Discharge Estimation With Improved Methods Using MODIS Data in Greenland: An Application in the Watson River

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Abstract—Greenland’s river discharge has important implications for the Greenland Ice Sheet (GrIS) mass balance, global sea-level rise, and climate change. However, the long-term and continuous in situ discharge data for Greenland are scarce. The water extent is an important proxy to estimate discharge using remote sensing, but previous studies on estimating the discharge in Greenland required the in situ reflectance data to construct the water extent and suffered from inefficient processing. Here, we derived the water extent solely from the moderate resolution imaging spectroradiometer daily reflectance product on the google earth engine cloud platform. To improve the accuracy and efficiency, we optimized the strategies for water extent estimation and the optimal gauge pixel selection. Our improved method was applied to the Watson River. The runoff data from the regional climate model RACMO2 were employed to compare with the estimated results. Our results provide the daily discharge of the Watson River from 2002 to 2021, covering the period when field observations are unavailable. The correlation coefficient (R) and the fractional root-mean-square error (fRMSE) between the daily estimated discharge and the in situ discharge are 0.69 and 0.73, respectively, whereas the R and fRMSE are 0.85 and 0.53 at a monthly timescale, respectively. The comparisons between our results and the RACMO2 runoff data suggest that the RACMO2 may generally underestimate the annual ice sheet melt runoff but overestimates the monthly runoff in July by 30% on average. The proposed method is highly automated and efficient, and has the potential to be applied in other rivers with field measurements to provide continuous and long-term discharge observations. It contributes to a better understanding of the response of the GrIS to climate change.

Index Terms—Google earth engine (GEE), Greenland, moderate resolution imaging spectroradiometer (MODIS), remote sensing, river discharge.

I. INTRODUCTION

The Greenland ice sheet (GrIS) has undergone significant mass loss in recent decades, with a total ice loss of 3902±342 Gt in 2010–2018 [1]. The increased melting water that enters the ocean through river discharge accelerates the global sea-level rise, weakens the thermohaline circulation and causes global climate change, which poses a major challenge to sustainable development [2], [3], [4]. Given that the discharge changes of Greenland’s rivers have profound implications for Greenland’s surface mass balance and sea-level rise as well as global climate change, it is imperative to estimate Greenland’s river discharge and analyze their variations. Despite the awareness of the important river discharge information, monitoring river discharge through the traditional way in the margin of the GrIS is still challenging. Many rivers in Greenland are braided rivers with unstable channel geometry, which causes difficulties for the traditional measurement based on water level [5]. Moreover, it is difficult to deploy and maintain gauging equipment near the periphery of GrIS [5].

In the last few decades, estimating river discharge using remote sensing data has become a burgeoning field ripe with great potential and innovation. The related achievement is reviewed by Gleason and Durand [6] and Tarpanelli et al. [7]. Passive microwave and optical data provide an indirect estimation of discharge. The potential for estimating discharge using the inundation signals derived from passive microwave observations has been tested in the early studies carried out by Smith et al. [8] and Vörösmarty et al. [9], respectively. Furthermore, Brakenridge et al. [10] expounded that the brightness temperature ratio between a target pixel and a dry pixel is well correlated with water extent. Based on this relationship, they used advanced microwave scanning radiometer Ka-band brightness temperature data to estimate the river discharge at a global scale, excluding Greenland. Tarpanelli et al. [11] applied Brakenridge’s concept to the moderate resolution imaging spectroradiometer (MODIS) data and sufficiently revealed the advantages of MODIS products in discharge estimation. To estimate the river discharge in Greenland, McGrath et al. [12] employed MODIS-derived sediment plumes as a proxy. Overeem et al. [5] first combined MODIS product and in situ dry land reflectance data to investigate the water extent and from this to estimate the discharge of the Watson and Naujat Kuat Rivers in west Greenland. Unlike spectral sensors, radar altimetry provides a direct measurement of water level to estimate discharge but the accuracy may be limited by the effect of heterogeneous surfaces and the coarse temporal resolution [13]. Currently, the discharge estimation

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using radar altimetry is only possible for some very large river basins (>10,000 km²) [14]. van Dijk et al. [14] combined MODIS data, passive microwave data, ENVISAT, and JASON-2 altimetry data to estimate river discharge at a global scale, but rivers in Greenland are not included in their study. Slater et al. [15] used CryoSat-2 satellite altimetry to estimate Greenland’s total runoff yet the discharge information of an individual river was overlooked due to the large study scale.

