Exploring the links between variations in snow cover area and climatic variables in a Himalayan catchment using earth observations and CMIP6 climate change scenarios

Dharmaveer Singh[1&2*], Yu Zhu[1], Shiyin Liu[1], Prashant K. Srivastava[3], Jaydeo K. Dharpure[4], Debrupa Chatterjee[2], Rakesh Sahu[5], Alexandre S. Gagnon[6*]

1. Institutes of International Rivers and Eco-security, Yunnan University, Kunming - 650091 (China)
2. Symbiosis Institute of Geo-informatics, Symbiosis International University (Deemed University), Pune-411004 (India)
3. Remote Sensing Laboratory, Institute of Environment and Sustainable Development Banaras Hindu University, Varanasi-211005 (India)
4. Centre of Excellence in Disaster Mitigation and Management, Indian Institute of Technology Roorkee, Roorkee-247667 (India)
5. Department of Civil Engineering, Indian Institute of Technology Bombay, Mumbai-400076 (India)
6. School of Biological and Environmental Sciences, Liverpool John Moores University, Liverpool L3 3AF (United Kingdom)

*Corresponding authors' email: veermnnit@gmail.com and A.Gagnon@ljmu.ac.uk

Abstract

The spatial extent of the Snow Cover Area (SCA) of the Bhagirathi River Basin (BRB) has changed in recent decades, impacting the hydrology of the region. Previous studies examining variations in SCA in the region have yet been limited to the effects of terrain variables, namely elevation, slope and aspect, without considering the influence of climate variability. This study first investigates temporal changes in SCA and Terrestrial Water Storage (TWS) in the BRB during the period 2001-2019, which were calculated using satellite images from the Moderate Resolution Imaging Spectroradiometer (MODIS) and Gravity Recovery and Climate Experiment (GRACE), respectively, and their linkages to variation in climatic variables, and then examines how future climate change could impact on the SCA of the basin and its implications for water resources.

A trend analysis revealed an increase in the SCA during the study period, correlating with an increase in precipitation and TWS over the basin. Statistically significant positive correlation coefficients were detected between the post-monsoon ($r = 0.49, p<0.05$) and winter ($r = 0.54, p<0.05$) SCA and precipitation, while a negative correlation was identified between SCA and Tmax during the post-monsoon ($r = -0.53$, $p < 0.05$) and winter ($r = -0.69$, $p < 0.05$) seasons. Climate change scenarios, obtained from the Coupled Model Intercomparison Project Phase 6 (CMIP6) and downscaled over the study region, project an increase in both maximum and minimum temperature, and precipitation for the pre-monsoon and winter seasons in the 2030s under two Shared Socio-economic Pathway (SSP) greenhouse gas (GHG) emission scenarios: SSP245 and SSP585. These scenarios, together with a multiple-linear regression (MLR) model developed on the basis of the relationships identified between variations in SCA and climatic variables, indicate a reduction in the SCA at 4000+ m altitudes in all seasons under both the scenarios, thereby resulting a decline in the Bhagirathi river flow in spite of a projected increase in precipitation. This study demonstrates the impact of projected changes in climate on the SCA of a Himalayan catchment, and the potential implications for regions where snowmelt is important to streamflow regimes.

Keywords: Bhagirathi River Basin; CMIP6; climate change; MODIS; snow cover area; terrestrial water storage.

1. Introduction

The Himalayan-Karakoram (HK) region is covered by an estimated glacier ice volume ranging from 2.9×10^3 to 4.7×10^3 km^3 (Frey et al., 2014). It is the largest cryospheric store of water outside of the polar regions, with ice melting providing approximately 8.6×10^3 m^3 of water every year to rivers downstream (Bolch et al., 2012; Frey et al., 2014; Srivastava et al. 2014). This region is the headwaters of major rivers in South Asia, including the Ganges, Indus, and Tsangpo-Brahmaputra. Together, these three river systems form one of the largest river basins in the world, providing a critical source of water to India, Pakistan, Bangladesh, Nepal and Bhutan for domestic and industrial uses, hydropower, and irrigation (Bookhagen, 2012; Singh et al., 2016). Collectively, these three river systems are often referred to as the Indo-Gangetic Basin (IGB) (MacDonald et al., 2016), which is a very fertile and one of the most extensively irrigated basins in the world, supporting the livelihoods of approximately 800 million people (Immerzeel et al., 2010; Kaser et al., 2010; Bolch et al., 2012).

The flow of rivers originating in the Himalayas depends on snowmelt and glacier melt (Immerzeel et al., 2012; Lutz et al., 2014) and, for this reason, snow and glacier melt are important hydrological processes in the region (Lutz et al., 2014; Chen et al., 2016). A number of studies have suggested that climate change is affecting the accumulation of snow and the snowmelt processes of the region (Collins et al., 2013; Masson-Delmotte et al., 2018; Wang et al., 2019), causing changes in the Snow Cover Area (SCA) and thereby a reduction in glacial ice volume, with inevitable hydrological impacts downstream (Singh et al., 2014a; Rai et al., 2019; Kumar et al., 2019; Chandel and Ghosh, 2021). For this reason, the mapping and monitoring of snow cover in the headwaters of major South Asian rivers is critical to water resource management. The latter is an extremely challenging task using *in-situ* measurements given the rugged topography and the severe climatic conditions of the Himalayas.

The advent of satellite remote sensing has provided an opportunity to regularly monitor the SCA of the Himalayas (Dozier et al., 2008; Gafurov et al., 2015). Remote sensing detects the physical characteristics of a given surface area by measuring its reflected/or emitted radiation and backscattered energy from a sensor on board a satellite (Berthier et al., 2007), which can be either active or passive, depending on whether it provides its own source of energy. Images from a number of satellites can be used to determine the SCA at various temporal (1-16 days) and spatial (8 m to ~1 km) resolutions, including the Indian Remote Sensing (IRS) satellites 1C and 1D, GaoFen-1 (GF-1) Panchromatic and Multi-Spectral (PMS) sensor from the China National Space Administration, the Geostationary Operational Environmental Satellites (GOES) from the National Oceanic and Atmospheric Administration (NOAA), the Advanced Very-High Resolution Radiometer (AVHRR) from the United States Geological Survey (USGS) and the Landsat Programme, a joint initiative between NOAA and the USGS, as well as RADARSAT from the Canadian Space Agency. Moreover, topographic data from satellite based Digital Elevation Models (DEMs) are routinely used in studies focusing on glacier distribution and dynamics, for instance Nuth and Kääb (2011).

Different algorithms have been developed to estimate the SCA from satellite images (Shreve et al., 2009; Hall et al., 2019), including a linear mixture approach for GOES (Romanov et al., 2003), and a Support Vector Machine technique (He et al., 2015) and a multi-temporal ensemble learning framework (Xiao et al., 2020) for GF-1. Indices are also widely used to estimate SCA from satellite images, notably the Normalized Difference Snow Index (NDSI) (Hall and Riggs, 2010). Estimating SCA from satellite images is a challenging task, and, for this reason, it has essentially been limited to specialists in the processing and analysis of satellite images. This has changed, however, with the launch of the Moderate Resolution Imaging Spectroradiometer (MODIS) sensor on board the Terra and Aqua satellites in 1999 and 2002, respectively, as the latter was used to develop products providing estimates of snow cover extent at high temporal (1-day and 8-day) and moderate spatial (500 m) resolutions. MODIS images have been used to calculate the NDSI, see for instance Hall and Riggs (2010) and Hall et al. (2019), with robust results (accuracy estimates greater than 80%) obtained in different landscapes and under varying environmental conditions. Hence, several studies worldwide have used the datasets derived from the MODIS satellite images to estimate the SCA and investigate its seasonal variation in glacierised catchments (Parajka and Blöschl 2006; Sirguey et al., 2009; Rittger et al., 2013).

