

From: [Grizzle, Betty](#)
To: [Stephen Torbit](#)
Subject: Re: IDFG comments
Date: Tuesday, December 19, 2017 4:44:54 PM
Attachments: [Walton et al 2017.pdf](#)

See attached for Walton et al. 2017.

On Tue, Dec 19, 2017 at 3:12 PM, Stephen Torbit <Stephen_Torbit@fws.gov> wrote:

Can you send me a link to the Walton article? I think this is another case of not reading the NOAA report and just trying to comment for the sake of comment.

Stephen C. Torbit

Assistant Regional Director

Science Applications

U.S. Fish and Wildlife Service

[134 Union Blvd.](#)

[Lakewood, Colorado 80228](#)

303-236-4602 – Office

720-626-7504 – Cell

From: Grizzle, Betty [mailto:betty_grizzle@fws.gov]
Sent: Tuesday, December 19, 2017 2:33 PM
To: John Guinotte; Stephen Torbit
Subject: IDFG comments

Comments re to CC and modeling from Idaho Fish and Game (some relate to discussion of other models):

Table 3, Wolverine Den Site Melt-out Dates

Page 34

The MODIS data from which this table is derived is currently available through 2016. Why was this limited to only include melt-out dates from 2002–2008?

Page 70, paragraph 2; Page 71, paragraph 2

The Department suggests further discussion on the spatial resolution of the global climate models and resulting estimates provided by Rupp et al. (2017) and Petersen et al. (2017). For both of these projects, knowledge of the spatial resolution of the data is significant in correctly interpreting the results.

Page 74, paragraph 2

Again, the resolution of global climate models used in the analysis should be noted and taken into consideration in interpretation.

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Betty J. Grizzle, D.Env.

Fish and Wildlife Biologist

U.S. Fish and Wildlife Service

Carlsbad Fish and Wildlife Office

[2177 Salk Ave, Suite 250](#)

[Carlsbad, CA 92008](#)

760-431-9440, ext. 215

760-431-5901 fax

--

Betty J. Grizzle, D.Env.

Fish and Wildlife Biologist

U.S. Fish and Wildlife Service

Carlsbad Fish and Wildlife Office

2177 Salk Ave, Suite 250

Carlsbad, CA 92008

760-431-9440, ext. 215

760-431-5901 fax



Incorporating Snow Albedo Feedback into Downscaled Temperature and Snow Cover Projections for California's Sierra Nevada

DANIEL B. WALTON

*Department of Atmospheric and Oceanic Sciences, and Institute of the Environment and Sustainability,
University of California, Los Angeles, Los Angeles, California*

ALEX HALL, NEIL BERG, AND MARLA SCHWARTZ

Department of Atmospheric and Oceanic Sciences, University of California, Los Angeles, Los Angeles, California

FENGPENG SUN

*Department of Geosciences, University of Missouri–Kansas City, Kansas City, Missouri, and Department of
Atmospheric and Oceanic Sciences, University of California, Los Angeles, Los Angeles, California*

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ABSTRACT

California's Sierra Nevada is a high-elevation mountain range with significant seasonal snow cover. Under anthropogenic climate change, amplification of the warming is expected to occur at elevations near snow margins due to snow albedo feedback. However, climate change projections for the Sierra Nevada made by global climate models (GCMs) and statistical downscaling methods miss this key process. Dynamical downscaling simulates the additional warming due to snow albedo feedback. Ideally, dynamical downscaling would be applied to a large ensemble of 30 or more GCMs to project ensemble-mean outcomes and intermodel spread, but this is far too computationally expensive. To approximate the results that would occur if the entire GCM ensemble were dynamically downscaled, a hybrid dynamical–statistical downscaling approach is used. First, dynamical downscaling is used to reconstruct the historical climate of the 1981–2000 period and then to project the future climate of the 2081–2100 period based on climate changes from five GCMs. Next, a statistical model is built to emulate the dynamically downscaled warming and snow cover changes for any GCM. This statistical model is used to produce warming and snow cover loss projections for all available CMIP5 GCMs. These projections incorporate snow albedo feedback, so they capture the local warming enhancement (up to 3°C) from snow cover loss that other statistical methods miss. Capturing these details may be important for accurately projecting impacts on surface hydrology, water resources, and ecosystems.