MODIS data performed excellently in detecting the variability of the river discharge, mainly thanks to its high temporal resolution [16]. In Greenland, rivers are generally located in narrow fjords covered with snow [5]. Therefore, passive microwave products are less applicable for estimating Greenland’s river discharge because of the coarse resolution and the significant influence of snow cover on brightness temperature [5]. High-spatial-resolution satellite data, such as Landsat products, provide more detailed inundation information than the MODIS data in small rivers (<100 m width) [17], [18], [19]. But it is more challenging to employ these high-spatial-resolution products to estimate Greenland’s river discharge because in situ measurements in Greenland are scarce and the revisit frequency of these products is rather lower than that of the MODIS.

In summary, the studies mentioned above enriched the methods for discharge estimation using remote sensing, but there are two issues worth noting. First, at present, the lack of in situ river discharge information in Greenland hampers the studies on the response of the GrIS to climate change and its impact on sea-level rise. Second, few studies have estimated river discharge in Greenland using remote sensing, which is a domain that remains underexplored. Besides, the data processing in these previous studies is inefficient due to the laborious manual selection of the gauging pixel.

To address the above two issues, a highly automated method of optimal discharge estimation is developed mainly based on google earth engine (GEE) cloud platform and MODIS data in the present study. The strategies for obtaining the water extent and selecting the optimal pixel are optimized in the proposed method. An application of this method is implemented in the Watson River. It is expected that a combination of MODIS product and the improved methods could provide more accurate and timely discharge estimates with higher efficiency, especially in the regions where discharge information is scarce yet urgently needed. On this basis, the objectives of this study are the following.

1) Design an efficient and generic method of optimal discharge estimation mainly based on GEE and MODIS product.
2) Estimate the discharge of the Watson River in 2002–2021 and fill the data gap in field measurements.

II. STUDY AREA AND DATA

A. Study Area

The study area is the Watson River in southwestern Greenland (see Fig. 1). The Watson River discharge basin covers an area of 1882 km², of which 1361 km² is ice and 521 km² is land [20]. Its branches start at the ice sheet margin and converge into the Kangerlussuaq Fjord, with a total length of about 26–33 km [21]. The Watson River gauge station is located at 67.01 °N, 50.68 °W. This station is built on the solid bedrock, which is desired for the observation and study of discharge. The Watson River ice sheet catchment boundary provided by Jason E. Box (see Table I) [22] is shown in Fig. 1.

B. MODIS Data

The MOD09GA product provides daily surface reflectance data for bands 1–7 of the MODIS sensor aboard the Terra satellite, with a spatial resolution of 500 m (https://doi.org/10.5067/MODIS/MOD09GA.006) (see Table I). A rigorous atmospheric correction has been applied to this product [23]. We selected the surface reflectance of band 6 (Near Infrared, 1628–1652 nm) to compute the area proportion of water extent. Overeem et al. [5] found that there is a significant contrast in the band 6 reflectance between water bodies and dry land. The band 6 reflectance of meltwater body and dry land is approximately 0 and 0.3,
respectively. This characteristic indicates that band 6 reflectance is suitable for deriving the area proportion of water extent.

C. Discharge Data

The in situ daily discharge data of the Watson River were obtained from the GrIS Monitoring Program Data Center (https://doi.org/10.22008/promice/data/watson_river_discharge) (see Table I) [21]. The period of this dataset is from June 1, 2006 to August 31, 2020 (~15 years). The daily discharge in each year and the average daily discharge are shown in Fig. 2. The discharge data from May to September (MJJAS) are available in this dataset and the discharge in June, July, and August (JJA) was selected for discharge estimation regression because the ice sheet ablation is more significant during this period. The selected data contain 1304 records of daily discharge.

D. RACMO2 Runoff Data

The RACMO2 (Version 2.3p2) is a high-resolution regional climate model with a spatial resolution of 5.5 km, statistically downscaled to 1 km. The model is forced by the ERA-Interim reanalysis provided by the European Centre for Medium-Range Weather Forecasts. The RACMO2.3p2 includes melt, water percolation, and retention in snow, refreezing, and runoff simulated by a multilayer snow module and has been widely used in surface mass balance studies [24], [25]. In this study, the daily RCMO2.3p2 runoff data from 2002 to 2020 were used for comparison with the estimated results and are available on request from Brice Noël [25].

