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Key Points:
- Comparisons to regional climate model simulations suggest that global data products underestimate cool-season precipitation at the watershed scale
- Precipitation underestimation is largely driven by biases within mountainous portions of watersheds
- Global data sets additionally underestimate snow accumulation in the mountains

Supporting Information:
- Supporting Information S1

Correspondence to:
M. L. Wrzesien,
wrzesien@unc.edu

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A Reassessment of North American River Basin Cool-Season Precipitation: Developments From a New Mountain Climatology Data Set

Melissa L. Wrzesien[1], Michael T. Durand[2], and Tamlin M. Pavelsky[1]

[1]Department of Geological Sciences, University of North Carolina at Chapel Hill, Chapel Hill, NC, USA, [2]School of Earth Sciences and Byrd Polar and Climate Research Center, Ohio State University, Columbus, OH, USA

Abstract Characterizing hydrological processes on large scales is challenging due to limitations of observational networks, remoting sensing platforms, and modeling techniques. Water balances have larger uncertainties in mountain regions, where orographic processes produce high spatial variability in precipitation patterns and snow accumulation. Recent work suggests current water budgets underestimate mountain snow water storage, perhaps indicating biases in modeled precipitation. We assess whether global hydroclimate data sets underestimate precipitation for six North American watersheds, ranging from 3–70% mountainous. By selecting a single representative year for each watershed, we compare relatively high-resolution precipitation estimates from the Weather Research and Forecasting (WRF) regional climate model with four global products: Modern-Era Retrospective Analysis for Research and Applications, version 2, the Global Land Data Assimilation System, the Global Precipitation Climatology Project, and the Climate Research Unit's climate data set. Comparisons to WRF precipitation suggest that observation-based gridded data products do not produce reasonable estimates of watershed-scale cool-season precipitation, underestimating by 1–69%. The Global Precipitation Climatology Project and the Climate Research Unit data set have average biases of −26% and −38%, respectively. The Modern-Era Retrospective Analysis for Research and Applications version 2 and the Global Land Data Assimilation System show smaller underestimates relative to WRF (−17% and −21%, respectively), with nearly all mean bias from the mountains (underestimated by 27% and 39%) rather than the topographically simpler lowlands (underestimated by 5% and 2%). We suggest global products fail to capture orographic enhancement of precipitation, resulting in large underestimates of precipitation, snowfall, and snow water storage in mountains of selected North American watersheds, which highlights the need for more accurate precipitation estimates to accurately assess spatiotemporal variations in the water cycle.

1. Introduction

Although foundational to large-scale water resource studies, and despite decades of work, characterization of water balance fluxes and storages at continental-to-global scales remains challenging. Recent studies have produced water balance estimates globally (Dirmeyer et al., 2006; Rodell et al., 2015; Trenberth et al., 2007; Trenberth & Fasullo, 2013a), for individual continents (Trenberth & Fasullo, 2013b; Xia, Mitchell, Ek, Sheffield, et al., 2012; Xia, Mitchell, Ek, Cosgrove, et al., 2012) and for a diverse range of large river basins (Gao et al., 2010; Leung et al., 2003; Louie et al., 2002; MacKay et al., 2003; Roads et al., 2003; Roads & Betts, 2000; Smith & Kummerow, 2013; Stewart et al., 1998; Szeto et al., 2008). However, the accuracy of these estimates remains in question, since observational networks are sparse (Hughes et al., 2017; Kidd et al., 2012; Lundquist et al., 2013; Serreze & Hurst, 2000; Shiklomanov & Nelson, 2003; Vörösmarty et al., 2001; Walsh et al., 1998), current remote sensing capabilities vary significantly among the various terms in the water balance (Lettenmaier et al., 2015), and modeling of hydrologic processes at large scales is challenging (Dirmeyer et al., 2006; Wood et al., 2011; Xu, 1999).

Large-scale precipitation estimates are particularly uncertain in mountainous basins. Due to orographic enhancement, precipitation patterns change with variations in mountain elevation at relatively short (~1 km) spatial scales (Barros & Lettenmaier, 1994; Daly et al., 1994; Dettinger et al., 2004; Henn et al., 2018; Lundquist et al., 2008, 2010; Margulis et al., 2016; Neiman et al., 2002). High spatial variability in orographic precipitation and other hydrologic processes combined with particularly limited observational networks (Hughes et al., 2017; Kidd et al., 2012; Lundquist et al., 2013) and poor satellite retrieval skill (Adler et al., 2003; Maggioni et al., 2016) complicate estimation of both fluxes and storages in the mountains.

These limitations are especially problematic because mountain ranges often play outsized roles in hydrological processes and water resources for regions downstream (Viviroli et al., 2007). For example, seasonal snowpacks are often critical to characterization of large-scale water balances but are challenging to model or measure over large regions, especially in mountainous areas. In the continental United States, an estimated two thirds of streamflow originating in mountainous areas begins as snow (Li et al., 2017). Seasonal snowpack leads to order-of-magnitude increases in residence time of water within the basin, controlling streamflow rates (Barnhart et al., 2016) and increasing the fraction of total precipitation that ultimately becomes runoff (Berghuijs et al., 2014). Snow also complicates water balance measurement and modeling: snowfall measurement is highly affected by wind speed at the time of the measurement, leading to undercatch that often exceeds 50% (Gray & Male, 1981) and to the need for post facto corrections (Yang et al., 2005). Even in highly gauged regions of the continental United States, high-resolution gridded precipitation data sets derived from in situ gauges exhibit significant uncertainty (Henn et al., 2018).

Regional climate models (RCMs) such as the WRF model have been shown to be remarkably accurate in simulating precipitation and snowpack dynamics in the mountains, due in part to recent developments in modeling snowfall processes. Leung and Qian (2003) recognized that orographic precipitation simulations would be highly dependent upon model resolution and thus used high-resolution RCMs to simulate processes in complex terrain. More recently, a new microphysics scheme was developed to better represent snowflake hydrometeor shape for modeling snowfall (Thompson et al., 2008). Following from these developments, considerable work has found WRF simulations to reliably estimate precipitation (Caldwell et al., 2009; Cardoso et al., 2013; Gutmann et al., 2012; Leung & Qian, 2009; Qian et al., 2010; Warrach-Sagi et al., 2013), including snowfall in the Sierra Nevada (Hughes et al., 2017) and high precipitation rates in the Olympic Mountains (Currier et al., 2017). Indeed, WRF simulations are emerging as one of the better options for estimating basin-scale precipitation in mountain environments where orographic processes are important. Though WRF's ability to estimate precipitation is better represented in the literature, WRF has also been shown to have skill in capturing snowpack dynamics in the Colorado Rockies (Rasmussen et al., 2011) and the Sierra Nevada (Berg & Hall, 2017; Caldwell et al., 2009; Pavelsky et al., 2011; Waliser et al., 2011; Wrzesien et al., 2015; Wrzesien et al., 2017), among other regions (e.g., Jin & Wen, 2012; Liu et al., 2017; Qian et al., 2010). Thus, a consensus has begun to develop that RCMs show enough skill to reproduce reasonable patterns of snowfall and snow water equivalent (SWE) accumulation in mountain terrain (Caldwell et al., 2009; Ikeda et al., 2010; Minder et al., 2016).

There is some evidence to suggest that our existing estimates of large-scale precipitation and snow accumulation dynamics are incorrect in mountainous areas. Data sets used to produce such estimates usually consist of coupled atmospheric reanalyses (e.g., the Modern-Era Retrospective Analysis for Research and Applications [MERRA], Rienecker et al., 2011) or global compilations of offline forcing data and hydrologic models (e.g., the Global Land Data Assimilation System [GLDAS], Rodell et al., 2004); for example, Rodell et al. (2015) characterized the global water balance using both MERRA and GLDAS. Alternatively, gauge-based gridded precipitation data sets (e.g., the Global Precipitation Climatology Project [GPCP], Adler et al., 2003) can inform water budgets (e.g., Trenberth et al., 2007), but they must contend with sparse observational networks in mountain regions. For modeling hydrologic processes, global reanalyses and land data assimilation products underestimate snow accumulation across the continental United States (Broxton et al., 2016), though moving to finer spatial resolution improves simulations within global climate models (Kapnick & Delworth, 2013). In mountain regions, global data sets can perform poorly (Snauffer et al., 2016), perhaps underestimating peak snow accumulation by up to 90% in the Sierra Nevada (Wrzesien et al., 2017). To refine mountain SWE estimation, Wrzesien et al. (2018) used WRF to develop a new representative climatology of snow water storage (SWS) across all North American mountains by simulating one average water year for individual mountain ranges, and their results suggested that global data sets underestimate SWS in North America by ~35%. Biases are particularly likely in mountainous regions, where SWS estimates from the Canadian Sea Ice and Snow Evolution (Mudryk & Derksen, 2017) ensemble global data product is 66% lower than the high-resolution WRF estimate. However, the potential implications for large-scale water balances of major river basins in North America has not yet been explored.