1. Introduction

California's Sierra Nevada is a high-elevation mountain range with complex topography and significant seasonal snow cover. Anthropogenic warming in the region is expected to cause large snowpack reductions by the end of the twenty-first century (Pierce and Cayan 2013). Locations with baseline temperatures near freezing are vulnerable to snow cover loss because of less snowfall as a fraction of precipitation (S/P) and earlier snowmelt. Areas experiencing snow cover loss are subject to extra warming due to snow albedo feedback (SAF). The

disappearance of snow cover reveals lower albedo surfaces, causing an increase in absorbed solar radiation and further warming. SAF is an important feature of climate change in snow-covered regions, leading to elevation-dependent outcomes (Giorgi et al. 1997; Kim 2001; Rangwala and Miller 2012; Pepin et al. 2015; Letcher and Minder 2015). Although SAF is present in global climate model (GCM) simulations (e.g., Qu and Hall 2014), GCMs often miss the local SAF in areas of complex topography because of their low spatial resolution (~ 100 – 200 km). In the case of the Sierra Nevada, their resolution is generally too low to resolve this mountain complex. To provide future projections that capture the effect of SAF on the warming in the Sierra Nevada, much higher resolution is necessary.

Corresponding author e-mail: Daniel B. Walton, waltond@atmos.ucla.edu

A variety of approaches are available for downscaling GCM output to higher resolution (Wilby and Wigley 1997; Benestad et al. 2008; Maraun et al. 2010). One approach, dynamical downscaling, explicitly simulates complex physical processes shaping local climate response using a regional climate model (RCM) forced at its boundaries by GCM output. Dynamical downscaling may be advantageous over the Sierra Nevada as it directly simulates both SAF and inhibition of air mass mixing due to the high peaks. As we will show, the region's high peaks effectively separate continental air masses experiencing large warming from coastal air masses experiencing moderate warming. While dynamical downscaling can simulate key mechanisms associated with regional climate change, it may also introduce errors and uncertainty, as RCM results vary depending on parameterizations choice (e.g., Plummer et al. 2006) and resolution (e.g., Mass et al. 2002). Furthermore, dynamically downscaling of a large GCM ensemble—critical for computing ensemble-mean outcomes and characterizing uncertainty associated with GCM spread—is usually impractical because of its high computational cost.

A second approach, statistical downscaling, employs statistical relationships from the historical period to translate low-resolution predictors into high-resolution predictands (Benestad et al. 2008). Statistical downscaling has a much lower computational cost than dynamical downscaling, which makes it a valuable tool to downscale multimodel ensembles and produce more robust estimates of likely outcomes and uncertainty (Giorgi et al. 2001; Tebaldi et al. 2005; Pierce and Cayan 2013; Pierce et al. 2013). However, the empirical relationships between large and fine scales employed in statistical downscaling can break down under climate change (Gutiérrez et al. 2013; Dayon et al. 2015; Dixon et al. 2016). Furthermore, as we will demonstrate in this study, commonly used statistical downscaling methods do not capture the Sierra Nevada's local warming enhancement due to SAF.

Another approach is to use simplified or linearized versions of a dynamical model to save computational resources while still capturing the desired physical mechanisms. For example, there is a long history of using linear orographic precipitation models instead of full weather prediction models to produce precipitation distributions in mountainous areas (e.g., Sarker 1966; Rhea 1978; Barros and Lettenmaier 1993; Sinclair 1994; Georgakakos et al. 2005; Minder 2010). A recent development is the Intermediate Complexity Atmospheric Research model (ICAR; Gutmann et al. 2016), a simplified but comprehensive model that can greatly decrease computation time versus full dynamical models. Another approach, taken by Walton et al. (2015) and Wakazuki and Rasmussen (2015), is to save computational resources by applying a full

dynamical model only to a small, carefully constructed set of scenarios. Then the results are extended statistically to provide projections for a wide range of scenarios. Here we follow the approach described by Walton et al. (2015), termed “hybrid dynamical–statistical downscaling” or “hybrid downscaling.” Under this approach, dynamical downscaling is applied to a small subset of GCMs that approximately span the range of temperature and precipitation changes in the full ensemble. Then the dynamically downscaled output is used to build a simple statistical model to emulate the dynamical model's behavior and downscale the remaining GCMs. This represents a variant of the “perfect prognosis” or “perfect model” approach, in which a statistical model is trained on dynamical model output instead of an observationally based dataset (Maraun et al. 2010). Hybrid downscaling can capture important features of the warming pattern that may be present only in dynamical downscaling, but at a fraction of dynamical downscaling's computational cost (Berg et al. 2015; Sun et al. 2015; Walton et al. 2015).

