral combination

In our development of the modified spectral combination estimator, we also provided a concise summary of the uncertainties associated with each GLDAS hydrological parameters. The uncertainties of SWE GLDAS are crucial for the application of spectral combination theory, as minimizing them can lead to improved estimations of SWE from GRACE/GRACE-FO observations. Fig. 3 illustrates the time series of SWE error derived from the GLDAS model across the 8 basins in Canada during their winter period spanning from 2003 to 2022. The shadowed areas represent the range between the minimum and maximum uncertainty values within each basin.

The analysis reveals that on average, the uncertainties were

Table 1
Number of snow season months out of the 240 months of the period 2003–2022.

Name of the basin	Number of snow season months
Fraser-Lower Mainland	142
Okanagan-Similkameen	93
Columbia	145
Peace-Athabasca	135
Ottawa	76
St. Lawrence	83
Saint John-St. Croix	78
Newfoundland-Labrador	159

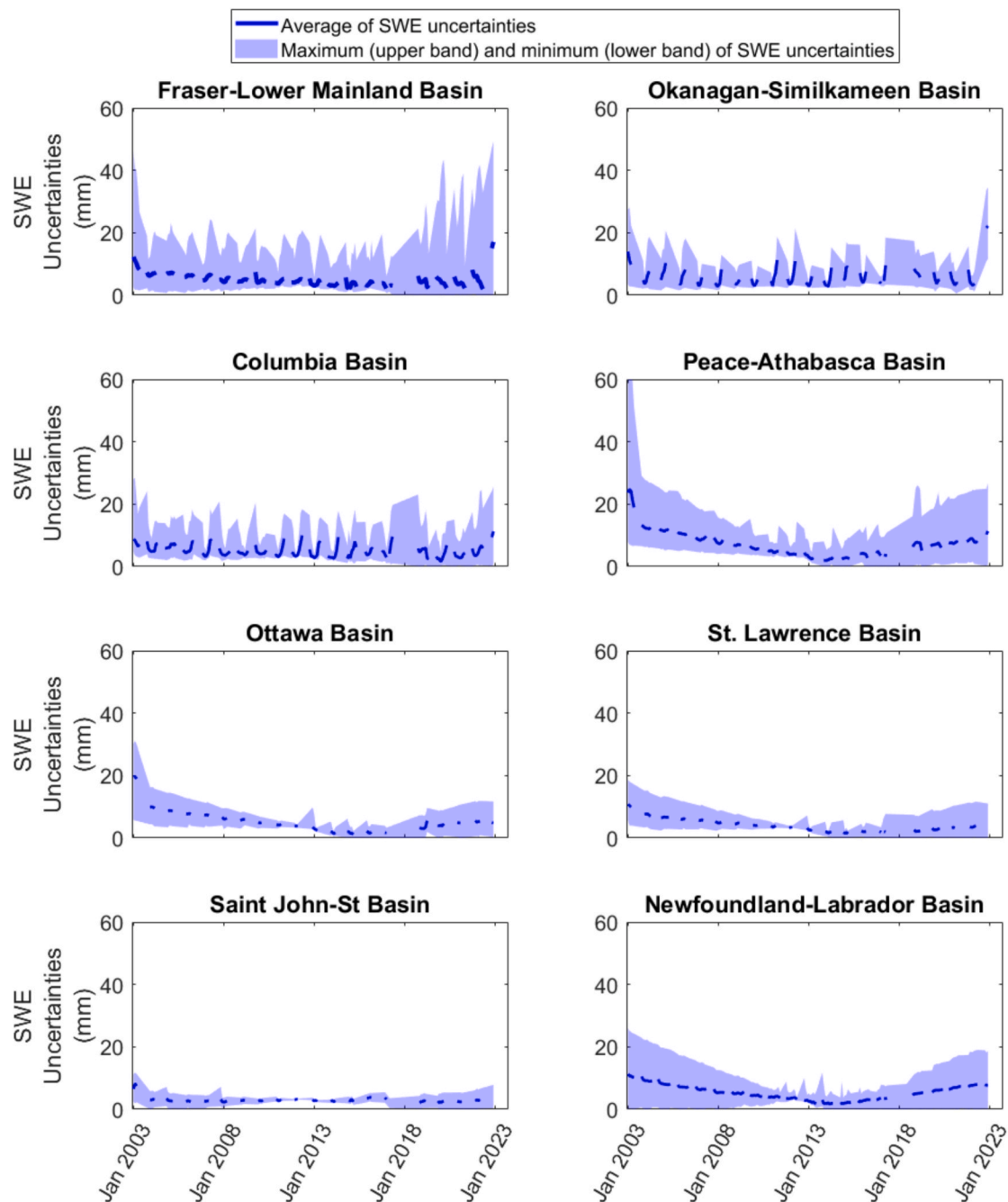


Fig. 3. Time series of calculated SWE GLDAS uncertainties. Blue dash line represents the mean values. Shaded areas represent the maximum (Upper line) and minimum (Lower line) SWE GLDAS uncertainties range. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

approximately 5 mm for Fraser-Lower Mainland, 6 mm for Okanagan-Similkameen, 5 mm for Columbia, 7 mm for Peace-Athabasca, 5 mm for Ottawa, 4 mm for St. Lawrence, 3 mm for Saint John-St. Croix, and 5 mm for Newfoundland-Labrador. In terms of minimum uncertainties, many of the basins exhibited their lowest error values around the middle of the study period, particularly around 2014. For instance, Peace-Athabasca, Ottawa, St. Lawrence, and Newfoundland-Labrador showed a consistent pattern where uncertainties decreased from initial high values (~20 mm) to as low as 2 mm by 2014. Conversely, the maximum uncertainties were typically observed at the start and end of the time series, where errors reached extreme values of approximately 20 mm. This pattern was particularly evident in the Peace-Athabasca, Ottawa, St. Lawrence, and Newfoundland-Labrador basins. For the

remaining basins, such as Fraser-Lower Mainland and Okanagan-Similkameen, fluctuations in uncertainty were more apparent throughout the time series, with no clear pattern of consistently high or low values.

Fig. 4 shows the average spatial location of SWE GLDAS uncertainties in the eight basins. The results indicate maximum uncertainties in Peace-Athabasca (about 15 mm) across its northeastern part. Similarly, significant errors were noted in the southern region of the Fraser-Lower Mainland basin and the western part of the Newfoundland-Labrador basin, where uncertainties were around 12 mm. Despite these localized areas of high uncertainty, the minimum errors across all basins were relatively low, averaging around 3 mm. Notably, the Saint John-St. Croix basin exhibited no significant variation between its maximum and