Whereas Wrzesien et al. (2018) identified a bias in current estimates of SWS over mountain ranges, the primary goal in this paper is to assess whether the role of precipitation is correctly estimated during the cool season (October through March) across entire watersheds. To achieve this objective, we compare representative-year wintertime precipitation and SWS estimates from existing global data sets to the WRF simulations performed by Wrzesien et al. (2018). Past studies cited above suggest that WRF produces reasonable results in mountain environments; though model evaluation against gridded SWE (Qian et al., 2010; Wrzesien et al., 2015), precipitation (Hughes et al., 2017), or even terrestrial water storage estimates from the Gravity Recovery and Climate Experiment satellite (Frappart et al., 2006; Wrzesien et al., 2018) is possible, no true validation data set exists. As such, in this paper, we assess only whether global data sets are consistent with WRF simulations rather than performing a formal validation. For six major North American River basins (the Columbia, Mackenzie, Missouri, Nelson, Upper Colorado, and Yukon), we evaluate precipitation and SWS for individual watersheds and, separately, for both the mountainous and lowland parts of each watershed. Based on the literature reviewed above, we hypothesize that (1) WRF simulations produce more precipitation and greater peak SWS than the global data sets and that (2) WRF simulations more accurately represent winter precipitation and SWS. If the first hypothesis is upheld by our analysis (as noted, the second is not formally testable), we will interpret this finding as evidence that existing climatological average water balance estimates for major North American River basins have underestimated the magnitude of precipitation, particularly snow, during winter months.

2. Data and Methods

2.1. Data

2.1.1. WRF

We use precipitation and snow storage estimates from the WRF regional climate model (Skamarock et al., 2008) to assess global data sets. Wrzesien et al. (2018) use WRF version 3.6.1 coupled to the Noah-MP land surface model (Niu et al., 2011) with the interim European Centre for Medium-Range Weather Forecasts Re-Analysis (ERA-Interim) providing the meteorological conditions at the boundary (Dee et al., 2011). Unlike the Noah land surface model, Noah-MP has a multilayer snowpack, which allows for more accurate simulation of snowpack temperature (Etchevers et al., 2004). Noah-MP allows for both liquid water and ice to accumulate on the vegetation canopy through the interception of snowfall, which improves simulation of heat exchanges between the canopy and surface snow, particularly in boreal forest regions (Niu et al., 2011; Niu & Yang, 2004). The WRF setup uses the Thompson microphysics scheme (Thompson et al., 2004, 2008), which provides accurate precipitation estimation (Liu et al., 2011) due to improved simulation of snowflake hydrometeor shape (Thompson et al., 2008). Further details on the simulations used here are in Wrzesien et al. (2018), and WRF SWS data are available for download at the National Snow and Ice Data Center (Wrzesien & Durand, 2018).

Instead of a traditional, 30-year climatology, Wrzesien et al. (2018) create a representative climatology for seasonal SWS accumulation over North America. They select a single, representative water year specific to each mountain range and estimate SWE at 9-km spatial resolution. Representative years are selected by comparing the interannual variability from GLDAS and the National Land Data Assimilation System (Mitchell et al., 2004; Xia, Mitchell, Ek, Sheffield, et al., 2012; Xia, Mitchell, Ek, Cosgrove, et al., 2012); specific details and evaluation of the selection process are in the supporting information of Wrzesien et al. (2018). Their comparisons show that each selected simulation year approximates long-term average mountain snow accumulation conditions. By simulating a single water year for each mountain range, instead of a multiyear simulation for the entire continent, the computational cost is greatly reduced. One limitation of the Wrzesien et al. (2018) data set for this analysis is that their method approximates average SWS for each mountain range; here we are interested in precipitation for entire watersheds. Annual watershed precipitation, or even watershed SWS, from their data set does not necessarily approximate the climatological average.

Here we use four of the domains in the WRF data set (centered on the Alaska Range, Cascades, Canadian Rockies, and U.S. Rockies but including surrounding smaller mountain ranges and subranges), where each WRF domain entirely encompasses at least one of our watersheds of interest. Since the WRF data are not a traditional 30-year climatology but rather a representative climatology that approximates long-term average conditions, we compare only a single water year of precipitation. While the data used here are from Wrzesien et al. (2018), they only compared SWS across mountain regions; here we consider total precipitation, snowfall, and SWS for entire watersheds, incorporating both mountain and lowland regions. WRF watershed precipitation data are available for download from Zenodo (Wrzesien et al., 2019).

2.1.2. GPCP

GPCP is a monthly precipitation data set based on observations—from station networks, satellites, and sounding observations—with estimates available from 1979 to the present (Adler et al., 2003; Huffman et al., 1997; Huffman et al., 2009). Gridded gauge data are from the Global Precipitation Climatology Centre with over 70,000 stations (Schneider et al., 2008). The global data set is produced at 2.5° spatial resolution. We use version 2.3, which can be downloaded at http://esrl.noaa.gov/psd/data/gridded/data.gpcp.html.

2.1.3. CRU

The Climatic Research Unit (CRU) provides a 0.5° resolution monthly climate data set based on over 4,000 meteorological observations, spanning 1901 through the present (Harris et al., 2014; Mitchell & Jones, 2005; New et al., 1999, 2000). First, a monthly climatology for 1961–1990 is created by interpolating station data (New et al., 1999). For monthly meteorological estimates, observations within each grid cell are used to create an anomaly estimate, relative to the 1961–1990 climatology, which can then be converted to a monthly value across the entire time period. When stations are not available for a particular grid cell, data are either infilled from more distant stations or relaxed to the climatological average. We use the CRU modeled precipitation (hereafter referred to as just CRU) output from CRU TS v3.24.01. CRU data can be downloaded from http://crudata.uea.ac.uk/cru/data/hrg.

2.1.4. MERRA-2

We use precipitation, snowfall, and SWE data from the MERRA reanalysis, version 2 ([MERRA-2] Rienecker et al., 2011). MERRA-2 data are available for download from the National Aeronautics and Space Administration (NASA) Goddard Earth Sciences Data and Information Services Center (https://disc.gsfc.nasa.gov/). The global reanalysis has a spatial resolution of 0.5° × 0.625°. MERRA-2 has two precipitation options, one entirely model generated and one with a correction algorithm based on the National Oceanic and Atmospheric Administration Climate Prediction Center Unified Gauge-Based Analysis of Global Daily precipitation (Chen et al., 2008; Xie et al., 2007) and the Climate Prediction Center Merged Analysis of Precipitation (Xie & Arkin, 1997) gridded observation-based precipitation estimates (Reichle et al., 2017). The corrected version, which is used to force the MERRA-2 land surface parameterization, is applied between 42.5°S and 42.5°N. Precipitation between 42.5°and 62.5° relaxes back to MERRA-2 precipitation estimates. Precipitation poleward of 62.5° is entirely generated by MERRA-2.

Previous work has evaluated MERRA-2 against other global models and reanalyses and found that it underestimates SWE compared to observations, though perhaps with a smaller negative SWE bias than other global products (Broxton et al., 2016; Snauffer et al., 2016; Wrzesien et al., 2017).

2.1.5. GLDAS

For an offline, assimilated data set, we use precipitation estimates from GLDAS version 2.1 (Rodell et al., 2004). Produced at 0.25°, GLDAS v2.1 provides 3-hourly estimates for the entire globe from 2000 to the near present. Atmospheric forcing, excluding precipitation, is from the National Oceanic and Atmospheric Administration/Global Data Assimilation System (GDAS; Derber et al., 1991), while precipitation forcing is from GPCP. GLDAS v2.1 uses the GPCP 1° daily version 1.2 data set (Huffman et al., 2001) and a disaggregation routine of GDAS precipitation fields to create 3-hourly GPCP estimates for precipitation forcing prior to November 2015; after November 2015, only GDAS is used for precipitation since GPCP is not available. GLDAS v2.1 can be downloaded from the NASA Goddard Earth Sciences Data and Information Services Center (http://disc.sci.gsfc.nasa.gov). For simplicity, we refer to GLDAS v2.1 as GLDAS.