This paper is structured in the following way. Section 2 describes the dynamical downscaling of five GCMs from phase 5 of the Coupled Model Intercomparison Project (CMIP5; Taylor et al. 2012) run under representative concentration pathway 8.5 (RCP8.5; Riahi et al. 2011). The resulting climate change projections are compared to existing statistically downscaled projections. In section 3 the dynamically downscaled output is used to develop a statistical model incorporating SAF. In section 4 the statistical model is applied to CMIP5 GCMs run under all four RCP scenarios: RCP2.6, RCP4.5, RCP6.0, and RCP8.5. Although we address results from all of the scenarios, we focus on RCP8.5 because emissions are currently tracking this pathway (Sanford et al. 2014). Important caveats related to the simulation of snow albedo feedback are discussed in section 5. Major results and their implications are summarized in section 6.

2. Dynamical downscaling

In this section, we first describe our dynamical downscaling procedure used to generate historical and future high-resolution simulations. Next, we evaluate the historical simulation's realism by comparing to observationally based gridded datasets. Finally, we examine the climate change patterns generated by differencing future and historical simulations. These results are essential to understanding the construction of the hybrid dynamical–statistical model in section 3.

a. Dynamical downscaling with WRF

Dynamically downscaled simulations are performed using the Weather Research and Forecasting (WRF)

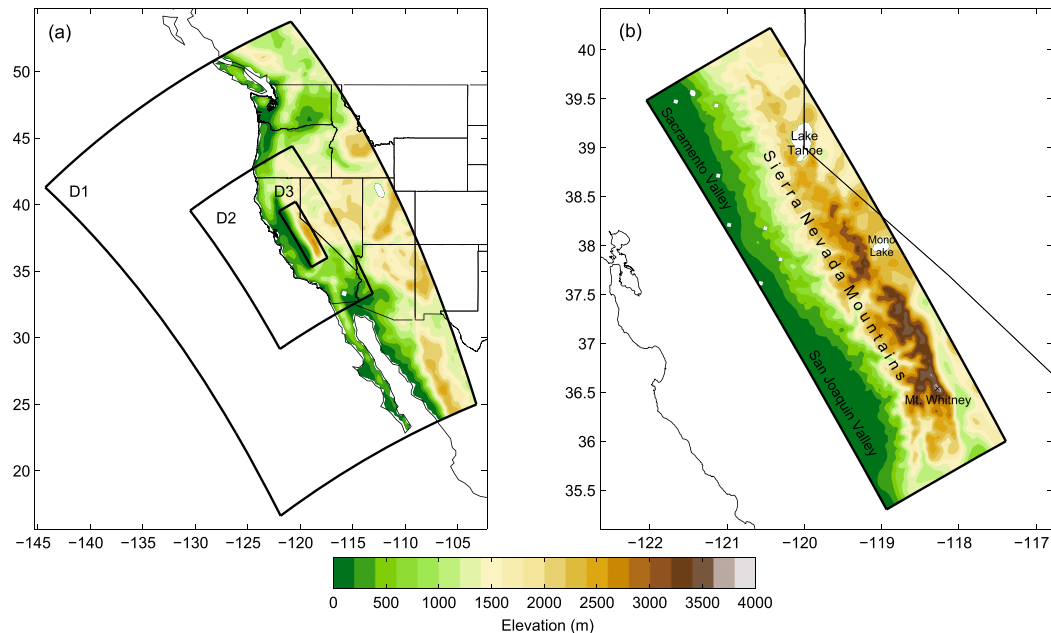


FIG. 1. (a) Elevation (m) and model setup with three one-way nested WRF domains (labeled D1, D2, and D3) at resolutions of 27, 9, and 3 km. (b) Innermost domain elevation (m).