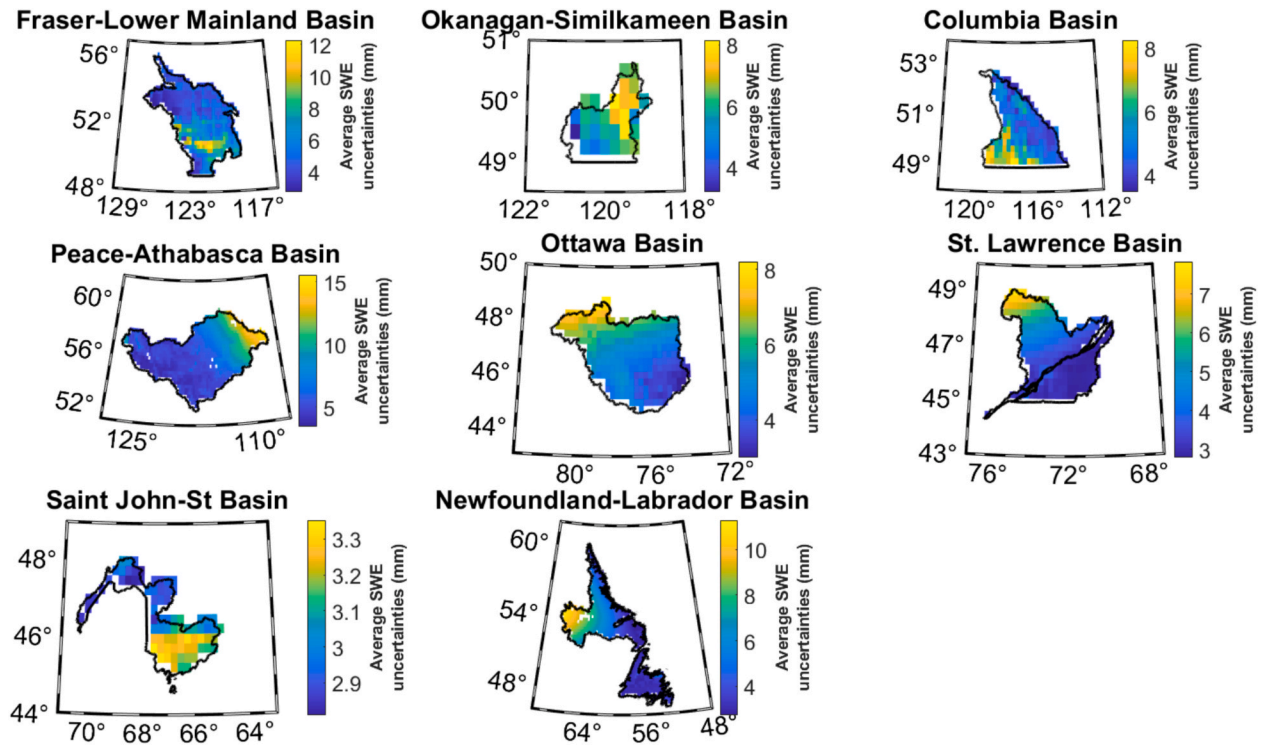


Fig. 4. Spatial map of calculated mean SWE GLDAS uncertainties (in unit of mm).

minimum errors, maintaining a consistent uncertainty level throughout.

Through enhancements to the spectral combination estimator, we improved its ability to separate and estimate SWE from total TWS measured by GRACE/GRACE-FO. We computed the spatial map of average SWE changes from 2003 to 2022. As an illustrative example, Fig. 5 presents these variations for the month of January. To generate

this map, we calculated the temporal variation in SWE for each January between 2003 and 2022 by determining the difference between the SWE values for each January and the average SWE over the entire period. These January variations were then averaged to produce a single representative map for the month, offering a clear spatial visualization of SWE changes across different basins. To ensure that the derived SWE

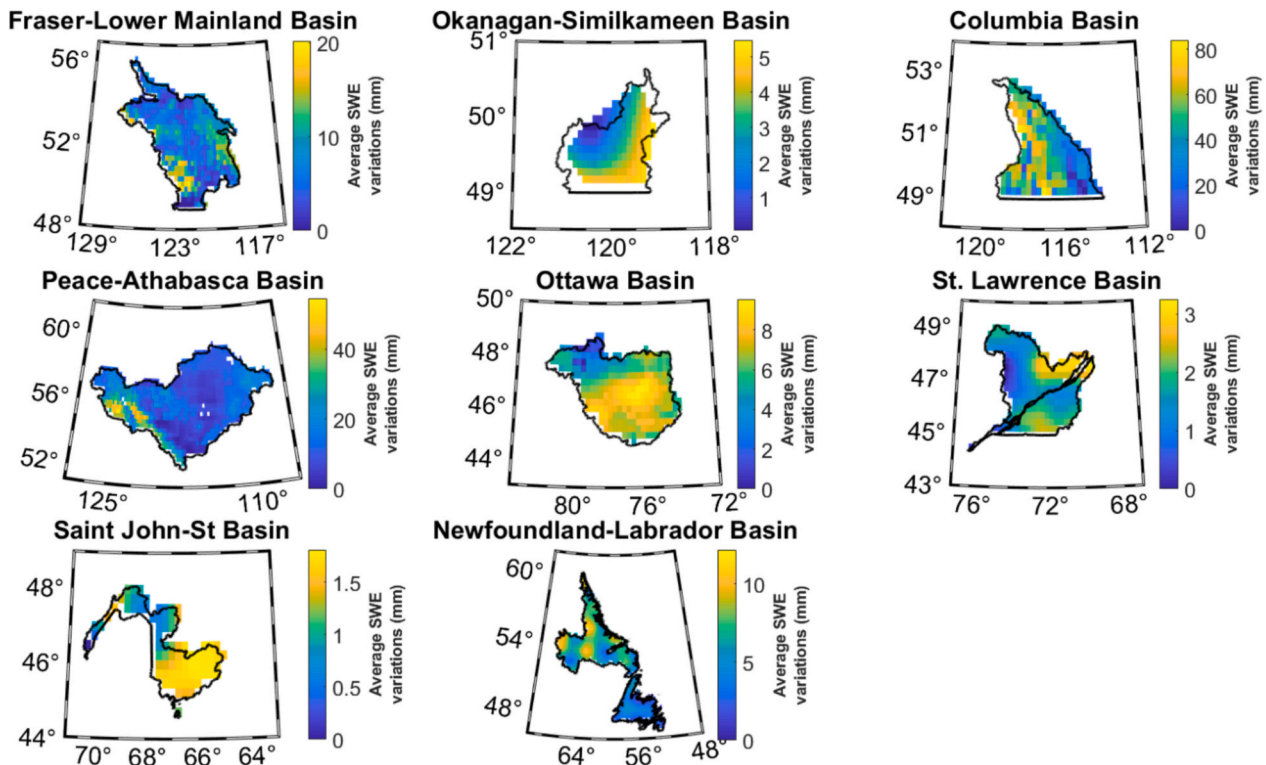


Fig. 5. Spatial map of average SWE changes in January from 2003 to 2022 (in unit of mm).

values remained positive, we added the minimum SWE value to the anomalies. This adjustment allowed us to represent the absolute SWE values while maintaining the relative variations observed in the anomalies.

The results reveal significant geographical disparities in SWE changes. The maximum SWE changes were observed in the western part of the Columbia basin, with increases reaching approximately 80 mm. Similarly, the western portion of the Peace-Athabasca basin exhibited notable SWE changes of around 50 mm. In contrast, the smallest SWE variations occurred in the Saint John-St. Croix, St. Lawrence, and Okanagan-Similkameen basins, where changes were consistently below 5 mm.

5.3. Results of SWE validation

In the data section, we discussed CanSWE observations across eight river basins to validate the results of SWE variations obtained from our proposed SWE estimator. These observations served as the primary benchmark for assessing the accuracy and reliability of our derived SWE estimates. Additionally, we discussed SWE data from the CMC and GlobSnow datasets to evaluate their consistency with our SWE estimator, helping identify which dataset aligns more closely with our results.

Table 2 presents the statistical metrics, including Pearson correlation coefficients, RMSE, and MAE, for these comparisons. Overall, our approach showed a strong agreement with both CMC and CanSWE, while GlobSnow consistently displayed the weakest performance. Specifically, the correlations between SWE variations derived from our approach and CanSWE were above $r = 0.55$ for all basins (except Saint John-St), with the highest correlation in the Fraser-Lower Mainland basin ($r = 0.73$). GlobSnow correlations ranged from $r = 0.37$ to $r = 0.77$, while CMC correlations were generally higher, varying between $r = 0.60$ in the Newfoundland-Labrador basin and $r = 0.83$ in the Peace-Athabasca basin. The only exception for CMC was the Okanagan-Similkameen basin, where the correlation was lower ($r = 0.46$).

Table 2

Correlation, RMSE, and MAE between SWE from our approach vs. CanSWE, GlobSnow, and CMC. All correlations are statistically significant at the 95% confidence level ($P < 0.05$).

Basin	SPECTRAL COMBINATION VERSUS:		
	CanSWE	GlobSnow	CMC
Correlation			
Fraser-Lower Mainland	0.73	0.50	0.68
Okanagan-Similkameen	0.72	0.60	0.46
Columbia	0.67	0.45	0.71
Peace-Athabasca	0.65	0.64	0.83
Ottawa	0.64	0.50	0.64
St. Lawrence	0.62	0.48	0.72
Saint John-St. Croix	0.28	0.77	0.79
Newfoundland-Labrador	0.55	0.37	0.60
RMSE (mm)			
Fraser-Lower Mainland	40	51	56
Okanagan-Similkameen	29	42	40
Columbia	35	30	22
Peace-Athabasca	28	26	23
Ottawa	39	59	48
St. Lawrence	18	25	14
Saint John-St. Croix	17	14	10
Newfoundland-Labrador	18	17	18
MAE (mm)			
Fraser-Lower Mainland	28	37	50
Okanagan-Similkameen	24	37	34
Columbia	26	21	17
Peace-Athabasca	20	18	20
Ottawa	31	44	39
St. Lawrence	15	19	11
Saint John-St. Croix	13	12	8
Newfoundland-Labrador	15	12	14

When looking at RMSE, we observed that the St. Lawrence, Saint John-St, and Newfoundland-Labrador basins had the lowest errors. The RMSE between our approach and CanSWE was consistently below 40 mm, with the lowest value in the Saint John-St basin (17 mm). Similarly, RMSE values were below 59 mm with GlobSnow, with the lowest value again in the Saint John-St basin (14 mm). For CMC, RMSE values were below 56 mm, with the Saint John-St basin yielding the lowest value (10 mm).