2.1.6. Methods

The six watersheds we analyze are shown in Figure 1. In Table 1, we describe each watershed in more detail and include previously published annual precipitation estimates. Most studies consider annual total precipitation, so cool-season precipitation and SWS, which we focus on here, are not available for comparison.

One limitation of the WRF data set described in section 3.1.1 is that each domain is simulated for only one water year, which was chosen to approximate average snow accumulation conditions for each mountain range. To ensure the simulated precipitation also represents average conditions for each watershed, we compare accumulated precipitation from the selected year to the 1980–2015 average from MERRA-2, GPCP, and CRU; for GLDAS, we compare from 2001 to 2015 (Figure 2). We also compare monthly precipitation from

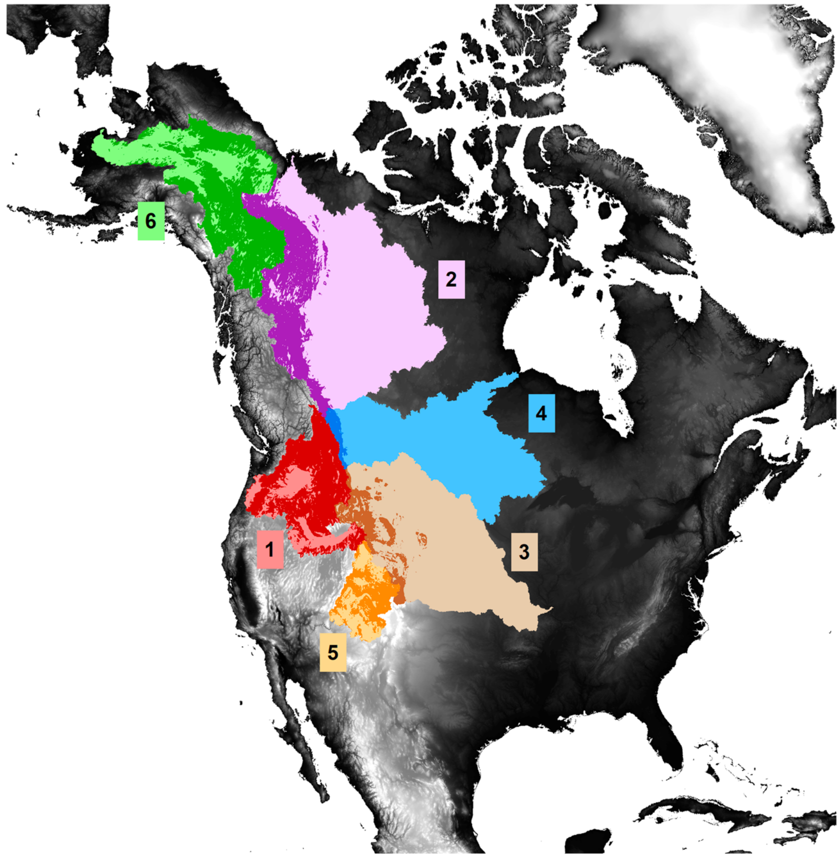

Figure 1. Map of river basins in this study. Darker areas indicate mountains within the watershed. Watersheds include the Columbia (1), the Mackenzie (2), the Missouri (3), the Nelson (4), the Upper Colorado (5), and the Yukon (6).

the long-term average and the selected representative year (supporting information Figure S1). For each, the long-term average presents a smoother seasonal pattern than our selected single year, though the accumulated annual precipitation amounts are quite similar and within the standard deviation (Figure 2). Table 2 gives the percent difference of the representative-year precipitation from the long-term average. The annual precipitation for our representative years is within 5.3% (4.4%) of the long-term average for MERRA-2 (GLDAS). Similarly, the annual precipitation of our selected years is within 4.4% (6.3%) of the long-term average for CRU (GPCP). The largest percent difference from each data set is 11%, 13%, 15%, and 15%, for MERRA-2, GLDAS, CRU, and GPCP, respectively. For MERRA-2 and CRU, the largest differences are over the Missouri watershed, while the largest difference for GLDAS is the Nelson and for GPCP, the Upper Colorado. The high-latitude watersheds (Mackenzie and Yukon) have the smallest differences. Since the WRF simulation years were selected to approximate average snow accumulation within mountains, it should not be surprising that we see some differences when comparing precipitation over entire watersheds. The WRF domain for the Missouri watershed, for example, was designed to estimate snow in the U.S. Rocky Mountains; therefore, while the selected year approximates average SWS in the mountains, there are differences in the accumulated precipitation beginning in May, which is outside of the period of analysis considered here. Despite differences in the selected year and the long-term average, particularly for the Missouri and the Upper Colorado, the SWS-representative years are generally representative of average precipitation conditions for each watershed. To ensure we do not introduce additional uncertainty from the differences of the selected year and the climatological average, throughout the rest of the study, we only consider the selected year for each watershed; that is, we compare the same representative year from the five data products over each watershed.

Here we compare not only precipitation to WRF estimates but also snowfall and SWS, where applicable. We consider how precipitation estimates differ over entire watersheds, in addition to the mountainous and

Table 1
Drainage Area, Mountain Percentage, and Precipitation Estimates for Each Watershed

Watershed	Drainage area (km^2)	Mountain percentage (%)	Other annual precipitation estimate	Point/subbasin precipitation estimates
Columbia	668,736	70	• 700 mm (Benke & Cushing, 2005)	• 1,570 mm for Willamette (Daly et al., 1994) • 200–2,500 mm from point measurements (Matheussen et al., 2000; Naik & Jay, 2005; Pulwarty & Redmond, 1997)
Mackenzie	1,807,920	25	• 258 mm (Benke & Cushing, 2005) • 375–463 mm (MacKay et al., 2003; Rouse et al., 2003; Stewart et al., 1998) • 400 mm (Louie et al., 2002)	
Missouri	1,371,017	11	• 501 mm (Benke & Cushing, 2005)	• 450 mm for Great Plains (70% of drainage area; Galat et al., 1998) • 1,050 mm for Interior Highlands (1.9% of drainage area; Galat et al., 1998) • 626–1,072 mm for small subbasins (Stone et al., 2003)
Nelson	1,104,354	3	• 520 mm (Benke & Cushing, 2005)	• 300–500 mm for Canadian prairies (Burn et al., 2008) • 321–514 mm for meteorological stations (Déry et al., 2005)
Upper Colorado	284,067	54	• 221 mm (Benke & Cushing, 2005) • 405 mm (Dawadi & Ahmad, 2012; Marlatt & Riehl, 1963) • 354 mm (Christensen et al., 2004; Christensen & Lettenmaier, 2007; Vano et al., 2012)	
Yukon	832,761	65	• 330 mm (Benke & Cushing, 2005) • 385 mm (Yang et al., 2009) • 483 mm (Brabets et al., 2000)	• 250–560 mm from precipitation gauges (Brabets & Wolvoord, 2009)

lowland portions of each basin. We divide watersheds into mountains and lowlands (see Figure 1) based on the Kapos et al. (2000) mountain classification, which was also used to select mountain areas by Wrzesien et al. (2018).

3. Results

Across our selected representative years, all five data sets have similar patterns of monthly cool-season precipitation (Figure 3). Of the five estimates, WRF is the highest in most months, though occasionally other data sets have larger monthly precipitation values, such as October–December in the Missouri. Figure 4 compares the total cool-season precipitation for each river basin. Again, WRF has the largest estimate for nearly all watersheds, with MERRA-2, GLDAS, GPCP, and CRU estimates being 17%, 21%, 26%, and 38% lower, respectively.