III. METHODS

Fig. 3 illustrates the workflow for estimating discharge from the MOD09GA product and the analysis processes, which include three parts. The first part aims at generating the optimal solution for discharge estimation, which includes locating the measurement pixel with the best performance, obtaining the optimal discharge estimation expression, and performance assessment with in situ data. All the JJA daily discharge data in 2006–2020 were used for discharge estimation regression because the sample size is too small to divide the dataset into the training and validation subdatasets. This operation is supported by the previous related studies [5], [26]. Notably, the daily discharge data in May and September in 2006–2020 were not included in the regression and used in the performance assessment with all JJA discharge data, which could further test the performance of the discharge estimation method. The second part is to estimate the Watson River discharge in 2002–2021. Finally, the interannual variability in river discharge was investigated by the time-series decomposition method, and the RACMO2 runoff data were used to compare with the estimated results. In the present study, the monthly discharge refers to the monthly mean discharge (m³/s) and the annual discharge is the total discharge (Gt) in MJJAS.

The emergence of GEE makes it possible to efficiently process massive amounts of big earth data [27]. GEE is a remote sensing big data cloud computing platform jointly developed by Google, National Aeronautics and Space Administration (NASA), Carnegie Mellon University, and the United States Geological Survey [28]. Users can directly explore multisource remote sensing datasets online and can use JavaScript or Python programming to design experimental code on GEE and complete the calculation on the cloud platform, which greatly promotes research efficiency [29].
A. Area Proportion of Water Extent Derived by MODIS Data

In this study, the area proportion of water extent time series within a single MODIS pixel and the in situ daily discharge series are used to construct a regression relationship. A single pixel has been proved to perform well in discharge estimation [26]. Our pre-experiments also demonstrate that a single pixel performs better than multiple pixels in the discharge estimation of the studied river. For a single pixel, the formula of its area proportion of water extent can be presented in the following form:

$$w = \frac{R_M - R_{dry}}{R_{water} - R_{dry}}$$  \hspace{1cm} (1)$$

where $w$ is the area proportion of the water body within the target pixel $M$, and $R_{dry}$ represents the reflectance of the dry surface around or within pixel $M$ [14]. $R_{dry}$ is derived by selecting the maximum reflectance of band 6 within the 7x7 pixel box centered on pixel $M$. $R_{water}$ is the band 6 reflectance of surface water. Previous studies suggested that the reflectance of surface water in near infrared bands is 0.008 derived from satellite observations [14] and 0.001 derived from in situ measurements [5], which implies that $R_{water}$ is negligible. Therefore, (1) can be collated as

$$w = 1 - \frac{R_M}{R_{dry}}.$$  \hspace{1cm} (2)$$

For pixel $M$, the increase of discharge generally leads to the increase of $w$. In this study, the discharge estimation is based on this positive correlation. The pixel $M$ with the strongest correlation between the in situ discharge and $w$ is selected as
the optimal pixel to construct the optimal discharge estimation expression.

B. Selection of the Optimal Measurement Pixel and Discharge Estimation Expression

The relation between \( w \) and discharge of different MODIS pixels around the river station varies remarkably depending on the distance between the measured pixel and the gauge station, the underlying surface, the water level, and the inundation extent [11], [14]. The pixel with the strongest correlation can perform best in estimating discharge. In this study, we designed a program to automatically obtain the MODIS pixel with the strongest correlation between \( w \) and discharge based on GEE and local Python programming. The processes include six main steps (see Fig. 3). The detailed processes for generating the \( R_{\text{dry}} \) images, the \( w \) and smoothed \( w \) time series, and obtaining the optimal discharge estimation expression are shown in Fig. 4. First, we used the internal cloud removal algorithm to remove the cloud from the MOD09GA band 6 image set. The maximum reflectance image set (i.e., the \( R_{\text{dry}} \) image set) was obtained by performing a maximum filtering on the cloud-free images using a 7×7 pixel window [see Fig. 4(a)]. Second, we drew a polygon of the measured area along the river channel near the gauge station. The measured area contains a certain number of MODIS pixels \( M \) to be selected. Previous studies usually selected a square box centered on the gauge site as the measured area and it may include the pixels far away from the river, which are not inundated in the calculation. This approach increases computational costs. In our method, the shape of the measured area polygon is arbitrary. This characteristic allows the measured area to fit the shape of the river channel and obtain the pixels with possible correlations as many as possible and improves the calculation efficiency. Third, we obtained the central longitude and latitude of each pixel \( M \) in the measured area and combined it with the time index of the in situ daily discharge to construct a filter. Based on this filter, we selected the cloud-free band 6 image and the maximum reflectance image of the specified date and then the band 6 reflectance \( R_M \) and the reflectance representing dry land \( R_{\text{dry}} \) of the specified pixel were selected. Fourth, we calculated \( w \) based on (2). After this processing, we obtained the \( w \) time series of each pixel \( M \). Fifth, to reduce the noise interference due to the high variability of surface reflectivity [26], an exponential smoothing filter was applied
to the \(w\) time series [see Fig. 4(b)]. The formula of exponential smoothing is written as