The Bhagirathi River Basin (BRB), located in the Western Himalayas, is an important river basin, as it is one of the headwaters of the Ganga (also known as Ganges) River. Part of this basin is covered with glaciers and snow throughout the year, which Khan et al. (2017) estimated that their melting contributes approximately 11and 12% of the total discharge of the Bhagirathi River near Devprayag during the pre-monsoon and post-monsoon seasons, respectively. A recent study focusing on this catchment has raised concerns about the impacts of changes in climate variability on hydrological extremes (Chug et al., 2020), given that a warming climate has caused changes in the spatial extent of the SCA in the western Himalayas (Thakur et al., 2017), with potential impacts on the flow of rivers originating in the region (Rai et al., 2019). Therefore, studying the variability of the SCA in the BRB in the context of climate change is essential for assessing the sustainability of the water resources and the socio-economic development of the regions located downstream of the basin. Some studies have previously used remote sensing to study the variability of the SCA in the BRB region (Joshi et al., 2015; Singh et al., 2019). These studies, however, focused on the effects of terrain parameters, for instance altitude, slope, and aspect on SCA variations rather than climate variability and climate change. Hence, this study examines the variability and trend in the SCA, as determined by MODIS satellite imagery, over the BRB during the period 2001-2019, and its relationship to changes in climatic parameters. The identified relationships were then used to investigate the potential impacts of climate change on the SCA using downscaled projections from four General Circulation Models (GCMs) part of the Coupled Model Intercomparison Project Phase 6 (CMIP6), and their implications on the water storage of the basin.

2. Study Area

The study focuses on the BRB, which is located within the administrative boundaries of the state of Uttarakhand in northern India (Figure 1). The catchment area of the Bhagirathi River at Devprayag is approximately 7650 km^2. An undulating topography is found at altitudes above 2000 m, while the catchment topography ranges from gentle to rugged at lower elevations, notably in the valleys. Given this mountainous terrain, the region comprises different types of climates. Below 3800 m altitude, a sub-humid tropical climate with four seasons prevails, namely the pre-monsoon (April-June), south-west monsoon (July-September), post-monsoon (October-November) and winter (December-March), while an alpine climate is found at higher altitudes. Precipitation in the region originates from both the south-west monsoon and the western disturbances that occur in the winter, the latter leading to precipitation falling mainly in the form of snow (Dimri et al., 2015). From May until September, the 0°C isotherm is found at elevations between 4500 m to 5500 m (Larsen, 2017), but it descends to an altitude of approximately 2600-3200 m in the winter. This altitudinal movement of the 0°C isotherm is hydrologically important, as it determines whether precipitation falls as snow or rain. Over the basin, total precipitation fluctuates between 1000 to 2000 mm, 60-80% of which falls during the south-west monsoon depending on the year. The mean annual maximum (Tmax) and minimum (Tmin) temperature based on 2001-2020 data is 14.2°C and 1.9°C, respectively.

Insert Figure 1

Glaciers cover approximately 10% of the surface area of the BRB. There are 238 glaciers of varying lengths covering an area of approximately 755 km^2, among which Gangotri Glacier (length: 30.20 km; width: 0.20–2.35 km; surface area: ~86 km^2) is the largest glacier[1]. Gangotri Glacier, together with the other glaciers of the basin, forms a cluster of glaciers known as the Gangotri Glacier System (GGS), a valley-type glacier system in which the trunk part is formed by the main Gangotri Glacier and fed by numerous glacier tributaries (Figure 1). The total area of the GGS is approximately 286 km^2 (Rai et al., 2019). Glaciers are generally found at altitudes above 3800 m. Also, a large area of the BRB, at altitudes above 2000 m is seasonally covered by snow (Thayyen and Gergan, 2010).

3. Materials and Methods

3.1 Satellite and meteorological data

The MODIS daily snow cover data were used to determine the extent of the SCA over the study basin. MODIS is a payload-imaging sensor launched by the National Aeronautics and Space Administration (NASA) on December 18, 1999, onboard the Terra satellite and on May 4, 2002, onboard the Aqua satellite. The first satellite has provided data since February 24, 2000, at 10:30 a.m., local time, in a descending node, while the Aqua satellite has supplied images since June 24, 2002, at 1:30 p.m., local time, in an ascending node. MODIS snow cover products Terra (MOD10A1) and Aqua (MYD10A1) are generated using a snow mapping algorithm (Riggs et al., 2017), and daily data from both products, version 6, were downloaded from the website of the National Snow and Ice Data Centre[2] for a 20-year period (1st October 2000 to 30th September 2019). However, due to an incomplete time series for the year 2000,

[1] http://117.252.14.242/Gangakosh/Water%20Resources/glaciers.htm
[2] http://nsidc.org/data/MOD10A2

that year was excluded, and this study focused on the period 2001-2019. Version 6 is the latest of MODIS snow products, which has shown higher accuracy than the previous version (Zhang et al., 2019). MODIS data are available in the Hierarchal Data Format (HDF) and supplied in the form of tiles (tile size: 10°x10°). In addition, a Digital Elevation Model (DEM) at a 30 m spatial resolution generated using CartoSat-1 stereo data (tile id: H44G) was obtained from Bhuvan, the Geo-Platform of the Indian Space Research Organization (ISRO)[3], and used to create a hypsometric area curve of the basin (Figure 2).

Insert Figure 2

Daily precipitation and maximum and minimum temperature (Tmax and Tmin) data were obtained for the period 2001-2020. Precipitation data were acquired from the Climate Hazards Group Infra-Red Precipitation with Station (CHIRPS) dataset, which provides precipitation estimates on the basis of measurements from rain gauges and satellite observations at a spatial resolution of 0.05°×0.05°[4], while temperature data were extracted from the National Centers for Environmental Prediction/National Centre for Atmospheric Research (NCEP/NCAR) reanalysis dataset[5], which has a spatial resolution of 2.5°×2.5°. The entire study area is covered by 11 grid cells in the CHIRPS dataset and two grid cells in the NCEP/NCAR reanalysis (one falling within the lower part of the catchment and the second is very close to the upper catchment). The coarse spatial resolution of the NCEP/NCAR reanalysis introduces uncertainty in the temperature data (Singh et al., 2015a). To address this, the NCEP/NCAR grid was interpolated from its 2.5°×2.5° spatial resolution to a higher grid resolution of 0.25°x0.25° using environmental temperature lapse rate (6.5°C/1000 m). The values of precipitation and temperature (Tmax and Tmin) at each grid were then averaged over the

[3] www.bhuvan.nrsc.gov.in
[4] https://www.chc.ucsb.edu/data/chirps
[5] https://psl.noaa.gov/data/gridded/data.ncep.reanalysis.derived.pressure.html

catchment using Thiessen polygon method to generate daily climatic data integrated at the catchment scale.

The Gravity Recover and Climate Experiments (GRACE) and GRACE Follow-On (GRACE-FO) satellite missions (Save, 2020), which produced the recently released monthly CSR GRACE/GRACE-FO RL06 Mascon Solutions products[6], were also obtained to investigate the implications of changes in SCA on the Terrestrial Water Storage (TWS) of the BRB. GRACE was launched in 2002 and discontinued in October 2017, but it was re-launched in May 2018 with the name of GRACE-FO[7], with the gap in GRACE and GRACE-FO bridged using an Artificial Neural Network (ANN) technique. The data cleaning process and extraction of the TWS from GRACE and GRACE-FO is explained in Zhu et al. (2021).