The MAE results closely mirrored the RMSE trends. The lowest MAE values were found in the St. Lawrence, Saint John-St, and Newfoundland-Labrador basins. In particular, using our approach, the lowest MAE was recorded in the Saint John-St basin, with 13 mm for CanSWE, 12 mm for GlobSnow, and 8 mm for CMC.

Considering the three metrics, correlation, RMSE, and MAE together, we can conclude that GlobSnow performed the worst overall. However, both CanSWE and CMC showed comparable results across the basins. While CMC had the highest correlations, CanSWE performed similarly in terms of RMSE and MAE. Therefore, our enhanced SWE estimator compares well to both CanSWE and CMC, both of which are primarily based on ground measurements, demonstrating the robustness of our approach.

To provide a visual representation, Fig. 6 illustrates the monthly time series of estimated SWE and its corresponding observations. The time series includes SWE extracted from our enhanced approach (blue line), CanSWE observations (black line), GlobSnow (green line), and CMC (magenta line). The visual comparison underscores the effectiveness of the modified spectral combination approach in capturing SWE dynamics, as the pattern was almost similar with other datasets with a bit differences in amplitude. Precisely, a pattern like hill (increase and then decrease) was observed in four basins of Fraser-Lower Mainland basin, Columbia basin, Peace-Athabasca basin, and Newfoundland-Labrador basin. However, a simple pattern (reaching to increase value) was observed for other four basins of Okanagan-Similkameen, Ottawa, St. Lawrence, and Saint John-St.

In our time-frequency analysis, we examined the correlation and phase relationships between SWE derived from our modified estimator and other reference datasets using wavelet methods to highlight regions of common power and significant coherence. This analysis provides understanding of the temporal and frequency-specific dynamics of SWE variations, validating the robustness of our approach, and ensuring that the derived SWE estimates accurately reflect the true hydrological conditions. Here, we show the comparison between the wavelet analysis of SWE GRACE/GRACE-FO and other references, as an example. The results were indicated in Figs. 7 and 8.

Generally, the wavelet transform of SWE derived from our method and other references shows that the main peaks occurred at time scales between 8 and 16 months across all basins, except for GlobSnow, where no significant power was concentrated in 5 basins. For basins with prominent peaks, SWE derived from our method displayed a similar pattern to the other references. Some powers can also be seen at higher periods (around 32 months) for the basins such as Ottawa, St. Lawrence, and Saint John-St basins, but they are quite weak. The coherency between SWE from our approach and both CanSWE and CMC was generally higher than that with GlobSnow. For example, unlike CanSWE and CMC, GlobSnow showed no coherency at higher time scales (16–64 months) in the Okanagan-Similkameen, Columbia, Peace-Athabasca, Ottawa, and St. Lawrence basins. However, there was notable agreement between our results and those from CanSWE and CMC in the Ottawa, Saint John-St, and Newfoundland-Labrador basins. The highest coherency was observed with CanSWE in the Okanagan-Similkameen basin, with CMC in the Peace-Athabasca basin, and with GlobSnow in the Saint John-St basin.

A relevant question arises: Since GLDAS itself provides SWE estimates, why were GRACE TWS data used instead of directly utilizing GLDAS SWE products? This is a valid concern, and our justification is based on the limitations of GLDAS SWE in high-latitude regions (Shao

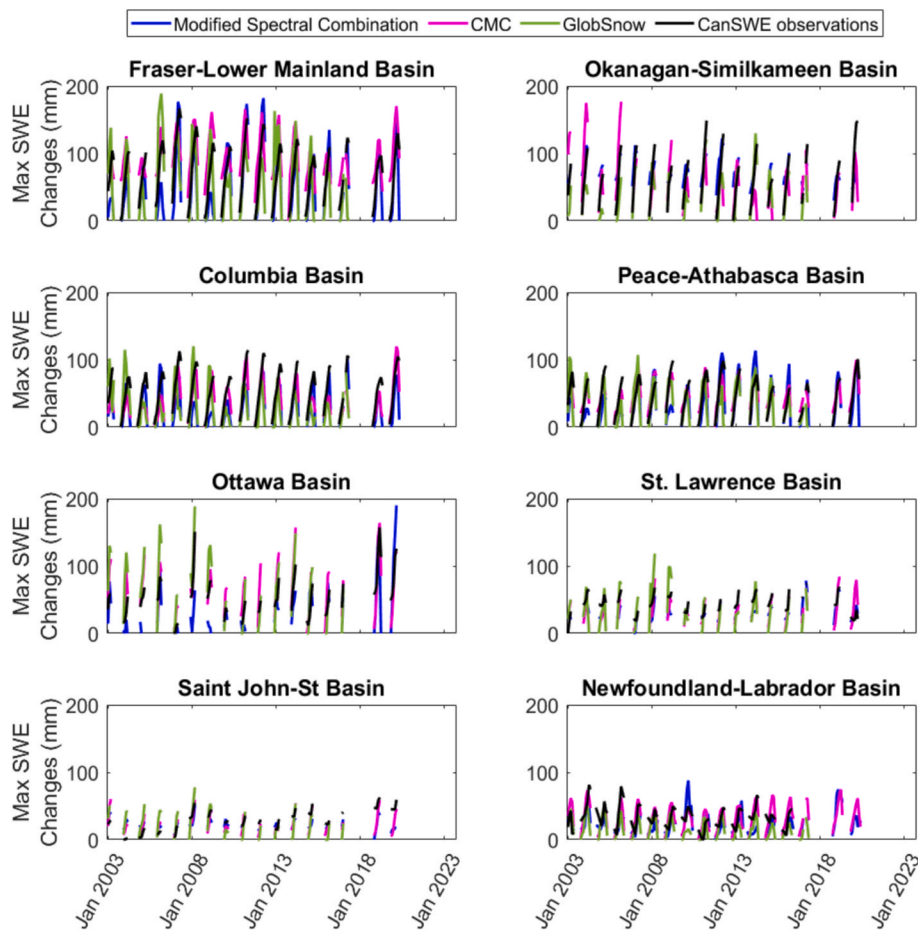


Fig. 6. Time series of SWE extracted from spectral combination approach (blue line), from CanSWE observations (black line), from GlobSnow (Green line), and from CMC (magenta line). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

et al., 2022). Our previous analysis in the Canadian Prairies demonstrated that SM and SWE storages are the largest sources of uncertainty in GLDAS TWS, contributing to errors of up to 40 mm (Fatolazadeh et al., 2020). While GRACE TWS also has known uncertainties, we accounted for these by modelling the misclosure in the water balance equation to estimate the relative error of each parameter. This allows SWE to be determined based on its variance, ensuring that the total variance across all components balances with the observed TWS misclosure.

Furthermore, to assess the reliability of our approach, we compared our estimator with GLDAS SWE across multiple basins by validating them against independent datasets (CanSWE, GlobSnow, and CMC). The results indicate that, in nearly all basins, our estimator exhibits a higher correlation with these reference datasets compared to GLDAS SWE. For example, in the Fraser-Lower Mainland basin, our estimator shows a correlation of 0.73 with CanSWE and 0.68 with CMC, compared to 0.62 and 0.66 for GLDAS, respectively. Similarly, in the Peace-Athabasca basin, our approach achieves a correlation of 0.83 with CMC, while GLDAS only reaches 0.70. In several other basins, such as Ottawa and Columbia, our estimator consistently outperforms GLDAS SWE, demonstrating stronger agreement with independent observations. These findings confirm that incorporating GRACE TWS through spectral combination provides a more accurate SWE estimation than using GLDAS SWE alone.