\[
w'_{i+1} = \alpha w_i + (1 - \alpha) w'_i. \tag{3}
\]

Here, \(w'\) and \(w_i\) refer to the smoothed data and original data, respectively. \(i\) is the time when \(w\) is obtained, where \(i = 1, 2, \ldots, N\) with \(N\) as the maximum number of records in a time series. \(w'_{i+1}\) is the smoothed data obtained in the next period of \(i\). \(\alpha\) is the smoothing coefficient.

Finally, we performed exponential regression analyses on the smoothed \(w\) time series and the in situ discharge. Based on the regression expression, the estimated discharge during the field observation period was calculated and validated against the in situ data using the squared Pearson correlation coefficient (\(R^2\)) and root-mean-square error (RMSE). Then, the pixel with the highest \(R^2\) was selected as the optimal pixel for discharge estimation [26], and the corresponding discharge estimation expression was given [see Fig. 4(c)]. The \(R^2\) is a better metric to locate the optimal measurement pixel for alleviating the underestimation effect of high flows [14].

### C. Performance Evaluation

The daily in situ and estimated discharge data in 2006–2020 were employed for the performance assessment of the regression model. To comprehensively evaluate the performance of the regression model and linear interpolation, the discharge estimates were further compared with the in situ discharge at a monthly scale. Note that the discharge estimates were only derived by the regression model in the daily timescale validation, whereas the estimated discharge was obtained from both the regression model and linear interpolation in the monthly timescale evaluation. The Pearson correlation coefficient \(R\), mean absolute error (MAE), RMSE, and fractional RMSE (fRMSE) were computed to assess discharge estimation performance using the following equations:

\[
R = \frac{\sum_{i=1}^{n} (Q_{est,i} - Q_{est,i}')(Q_{obs,i} - Q_{obs,i})}{\sqrt{\sum_{i=1}^{n} (Q_{est,i} - Q_{est,i}')^2 \sum_{i=1}^{n} (Q_{obs,i} - Q_{obs,i})^2}} \tag{4}
\]

\[
\text{MAE} = \frac{\sum_{i=1}^{n} |Q_{est,i} - Q_{obs,i}|}{n} \tag{5}
\]

\[
\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n} (Q_{obs,i} - Q_{est,i})^2}{n}} \tag{6}
\]

\[
\text{fRMSE} = \frac{\text{RMSE}}{\sigma_{obs}} \tag{7}
\]

where \(Q_{est}\) is the estimated values of discharge \(i\), and \(Q_{obs}\) is the in situ observation value of discharge \(i\), and \(\sigma_{obs}\) refers to the standard deviation of the observed discharge time series, \(n\) is the total number of the estimated discharge data. The fRMSE ranges from 0 to \(\infty\). The value 0 refers to perfect estimates, while the values greater than 1 indicate poor performance [30].

### D. Discharge Estimation and Analytical Method

We calculated the \(w\) time series of the Watson River during the MODIS observation period from 2002 to 2021 and then estimated the daily discharge in this period. The missing discharge data due to cloud cover were linearly interpolated.

The discharge estimation expression should be performed in the period when river discharge exists. But it is unrealistic to continuously identify the water body based on MODIS data because the MODIS data are unavailable during the cloudy periods. Here, we employed the average onset and end dates of the field-measured discharge to constrain the discharge period and performed the discharge estimation expression during this period.