3.2 Climate change scenarios

To investigate the impact of climate change on the SCA, outputs from GCMs are used. GCMs forced by different trajectories of greenhouse gas (GHG) emissions, each one based on a set of assumptions about demographic change and future economic and technological development, are used to examine potential future changes in the state of the climate (Riahi et al., 2017). As they are computationally expensive to run, they have a coarse spatial resolution and are therefore not always adequate for regional studies (Singh et al, 2015a), especially in mountainous regions where simulating the complexity of the landscape is required to obtain reliable projections (Singh et al, 2015b). For this reason, GCM outputs are typically downscaled using Regional Climate Models (RCMs), nonetheless, the RCM outputs still inherit the biases from the GCM from which they take their boundary conditions. The latter,

[6] http://www2.csr.utexas.edu/grace/RL06_mascons.html
[7] https://gracefo.jpl.nasa.gov/mission/overview/).

however, were corrected in a dataset providing downscaled climate change scenarios for South Asia, as described in Mishra et al. (2020). This dataset provides bias-corrected downscaled climate change projections for a number of CMIP6 models and four Shared Socio-economic Pathway (SSP) greenhouse gas GHG emission scenarios: SSP126, SSP245, SSP370, and SSP585, which are briefly summarised in Riahi et al. (2017). The data are available at a daily time-scale and at a horizontal spatial resolution of 0.25°×0.25°. This study uses outputs from four of those GCMs: the Beijing Climate Centre Climate System Model version 2 (BCC-CSM2-MR), the Canadian Earth System Model version 5 (CanESM5), the Earth Consortium-Earth 3 Model (EC-Earth3), and the Max Planck Institute for Meteorology Earth System Model version 1.2 (MPI-ESM1.2. These GCMs were selected given their performance in simulating the precipitation and temperature conditions of the western Himalaya (Joseph et al., 2018). The climate change projections were obtained for the period 2021-2050 (2030s) over the BRB according to two GHG emissions scenarios: SSP245 and SSP585.

3.3 Assessment of the normality and homogeneity of the climatic data

Violating the assumption of normality of data in small datasets, as well as the presence of inhomogeneity in time series may yield inaccurate results assumption in a distribution (Peterson et al, 1998; WMO, 2011), and it is therefore recommended that these be checked prior to conducting the statistical analyses (WMO, 2011). There are number of graphical and statistical methods available to check for normality in a dataset (Altman and Bland, 1995; Mishra et al., 2019), and this study used Shapiro-Wilk (*W*) test (Shapiro and Wilk., 1965) for that purpose. The presence of inhomogeneity in the time series, for its part, was examined using the Buishand's Range test (Buishand, 1982). Table 1 shows the results of these tests on the temperature and precipitation, respectively, revealing that all the time series of temperature and precipitation follow normality at 5% significance level, except for Tmin at the annual time-scale and during the monsoon season, Tmax and Tmin during the monsoon season, and precipitation in the pre-monsoon and monsoon seasons. Similarly, inhomogeneity (Q/sqrt (n)>1.22, for n =20 at 5% significance level) in Tmean and Tmax during the post-monsoon season were identified according to the Buishand's Range test. These time series were, further, homogenised using a multistep process based on non-parametric statistics as described in Peterson and Easterling (1994).

Insert Table 1

3.4 Cloud removal and estimating SCA

The downloaded MODIS data were provided in a sinusoidal map projection and were projected into a Universal Transverse Mercator (UTM) Zone 44N coordinate system with the World Geodetic System (WGS) 84. There were 49 missing Terra images and 16 missing Aqua images during the study period, and the missing Terra images were replaced by the corresponding Aqua images and vice-versa. The MODIS raw data contain different parameters, one of which being the NDSI snow cover parameter, which was used to determine the SCA. The NDSI is calculated using equation 1:

$$\boldsymbol{NDSI} = \frac{\boldsymbol{VIS(band4) - SWIR(band6)}}{\boldsymbol{VIS(band4) + SWIR(band6)}} \quad \text{...(1)}$$

where VIS and SWIR represent the visible and shortwave infrared reflectance, respectively. When a pixel has a NDSI ≤ 0.0, it is normally considered to be snow-free, while some snow is present when it is greater than zero (Hall et al., 2019). Sometimes, non-snow pixels may also have *NDSI* values greater than 0.0, owing to the presence of clouds. Thus, cloud coverage is a significant problem when using MODIS images to estimate the SCA, notably in the Himalayan region where persistent cloud coverage is common during the southwest monsoon as well as during the winter because of western disturbances (Lopez-Burgos et al., 2013; Snehmani et al., 2016). Therefore, a five-step non-spectral composite methodology, as described in Dharpure et al. (2021) was applied to remove and substitute the cloud contaminated pixels, and which consisted of combining the Terra and Aqua products and using a temporal filter, a spatial filter, a regional snowline filter, and a multiday backward filter to remove the cloud contaminated pixels and to generate snow cover images to fill the gaps. The overall mean accuracy achieved through this methodology was 92.8%. Furthermore, a *NDSI* threshold ≥ 0.4, as recommended by Riggs et al., (2017), was used for considering whether a pixel is covered by snow or not, and the MODIS snow product images were reclassified using that criteria, as described in Table 2.

Insert Table 2

3.5 Trend detection and change point analysis

The non-parametric Mann-Kendall (MK) test (Mann, 1945) and the associated Sen's slope estimator (Sen, 1968) were used to determine whether there is a statistically significant trend in the SCA, temperature and precipitation time series, and their magnitude, respectively. A cumulative sum chart (CUSUM) was then used to identify potential shifts in a time series, including an examination of changes in the thermal regime of the region during the study period. The CUSUM chart depicts the cumulative sum (S_i) of the deviations of data in a time series about a target value (which in this study is the mean of value of each time series), and is computed using equation 2:

$$S_i = \sum_{j=1}^{i} (x_j - \mu_0) \quad \ldots\ldots \quad (2)$$

where, x_j and μ_0 are the mean of j^{th} sample and sample, respectively (Page, 1961; Singh et al., 2015b). The Upper Control Limit (UCL) and Lower Control Limit (LUC) on the CUSUM chart are defined by a statistical parameter H (decision interval) that should not exceed five times the sample standard deviation. The change point in a time series was identified in a CUSUM chart using the allowable value (k), which is positioned halfway between μ_0 and x_j- μ_0. In this study, limits of UCL and LCL have been estimated between $\pm 2\sigma$ and k = 0.5.

3.6 Development of a multiple linear regression model for projecting changes in SCA under future climate change

A multiple linear regression model (MLR) was developed to establish a relationship between daily SCA and climatic variables at different elevation zones (e.g., 2000-3000m, 3000-4000m, 4000-5000m, 5000-6000m and 6000-7010m). There are occasions, however, when two explanatory (independent) variables are highly linearly related, which can affect the validity of a MLR if both variables are used in its construction (Gough et al., 2004). Hence, multicollinearity among independent variables are recommended to be removed in the MLR. The variance Inflation Factor (VIF), which measures the dependence between a predictor and the other independent variables is used as a diagnostic tool for multicollinearity (Helsel and Hirsch, 1992; Neter et al., 1996). A VIF score greater than four indicates that multicollinearity might be a problem, while serious problems exist with multicollinearity when the VIF is greater than ten (Neter et al., 1996). In this study, all regression models of different elevation zones were tested for multicollinearity in the predictors, and in all cases the VIF was found to be less than four. However, with the given threshold of VIF values for multicollinearity, only three independent climatic variables namely, precipitation, Tmax and Tmin were found suitable at all elevation zones for the model development and the developed MLR was expressed as

$$Y_{sca} = w_1 X_{prcp} + w_2 X_{tmax} + w_3 X_{tmin} + w_0 \quad (3)$$

where, $X_{prcp}, X_{tmax}, X_{tmin}$, are daily values of precipitation, Tmax and Tmin, respectively, the vector w= (w_1,w_2,w_3,) represents the weight of each parameter, and the w_0 is the intercept value. There are four steps for forecasting the SCA based on MLR in each elevation zone. Firstly, multicollinearity in the climate variables was detected to avoid autocorrelation. Secondly, the data involved in the MLR were normalized to 0-1 by using max-min scale method. Thirdly, the normalized data were split into two parts, and the 80% of data were used for training the model and the rest of data for validation. Finally, the established model was employed to predict the standardized SCA and transform standardized SCA to SCA by using established scaler.

Insert Figure 3

The low Root Mean Square Error (RMSE) and Mean Absolute Deviation (MAE) between the observed and predicted SCA suggest that the developed MLRs have a stronger association with predictors (climatic variables), and can be used for simulating SCA (Table 3). By reconstructing the SCA using the MLR, it was observed that the model showed good performance in simulating the inter-annual variability in SCA (Figure 3). Despite the peak values were not captured due to limited samples for training, the forecast results included most effective information (e.g., the long-term changes and the seasonal cycles). The developed models were further used to simulate temporal changes in SCA over the BRB under projected climate change scenarios.