5.4. Results of SWE variability and dynamics

After validating the results of SWE derived from our modified spectral combination approach, a detailed analysis of variability and dynamics was performed to assess fluctuations and identify patterns within

the datasets. Fig. 9 presents the spatial map of the signal-to-noise ratio of SWE changes for January, covering the period from 2003 to 2022, with a confidence level of 95 %. The map highlights regions where the SWE changes are significant. Specifically, areas with values between -1.96 and 1.96 (indicated in black) represent regions where the signal-to-noise ratio is not significant, implying that the observed SWE changes could be due to random noise rather than a true signal. Conversely, areas with values outside this range (less than -1.96 or greater than 1.96 , shown in gray) indicate statistically significant changes in SWE, with these regions demonstrating a meaningful signal that stands out above the noise. This map is crucial for identifying where changes in SWE are robust and significant, helping to discern true climatic trends from variability. Based on Fig. 9, most of the SWE changes in Ottawa, Columbia, and Saint John-St basins are significant, compared to the Okanagan-Similkameen, east of St. Lawrence, centre of Peace-Athabasca, and north of Newfoundland-Labrador basins, where the ratio is not significant.

Analyzing annual variations in SWE is critical for understanding year-to-year changes in snowpack and their implications for hydrology and climate. Annual analysis offers insights into how SWE responds to various climatic factors over extended periods. By focusing on specific months, such as January and February, we can gain a deeper understanding of winter snow dynamics, which are pivotal for water resource management, predicting seasonal water availability, and emergency response. Fig. 10 illustrates the time series of annual SWE variations for January and February, derived using our approach. This time series highlights the year-to-year fluctuations in SWE for these two winter months, capturing both the interannual variability and any underlying long-term trends. The spectral combination method enhances the signal

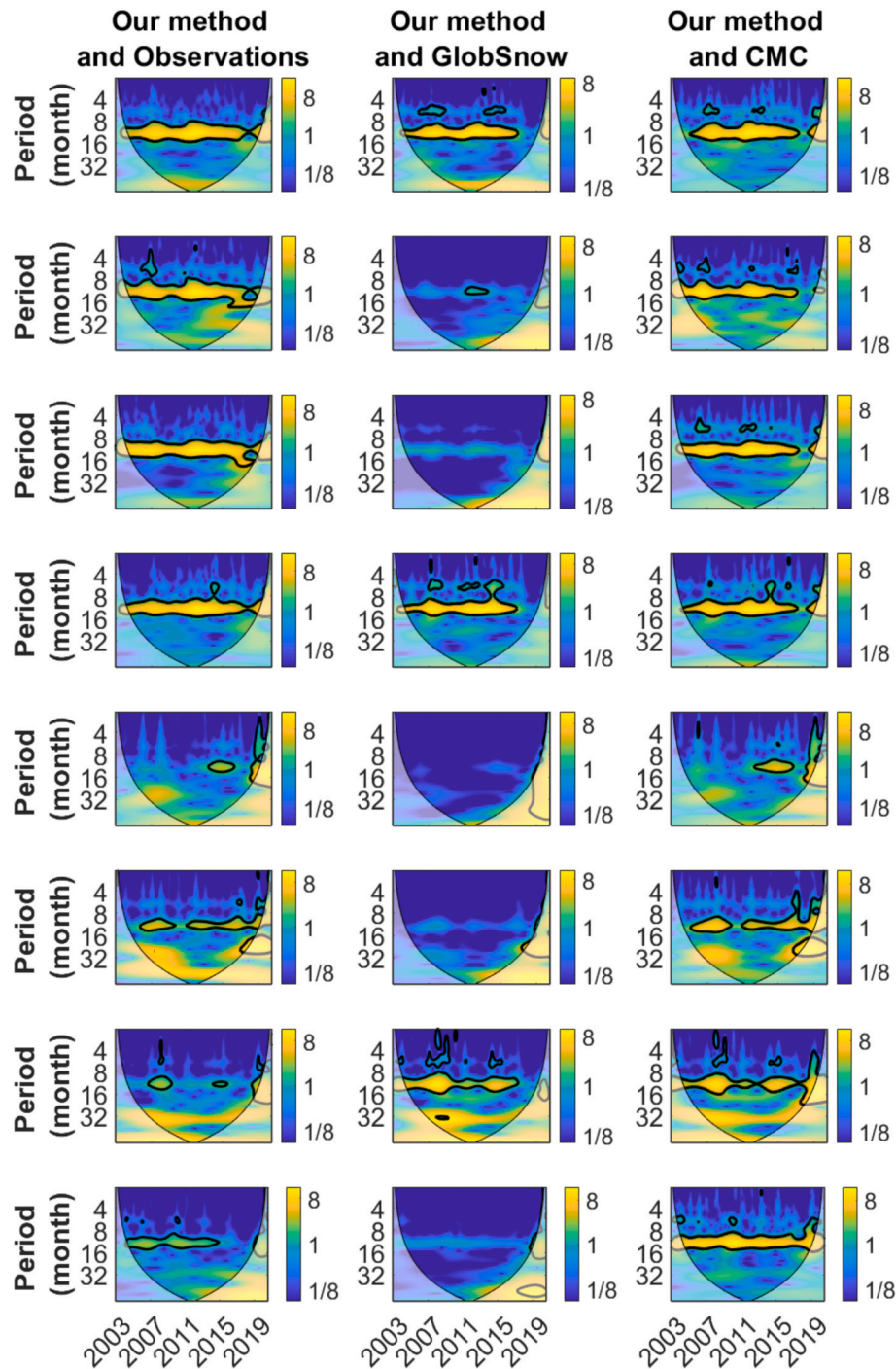


Fig. 7. Time-frequency spectra of Cross Wavelet Transform between SWE extracted from our method vs. CanSWE, GlobSnow, and CMC. The first row until last row shows Fraser-Lower Mainland, Okanagan-Similkameen, Columbia, Peace-Athabasca, Ottawa, St. Lawrence, Saint John-St, and Newfoundland-Labrador basins, respectively. The 95 % level of confidence is reported in full black line.

detection, providing a clearer representation of the SWE dynamics over the study period from 2003 to 2022. The time-series of annual changes show increasing behaviour in all the basins, except for Okanagan-Similkameen basin and Saint John-St basin with a decreasing pattern. The behaviour of annual SWE changes in these two months was almost similar across Ottawa, St. Lawrence, and Newfoundland-Labrador basins, with two important jumps, one between 2006 and 2009 and one at the end of the period in 2019 to 2020. The annual SWE variations were lowest in Saint John-St basin among other basins, with a maximum of 65 mm.

To comprehensively analyze SWE signals, we investigated the

seasonal, interannual, and long-term variations across multiple basins in Canada. This multi-faceted approach allowed us to capture the full spectrum of SWE dynamics and their underlying drivers. In fact, we decomposed the SWE time series into its constituent components to examine their respective contributions to overall variability. Precisely, SWE exhibits complex variability driven by seasonal cycles, interannual fluctuations, and long-term trends.