Model version 3.5 (Skamarock et al. 2008). WRF was tested with multiple land surface models, domain configurations, nudging options, microphysics, and other parameterizations in order to determine which combination best simulated snow and precipitation over the Sierra Nevada. Based on this testing, we adopt the following WRF configuration. WRF is coupled to the community Noah land surface model with multi-parameterization options (Noah-MP; Niu et al. 2011). Three one-way nested domains (27-, 9-, and 3-km resolution, from the outermost to innermost domain, respectively) are used (Fig. 1a). In each domain, all variables within five grid cells of the horizontal lateral boundary are relaxed toward corresponding values at the boundaries. To improve representation of surface and boundary layer processes, vertical resolution is enhanced near the surface, with 30 out of 43 total sigma levels below 3 km. The physical parameterization package consists of the new Thompson microphysics scheme (Thompson et al. 2008), Dudhia shortwave radiation scheme (Dudhia 1989), Rapid Radiative Transfer Model (RRTM) longwave radiation scheme (Mlawer et al. 1997), Mellor–Yamada and Nakanishi–Niino (MYNN) level-2.5 surface and boundary layer scheme (Nakanishi and Niino 2006), and the old Kain–Fritsch cumulus convection scheme (Kain and Fritsch 1990). Spectral nudging of temperature, zonal and meridional winds, and geopotential height above the boundary layer (roughly at 850 hPa) is employed over

the outermost domain. In this study we focus on information from the innermost domain, which goes from the eastern edge of the California Central Valley to the leeside of the Sierra Nevada (Fig. 1b).

Climatic changes are projected using a single baseline simulation and five future simulations, following the pseudoglobal warming (PGW) method (Schär et al. 1996; Sato et al. 2007; Kawase et al. 2009; Rasmussen et al. 2011). The baseline simulation, spanning 1981–2006, is forced at the ocean surface and along the outermost boundary with 6-hourly North American Regional Reanalysis (NARR; Mesinger et al. 2006). This simulation is used to evaluate WRF through comparison with the observational record (section 2b). The 1991–2000 subperiod is used to compare with future simulations. The five future simulations represent how the 1991–2000 historical subperiod would have unfolded if its mean climate were altered to reflect climate change signals of five CMIP5 GCMs run under the RCP8.5 scenario. These five GCMs (CNRM-CM5, GFDL CM3, INM-CM4.0, IPSL-CM5A-LR, and MPI-ESM-LR; see Table 1) were selected to approximately span California’s temperature and precipitation changes in the full CMIP5 ensemble (Fig. 2). Each future simulation is forced with boundary conditions created by adding GCM monthly climatology differences (2081–2100 minus 1981–2000) to the 1991–2000 NARR data. This process was applied to temperature, specific humidity, zonal and meridional winds, and geopotential height. The future WRF simulations are then

TABLE 1. Details of the 35 CMIP5 GCMs statistically downscaled. For a particular GCM, averages were taken over all available realizations run under a particular RCP in order to damp internal variability. Realizations used for each GCM are noted in the rightmost column. Those GCMs that are also dynamically downscaled are shown in boldface. Expansions of model names are available online at <http://www.ametsoc.org/PubsAcronymList>. Further model details are available online at <http://cmip-pcmdi.llnl.gov/cmip5/availability.html>.