4. Results

4.1 Altitudinal variability and trends in SCA

Variability as well as trends in SCA were investigated for different elevation zones (e.g., 3000-4000, 4000-5000, 5000-6000 and a 6000-7010 m) of the BRB to comprehend sensitivity of SCA with elevation. The elevation zones below 2000 m were excluded due to their insignificant SCA contributions. It was observed that most of SCA (28.62% of the catchment area) in the BRB was concentrated within zones ranging from 3000 to 6000 m, with a maximum of 15.57% of the catchment area in the elevation zone of 5000-6000 m. The zones lying between 2000-3000 m and 6000-7010 m were marked with a minimum SCA of 0.47% and 1.15% of the catchment area, respectively. The trend analysis revealed an increase in SCA for all elevation zones, albeit lacking statistical significance. The SCA increased by 0.46 km²/year in the elevation zone of 2000-3000 m, by 1.86 km²/year in the elevation zone of 3000-4000 m, by 0.76 km²/year in the elevation zone of 4000-5000 m, by 1.69km²/year in the elevation zone of 5000-6000 m and by 0.13 km²/year in the elevation zone of 6000-7010 m over the period 2000-2019. Thus, the rate of change was maximum in the elevation zone of 3000-4000 m and minimum in that of the 6000-7010 m zone during the study period.

4.2 Inter- annual variability and trends in SCA

Figure 4 depicts the inter-annual variability in the SCA of the BRB during the period 2000-2019. During that period, the mean annual SCA varied from a maximum of 33.23% of the catchment area to a minimum of 22.36% in 2019 and 2016, respectively. The Sen's slope estimator revealed a positive trend of approximately 13.62 km²/year (approximately 0.02% per year) in the SCA at the annual time-scale over the basin, albeit lacking statistical significance. It was also found that the increasing trend in the annual SCA was of higher magnitude, and showing statistical significance, during the earlier 2000-2009 period (38.20 km²/year) than in the latter 2010-2019 period (13.40 km²/year). An examination of the time series of the annual maximum SCA revealed a downward trend, although lacking statistical significance, but a statistically significant increasing trend in the time series of the annual minimum SCA. This implies that it might be a reason of relatively lower magnitude observed in mean annual SCA between 2010-2019. Figure 4 also shows that the highest and lowest SCA is recorded during the winter (57.07% in 2019) and monsoon (6.44% in 2001) seasons, respectively. Within months, the maximum and minimum snow cover extent were recorded in February (59.8% in 2005) and August (4.6% in 2001), respectively. The SCA typically increases from September until February, after which it begins to decline (Figure 5), following the seasonality of snowfall, its accumulation, and melting. Snow begins to accumulate in September/October, and the maximum snow cover thickness is reached in February and March. From April onwards, the snow cover starts to deplete due to the warmer temperatures and precipitation (rainfall), resulting with the minimum SCA in August. The trend analysis detected an increase in SCA during all the seasons. The SCA increased by 21.85 km^2/year during the pre-monsoon season, by 3.44 km^2/year during the monsoon season, by 4.51 km^2/year during the post-monsoon season and by 3.01 km^2/year in the winter over the period 2000-2019.

Insert Figure 4

This result of annual and seasonal change in SCA agrees with the findings of Joshi et al. (2015) and Rathore et al. (2015), who also reported an increasing, although lacking statistical significance, in the annual and seasonal SCA of the BRB for the period 2000-2010 and 2004-2014, respectively. However, it differs from the study of Gusain et al. (2015) who reported a declining trend in annual snowfall by analysing annual time series of Bhojwasa station located at an altitude of approximately 3900 m in the basin during the period 2000-2012. This difference in observation is likely because of the length of data period and the presence of various distinct topoclimatic zones in the catchment (Yadav et al., 2020), where snowfall events are largely controlled with the movement of the Indian Summer Monsoon (ISM) and the Indian Winter Monsoon (IWM) and their interaction with the local topography (Dimri et al., 2015). The northern region of the basin (altitude: ~5200m and above), characterised as monsoon deficit zone, receives maximum snowfall as compared to the southern part of the basin (Yadav et al., 2020). The station of which data was analysed falls in southern part of the basin. Moreover, rising trends in annual SCA were also reported in Indus basin (2000-2017; Singh et al., 2014b), Kashmir Himalaya (2000-2016; Shafiq et al., 2019) and Chenab basin (2001-2017; Dharpure et al., 2020; Sahu and Gupta, 2020).

Insert Figure 5

4.3 Temporal variations in Terrestrial Water Storage (TWS) in the BRB

Snow is one of the most important components in TWS. The linear trend of the TWS represents the influence of long-term signals such as the extraction of groundwater on TWS and the detrended TWS can be used as an indicator of snow mass changes in a basin where the hydrological processes are largely affected by snowmelt and glacier melt (Zhu et al., 2021). The anomalies in TWS, hereafter referred as TWSA, derived from GRACE/GRACE-FO showed inter-annual variability in the BRB (Figure 6a). A rising trend in TWSA is indicative of an increase in TWS, which is consistent with the increasing trend in mean annual SCA (Figure 4(a)).

Insert Figure 6

The first wave crest in the seasonal cycle of TWSA agree with the intra-annual variability of snowfall in the region and thus the variations in SCA and TWSA were unchanged (e.g., two features present the rising trends from 2006 to 2009) except for individual year (e.g., 2016). It should be noticed that another peak in TWSA (Figure 6b) presented the signal of monsoon rainfall. The different performance in SCA indicated that winter snowfall was the main positive factor affecting the SCA pattern. However, the snowfall during the monsoon is mainly limited to high altitudes, above approximately 5500 m (Yadav et al., 2020), and, for this reason, it has a minimal impact of the overall SCA of the catchment as a whole. This is also an important reason why the variations in TWS partly different from SCA despite having a similar long-term rising trend and seasonal pattern between them. Therefore, the variability in TWSA from January to June may be considered as variability in snow water equivalent.

4.4 Trends in temperature and precipitation

Temperature (Tmean, Tmax, Tmin, and DTR) and precipitation influence the extent of snow cover area over the catchment. This variability is best explained by examining anomalies in Tmean, Tmax, Tmin and precipitation, and investigating their trends over the study period (Singh et al., 2016). Time series of anomalies in temperature and precipitation were derived by subtracting the annual mean value averaged over the period 2001-2020. The MK test and the Sen's slope estimator revealed increasing trends in annual Tmean, Tmax, Tmin and DTR over the BRB during the study period (Table 4). Increasing trends in annual Tmean, Tmax, Tmin and DTR were observed in the BRB for the study period, however, these were statistically insignificant. Further, Tmax (+0.06°C/year) was found to be rising as much faster rate than Tmin (+0.04°C/year) resulting increase in DTR (+0.01°C/year). Similar patterns were also observed in seasonal trends of Tmean, Tmax, Tmin and DTR. It was statistically significant for Tmean, Tmax and Tmin during monsoon and for Tmean and Tmax in post-monsoon. It ranged from -0.02°C/year (winter) to +0.11°C/year (post-monsoon) for Tmean, +0.003°C/year (winter) to +0.11°C/year (post-monsoon) for Tmax, -0.01°C/year (winter) to +0.10°C/year (monsoon) for Tmin and +0.01°C/year (winter) to +0.04°C/year (post-monsoon) for DTR. The rate of increase in Tmean, Tmax and Tmin was relatively higher during monsoon and post-monsoon. Additionally, Tmax was found to be rising as much faster rate than Tmin and hence caused DTR to increase. Rathore et al. (2013) also reached on similar conclusions through their studies conducted in Uttarakhand (1951-2010).