Fig. 11 shows the monthly time series of SWE across the studied basins from 2003 to 2022 for the selected snow cover seasons. The gaps in the time series correspond to the months without snow in each basin (see Table 5 for number of snow months in each basin, and Section 4.5

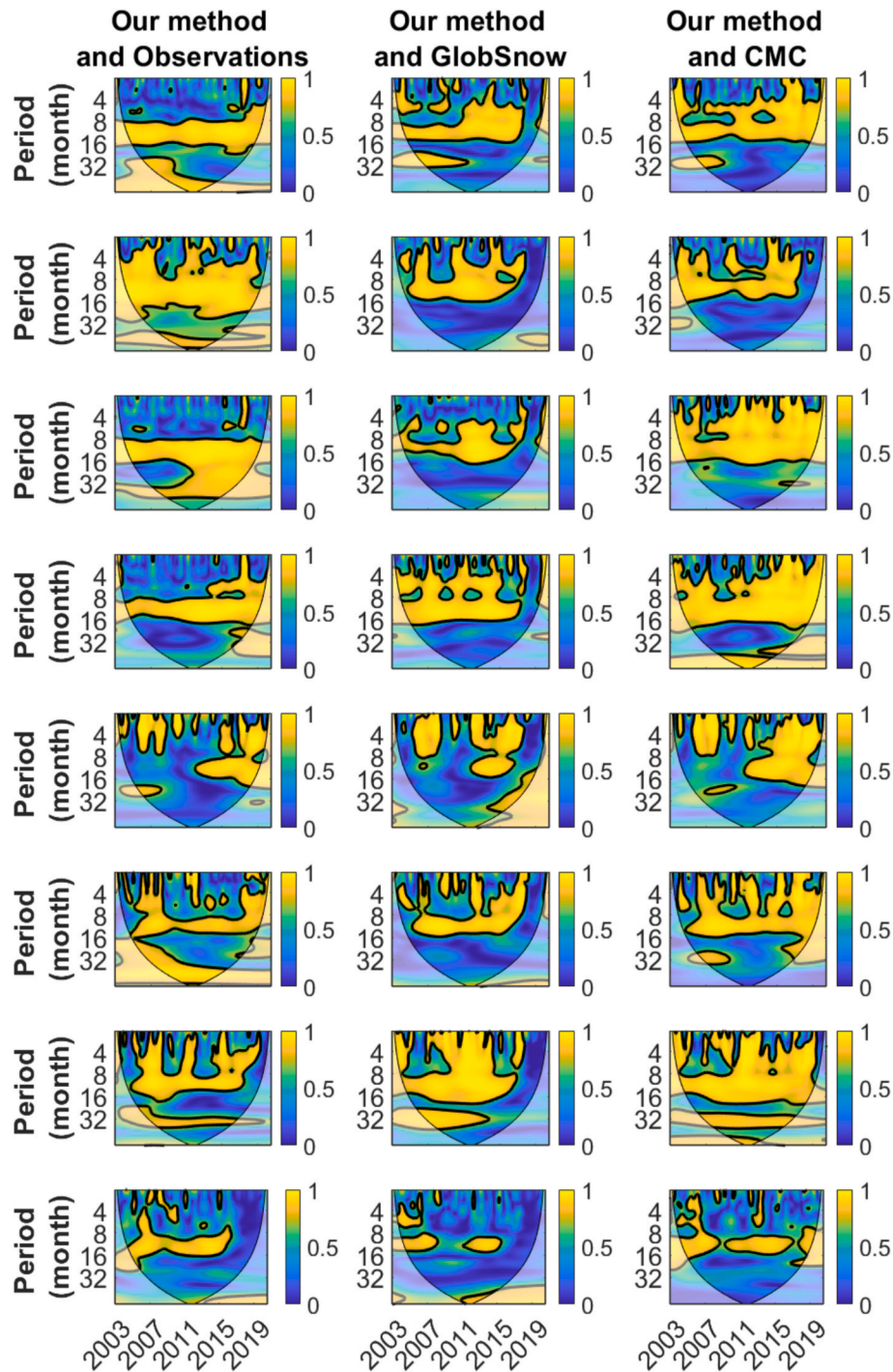


Fig. 8. Wavelet Coherence between SWE extracted from our method vs. CanSWE, GlobSnow, and CMC. The first row until last row shows Fraser-Lower Mainland, Okanagan-Similkameen, Columbia, Peace-Athabasca, Ottawa, St. Lawrence, Saint John-St, and Newfoundland-Labrador basins, respectively. The 95 % level of confidence is reported in full black line.

for the methodology used). Results indicate a positive behaviour for all the basins, except for Okanagan-Similkameen basin and Saint John-St basin with negative pattern. The maximum SWE changes happened in Fraser-Lower Mainland basin and Ottawa basin with maximum 200 mm. In contrast, the maximum changes observed over Saint John-St basin are much smaller (about 50 mm). Note that seasonal variations in SWE arise from the natural cycle of snow accumulation and melt, where SWE typically increases during winter months, reaches a peak, and then decreases with the onset of spring and summer melting. These seasonal changes are crucial for understanding the hydrological cycle, impacting

water availability, river flow, and ecosystem dynamics throughout the year. Generally, most of the basins showed a gradual increase in snow accumulation, except for two basins with a gradual decrease. Clearly, the maximum SWE trend was observed in Ottawa basin with about +2.3 mm/month. In contrast, the Okanagan-Similkameen basin showed a negative SWE trend with about −1.7 mm/month. Long-term variations in SWE are indicative of persistent trends and changes over extended periods, often driven by climate change and anthropogenic factors. Long-term trends are essential for detecting shifts in snowpack behaviour and understanding the broader implications for water resources in

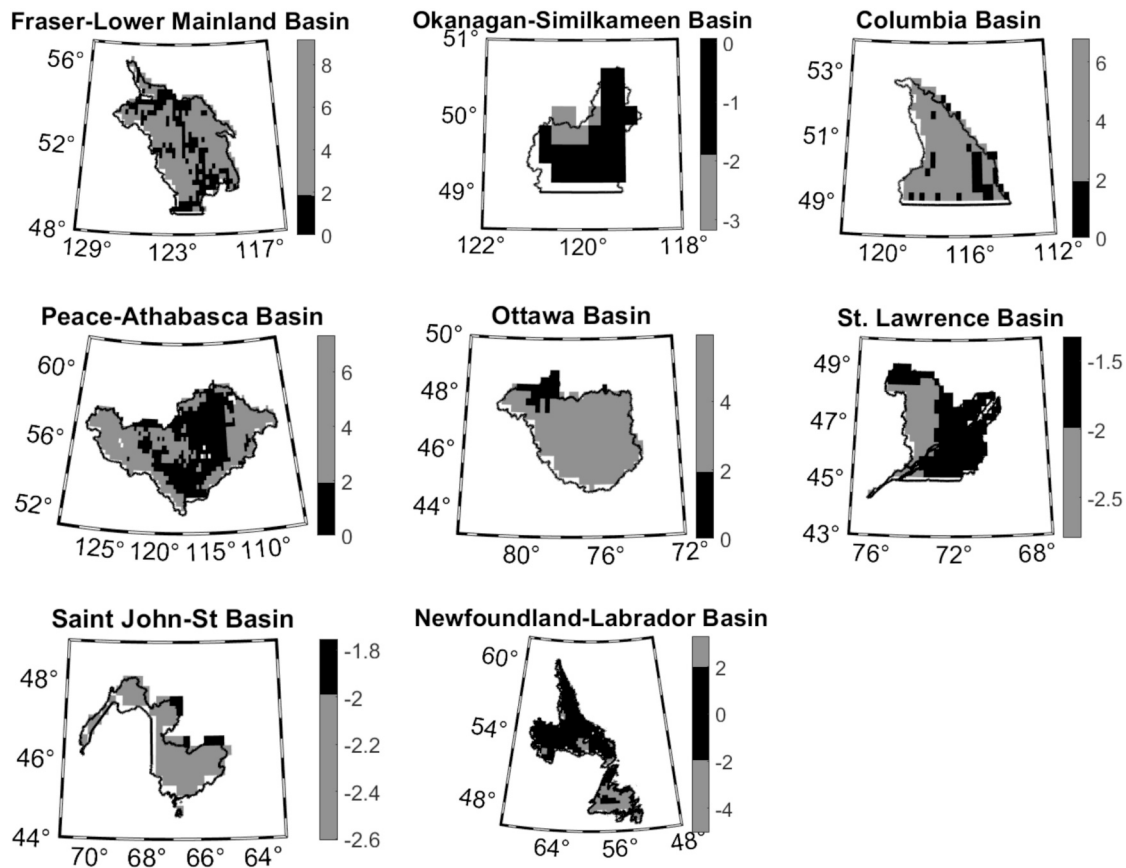


Fig. 9. Map of basins showing statistically significant Snow Water Equivalent (SWE) trends for January from 2003 to 2022 at a 95% confidence level. Insignificant SWE trends are shown in black, while significant trends are represented in gray.