To examine spatial patterns of precipitation, we map the cool-season accumulated precipitation for each watershed (Figures 5 and S2–S6). The precipitation maxima over mountains are evident in the WRF visualizations, due in part to WRF's high spatial resolution compared to the other data sets. To quantify the difference between WRF and the other data sets in mountains, we compare the total cool-season precipitation for mountainous areas and the percentage of precipitation that falls within mountains (Table 3). In increasing order, the Nelson has the smallest fraction of precipitation falling in the mountains, followed by the Missouri, Mackenzie, Upper Colorado, Yukon, and the Columbia with the largest fraction, which is the same order as the basins sorted by mountainous area percentage. Of the data sets examined here, WRF almost always has the largest fraction of its precipitation within the mountains; no data

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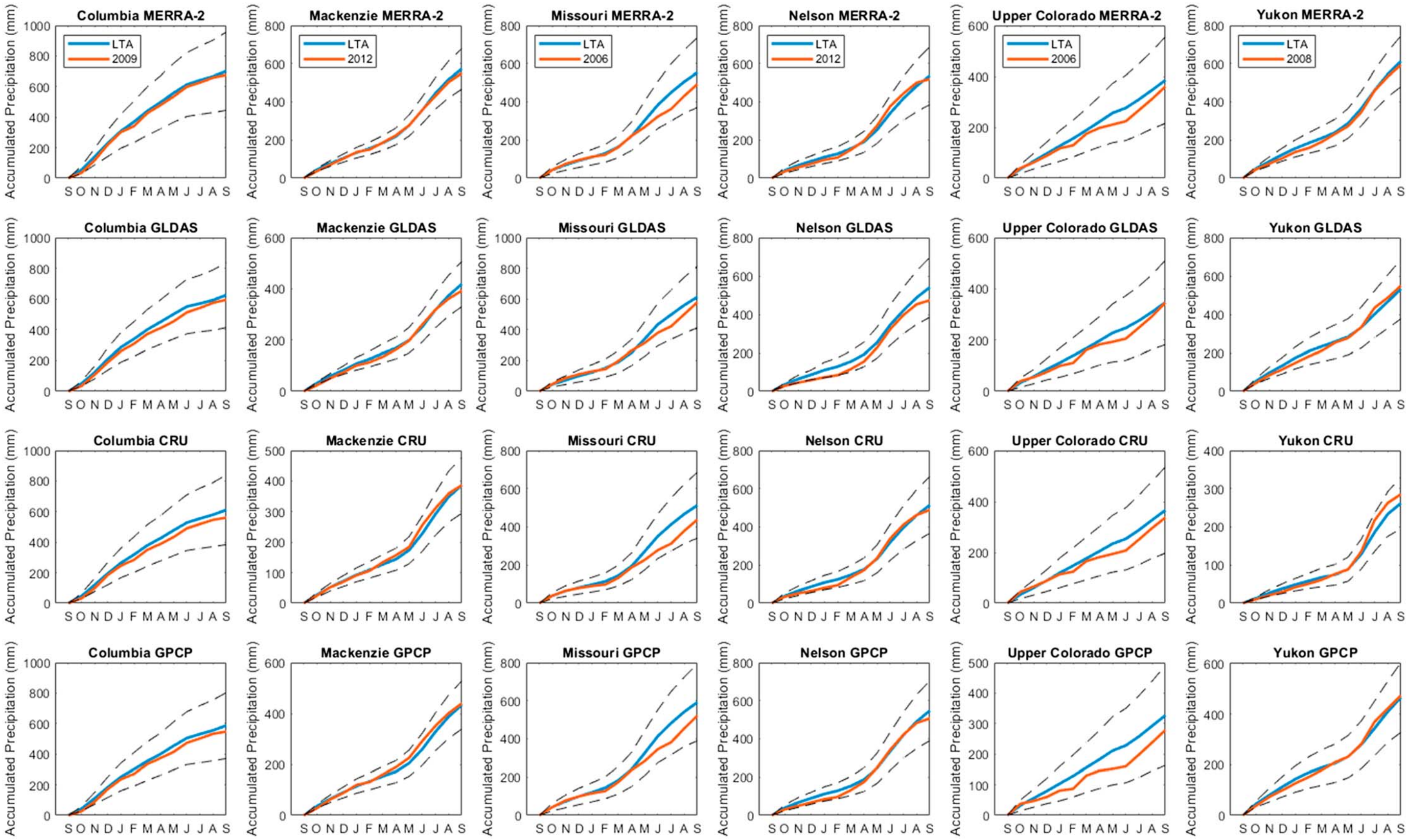

Figure 2. Monthly accumulated watershed precipitation, in millimeters, for the selected representative year (orange) compared to the monthly long-term average (LTA, blue line). Dashed lines indicate one standard deviation of the long-term average. CRU = Climate Research Unit; MERRA-2 = the second Modern-Era Retrospective Analysis for Research and Applications; GLDAS = Global Land Data Assimilation System.

product consistently has the lowest fraction. Though fractions of mountain precipitation are similar, the four global products have much less total cool-season mountain precipitation than WRF (Tables 3 and 4), with MERRA-2 and GLDAS 27% and 39% lower than WRF, respectively, when averaged across all six watersheds. Note that we produce no estimate from GPCP in the Nelson; due to the coarse spatial resolution of GPCP, we cannot isolate the small mountain headwaters of the Nelson River.

We also compare precipitation estimates over the nonmountainous lowlands (Table 4). Here we compare only GLDAS and MERRA-2 to WRF, since GPCP and CRU consistently underestimate WRF precipitation across the entire watershed (Table 3 and Figure 4). When we evaluate precipitation estimates across full watersheds, MERRA-2 and GLDAS are 17% and 21%, respectively, lower than WRF, on average. In the mountains, MERRA-2 is 27% lower than WRF estimates, while GLDAS is 39% lower. In contrast, in lowland regions, MERRA-2 and GLDAS are nearly unbiased relative to WRF, with mean biases of 5% and 2%, respectively. Thus, the negative bias over the full watershed is largely driven by underestimated precipitation in the mountains. In the lowlands, the three data sets have similar accumulated precipitation estimates (Figure 6), and no one data set consistently has the highest precipitation. In the mountains, WRF always has the largest precipitation value (Figure 6).

The precipitation underestimates in the mountains compared to the lowlands highlight a potential systematic bias in the global data sets. To understand if the mountain precipitation biases are a source of the SWS

Table 2
Percent Difference of Precipitation Estimates From Our Representative Year Compared to the Long-Term Average for Each Global Data Set

Watershed	MERRA-2	GLDAS	CRU	GPCP	Watershed average
Columbia	3.6	4.9	8.3	6.8	5.9
Mackenzie	3.9	6.3	−0.1	−1.3	2.2
Missouri	11.2	5.7	14.5	11.9	10.8
Nelson	3.2	12.6	4.9	7.4	7.0
Upper Colorado	6.5	0.3	7.8	14.7	7.3
Yukon	3.2	−3.2	−9.0	−1.6	−2.7
Data set average	5.3	4.4	4.4	6.3	

Note. MERRA-2 = the second Modern-Era Retrospective Analysis for Research and Applications; GLDAS = Global Land Data Assimilation System; CRU = Climate Research Unit; GPCP = Global Precipitation Climatology Project.