Model	Realizations used			
	RCP2.6	RCP4.5	RCP6.0	RCP8.5
ACCESS1.0	—	r1i1p1	—	r1i1p1
ACCESS1.3	—	r1i1p1	—	r1i1p1
BCC_CSM1.1	r1i1p1	r1i1p1	r1i1p1	r1i1p1
BCC_CSM1.1(m)	r1i1p1	r1i1p1	r1i1p1	r1i1p1
BNU-ESM	r1i1p1	r1i1p1	—	r1i1p1
CanESM2	r[1,2,4,5]i1p1	r[1,2,4,5]i1p1	—	r[1,2,4,5]i1p1
CCSM4	r[1,2]i1p1	r[1,2,6]i1p1	r[1,2,6]i1p1	r[1,2]i1p1
CESM1(BGC)	—	r1i1p1	—	r1i1p1
CESM1(CAM5)	r[1,2]i1p1	r1i1p1	r[1,2]i1p1	r[1,2]i1p1
CESM1(WACCM)	r2i1p1	r2i1p1	—	—
CMCC-CESM	—	—	—	r1i1p1
CMCC-CM	—	r1i1p1	—	r1i1p1
CMCC-CMS	—	—	—	r1i1p1
CNRM-CM5	r1i1p1	r1i1p1	—	r[1,2,4,6]i1p1
CSIRO Mk3.6.0	r[1–10]i1p1	r[1–10]i1p1	r[1–10]i1p1	r1i1p1
EC-EARTH	—	r[1,2,6,8,9]i1p1	—	—
FGOALS-g2	r1i1p1	r1i1p1	—	r1i1p1
GFDL CM3	r1i1p1	r1i1p1	r1i1p1	r1i1p1
GFDL-ESM2G	r1i1p1	r1i1p1	r1i1p1	r1i1p1
GFDL-ESM2M	r1i1p1	r1i1p1	r1i1p1	r1i1p1
GISS-E2-H	r1i1p1	r[1–5]i1p1	r1i1p1	r[1,2]i1p1
GISS-E2-H-CC	—	r1i1p1	—	—
GISS-E2-R	r1i1p1	r[1–6]i1p1	r1i1p1	r[1,2]i1p1
GISS-E2-R-CC	—	r1i1p1	—	—
HadGEM2-AO	r1i1p1	—	r1i1p1	r1i1p1
HadGEM2-CC	—	r1i1p1	—	r[1–3]i1p1
HadGEM2-ES	r1i1p1	r[1,2]i1p1	r[1,2]i1p1	r[1,2]i1p1
INM-CM4.0	—	r1i1p1	—	r1i1p1
IPSL-CM5A-LR	r[1–4]i1p1	r[1–4]i1p1	r1i1p1	r[1–4]i1p1
IPSL-CM5A-MR	r1i1p1	r1i1p1	r1i1p1	r1i1p1
IPSL-CM5B-LR	—	r1i1p1	—	r1i1p1
MIROC5	r[1–3]i1p1	r[1–3]i1p1	r[1–3]i1p1	r1i1p1
MIROC-ESM	r1i1p1	r1i1p1	r1i1p1	r1i1p1
MIROC-ESM-CHEM	r1i1p1	r[1–3]i1p1	r1i1p1	r1i1p1
MPI-ESM-LR	r[1–3]i1p1	r[1–3]i1p1	—	r[1–3]i1p1
MPI-ESM-MR	r1i1p1	r[1–3]i1p1	—	r1i1p1
MRI-CGCM3	r1i1p1	r1i1p1	r1i1p1	r1i1p1
NorESM1-M	r1i1p1	r1i1p1	r1i1p1	r1i1p1
NorESM1-ME	r1i1p1	r1i1p1	r1i1p1	r1i1p1

differenced with the 1991–2000 portion of the baseline WRF simulation to determine regional climate change signals. Because each future year has the same climatological perturbation added to its boundary conditions, only a few downscaled future years are necessary to determine regional climate change signals. Thus a 10-yr period is used for the future to conserve scarce computational resources.

There are several advantages and disadvantages of the PGW method. First, forcing the baseline simulation with reanalysis allows for direct comparison to historical observations. If raw GCM output were used as forcing, only statistical properties could be compared. Furthermore, by

using reanalysis for the baseline (and perturbed reanalysis for the future), we avoid the implications of potentially large mean-state biases often found in GCMs. This may be important in regions where SAF plays an important role in warming. For example, significant mean-state temperature biases would lead to unrealistic snow cover and to unrealistic warming amplification due to SAF in a perturbed climate state. A downside to the PGW method is that future simulations are driven by climatological perturbations to historical boundary conditions, so no changes in large-scale interannual variability or daily extremes are downscaled. (Changes in the mean state may still affect how