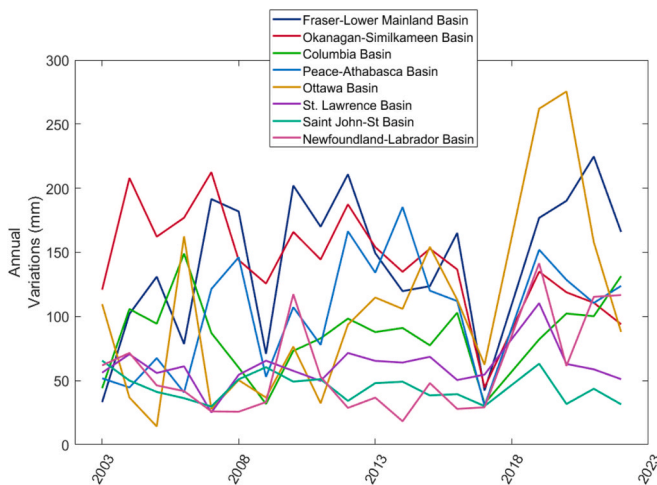


Fig. 10. Time series of annual SWE variations (for only January + February) extracted from our approach.

snow-dominated regions. Table 3 shows the values of computed inter-annual variations over the selected snow cover seasons from 2003 to 2022. The maximum interannual variations were observed in Fraser-Lower Mainland basin (about 52 mm), followed by Ottawa basin (around 41 mm). The lowest interannual changes occurred in Saint John-St basin (around 9 mm).

5.5. Results of mass balance analysis in relation to SWE

Based on water mass balance theory, there is a linkage between streamflow and SWE in winter conditions. This approach assumes minimal water loss through soil evaporation due to frozen ground, allowing for a clearer relationship between SWE, streamflow, and TWS. To explore this relationship, we considered different scenarios to investigate the connections between SWE, TWS, and flow. In the first scenario, we compared SWE estimates with only GRACE TWS to assess the linkage between TWS and SWE. This approach was applied across eight basins using SWE data from multiple sources, including CanSWE, GlobSnow, and CMC. The results are presented in Table 4, showing that the correlation between SWE derived from GRACE TWS and CanSWE was highest in 6 of the 8 basins, ranging from 0.57 to 0.91. The Columbia basin exhibited the strongest correlation (0.91), indicating that TWS alone was a significant predictor of SWE. Similarly, the Fraser-Lower Mainland basin had a high correlation with CanSWE (0.79), further supporting the strong relationship between TWS and SWE in these regions. In contrast, basins such as Ottawa and Newfoundland-Labrador demonstrated weaker correlations, particularly with GlobSnow SWE in Ottawa (0.10) and CanSWE in Newfoundland-Labrador (0.33), suggesting that factors beyond TWS, such as flow, may play a more prominent role in these areas.

In the second scenario, we focused on the role of flow in the relationship between SWE and streamflow. For this, we analyzed detailed flow data from four basins obtained from the Water Survey of Canada, including peak flow measurements in the spring season. Fig. 12 illustrates the time series of spring peak flow across the basins. By analyzing the peak flow data, we can better understand the temporal patterns and trends in streamflow, reinforcing the reliability of the mass balance method in estimating SWE. This analysis is helpful for evaluating our

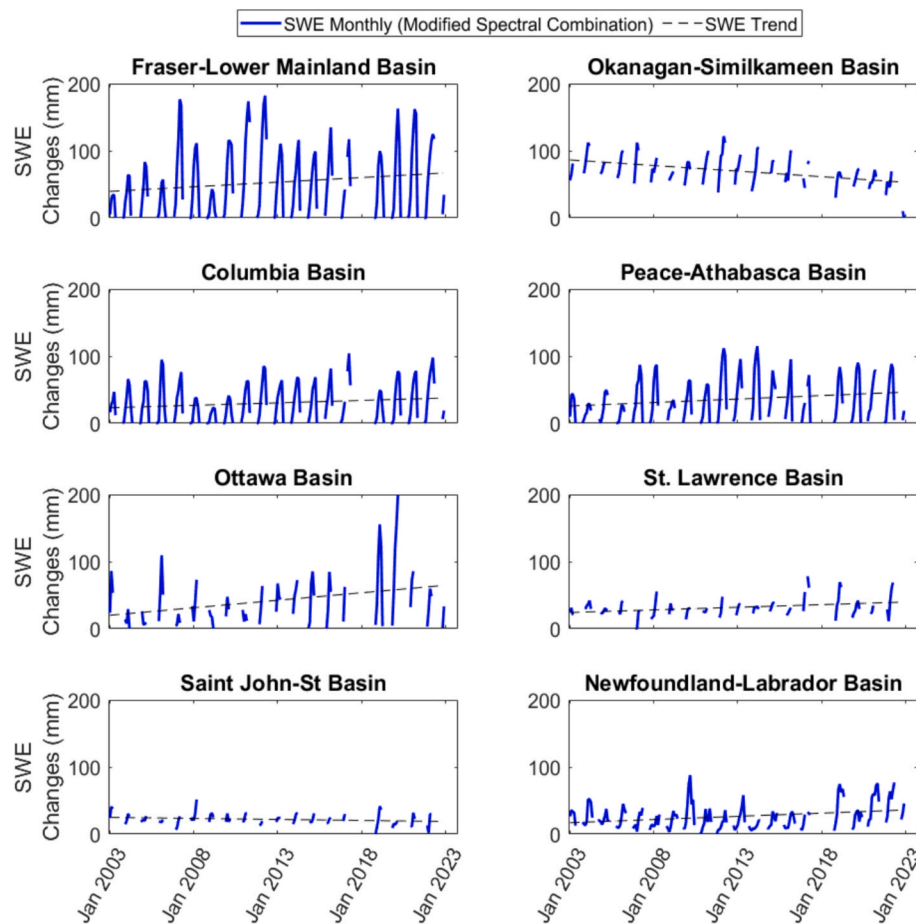


Fig. 11. Time series of SWE extracted from our approach. Blue color show monthly variations (mm), dashed line shows trend line. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 3

Interannual variations of SWE across different basins.

Name of the basin	SWE interannual variations (mm)
Fraser-Lower Mainland	51.5
Okanagan-Similkameen	21.7
Columbia	28.1
Peace-Athabasca	31.6
Ottawa	40.2
St. Lawrence	14.2
Saint John-St. Croix	8.7
Newfoundland-Labrador	18.6

SWE estimates. Generally, the value of peak flow was highest in Saint John-St basin with maximum 3300 mm/d in 2008 among the four studied basins. The lowest flow values are found in Newfoundland-Labrador basin (lower than 100 mm/d, except for 2022 with about 2000 mm/d). The results show that there was various peak flows in different periods of time, for instance in 2004, 2007, 2008, 2010, 2012, and 2013 across Ottawa basin. Moreover, St. Lawrence basin had the high peak values (around 1200 mm/d) for the period between 2016 and 2020.

A comparison of annual late winter SWE (or maximum SWE in the winter) with spring peak flow was conducted to explore the correlation between snowpack melt and streamflow. This consideration was due to different reasons. First, the maximum SWE in winter represents the total amount of water stored in the snowpack before it begins to melt. As temperatures rise and snow starts to melt in the spring, this stored water contributes significantly to streamflow. Second, correlations between

Table 4

Correlation computed between right and left side of the three equations provided inside the table. All correlations are significant at 0.95% confidence ($P < 0.05$) except for those which are highlighted as bold face.