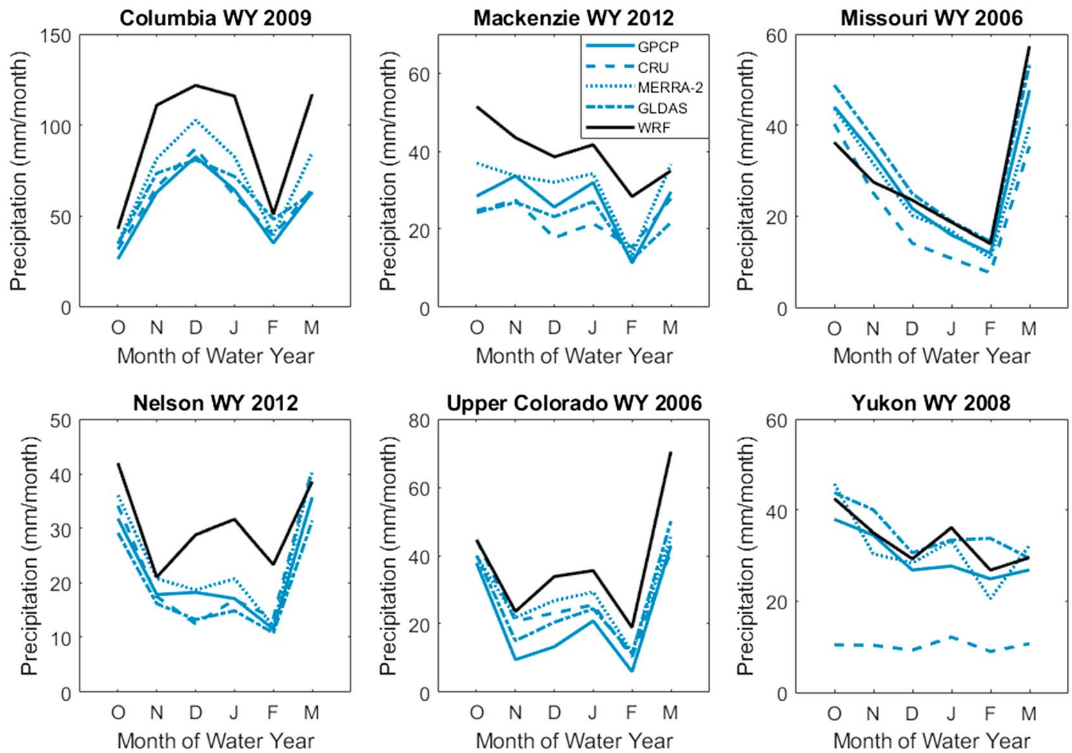

Figure 3. Monthly cool-season precipitation for each watershed, in millimeters, from the five data sets. The black line is WRF, the solid blue is GPCP, the dashed blue is CRU, the dotted blue is MERRA-2, and the dashed-dotted line is GLDAS. CRU = Climate Research Unit; MERRA-2 = the second Modern-Era Retrospective Analysis for Research and Applications; GLDAS = Global Land Data Assimilation System; GPCP = Global Precipitation Climatology Project; WRF = Weather Research and Forecasting; WY = water year.

underestimation, we partition rain and snow in the WRF, GLDAS, and MERRA-2 estimates (Figure 7); GPCP and CRU do not provide estimates of snowfall. Since we analyze winter precipitation, it is unsurprising that both WRF and MERRA-2 have a snowfall fraction of >0.5 for each watershed. GLDAS generally has smaller fractions of snowfall, with values of 0.30–0.95. The higher-latitude watersheds have larger snow fractions, with ~90% of the total precipitation in the Mackenzie and Yukon basins falling as snow. Interestingly, the MERRA-2 snow fraction is nearly always higher than the WRF value (Figure 7), though MERRA-2 generally has less rainfall and snowfall than WRF across the cool season (Figure 8). WRF has the highest rainfall and snowfall totals across all watersheds (Figure 8) apart from the Missouri,

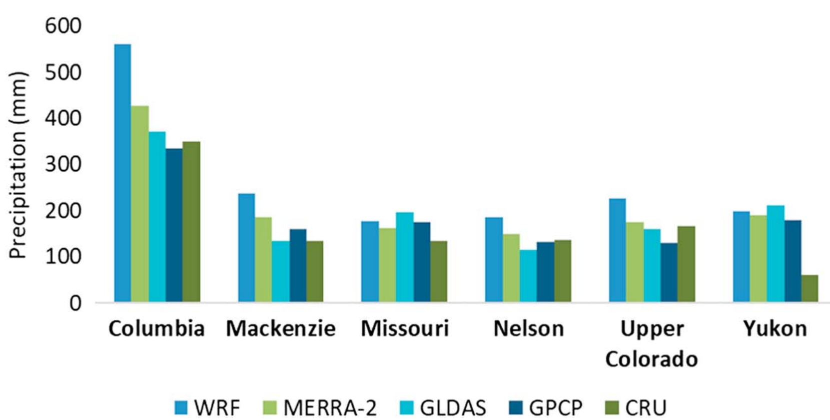

Figure 4. Average cool-season precipitation, in millimeters, for each watershed. CRU = Climate Research Unit; MERRA-2 = the second Modern-Era Retrospective Analysis for Research and Applications; GLDAS = Global Land Data Assimilation System; GPCP = Global Precipitation Climatology Project; WRF = Weather Research and Forecasting.

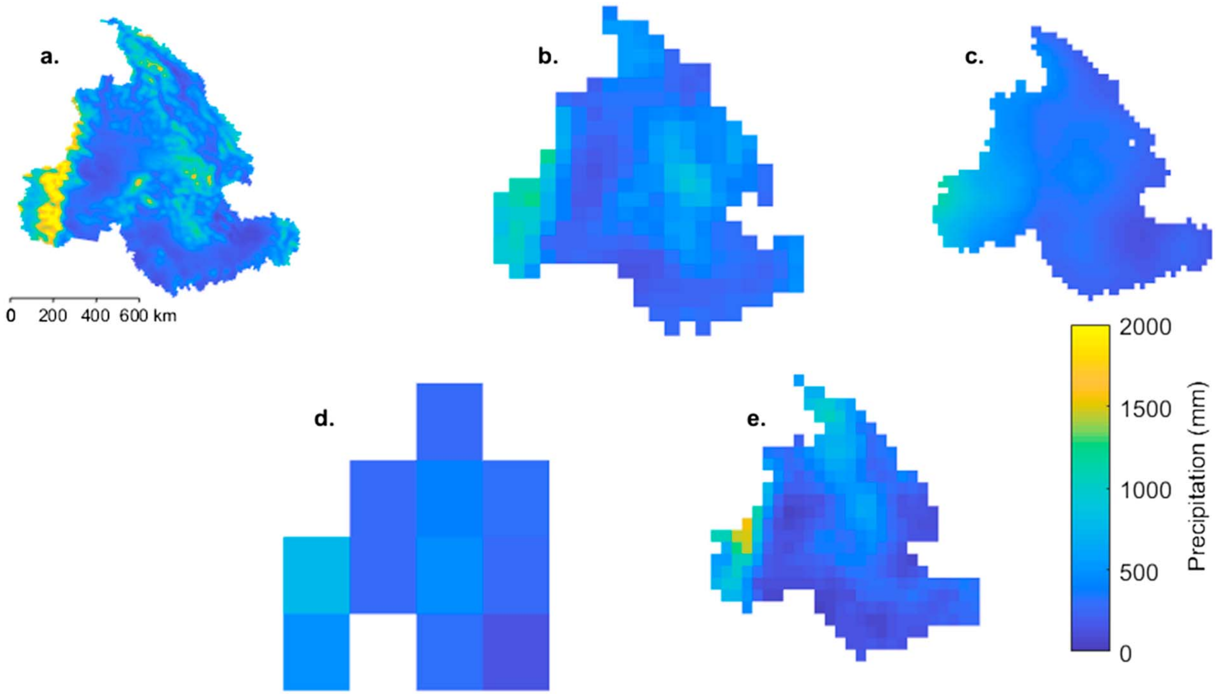

Figure 5. Accumulated cool precipitation (October–March) over the Columbia River basin from (a) Weather Research and Forecasting, (b) the second Modern-Era Retrospective Analysis for Research and Applications, (c) Global Land Data Assimilation System, (d) Global Precipitation Climatology Project, and (e) Climate Research Unit. Accumulated precipitation is measured in millimeters. Each data product is shown at its native grid resolution.

where GLDAS has more rainfall than WRF or MERRA-2, and the Yukon, where all three products have similar amounts of snow. The higher snowfall fraction for MERRA-2 coupled with the lower total precipitation (Figure 4) indicates that MERRA-2 has a larger percent difference from WRF in rainfall than in snowfall. For example, for the Columbia at the end of March, MERRA-2 has 15% less accumulated snowfall than WRF, but 34% less rainfall. This is evident in Figure 8, where MERRA-2 and WRF have similar snowfall amounts for most watersheds (MERRA-2 is 12% lower), but MERRA-2 has much less rainfall (34% lower). In contrast, GLDAS almost always has more rainfall than MERRA-2 but less snowfall. Further, GLDAS has 34% less accumulated snowfall than WRF, on average, but only 13% less rainfall. Differences between GLDAS and MERRA-2 may be due to how they partition rain and snow.

Finally, we compare watershed SWS from WRF, MERRA-2, and GLDAS (Figure 9). For the Yukon, the three data sets have similar values of SWS throughout the accumulation and ablation seasons. For the other river basins, however, MERRA-2 (GLDAS) peak SWS ranges from 26–63% (48–72%) lower than the WRF peak SWS estimate. Differences are more pronounced in the midlatitude Columbia, Missouri, and Upper Colorado basins. When considering just the mountains of each watershed (Figure 9, dashed lines), the pattern is similar: MERRA-2, GLDAS, and WRF SWS are comparable for the mountains of the Yukon, but MERRA-2 has 38–63% less SWS in the mountains of all other watersheds, and GLDAS has 47–84% less. On average, MERRA-2 SWS for the full watershed is 43% lower than WRF and mountain SWS is 51% lower; GLDAS SWS is 51% and 58% lower than WRF for the full watershed and the mountains, respectively.