After that, we resampled the estimated daily discharge to monthly and annual scales, respectively. The seasonal trend decomposition using loess (STL) method was deployed to decompose the daily discharge time series. We removed the variabilities with frequencies less than or equal to a year from the daily time series to obtain the interannual variability. STL can decompose a time series into three components: trend, seasonal, and remainder [31]

\[
D_{raw} = D_{trend} + D_{seasonal} + D_{remainder} \tag{8}
\]

where \(D_{raw}\) is the raw data, \(D_{trend}\) is the trend in the data, \(D_{seasonal}\) is the seasonal variation in the data, and \(D_{remainder}\) is the remaining variation.

Moreover, we employed the Watson River ice sheet catchment boundary to extract the RACMO2 runoff data and computed the daily runoff of the Watson River ice sheet catchment in units of m³/s in 2002–2020. The daily RACMO2 runoff time series were resampled to the monthly and annual scale, respectively, and compared with the estimated discharge.

### IV. RESULTS

#### A. Optimal Solution for Discharge Estimation in the Watson River

The measured area of the Watson River is shown in Fig. 1. Total 92 pixels were tested in the measured area in the Watson River. The central coordinate of the optimal pixel is 66.97 °N, 50.83 °W.

The optimal pixel is about 6 km downstream from the Watson River gauge station, where the water is open and there are many braided channels. The performance of the pixels close to the station is not ideal. The possible reason is that the river channel and the water surface near the station are too narrow [5]. The \(w\) is saturated when the water level exceeds a certain limit. This results in the poor performance of discharge estimation. At the optimal pixel, 215 pairs of smoothed \(w\) and discharge data were selected from June 1, 2006 to August 31, 2020, which met the conditions of being cloud-free and having in situ daily discharge records. The optimal expression for discharge estimation of the Watson River is as follows:

\[
Q = 66.27e^{3.44w} \tag{9}
\]
where $Q$ refers to the river discharge. The $R^2$ between the estimated and in situ discharge is 0.60, as shown in Fig. 5.

Fig. 6 shows the monthly estimated and in situ discharge of the Watson River in JJA during the in situ discharge period (2006–2020). Overall, the estimated discharge is close to the in situ discharge. The RMSE between the estimated and in situ discharge is 366 m$^3$/s. The relative errors of estimation in July and August 2010, June 2012, July 2014, June and August 2015, and 2018 are all less than 5%. The discharge estimates in 2006–2009 were generally on average 51% higher than the in situ values. The discharge estimates in July 2011, 2012, 2015, and 2016 were 28%, 37%, 60%, and 34% lower than the in situ values, respectively.

B. Performance Assessment With in situ Data

Total 232 field-measured daily discharge data and 67 field-measured monthly discharge data were used for performance assessment (see Fig. 7). In Fig. 7(a), the $R$, MAE, RMSE, and fRMSE are 0.69, 335 m$^3$/s, 446 m$^3$/s, and 0.73, respectively. The $R$, MAE, RMSE, and fRMSE between the monthly estimated and in situ discharge were 0.85, 163 m$^3$/s, 226 m$^3$/s, and 0.53, respectively [see Fig. 7(b)]. The monthly discharge estimates are consistent with the monthly in situ discharge and they are distributed closely around the 1:1 regression line. Estimates of low flow are more accurate, while the high flow is underestimated, especially when the discharge is higher than 1250 m$^3$/s. Overall, the assessment against the in situ data suggests a relatively good performance of discharge estimation at a monthly timescale, whereas the daily discharge estimates are slightly biased.

Table II further presents the discharge estimation performance in each year. The performance in 2006 and 2018 is not ideal, with the fRMSE of 2.36 and 1.45, respectively. The $R$, MAE, RMSE, and fRMSE are 0.99, 87 m$^3$/s, 96 m$^3$/s, and 0.19 for discharge estimates in 2019, which performs best among the 20 years. High performance also includes the estimates in 2010, 2013, 2014, 2016, and 2017. The MAE and fRMSE for these estimates are less than 170 m$^3$/s and less than 0.5, respectively.