	Correlation SWE_{CanSwe} vs. TWS_{GRACE}	Correlation $SWE_{GlobSnow}$ vs. TWS_{GRACE}	Correlation SWE_{CMC} vs. TWS_{GRACE}
Fraser-Lower Mainland	0.79	0.44	0.57
Okanagan-Similkameen	0.75	0.67	0.53
Columbia	0.91	0.39	0.68
Peace-Athabasca	0.72	0.35	0.53
Ottawa	0.57	0.10	0.30
St. Lawrence	0.38	0.37	0.61
Saint John-St. Croix	0.68	0.35	0.61
Newfoundland-Labrador	0.33	0.21	0.46

Table 5

Correlation between max SWE extracted from our approach in winter and spring peak flow. All correlations are significant at 0.95% confidence ($P < 0.05$) except for those which are highlighted as bold face.

	r with Peak Flow
Ottawa	0.74
St. Lawrence	0.56
Saint John-St. Croix	0.74
Newfoundland-Labrador	0.76

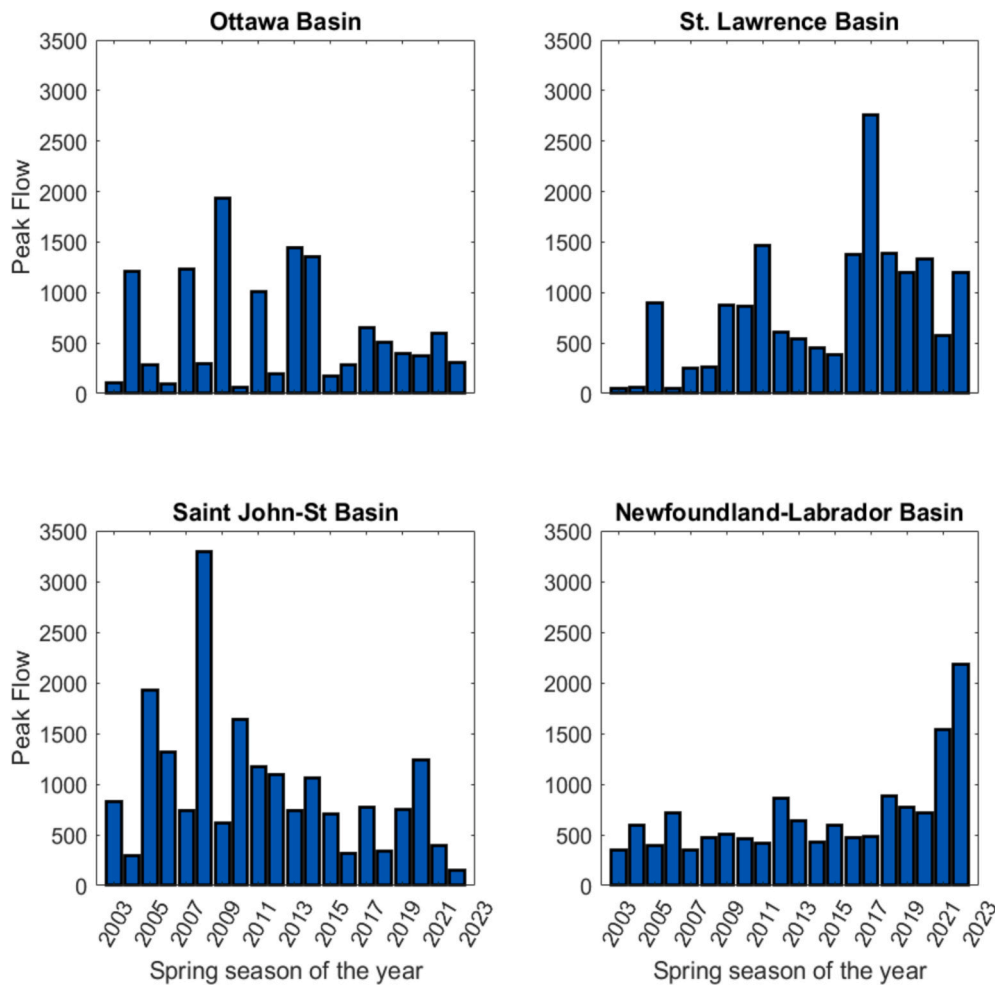


Fig. 12. Time series of Peak Flow in spring season extracted from the Water Survey of Canada database (in unit of mm/d).

late-winter SWE and spring season peak flow from snowmelt can help understand the role of snowmelt in the formation of spring floods. The results, shown in Table 5, revealed a strong positive correlation between maximum SWE and peak flow in most basins, with a correlation of $r = 0.76$ (p -value = 0.003) observed in three basins, while Saint John-St had a slightly lower correlation of $r = 0.56$ (p -value = 0.40). This indicates that snowmelt plays a critical role in generating peak flow in these regions, but other hydrological factors may influence the variations in the Saint John-St basin.

In the final scenario, we incorporated streamflow into the mass balance equation (Eq. 18) to evaluate its role in improving SWE estimates. Using CanSWE as the reference, we compared SWE derived from the summation of GRACE TWS and streamflow with the SWE observations. The correlation results are displayed in Table 6, where we observed notable improvements in the Ottawa and St. Lawrence basins, with correlations of $r = 0.80$. In contrast, the Newfoundland-Labrador basin showed less improvement, implying that streamflow alone might

not fully capture the variations in SWE for this region.

In summary, the correlation analysis across different scenarios reveals that the relationship between SWE and TWS varies depending on the presence of streamflow. In some basins, TWS alone provides a strong estimate of SWE, while in others, particularly where the correlation between SWE and TWS is weak, the inclusion of streamflow significantly improves the estimates. These findings suggest that while the inclusion of flow enhances the accuracy of SWE estimates in some basins, other variables may need to be considered to account for the full complexity of water mass system, particularly in regions with weaker correlations. Furthermore, the water mass balance equation itself may carry uncertainties that could affect the relationship between SWE and TWS.

6. Discussion

Our SWE retrieval is based on modified spectral combination of GRACE/GRACE-FO and a hydrological model (GLDAS) with an effective handling of their associated uncertainties through least-squares modelling. The consideration of uncertainties plays a critical role in the successful performance of the approach. Unlike our previous studies, we introduced here a new method that considers both the magnitude and contribution (weight) of each hydrological parameter in TWS. This approach allows for a more accurate estimation of hydrological parameter errors. It could be applied to hydrological models other than GLDAS as well, or to analytical models. The approach does not need any initial inputs or training observations. It is important to note that one of the main limitations of GLDAS is the absence of the surface water

Table 6

Correlation computed between right and left side of the equation: $SWE_{CanSWE} = TWS_{GRACE} + Flow$. All correlations are significant at 0.95 % confidence ($p < 0.05$) except for those which are highlighted as bold face.

	Correlation of $SWE_{CanSWE} = TWS_{GRACE} + Flow$
Ottawa	0.80
St. Lawrence	0.79
Saint John-St. Croix	0.66
Newfoundland-Labrador	0.42

component. However, based on previous findings by [Fatolazadeh and Goita \(2022\)](#), which indicated a low contribution of this parameter to TWS across Canada, we neglected this component in our analysis.

We used a combination of the freeze–thaw status period in each basin and continuity of SWE GLDAS for 14 consecutive days in each month of the study to determine the months that SWE could be retrieved. However, we faced different limitations on that. In fact, we worked with daily information (freeze–thaw is even twice a day), while GRACE which was provided on a monthly basis rather than daily data. This discrepancy introduced uncertainties in determination of onset (e.g., October) and end (e.g., May) of the snow season for each basin ([Zhu et al., 2024](#)). For mass balance approach, excluding them would reduce the error, as these months had soil evaporation water and snowmelt (if snow melt water left the snowpack, it would cause errors). The starting month would normally have small SWE, but could have significant land evapotranspiration, lake evaporation (delayed frozen relative to land), streamflow, and possible snowmelt included runoff. The spring melting months would have substantial change of snow into liquid water. This liquid water usually stays within the basin (SWE disappears without causing GRACE/GRACE-FO signal to change) for a certain time before being discharged out of the basin ([Musselman et al., 2021](#)). Overall, the proposed approach could be considered as realistic. The impacts of eventual uncertainties emanating from the process could be reduced, since all the computations are done with anomalies, instead of absolute values.

We displayed average SWE changes in January, showing that the Columbia and Peace-Athabasca basins had the highest SWE changes (around 80 mm and 50 mm, respectively), while the Saint John-St and St. Lawrence basins exhibited the lowest variations (approximately 3 mm) ([Fig. 5](#)). In general, basins in northern and western Canada experienced colder temperatures and heavier snowfall due to their higher elevations and mountainous terrain, which contributed to maintaining higher SWE levels. Conversely, eastern basins were at lower elevations with milder winters, which resulted in lower snowfall and increased snowmelt or mixed precipitation, leading to lower SWE ([Sabatghadam et al., 2024; Zahmatkesh et al., 2019](#)).

We calculated the long-term SWE variations across different basins in Canada ([Fig. 11](#)). The analysis of SWE variations in the 8 basins of Canada revealed contrasting trends in different regions. The central Canada and Atlantic regions exhibited an increasing trend in SWE variations, suggesting a potential increase in snowfall or prolonged winter seasons with greater snow accumulation. These factors could contribute to the observed upward trend in SWE. Conversely, the western part of Canada showed a decreasing trend in SWE variations. The findings of this study align closely with the results reported in previous researches ([Brown et al., 2021; Mudryk et al., 2018](#)). This trend might be attributed to various factors such as changes in climate patterns, alterations in atmospheric circulation, or natural climate variability ([Urban, 2024](#)). Further research and investigations are necessary to unravel the underlying causes of the observed SWE trends in different regions of Canada.