Though we aim to compare SWS estimates for a representative year, we note that 1 year will never match a climatology. For example, in the Missouri watershed, all data sets show a spike in SWS at day 175 from a snowfall event in the lowland portion of the watershed (see lowland precipitation increase in March in Figure 6). By comparing 1 year, we can only evaluate a single instance of snowpack accumulation and ablation,

Table 3
Average Watershed Precipitation, in Millimeters, From October Through March in the Mountainous Portion of the Basin, With the Percent of Total Cool-Season Precipitation That Falls Within the Mountains in Parentheses

Mountains	WRF	MERRA-2	GLDAS	GPCP	CRU
Columbia	652 (82)	451 (77)	366 (69)	355 (73)	390 (78)
Mackenzie	387 (41)	253 (35)	220 (41)	275 (44)	167 (32)
Missouri	317 (20)	271 (18)	205 (12)	201 (9)	153 (12)
Nelson	590 (10)	317 (6)	180 (5)	—	282 (6)
Upper Colorado	293 (70)	222 (67)	177 (59)	174 (34)	215 (70)
Yukon	221 (72)	194 (67)	211 (64)	176 (60)	50 (51)

Note. MERRA-2 = the second Modern-Era Retrospective Analysis for Research and Applications; GLDAS = Global Land Data Assimilation System; CRU = Climate Research Unit; GPCP = Global Precipitation Climatology Project; WRF = Weather Research and Forecasting.

Table 4
Cold-Season Precipitation Biases, in Percentages, for the Full Watershed, the Mountains, and the Lowlands From MERRA-2 and GLDAS, Compared to Weather Research and Forecasting Values

	Full watershed		Mountains		Lowland	
Watershed	MERRA-2	GLDAS	MERRA-2	GLDAS	MERRA-2	GLDAS
Columbia	−24	−34	−31	−44	6	13
Mackenzie	−22	−43	−35	−43	−13	−44
Missouri	−8	11	−14	−35	−6	23
Nelson	−20	−38	−46	−69	−17	−34
Upper Colorado	−23	−29	−24	−40	−18	−5
Yukon	−4	6	−13	−5	17	33
Average	−17	−21	−27	−39	−5	−2

Note. MERRA-2 = the second Modern-Era Retrospective Analysis for Research and Applications; GLDAS = Global Land Data Assimilation System.

which will almost certainly not match a 30-year climatology. Regardless of differences from our representative year and a true climatology, by comparing the same year from WRF, MERRA-2, and GLDAS, we can still evaluate how the three data sets differ.

4. Discussion

Cool-season water balances are largely controlled by the amount and phase of precipitation, impacting the partitioning and timing of runoff (Berghuijs et al., 2014; Li et al., 2017; Musselman et al., 2017) and evapotranspiration (Hamlet et al., 2007), as well as affecting storage changes in snowpack, soil moisture, and groundwater. In this study, we compared WRF to data sets often used to construct large-scale water balances. We find that GLDAS, MERRA-2, and GPCP total precipitation estimates to be on the order of 20% less than WRF, with some variability among the six basins; CRU is 38% less than WRF. Though WRF precipitation is consistent with GLDAS and MERRA-2 in the lowlands (Figure 10), WRF estimates are over 30% larger than GLDAS and MERRA-2 in the mountains. These differences are generally consistent across the six

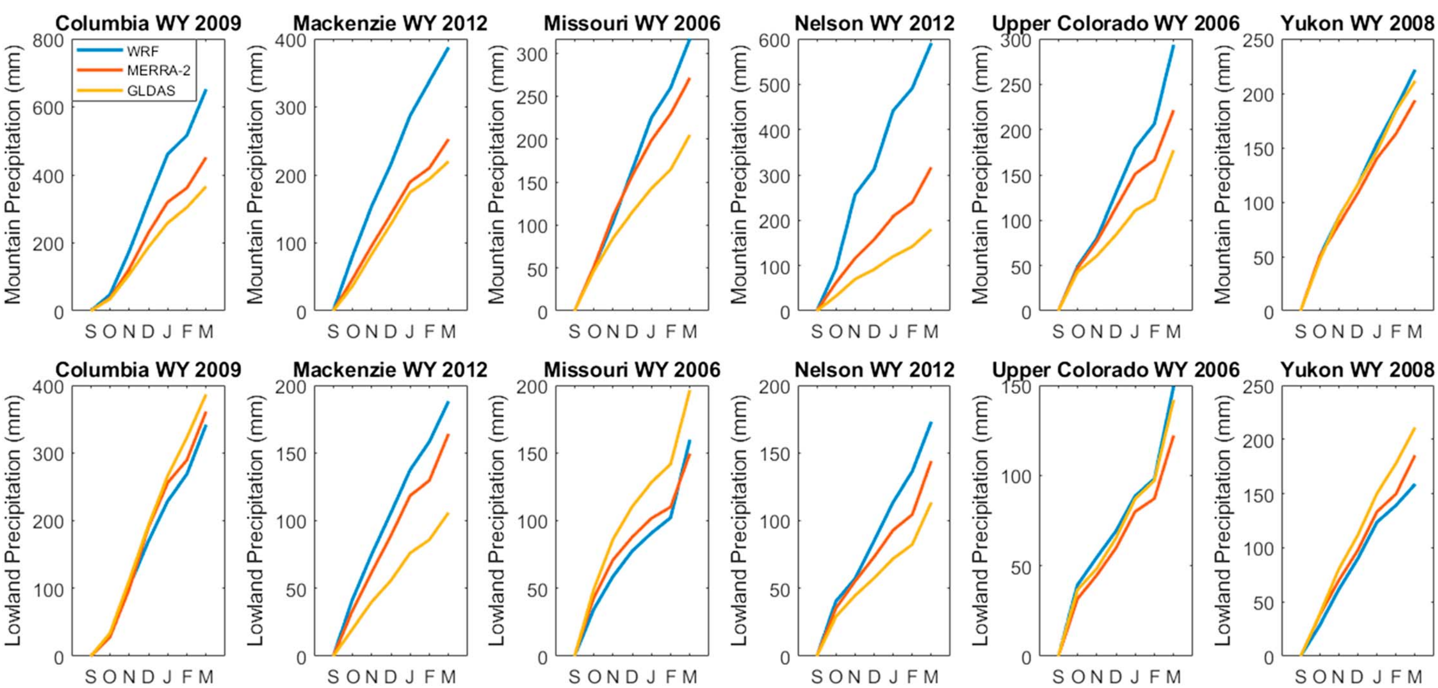

Figure 6. Cool-season accumulated precipitation in the mountains (top row) and lowlands (bottom row) of each watershed from WRF (blue line), MERRA-2 (orange line), and GLDAS (yellow line). MERRA-2 = the second Modern-Era Retrospective Analysis for Research and Applications; GLDAS = Global Land Data Assimilation System; WRF = Weather Research and Forecasting; WY = water year.

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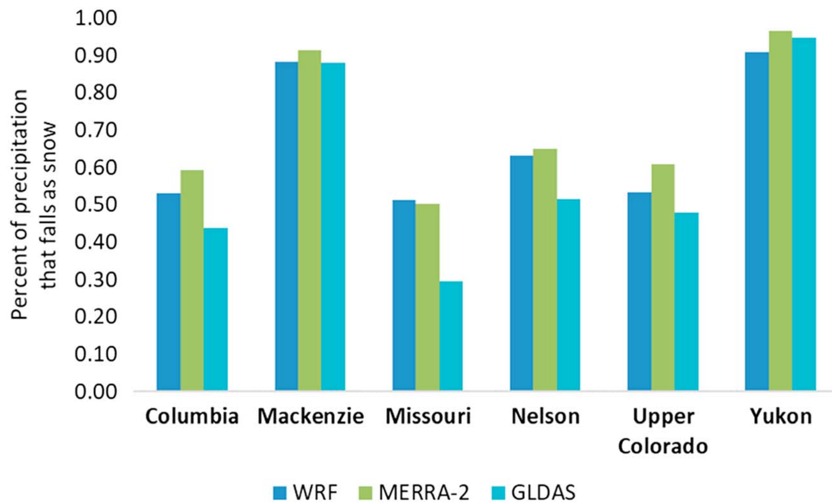

Figure 7. Fraction of cool-season (October–March) precipitation that falls as snow for each watershed. MERRA-2 = the second Modern-Era Retrospective Analysis for Research and Applications; GLDAS = Global Land Data Assimilation System; WRF = Weather Research and Forecasting.

watersheds, with one exception: for the Columbia (the watershed with greatest precipitation), WRF is >30% greater than all other estimates. The Columbia is also the most mountainous of the watersheds at 70.3% and has the highest fraction of precipitation that falls in the mountains (82% in WRF); this substantial contrast in the Columbia highlights that basin-wide precipitation differences are driven primarily by differences in the mountains.