C. Discharge Estimation in 2002–2021

Fig. 8(a) shows the daily estimated discharge and the in situ discharge. The estimated discharge is generally in good agreement with the in situ discharge but the results are still biased in high flow years, such as 2010–2012 and 2020. In Fig. 8(b), the daily RACMO2 runoff is lower than our estimated discharge in 2004–2005 but rather higher in 2011–2013, 2015, and 2020. Fig. 8(c) reveals the interannual variability in river discharge. The interannual variability curve recorded the peaks of increasing discharge of the Watson River in 2003, 2007, 2010, 2014, 2016, and 2019, with the maximum value exceeding 300 m$^3$/s. We also found that the Watson River discharge reached a minimum in 2013 and 2015. The minimum interannual discharge variability in both years is approximately 150 m$^3$/s. The discharge of the Watson River decreased considerably in 2020–2021, with the interannual variability value less than 150 m$^3$/s. Moreover, our discharge estimates fill the data gap and discover more information on the discharge dynamics when the field observations are unavailable in 2002–2005. Based on the results, we found an overall increase in the interannual variability of the Watson River discharge in 2002–2007, at a rate of 0.41 Gt/yr. The interannual discharge variability significantly increased by up to ~300 m$^3$/s in 2003 and, subsequently, decreased in 2004. Notably, the interannual variability of the river discharge decreased at a rate of −0.25 Gt/yr in 2007–2021, which is the opposite during the period when field observations are missing.

The annual estimated and in situ discharge time series of the Watson River are shown in Fig. 9. Our estimated annual discharge is 7.08 Gt/yr on average in 2002–2021. The standard deviation of the annual discharge is 1.67 Gt. The annual discharge showed a slightly decreasing trend in 2002–2021, with a rate of −0.15 Gt/yr, while the annual discharge increased at a rate of 0.38 Gt/yr in 2002–2007. The annual discharge of the Watson River was high in 2007 and 2010, approximately 10 Gt. The annual discharge in the Watson River from 2020 to 2021 was the smallest (<6 Gt/yr) in the 20 years. Our annual discharge estimates of the Watson River are in good agreement with in situ discharge in 2010–2011, 2013–2017, and 2019–2020.
Watson River discharge is underestimated in 2011–2012 and overestimated in 2006–2009 and 2013–2015.

D. Comparison With RACMO2 Runoff

Fig. 9 also reveals that the RACMO2 runoff was on average 24% lower than our estimated discharge in 2002–2009 but much closer to our estimates in 2010–2020. In extreme melting years, such as 2012, the modeled runoff agreed well with in situ discharge. In 2017–2020, the modeled runoff was generally 22% higher than the in situ discharge. A further comparison between the estimated discharge and the RACMO2 runoff is shown in Fig. 10. In low flow cases (May and September), there is a considerable underestimation of the modeled runoff, while the RACMO2 generally provides higher estimates in August and especially in July when the river flow is high [see Fig. 10(a)]. The RACMO2 runoff is on average 30% higher than the estimated discharge in July. In Fig. 10(b), the points are mainly distributed in the area below the 1:1 regression line and it may suggest the model underestimated the surface runoff.

V. DISCUSSION

A. Uncertainty Analysis

Uncertainties of the discharge estimates in this study stem from the relationship between discharge and water extent, the interpolation, the determination of the inundation period, and the effect of snow cover on the reflectance of MODIS data. Our discharge estimates failed to capture the high discharge signal in 2012 when there was an extreme melt event in the GrIS [32], [33]. Under the ultrahigh discharge condition, the water is almost saturated and it is not very sensitive to high flows. Thus, the method based on the relationship between water and discharge tends to underestimate high flows [5], [26], [34]. To alleviate this effect, the MODIS product with 500 m resolution was selected to obtain the optimal pixel in this study because the pixel with an appropriately coarse spatial resolution has higher stability, i.e., it is unlikely to be completely inundated. Due to the cloud cover, approximately 26% of the data gap in the study period and need to be filled using interpolation. The linear interpolation may contribute to the overestimation of discharge. The onset and end of the Watson River discharge are set to be May 26 and September 13, respectively. This constraint represents the average period of discharge rather than the real situation in each year. Nevertheless, the impact of this constraint is negligible because the river discharge is small during the initial and final inundation period of the Watson River (see Fig. 2). In addition, the snow near the braided river channel affects the reflectivity of MODIS data, thereby interfering with the discharge estimates [5].

Uncertainties in the model also contribute to the discrepancy between our estimated discharge and the modeled runoff.
uncertainties of addressing the water storage, release, and other physical processes in firm [35], [36], supraglacial streams, and lakes [37], [38], [39] contribute to the uncertainties in RACMO2 runoff. A subglacial system is not included in the model [20], which may increase temporal uncertainty in the modeled runoff because the subglacial routing is highly dynamic and influences runoff delay [40]. The variability in snowmelt timing may also contribute to the temporal uncertainty in the model as the snowmelt onset becomes later in Greenland [41]. Mankoff et al. [20] and van As et al. [21] found that the RACMO2 generally underestimates runoff in the Watson catchment. In the present study, the considerable overestimation of the modeled runoff in July probably results from the model underestimation of the volumes of meltwater retention [39]. Furthermore, it is worth noting that the errors in the relationship between stage and discharge used by van As et al. [21] may also bring uncertainty in the in situ Watson River discharge. Uncertainty in this relationship increases at high water levels [20].