The performance of the modified spectral combination approach was assessed based on different SWE references (CanSWE, GlobSnow, and CMC). Pearson correlation, RMSE, and MAE were used to evaluate the results ([Table 2](#)). Using our proposed method, the correlation was more than 0.60 for 75 %, 40 %, and 88 % of the basins with CanSWE, GlobSnow, and CMC, respectively. The results of RMSE, and MAE confirmed the lowest agreements with GlobSnow, likely due to two key limitations of microwave remote sensing for SWE. First, microwave signals “saturate” in deep snow (>150 mm), making SWE measurements unreliable at greater depths. Second, wet snow absorbs rather than scatters microwave signals, hindering SWE estimates in areas with frequent freeze–thaw cycles (periodically wet snow) or during snowmelt ([Luo et al., 2021; Larue et al., 2017](#)).

We employed wavelet transforms to identify regions of shared power and significant coherence across various temporal and frequency scales.

The results confirmed statistical comparisons between our method and other data references ([Figs. 7 and 8](#)). CanSWE and CMC displayed similar periodic patterns, with notable peaks in the wavelet power spectrum around the 4–16 month range in most basins, indicating common seasonal trends or cycles. An exception was the Saint John-St basin, where these patterns were less pronounced. In contrast, GlobSnow showed no significant power concentrations in five basins, likely due to interference from forest cover, wet snow conditions, snow depth, and mountainous terrain. Both CanSWE and CMC demonstrated high coherence with our method in seasonal cycles (around 4–8 months) for most basins, such as Ottawa and St. Lawrence, suggesting that these datasets effectively capture similar seasonal SWE variability. Differences in shorter periods and certain regions may reflect limitations in SWE retrieval or unique basin characteristics ([Oveisgharan et al., 2020](#)).

We analyzed the relationship between SWE and streamflow by using mass balance approach. First, we observed some variations on the time series of peak flows ([Fig. 12](#)). In fact, there are various environmental factors influencing peak flows, specifically in cold regions. Spring floods can be affected by conditions like heavy precipitation in the previous fall and deep ground freezing before snowfall, which creates an impermeable surface for spring meltwater ([Grenier et al., 2024](#)). Additionally, certain water processes, such as rain, evapotranspiration, soil thawing, groundwater recharge, lake storage, and river ice dynamics, can significantly impact peak flows ([Khaliq, 2024; Willkofer et al., 2024; Kay et al., 2021](#)). Then, we calculated the correlation between maximum SWE in winter and late spring flow. The reason was that SWE directly contributes to the late spring (snow melt season) river flow (often the peak river flow in a year in Canada). The temperature patterns at that season may affect the sharpness of the peak ([Wang et al., 2017; Wang and Russell, 2016](#)). Our results showed that the peak flows in late spring ([Table 5](#)) correlate well with annual SWE in late winter, supporting previous findings ([Assani, 2023; Dibike et al., 2021](#)). However, this kind of correlation is hard to serve as a direct validation, as snowmelt (from SWE) mainly contribute to surface runoff, which is only part of the river flow (the other part is baseflow, or groundwater discharge), although surface runoff is often the dominant part ([Gan et al., 2022](#)). Separating surface runoff from the total river flow is not a straightforward thing ([Wang et al., 2021; Ardekani et al., 2021](#)). Even after the separation, the surface runoff still does not necessarily equal to snowmelt, as snowmelt water may infiltrate into soil, or evaporates. Additionally, if there is a rain, it will contribute to surface runoff too. Moreover, determining the time period for these calculations is also difficult. This matter will be investigated further in forthcoming studies to improve the results.

We employed different scenarios to understand the relationship between SWE, TWS, and streamflow. When SWE was compared solely with GRACE TWS, the results revealed varying degrees of correlation across different basins ([Table 4](#)). The high correlation in the Columbia basin (0.91) and Fraser-Lower Mainland basin (0.79) underscores the strong predictive power of TWS for SWE in these regions, indicating that flow has a negligible impact. These findings suggest that in certain basins, TWS alone is sufficient to explain SWE variations, reflecting a more direct and possibly linear relationship between snow accumulation and total water storage ([Niu et al., 2007](#)). Conversely, when SWE was compared solely with peak flow, high correlations were observed in Maritime areas like Saint John-St. Croix (0.74) and Newfoundland-Labrador (0.76) basins, highlighting the significant role that flow plays in these regions. In the Maritimes, river flow is highly responsive to snowmelt-driven runoff due to moderate snowpack depths, frequent spring warming, and coastal weather patterns that accelerate snowmelt ([Han et al., 2024](#)). This direct transition from snowpack to streamflow results in a strong SWE-peak flow correlation. Additionally, the substantial improvements in correlation observed in the Ottawa and St. Lawrence basins (0.80) suggest that the inclusion of both TWS and flow together captures a more comprehensive picture of SWE dynamics ([Table 6](#)).

Errors can occur for the mass balance approach when the conditions cannot be met. Problems may occur when (1) the region is not fully covered by snow, which led to soil surface evaporation; (2) snowmelt occurs, and the meltwater has to leave the snowpack (if it stays in the snowpack, it is not a problem). For the first case, soil evaporation in winter is only a few mm/month for most Canada, so we would believe it causes a small problem. Obviously, those two conditions mostly occur in the early snow season or snowmelt season. As such, the potential uncertainties for the mass balance approach can be reduced by carefully selecting winter months to ensure that conditions are met.

The limitations in the quality of the CanSWE data and streamflow observations are important considerations in any analysis that relies on these datasets. Spatial and temporal coverage issues, as well as gaps in the data, can indeed impact the representativeness and accuracy of the observations. The availability and maintenance of measurement stations, as well as other factors, can lead to gaps in the dataset, resulting in incomplete spatial and temporal coverage (Islam and Déry, 2017; López Moreno et al., 2020). In order to address these limitations, interpolation techniques may be employed to fill in the gaps and create a more consistent dataset. However, it is important to note that interpolation introduces its own set of assumptions and uncertainties, which should be considered when interpreting the results. It is reasonable to expect that higher-quality and more comprehensive CanSWE and streamflow datasets would lead to improved results, including higher correlation and lower RMSE. More extensive spatial and temporal coverage would provide a representative picture of the hydrological processes and allow for more accurate analysis and modelling.

7. Conclusion

In this study, we proposed a modified spectral combination approach to estimate SWE using TWS data derived from GRACE and GRACE-FO satellites. The results were validated against multiple SWE data sources, including CanSWE, CMC, and GlobSnow. Our analysis demonstrated that the modified spectral combination approach yielded SWE estimates with significant consistency across various basins when compared to other SWE sources. Specifically, the correlation with CanSWE and CMC was higher than that with GlobSnow. The cross-wavelet transform analysis further validated the temporal and frequency-specific coherence between SWE derived from the modified spectral combination and other sources, revealing strong consistency with CanSWE and CMC across multiple basins. This study revealed distinct regional relationships between SWE, TWS, and streamflow across Canadian basins. In western basins like Columbia, TWS alone strongly estimated SWE, indicating a direct link between snow and water storage. Conversely, in Maritime basins, peak flow correlated more with SWE, driven by snowmelt dynamics. Including both TWS and flow data improved correlations in certain areas, suggesting that a combined approach best captures SWE variability across diverse regions. Overall, the modified spectral combination approach proved to be a powerful tool for estimating SWE, offering a more accurate representation of snow dynamics compared to traditional methods. The findings of this study underscore the potential of combining GRACE/GRACE-FO-derived TWS with other hydrological data to enhance the monitoring and understanding of snow-related water resources, with important implications for water management in snow-dominated regions.

CRedit authorship contribution statement

Farzam Fatolazadeh: Writing – original draft, Validation, Conceptualization, Visualization, Software. **Shusen Wang:** Methodology, Writing – review & editing, Funding acquisition. **Mehdi Eshagh:** Writing – review & editing, Methodology, Supervision. **Kalifa Goïta:** Writing – review & editing, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data will be made available on request.

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