For snowfall, we find that WRF is fairly consistent with MERRA-2 (12% different) but that WRF has more snowfall than GLDAS (33% different). Neither GPCP nor CRU provide snowfall estimates. All snowfall biases from MERRA-2 and GLDAS are negative, compared to WRF, except for the Yukon basin. Finally,

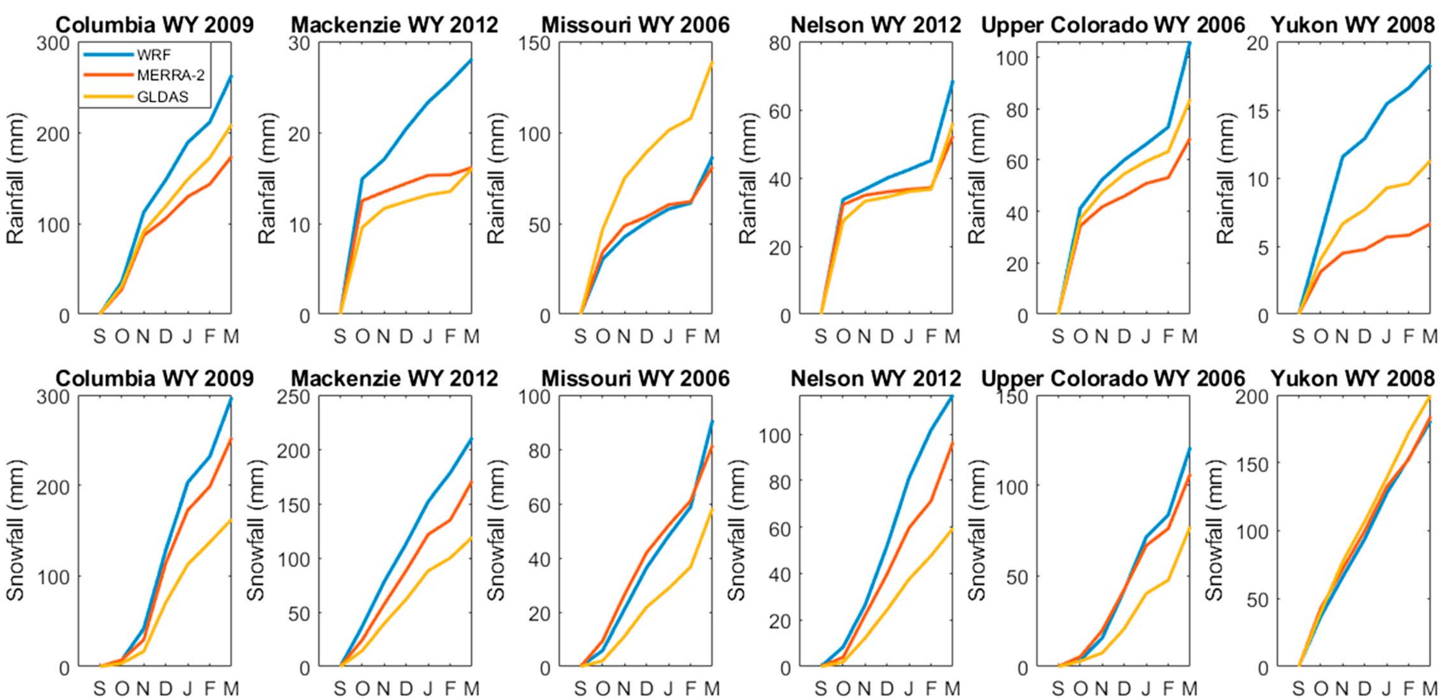

Figure 8. Monthly accumulated cool-season rainfall (top row) and snowfall (bottom row), in millimeters, for each watershed from WRF (blue lines), MERRA-2 (orange lines), and GLDAS (yellow lines). MERRA-2 = the second Modern-Era Retrospective Analysis for Research and Applications; GLDAS = Global Land Data Assimilation System; WRF = Weather Research and Forecasting; WY = water year.

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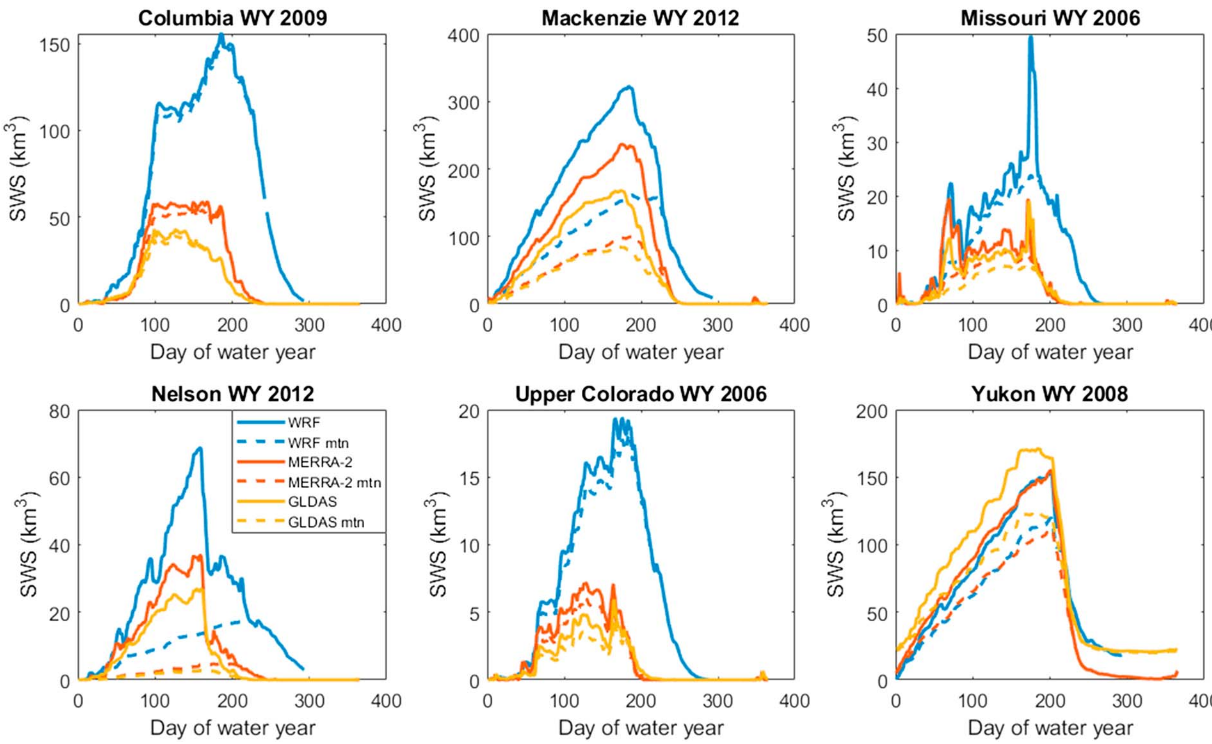

Figure 9. Watershed snow water storage, in cubic kilometers, from WRF (blue lines), MERRA-2 (orange lines), and GLDAS (yellow lines). Solid lines indicate the entire watershed and dashed lines indicate the mountains of the watershed. MERRA-2 = the second Modern-Era Retrospective Analysis for Research and Applications; GLDAS = Global Land Data Assimilation System; WRF = Weather Research and Forecasting; SWS = snow water storage; WY = water year.

we find that WRF has larger peak SWS than either MERRA-2 or GLDAS (again, GPCP and CRU do not provide estimates of SWS). On average, MERRA-2 and GLDAS produce 43% and 50% less SWS, respectively. Once again, this difference is almost entirely due to differences in the mountains (Figure 10). In the lowland, MERRA-2 (GLDAS) peak SWS is 9% (23%) less than WRF. WRF has far more SWS in the mountains however: MERRA-2 and GLDAS values are 51% and 58% less than WRF, respectively. This finding is generally consistent across all watersheds, though differences are more extreme for midlatitude basins and less extreme at higher latitudes.