Insert Table 4

The variability in the time series of annual and seasonal Tmean, Tmax and Tmin was also investigated using CUSUM charts. In this method, individual values are compared with the overall average, and a sudden variation (±2σ) in slope of CUSUM charts from the mean values is considered to be an indicative of regime shift (Singh et al., 2015b), as it implies that the value is either above (positive shift (C^+)) or below (negative shift (C^-)) the climatic average. From examining the CUSUM charts, one can see a negative regime shift in annual Tmean, Tmax and Tmin in 2003 with a small negative departure from their mean values between 2001 and 2006. However, CUSUM slope showed a positive departure from their mean values from 2012 to 2014 and 2015 to 2018. Thus, warming of the recent decade (2011-2020) surpassed cooling effects detected during 2001-2010, which eventually attributed to the rising trends in annual Tmean, Tmax and Tmin in the BRB. Furthermore, all warming in the region could be attributed to Tmax and Tmin increase. Similarly, analysis of seasonal CUSUM charts showed sporadic positive/or negative regime shifts in Tmean, Tmax and Tmin. For examples: positive regime shifts in monsoon Tmax were observed at 2014, 2015 and 2016 whereas a negative regime shift was reported in 2003. For Tmean, positive regime shifts were observed at 2014 and 2019, while a negative regime shift at 2003. However, negative regime shifts in monsoon Tmin were observed at 2003, 2004 and 2005 with large positive departures from their mean values after 2011. In post-monsoon season, negative regime shifts were observed in Tmean, Tmax and Tmin at 2003-2006. Despite these negative regime shifts, statistically significant increasing trends observed in monsoon Tmean and Tmin, and post-monsoon Tmax are attributed to the recent warming (2011-2020). However, increase in DTR might be attributed to the increase in solar irradiance, and decrease in clouds and soil moistures (Rai et al., 2012).

Insert Figure 7

In addition, a weak increasing trend and lacking statistical significance, in annual (3.85mm/year) and seasonal precipitation was observed. The rate of increase during pre-monsoon, monsoon, post-monsoon and winter seasons was 0.77mm/year, 5.81mm/year 0.61mm/year and 0.71 mm/year, respectively. This finding is different from the previous studies conducted over Uttarakhand by Rathore et al. (2013) and Malik et al. (2019) who had reported a decreasing trend in annual and seasonal rainfall. This dissimilarity might be linked to the length of data period and controls of local topography on rainfall. Rathore et al. (2013) and Malik et al. (2019) had analysed data (13 stations) of 1951-2010 and 1966-2015, and estimated trends in rainfall for Uttarakhand state and Uttarkashi (district), respectively. This was a generalised trend without considering effect of altitude on rainfall measurement. However, within the BRB, altitude ranges from ~420 to7010m and there is no observing station above 4000m. CHIRPS rainfall data used in this study is available at a spatial resolution of $0.05° \times 0.05°$, which is able to capture rainfall variability at much finer scale in the mountainous region and considered to be a good representative of spatially distributed rainfall patterns (Prakash, 2019).

4.5 Projected changes in temperature and precipitation

Figure 8 shows the projected changes in mean annual temperature (Tmean, Tmax and Tmin) and precipitation for the 2030s under both the SSP245 and SSP585 GHG emission scenarios. All four models project an increase in annual Tmean, Tmax and Tmin under both GHG scenarios, although the magnitude of the warming varies between models, while for precipitation an increase is projected for most models, with the exception of the least severe GHG emission scenario for the CanESM5 model, which project a decrease in precipitation. The projected warming varies between models from 0.9°C to 2.2°C under SSP245 and from 1.1°C to 2.4°C under SSP585 for Tmean, 0.4-1.7°C under SSP245 and 0.6-2.1°C under SSP585 for Tmax, 1.4-2.8°C under SSP245 and 1.6-3.2°C under SSP585 for Tmin, clearly showing that a greater warming is projected for Tmin than Tmax. The projected change in precipitation also varies between models, from -0.29% to 4.3% under SSP245 and from +3.9% to 28.8% under SSP585.

The projected changes in seasonal precipitation under both the SSP245 and SSP585 GHG emission scenarios for the period 2021-2050 are shown in Table 5. In general, all models under both scenarios predict a significant decrease in monsoonal precipitation. It was in range of ~-8 to -75% under SSP245 and ~-29 to -82% under SSP585. However, considerable increase in precipitation of pre-monsoon, post-monsoon and winter are anticipated in the future. Maximum and minimum increase in seasonal precipitation was predicted during post-monsoon and pre-monsoon seasons, respectively. Joseph et al. (2018) showed that GCMs had overestimated precipitation in post-monsoon and winter season over the upper Ganga basin. Therefore, such a high increase in projected precipitation includes large uncertainties and may be unrealistic on the ground. However, they agreed over the rising trend of precipitation during these seasons. Similarly, analysis of future scenarios data in general revealed increase in Tmean, Tmax and Tmin for pre-monsoon and winter seasons under both scenarios for all the models. It was in range of +1.1°C to +5.5°C for Tmean, +0.3°C to +4.4°C for Tmax, and +1.3°C to +6.6°C for Tmin during pre-monsoon, and +1.1°C to +7.7°C for Tmean, +1.1°C to +9.0°C for Tmax, and +2.5°C to 11.4°C for Tmin during winter season. Thus, the projected increment is substantial in winter temperature and it would be highest for Tmin. Opposite to this, a decrease in Tmin is predicted for the monsoon season under both scenarios for all models. The variability in results of models owe to their parameterisation and grid resolution (Singh et al., 2015b).

Insert Table 5

The results obtained in this study agree with previous work of other researchers conducted over the western Himalaya and Ganga basin. Tiwari et al. (2018) analysed data of seven fifth generation of the CMIP models and reported an increase of +1.5°C to +5.0°C in mean annual temperature for future periods (2006-2060) under RCP4.5 and RCP8.5 over the western Himalaya. Their studies also predicted decrease in monsoon precipitation and overall increase in annual precipitation. Similarly, Joseph et al. (2018) also observed overall increase in mean annual temperature and precipitation (based on 3 GCMs) over the Ganga basin, with large seasonal variability for the period 2011-2037.

Insert Figure 8

4.6 The relationship between SCA and climatic variables

Table 6 presents the results of a cross correlation analysis between the variability in SCA and different climatic variables during the period 2001-2019, while Figure 9 and Figure 10 show the regression of the SCA against different climatic variables at the annual and seasonal time-scales, respectively. These analyses were performed after removing multicollinearity among the climatic variables that eventually reduced the number of independent variables from five to three. Overall, it was found that the annual SCA is negatively correlated with changes in Tmax and Tmin while positively with that of the precipitation. But, it lacks statistical significance. However, moderate to high negative correlations of SCA with Tmax and Tmin are observed during pre-monsoon, post-monsoon and winter seasons. The negative correlations are found to be statistically significant with Tmax for pre-monsoon (r = -0.59, p<0.05), post-monsoon (r = -0.53, p<0.05) and winter r = -0.69, p<0.05) seasons; and with Tmin for pre-monsoon (r = -0.60, p<0.05) seasons. It is also observed that SCA is positively correlated with monsoon , post-monsoon and winter precipitation , while negatively with the pre-monsoon precipitation . However, the correlation coefficient is statistically significant only for post-monsoon (r = 0.49, p<0.05) and winter (r = 0.54, p<0.05) precipitation.

Insert Table 6

Insert Figure 9

Thus, annual and seasonal (monsoon and winter) SCA has been increasing, but the trend is not statistically significant, and that this increasing trend is associated with an increase in precipitation, although the latter also lacks statistical significance. This positive correlation between SCA and precipitation at the annual time-scale and during the post-monsoon and winter seasons is in accordance with previous studies conducted in other Himalayan basins (Dharpure et al., 2020; Sahu and Gupta, 2020), but completely fluctuates for the pre-monsoon and monsoon seasons. For example: Dharpure et al. (2020) reported a positive correlation between SCA and precipitation for pre-monsoon and negative correlation in monsoon season. Therefore, this relationship is required to be re-investigated in other catchments across the Himalaya, so as to validate the current observations, and comprehend the processes responsible for such behaviours.