B. Discharge Changes Analysis

Discharge changes in the Watson River are closely related to the changes in Greenland’s ablation zone, which respond to atmospheric forcing [15] and natural variability of climate (i.e., the climate variability without anthropogenic forcing) [42]. The frequent occurrence of central Pacific El Niño events has slowed
down the Greenland summer warming in the past decade [42]. In the present study, the slightly decreasing trend in the Watson River discharge during the past 20 years is consistent with the recent slowdown of Greenland warming. In 2012 and 2019, the North Atlantic Oscillation (NAO) turned to a significantly negative phase and increased the prevalence of high-pressure systems [43]. The dominant high-pressure system led to intensified warm air advection from southern latitudes into west Greenland and more clear-sky conditions, which further enhanced melt-albedo feedbacks [44], [45]. During the two years, the negative phase of the NAO enhanced surface melting and reduced snowfall, especially in west Greenland, resulting in increment of river discharge [15], [43]. Although our results underestimated the high flows in 2012, the estimated discharge captured the high discharge signal in 2019 (see Fig. 9). In contrast, the NAO shifted to a positive phase in 2013 and led to a lower temperature and more cloudy conditions, which weakened ice sheet melting and decreased discharge [15], [43]. In 2020, heavy precipitation increased surface albedo and reduced melt, and further reduced discharge [15]. In August 2021, an atmospheric river triggered rainfall at the GrIS Summit and high flows in proglacial rivers in Greenland [22]. The high flow signal in August was well recorded in our discharge estimates [see Fig. 8(a)].

C. Advantages and Implications

From the performance assessment and comparison section, we have shown that our method performs well in discharge estimation, and the results are generally well consistent with the in situ data. The advantages of our method and results can be summarized in the following three aspects.

1) Our optimal pixel selection program is highly automated and designed mainly based on GEE, which greatly improves computing efficiency. Unlike the searching strategy with a square box in some previous studies [14], [26], the measured area for the optimal pixel selection is custom delineated by researchers in the present study. Moreover, this program has the potential to be applied to other rivers around the world with high efficiency and thereby inspires discharge estimation in other Greenland’s major rivers with field observations by using remote sensing.
2) Our results provide the daily estimated discharge in the period when in situ data are unavailable and reveal the details of the discharge changes and more information about the GrIS dynamics during this period. The estimates can also be used to analyze the river discharge and other hydrological elements over more complete and longer periods.

3) As satellite-derived water extent is with high accuracy and well correlated with modeled runoff [46], the remote sensing derived discharge has the potential to serve as an effective metric for improving the modeled runoff accuracy.

VI. CONCLUSION

In this study, we produced the Watson River discharge estimates in 2002–2021 from MOD09GA product on the GEE cloud platform with improved strategies, including the derivation of the water extent and the selection of the optimal gauge pixel. The water extent derived solely from remote sensing observations was investigated for river discharge estimation in Greenland for the first time. The proposed method is efficient and the results agree well with the in situ discharge at a monthly scale, and with the R and rRMSE of 0.85 and 0.53, respectively. However, the R and rRMSE between the daily estimated discharge and in situ data are 0.69 and 0.73, respectively, which indicates that the discharge estimates are relatively biased at a daily scale.

Our results revealed that the discharge of the Watson River increased at a rate of 0.38 Gt/yr in 2002–2007 when field observations were missing in the first four years, while the river discharge decreased in 2007–2020. Furthermore, comparisons between the RACMO2 runoff and the estimated discharge showed that the model generally underestimated the melt runoff at an annual scale, while there was a 30% monthly overestimation in July. Overall, the reliable and efficient method proposed in this study inspires for discharge estimation in Greenland’s major rivers by combining remote sensing and field observations. And the discharge estimates fill the in situ measurements gap and reveal more details about the GrIS dynamics when field observations are unavailable, which provides insights into research on the GrIS mass balance, climate change as well as sea-level rise.

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