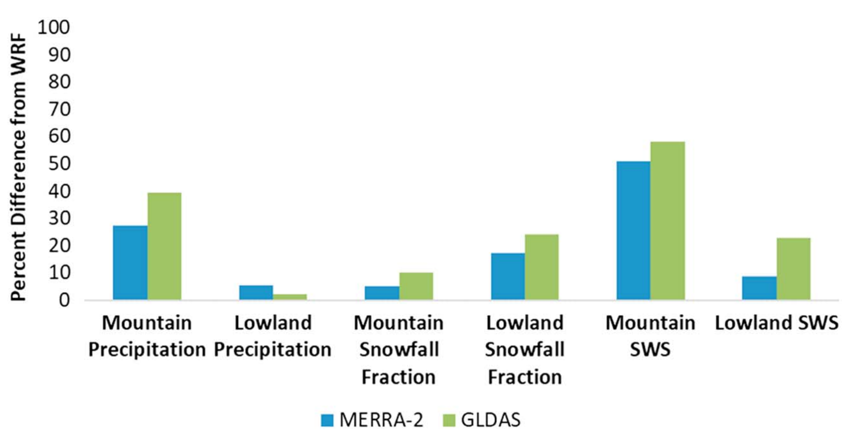

Figure 10. Mean percent difference, in absolute value, of MERRA-2 and GLDAS precipitation, fraction of precipitation from snowfall, and SWS for the mountains and lowlands, as compared to WRF values. MERRA-2 = the second Modern-Era Retrospective Analysis for Research and Applications; GLDAS = Global Land Data Assimilation System; WRF = Weather Research and Forecasting; SWS = snow water storage.

Though true validation of WRF precipitation and snow values remains impossible due to the inherent mismatch in scale between the limited gauge network and the much coarser WRF grid, numerous recent studies suggest that WRF produces reasonable estimates of precipitation (Caldwell et al., 2009; Cardoso et al., 2013; Currier et al., 2017; Gutmann et al., 2012; Hughes et al., 2017; Leung & Qian, 2009; Qian et al., 2010; Warrach-Sagi et al., 2013) and snowpack (Ikeda et al., 2010; Liu et al., 2017; Minder et al., 2016; Rasmussen et al., 2011; Wrzesien et al., 2018). As such, large divergences from WRF precipitation may represent inaccuracies in global hydroclimate data sets. In some of our comparisons, we observe relatively small differences between WRF, MERRA-2, and GLDAS. Basin-wide MERRA-2 cold-season precipitation is within 24% of WRF values in all six basins (−17% mean bias), and MERRA-2 lowland precipitation is even more similar to WRF (maximum bias 18%, mean −5%). In each of these cases, GLDAS is somewhat more different from WRF than is MERRA-2 on a basin-by-basin comparison (with some cases >30% different) but with mean biases relative to WRF similar to those from MERRA-2. In contrast, MERRA-2 and especially GLDAS produce much larger (and consistently negative) biases in mountain precipitation (Table 4). Though certainly not definitive, this result suggests that careful further examination of mountain precipitation is warranted in these two widely used global products.

Our results suggest similar skill levels for MERRA-2 and GLDAS SWS. In each global data set, lowland SWS remains reasonably close to WRF values, with average differences of −8.8% and −22.7% for MERRA-2 and GLDAS, respectively. In contrast, mountain SWS values are often >50% different from WRF values. SWS differences for entire watersheds are largest in the Columbia, Missouri, and Upper Colorado. In the mountains, results are similar, with large differences in the midlatitudes (Columbia, Nelson, and Upper Colorado) and smaller differences in the high latitudes (Mackenzie and the Yukon). SWS differences in the midlatitude mountains are likely driven by both precipitation (Figures 6 and 10) and temperature biases due to orographic processes at warmer air temperatures. Once the snow is on the ground, MERRA-2 and GLDAS are also characterized by earlier snowmelt than WRF, suggesting snow processes are likely handled incorrectly, perhaps due to energy balance biases. Previous work suggests that MERRA-2 has large ground heat flux errors during spring snowmelt (Lytle & Zeng, 2016). The fact that peak SWS biases are worse in midlatitudes fits with this theory; snow at lower latitudes is likely to be closer to the melting point and thus more susceptible to a temperature bias. Early snowmelt would have implications for other water cycle processes throughout the spring and summer.

A difference from WRF of >50% in SWS was suggested by Wrzesien et al. (2018) as a conservative threshold for reasonable values. When compared to WRF estimates, MERRA-2 (GLDAS) SWS has an average bias of −51% (−58%) for the mountains, while only −8% (−23%) in the lowlands. Therefore, our analysis suggests that MERRA-2 and GLDAS produce reasonable values of SWS in lowlands but not in mountains.

Regardless of the differences between WRF, MERRA-2, and GLDAS precipitation, our analyses and conclusions are hindered by being limited to only a single simulation year. As discussed above, though the Wrzesien et al. (2018) data set was created to approximate average SWS conditions for the mountains of North America, it does not necessarily provide climatological precipitation for the six watersheds. Further, it would be better to compare the data products across a range of hydrological conditions—wet, dry, and average water years. Though multiyear WRF simulations would greatly increase the computational cost, we suggest that future studies should consider multiple water years, such as the 13-year simulation of the contiguous United States developed by Liu et al. (2017). Simulating multiple years also provides an opportunity to capture more diverse hydrologic conditions. For example, a low snowpack year could be due to low precipitation or above-average temperatures. Through careful selection of water years, future studies could compare how WRF and MERRA-2, for example, differ in how they simulate snow droughts. Addressing these considerations is beyond the scope of this study, but with ever-improving computational abilities, future work should prioritize multiyear simulations to evaluate over a broader range of hydrologic conditions.

5. Conclusions

Our main objective was to determine whether cool-season precipitation estimates from global data sets are biased for major North American watersheds. We approached this goal by comparing a new data set from high-resolution WRF RCM simulations to four data sets: two that have precipitation amount only (CRU and GPCP) and two that include precipitation amount, phase, and snow accumulation (MERRA-2 and GLDAS). Three of the four global data sets (MERRA-2, GLDAS, and GPCP) have mean basin-wide, cold-season precipitation estimates <30% different from WRF. Both MERRA-2 and GLDAS produce reasonable fractions of snowfall. However, neither MERRA-2 nor GLDAS retains the snowpack long enough: They have 43% and 50% less peak SWS than WRF, on average.

Here we have shown that this disparity is almost entirely due to differences in the mountains, where orographic enhancement has been shown to have a critical role in regional water balances (Luce et al., 2013). Indeed, all data sets produce substantially (27–39%, on average) less precipitation and snowfall than WRF in mountainous areas. Remarkably, MERRA-2 and GLDAS peak SWS is somewhat consistent with WRF in the lowlands but 51% and 58% less than WRF in the mountains.

Our results point toward a possibility that global data sets produce too little cold-season precipitation in the mountains, which complements the findings of Wrzesien et al. (2018), who suggest global models underestimate mountain snow accumulation. However, when considering the nonmountainous portions of each watershed, global data sets appear to have adequate precipitation in lowland areas. MERRA-2 and GLDAS precipitation estimates are within 5% of WRF values, on average, suggesting that global products likely perform better in regions with simpler topography and precipitation processes. Here we also show that MERRA-2 and GLDAS do not retain snow long enough in the mountains, perhaps due to energy balance biases. One possible source of bias may be that air temperatures simply do not stay cool enough to maintain montane snowpack due to coarse resolution used to represent topography. When snowmelt comes too early, it may also come too slowly. Slower snowmelt may shift the overall partitioning of precipitation from runoff toward evapotranspiration (Berghuijs et al., 2014; Musselman et al., 2017). Thus, the low spatial resolution of these models may lead to underestimation of mountain precipitation, impacting other water cycle processes, such as runoff timing.

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