Insert Figure 10

5. Discussion

5.1 Implications of projected changes in temperature and precipitation on SCA

The impact of projected changes in temperature and precipitation on SCA were examined using the developed MLR which was based on mean of the multi-model ensembles. Figure 11 shows the projected mean annual patterns in SCA of different elevation zones over the BRB under the SSP245 and SSP585 GHG emissions scenarios for period 2021-2050 (2030s). A reduction in mean annual SCA of the basin was predicted and it was slightly lower under SSP585(-0.58%) compared to SSP245 (-0.95%) (Table 7). However, the nature of change in mean annual SCA was not found identical for all the elevation zones. The model predicted an increase in mean annual SCA of the zones below 4000 m while decrease for the zones above 4000 m. Within the zones, the highest decrease in mean annual SCA was observed at the elevation zone of 5000-6000 m (1.29%) under SSP245. Likewise, a decrease in mean seasonal (pre-monsoon, post-monsoon and winter) SCA ranging from -0.3% to -1.2% and -0.6% to -1.2% was also predicted under SSP585 and SSP245 for the study period, respectively.

Insert Figure 11

Insert Table 7

Moreover, a large inter-annual variability in mean annual SCA of different elevation zones was predicted under both the scenarios (Figure 12). From the interpretation of the Figure 11, it is evident that mean annual SCA would decline for elevation zones above 3000 m between 2021 and 2050. The rate of decrease would be higher in the elevation zone of 5000-6000 m. Opposite to this, the zone of 2000-3000 m would record increase in the mean annual SCA, but it is not of a statistical significance due to its lower areal coverage (below 10% of the zone area). This difference in SCA reduction is attributed to the varied increase in projected temperature which under both scenarios is negatively correlated with SCA. The predicted SCA under both scenarios reveal similarity with the observed pattern of SCA derived from the MODIS. For example, monthly patterns (averaged over period of 2021-2050) in SSP245 and SSP585 shows minimum SCA in July and is consistent with the MODIS SCA (Figure 5), which indicates that the change in SCA will be in line with the given scenarios in the future.

Insert Figure 12

The changes revealed in SCA during pre-monsoon and winter are in line with previous studies conducted over the western Himalaya. Tiwari et al. (2018) showed that snow amount would be less by about 30 to 40 mm (RCP4.5 scenario) and about 50 mm (RCP8.5 scenario) in February by the end of mid-century as compared to present climate. These seasonal transformations in snow cover can adversely influence the climate into a responsive system. In comparison to other natural land surfaces snow cover has a high reflectance capability with high proportion of the incoming solar radiation and a much higher albedo. Hence the decrease in the snow cover may increase amount of solar radiation absorbed by the surface thereby disturbing the region's heat balance, leading changes in the hydrological cycle (Huntington, 2006).

5.2 Implications of changes in SCA on water resources

Snow cover is a vital source of water; any alteration in snow cover is likely to impact glaciers and affect the flow of rivers and their regime. Water stored in glaciers serves as a natural reservoir, discharging water into the Bhagirathi River and its tributaries during the ablation (May-September) period. The warming climate has not only caused changes in the temporal and spatial extent of SCA over the BRB, but also in snowpack and glacier melting, which has resulted in a decrease in length and surface area, volume and mass of glaciers. For example, Gangotri Glacier experienced a reduction of ~2.65±1.78 km^2 in its area between 2000 and 2020 (Figure 13). The snout of the glacier has retreated by 256±24.50 m during this period (Figure 14). Bhambri et al. (2012) found that the glacier retreated by 819±14 m from its initial position over the span of 41 years (1965-2006). Other glaciers of the catchment also have exhibited retreats in their snouts and area in recent decades, with the smaller glaciers being most vulnerable (Bhambri et al., 2011).

The melting of glaciers is intrinsically related to seasonal climate variability and change. This could be explained from the results of trend analysis of temperature and precipitation, and pattern of river flows. The analysis of discharge data (2000, 2004, 2005, and 2016) collected during ablation period near the snout of the Gangotri Glacier revealed a decline in the flow of the Bhagirathi River. This attributes to the rise in seasonal (monsoon) temperature. The warmer monsoon temperature (1.6-2.0°C) accelerated glacier melting, thereby reducing the amount of river flow over the time periods. However, in future, most the models predict decrease in monsoon temperatures, but relatively higher increases are predicted during pre-monsoon and winter seasons. This may result in the earlier melting of glaciers and reduction in snow accumulation processes.

Insert Figure 13

Insert Figure 14

6. Conclusions

In this study, remote sensing datasets along with the latest CMIP6 climate change scenarios were used to assess the impact of projected changes in climate on the snow cover of Himalayan catchment and deducing its potential implications on the cryospheric water store of the basin. The study on correlation of SCA with climatic variables has revealed that SCA is more sensitive to temperature (Tmax and Tmin) change as compared to precipitation. The overall analysis of this research indicates that mean annual and seasonal (pre-monsoon, post-monsoon and winter) SCA in the catchment would decrease in the 2030s under both the scenarios (SSP245 and SSP585) owing to the projected increase in temperatures (Tmax and Tmin) for the region. The decrease in mean annual SCA would be in range of -.58% (SSP585) to -0.95% (SSP245), however, it would be decreased by -0.35% to -0.64% during the pre-monsoon and -1.22% to -1.21% during winter under SSP585 and SSP245, respectively. Further, the elevation zones above 4000 m would record decrease in their mean annual and seasonal snow cover area. Moreover, the projected rise in temperatures may cause early start in the melting of glaciers and affect the flow of rivers and their regime. This would directly have an effect on water accessibility, notably for hydro-power generation and irrigation.

Acknowledgement

We acknowledge the Institute of International Rivers and Eco-Security (IRES) of Yunnan University (The Peoples Republic of China) for providing a Visiting Scientist Fellowship to Dr. Dharmaveer Singh (under the auspices of the National Natural Science Foundation of China grant no 42171129 and the grant (2021YFE0116800) for international collaboration of the Ministry of Science and Technology of China). We also extend our gratitude to the Director of the Symbiosis Institute of Geoinformatics, Symbiosis International (Deemed University), Pune, for his administrative and moral support for carrying out this study.

References

Altman DG, Bland JM. Statistics notes: the normal distribution. BMJ. 1995;310(6975):298. https://doi.org/10.1136/bmj.310.6975.298

Berthier, E., Arnaud, Y., Kumar, R., Ahmad, S., Wagnon, P., & Chevallier, P. (2007). Remote sensing estimates of glacier mass balances in the Himachal Pradesh (Western Himalaya, India). *Remote Sensing of Environment*, *108*(3), 327-338.

Bhambri, R., Bolch, T., & Chaujar, R. K. (2012). Frontal recession of Gangotri Glacier, Garhwal Himalayas, from 1965 to 2006, measured through high-resolution remote sensing data. *Current Science, 102(3),* 489-494.

Bhambri, R., Bolch, T., Chaujar, R. K., & Kulshreshtha, S. C. (2011). Glacier changes in the Garhwal Himalaya, India, from 1968 to 2006 based on remote sensing. *Journal of Glaciology*, *57*(203), 543-556.

Bolch, T., Kulkarni, A., Kääb, A., Huggel, C., Paul, F., Cogley, J. G., ...& Stoffel, M. (2012). The state and fate of Himalayan glaciers. *Science*, *336*(6079), 310-314.

Bookhagen, B. (2012). Himalayan groundwater. *Nature Geoscience*, *5*(2), 97-98.

Buishand, T. A. (1982). Some methods for testing the homogeneity of rainfall records. *Journal of hydrology*, *58*(1-2), 11-27.

Chandel, V. S., & Ghosh, S. (2021). Components of Himalayan River Flows in a Changing Climate. *Water Resources Research*, *57*(2), e2020WR027589. https://doi.org/10.1029/2020WR027589

Chen, Y., Li, W., Deng, H., Fang, G., & Li, Z. (2016). Changes in Central Asia's water tower: Past, present and future. *Scientific reports*, *6*(1), 1-12.

Chug, D., Pathak, A., Indu, J., Jain, S. K., Jain, S. K., Dimri, A. P., ... & Ghosh, S. (2020). Observed Evidence for Steep Rise in the Extreme Flow of Western Himalayan Rivers. *Geophysical Research Letters*, *47*(15), e2020GL087815.

Collins, D. N., Davenport, J. L., & Stoffel, M. (2013). Climatic variation and runoff from partially-glacierised Himalayan tributary basins of the Ganges. *Science of the Total Environment*, *468*, S48-S59.

Dharpure, J. K, Goswami, A., Patel, A., Kulkarni, A. V., & Snehmani. (2021). Assessment of snow cover variability and its sensitivity to hydro-meteorological factors in the Karakoram and Himalayan region. *Hydrological Sciences Journal*. https://doi.org/10.1080/02626667.2021.1985125

Dharpure, J. K., Patel, A., Goswami, A., Kulkarni, A. V., & Snehmani. (2020). Spatiotemporal snow cover characterization and its linkage with climate change over the Chenab river basin, western Himalayas. *GIScience & Remote Sensing*, *57*(7), 882-906.

Dimri, A. P., Niyogi, D., Barros, A. P., Ridley, J., Mohanty, U. C., Yasunari, T., & Sikka, D. R. (2015). Western disturbances: a review. *Reviews of Geophysics*, *53*(2), 225-246.

Dozier, J., Painter, T. H., Rittger, K., & Frew, J. E. (2008). Time–space continuity of daily maps of fractional snow cover and albedo from MODIS. *Advances in Water Resources*, *31*(11), 1515-1526.

Frey, H., Machguth, H., Huss, M., Huggel, C., Bajracharya, S., Bolch, T., ...& Stoffel, M. (2014). Estimating the volume of glaciers in the Himalayan–Karakoram region using different methods. *The Cryosphere*, *8*(6), 2313-2333.

Gafurov, A., Vorogushyn, S., Farinotti, D., Duethmann, D., Merkushkin, A., &Merz, B. (2015). Snow-cover reconstruction methodology for mountainous regions based on historic in situ observations and recent remote sensing data. *The Cryosphere*, *9*(2), 451-463.

Gough, W. A., Gagnon, A. S., & Lau, H. P. (2004). Interannual variability of Hudson Bay ice thickness. *Polar Geography*, *28*(3), 222-238.

Gusain, H. S., Kala, M., Ganju, A., Mishra, V. D., & Snehmani. (2015). Observations of snow–meteorological parameters in Gangotri glacier region. *Current Science*, 2116-2120.

Hall, D. K., & Riggs, G. A. (2010). Normalized-difference snow index (NDSI).

Hall, D. K., Riggs, G. A., DiGirolamo, N. E., & Román, M. O. (2019). Evaluation of MODIS and VIIRS cloud-gap-filled snow-cover products for production of an Earth science data record. *Hydrology and Earth System Sciences*, *23*(12), 5227-5241.

He, G., Xiao, P., Feng, X., Zhang, X., Wang, Z., & Chen, N. (2015). Extracting snow cover in mountain areas based on SAR and optical data. *IEEE Geoscience and Remote Sensing Letters*, *12*(5), 1136-1140.

Helsel, D. R., & Hirsch, R. M. (1992). *Statistical methods in water resources* (Vol. 49). Elsevier.

Huntington, T. G. (2006). Evidence for intensification of the global water cycle: Review and synthesis. *Journal of Hydrology*, *319*(1-4), 83-95.

Immerzeel, W. W., Van Beek, L. P. H., Konz, M., Shrestha, A. B., &Bierkens, M. F. P. (2012). Hydrological response to climate change in a glacierized catchment in the Himalayas. *Climatic change*, *110*(3), 721-736.

Immerzeel, W. W., Van Beek, L. P., &Bierkens, M. F. (2010). Climate change will affect the Asian water towers. *Science*, *328*(5984), 1382-1385.

Joseph, J., Ghosh, S., Pathak, A., & Sahai, A. K. (2018). Hydrologic impacts of climate change: Comparisons between hydrological parameter uncertainty and climate model uncertainty. *Journal of Hydrology*, *566*, 1-22.

Joshi, R., Kumar, K., Pandit, J., & Palni, L. M. S. (2015). Variations in the seasonal snow cover area (SCA) for Upper Bhagirathi Basin, India. In *Dynamics of Climate Change and Water Resources of Northwestern Himalaya* (pp. 9-21). Springer, Cham.

Kaser, G., Großhauser, M., &Marzeion, B. (2010). Contribution potential of glaciers to water availability in different climate regimes. *Proceedings of the National Academy of Sciences*, *107*(47), 20223-20227.

Khan, A. A., Pant, N. C., Sarkar, A., Tandon, S. K., Thamban, M., & Mahalinganathan, K. (2017). The Himalayan cryosphere: a critical assessment and evaluation of glacial melt fraction in the Bhagirathi basin. *Geoscience Frontiers*, *8*(1), 107-115.

Kumar, P., Saharwardi, M. S., Banerjee, A., Azam, M. F., Dubey, A. K., & Murtugudde, R. (2019). Snowfall variability dictates glacier mass balance variability in Himalaya-Karakoram. *Scientific reports*, *9*(1), 1-9.

Larsen, K. (2017). *Influence of summer snowfall on discharge emanating from the Gangotri glacier* (Doctoral dissertation, University of Salford). http://usir.salford.ac.uk/id/eprint/42951/

López-Burgos, V., Gupta, H. V., & Clark, M. (2013). Reducing cloud obscuration of MODIS snow cover area products by combining spatio-temporal techniques with a probability of snow approach. *Hydrology and Earth System Sciences*, *17*(5), 1809-1823.

Lutz, A. F., Immerzeel, W. W., Shrestha, A. B., &Bierkens, M. F. P. (2014). Consistent increase in High Asia's runoff due to increasing glacier melt and precipitation. *Nature Climate Change*, *4*(7), 587-592.

MacDonald, A. M., Bonsor, H. C., Ahmed, K. M., Burgess, W. G., Basharat, M., Calow, R. C., ...& Yadav, S. K. (2016). Groundwater quality and depletion in the Indo-Gangetic Basin mapped from in situ observations. *Nature Geoscience*, *9*(10), 762-766.

Malik, A., Kumar, A., Guhathakurta, P., & Kisi, O. (2019). Spatial-temporal trend analysis of seasonal and annual rainfall (1966–2015) using innovative trend analysis method with significance test. *Arabian Journal of Geosciences*, *12*(10), 1-23.

Mann, H. B. (1945) Nonparametric tests against trend. *Econometrica, 13*, 245–259.

Masson-Delmotte, V., Zhai, P., Pörtner, H. O., Roberts, D., Skea, J., Shukla, P. R., ...& Waterfield, T. (2018). Global warming of 1.5 C. *An IPCC Special Report on the impacts of global warming of*, *1*, 1-9.

Mishra P, Pandey CM, Singh U, Gupta A, Sahu C, Keshri A. Descriptive statistics and normality tests for statistical data. Ann Card Anaesth 2019;22:67-72

Mishra V, Bhatia U, Tiwari A.D. 2020. Bias-corrected climate projections for South Asia from Coupled Model Intercomparison Project-6. Sci. Data. 7, 338. https://doi.org/10.1038/s41597-020-00681-1.

Neter, J., Kutner, M. H., Nachtsheim, C. J., & Wasserman, W. (1996). *Applied linear statistical models*, 1-318.

Nuth, C., & Kääb, A. (2011). Co-registration and bias corrections of satellite elevation data sets for quantifying glacier thickness change. *The Cryosphere*, *5*(1), 271-290.

Page ES 1961 Cumulative sum charts; *Technometrics*, 3(1):1-9.

Parajka, J., & Blöschl, G. (2006). Validation of MODIS snow cover images over Austria. *Hydrology and Earth System Sciences*, *10*(5), 679-689.

Peterson, T. C., & Easterling, D. R. (1994). Creation of homogeneous composite climatological reference series. *International Journal of Climatology, 14(6)*, 671-679.

Peterson, T. C., Easterling, D. R., Karl, T. R., Groisman, P., Nicholls, N., Plummer, N., ... & Parker, D. (1998). Homogeneity adjustments of in situ atmospheric climate data: a review. *International Journal of Climatology, 18(13)*, 1493-1517.

Prakash, S. (2019). Performance assessment of CHIRPS, MSWEP, SM2RAIN-CCI, and TMPA precipitation products across India. *Journal of hydrology*, *571*, 50-59.

Rai, A., Joshi, M. K., & Pandey, A. C. (2012). Variations in diurnal temperature range over India: under global warming scenario. *Journal of Geophysical Research: Atmospheres*, *117*(D2).

Rai, S. P., Singh, D., Jacob, N., Rawat, Y. S., & Arora, M. (2019). Identifying contribution of snowmelt and glacier melt to the Bhagirathi River (Upper Ganga) near snout of the Gangotri Glacier using environmental isotopes. *Catena*, *173*, 339-351.

Rathore, B. P., Singh, S. K., Bahuguna, I. M., Brahmbhatt, R. M., Rajawat, A. S., Thapliyal, A., ... & Ajai. (2015). Spatio-temporal variability of snow cover in Alaknanda, Bhagirathi and Yamuna sub-basins, Uttarakhand Himalaya. *Current Science*, 1375-1380

Rathore, L. S., Attri, S. D., & Jaswal, A. K. (2013). State level climate change trends in India. India Meteorological Department, 25. https://doi.org/10.13140/RG.2.1.4980.2400.

Riahi, K., Van Vuuren, D. P., Kriegler, E., Edmonds, J., O'neill, B. C., Fujimori, S., ... & Tavoni, M. (2017). The shared socioeconomic pathways and their energy, land use, and greenhouse gas emissions implications: an overview. *Global Environmental Change, 42*, 153-168.

Riggs, G. A., Hall, D. K., & Román, M. O. (2017). Overview of NASA's MODIS and visible infrared imaging radiometer suite (VIIRS) snow-cover earth system data records. *Earth System Science Data*, *9*(2), 765-777.

Rittger, K., Painter, T. H., & Dozier, J. (2013). Assessment of methods for mapping snow cover from MODIS. *Advances in Water Resources*, *51*, 367-380.

Romanov, P., Tarpley, D., Gutman, G., & Carroll, T. (2003). Mapping and monitoring of the snow cover fraction over North America. *Journal of Geophysical Research: Atmospheres*, *108*(D16).

Sahu, R., & Gupta, R. D. (2020). Glacier mapping and change analysis in Chandra basin, Western Himalaya, India during 1971–2016. *International Journal of Remote Sensing*, *41*(18), 6914-6945.

Save, Himanshu, (2020) "CSR GRACE and GRACE-FO RL06 Mascon Solutions v02", Doi: 10.15781/cgq9-nh24.

Sen, P.K., (1968). Estimates of the regression coefficient based on Kendall’s tau. *Journal of the American Statistical Association, 63,* 1379–1389.

Shafiq, M. U., Ahmed, P., Islam, Z. U., Joshi, P. K., & Bhat, W. A. (2019). Snow cover area change and its relations with climatic variability in Kashmir Himalayas, India. *Geocarto International*, *34*(6), 688-702.

Shapiro, S. S., & Wilk, M. B. (1965). An analysis of variance test for normality (complete samples). *Biometrika*, *52*(3/4), 591-611.

Shreve, C. M., Okin, G. S., & Painter, T. H. (2009). Indices for estimating fractional snow cover in the western Tibetan Plateau. *Journal of Glaciology*, *55*(192), 737-745.

Singh, D. K., Gusain, H. S., Mishra, V., & Gupta, N. (2018). Snow cover variability in North-West Himalaya during last decade. *Arabian Journal of Geosciences*, *11*(19), 1-12.

Singh, D., Gupta, R. D., & Jain, S. K. (2014a). Study of long-term trend in river discharge of Sutlej River (NW Himalayan region). *Geography, Environment, Sustainability*, *7*(3), 87-96.

Singh, D., Gupta, R. D., & Jain, S. K. (2015a). Statistical analysis of long term spatial and temporal trends of temperature parameters over Sutlej river basin, India. *Journal of Earth System Science, 124*(1), 17-35.

Singh, D., Jain, S. K., & Gupta, R. D. (2015b). Statistical downscaling and projection of future temperature and precipitation change in middle catchment of Sutlej River Basin, India. *Journal of Earth System Science, 124*(4), 843-860.

Singh, D., Rai, S. P., Kumar, B., Jain, S. K., & Kumar, S. (2016). Study of hydro-chemical characteristics of Lake Nainital in response of human interventions, and impact of twentieth century climate change. *Environmental Earth Sciences*, *75*(20), 1-15.

Singh, M. K., Thayyen, R. J., & Jain, S. K. (2019). Snow cover change assessment in the upper Bhagirathi basin using an enhanced cloud removal algorithm. *Geocarto International*, 1-24.

Singh, S. K., Rathore, B. P., & Bahuguna, I. M. (2014b). Snow cover variability in the Himalayan–Tibetan region. *International Journal of Climatology*, *34*(2), 446-452.

Singh, S., Kumar, R., Bhardwaj, A., Sam, L., Shekhar, M., Singh, A., ...& Gupta, A. (2016). Changing climate and glacio-hydrology in Indian Himalayan Region: a review. *Wiley Interdisciplinary Reviews: Climate Change*, *7*(3), 393-410.

Sirguey, P., Mathieu, R., & Arnaud, Y. (2009). Subpixel monitoring of the seasonal snow cover with MODIS at 250 m spatial resolution in the Southern Alps of New Zealand: Methodology and accuracy assessment. *Remote Sensing of Environment*, *113*(1), 160-181.

Snehmani, Dharpure, J. K., Kochhar, I., Hari Ram, R. P., & Ganju, A. (2016). Analysis of snow cover and climatic variability in Bhaga basin located in western Himalaya. *Geocarto International*, *31*(10), 1094-1107.

Srivastava, D., Kumar, A., Verma, A., &Swaroop, S. (2014). Analysis of climate and melt-runoff in Dunagiri Glacier of Garhwal Himalaya (India). *Water resources management*, *28*(10), 3035-305

Thakur, P. K., Aggarwal, S. P., Arun, G., Sood, S., Kumar, A. S., Mani, S., &Dobhal, D. P. (2017). Estimation of snow cover area, snow physical properties and glacier classification in parts of Western Himalayas using C-Band SAR data. *Journal of the Indian Society of Remote Sensing*, *45*(3), 525-539.

Thayyen, R. J., & Gergan, J. T. (2010). Role of glaciers in watershed hydrology: a preliminary study of a" Himalayan catchment". *The Cryosphere*, *4*(1), 115-128.

Tiwari, S., Kar, S. C., & Bhatla, R. (2018). Mid-21st century projections of hydroclimate in Western Himalayas and Satluj River basin. *Global and Planetary Change*, *161*, 10-27.

Wang, R., Liu, S., Shangguan, D., Radić, V., & Zhang, Y. (2019). Spatial heterogeneity in glacier mass-balance sensitivity across High Mountain Asia. *Water*, *11*(4), 776.

World Meteorological Organization. (2011). *Guide to climatological practices (WMO-No. 100)*. Geneva, Switzerland: World Meteorological Organization.

Xiao, P., Li, C., Zhu, L., Zhang, X., Ma, T., & Feng, X. (2020). Multitemporal ensemble learning for snow cover extraction from high-spatial-resolution images in mountain areas. *International Journal of Remote Sensing*, *41*(5), 1668-1691.

Yadav, B. C., Thayyen, R. J., & Jain, K. (2020). Topoclimatic zones and characteristics of the upper Ganga basin, Uttarakhand, India. *International Journal of Climatology*, *40*(14), 6002-6019.

Zhang, H., Zhang, F., Zhang, G., Che, T., Yan, W., Ye, M., & Ma, N. (2019). Ground-based evaluation of MODIS snow cover product V6 across China: Implications for the selection of NDSI threshold. *Science of the Total Environment*, *651*, 2712-2726.

Zhu, Y., Liu, S., Yi, Y., Xie, F., Grünwald, R., Miao, W., ... & Singh, D. (2021). Overview of terrestrial water storage changes over the Indus River Basin based on GRACE/GRACE-FO solutions. *Science of The Total Environment*, 149366. https://doi.org/10.1016/j.scitotenv.2021.149366