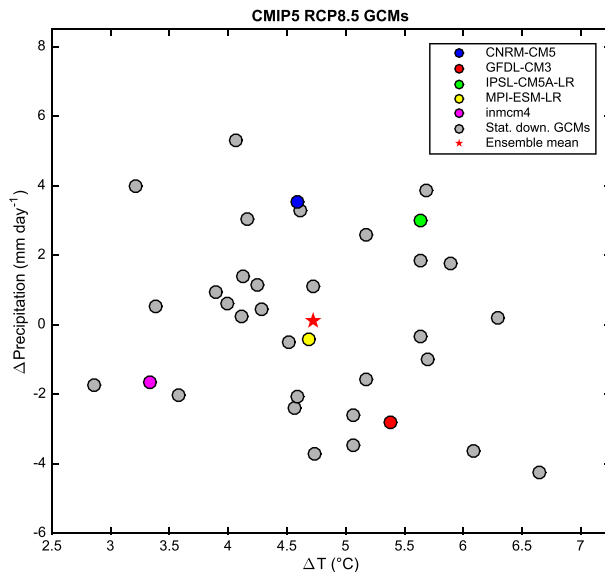


FIG. 2. Changes in annual-mean precipitation (mm day^{-1}) vs annual-mean changes in surface air temperature (K) between the periods 2081–2100 and 1981–2000 averaged over California in 35 CMIP5 GCMs run under the RCP8.5 scenario. The five GCMs selected for dynamical downscaling are highlighted (colors). The gray dots represent GCMs that are downscaled with StatWRF. Dots represent averages over all realizations for that particular GCM run under RCP8.5 in the CMIP5 archive (see Table 1 for details). The ensemble mean is indicated with a red star.

variability develops inside the WRF domain.) A related upside, however, is that historical variability in the reanalysis is much more realistic than in GCMs. For example, many GCMs struggle to realistically simulate El Niño–Southern Oscillation (Guilyardi et al. 2009), a key climate variability driver in California. So we would not necessarily trust GCM-predicted changes in variability, even if they were included. Another issue with the PGW method is that historical El Niño years receive the same perturbation as La Niña years (i.e., perturbations are not tailored to specific phases of variability). To mitigate negative consequences arising from not downscaling changes in variability, the scope of this study is limited to changes in mean climate.

b. Evaluation of the WRF baseline simulation

An evaluation of surface air temperature and snow cover output from WRF's baseline simulation is presented in Figs. 3 and 4, respectively. WRF temperatures (at 3-km resolution) are compared to output from the Parameter–Elevation Relationships on Independent Slopes Model (PRISM; Daly et al. 2008), an observationally based gridded product at 4-km resolution. PRISM provides monthly averages of daily maximum and minimum temperatures, which we averaged to generate monthly mean temperatures. We linearly interpolated PRISM data to 3-km resolution to match WRF's grid. The

linearly interpolated PRISM data are also adjusted to account for elevation differences between interpolated PRISM and WRF grids, using a lapse rate of $6.5^{\circ}\text{C km}^{-1}$.

Differences between WRF and PRISM in climatological annual-mean temperatures for the 1981–2000 period are generally small (Figs. 3a–c). The domain-average difference is only -0.1°C . However, WRF tends to be colder (-1.2°C) at higher elevations ($>2500\text{ m}$). WRF and PRISM report similar composite seasonal cycles and are calculated by averaging temperature for each calendar month. The mean absolute error (MAE) between the 12 monthly values (Fig. 3d) has a domain average of 1.0°C , with slightly larger errors (1.5°C) at higher elevations ($>2500\text{ m}$). Monthly-mean variability of surface air temperature also shows strong agreement between WRF and PRISM (Fig. 3e). The WRF and PRISM anomalies are highly correlated (0.95 average over the domain). Moreover, the MAE in monthly anomalies is generally small, with the largest errors again found at higher elevations (Fig. 3f).

Taken as a whole, Fig. 3 shows that WRF matches PRISM's temperature climatology and temporal variability, although it produces slightly colder temperatures at higher elevations. Cooling effects of snow cover are a likely cause of this disagreement (Fig. 4). PRISM is based on station observations, but high-elevation observations are sparse in the Sierra Nevada. The gridding procedure used in PRISM extrapolates the high-elevation temperatures from low elevations without explicitly including snow cover's additional cooling effect. This may explain why the WRF temperature patterns—which include this effect—are systematically cooler at locations in which WRF has snow cover. If WRF were compared to a satellite temperature product instead, we would expect the differences to be smaller than the differences between WRF and PRISM.

We also evaluate WRF's snow cover simulation. We define snow cover as the fraction of a grid cell covered by snow [snow cover fraction (SCF)]. We compare to monthly level-3 snow cover data on a 0.05° climate model grid from the Moderate Resolution Imaging Spectroradiometer on board the *Terra* satellite (MODIS/*Terra* MOD10C1 dataset, available at <http://nsidc.org/data/MOD10CM>; Hall et al. 2006). These data have been linearly interpolated to the 3-km WRF grid. MODIS/*Terra* data coverage began in April 2000, providing overlap for comparison with the 1981–2006 baseline WRF simulation from April 2000 to December 2006 (Fig. 4). The patterns generally resemble one another closely, although a similar bias emerges in each month: WRF tends to produce slightly higher SCF than MODIS/*Terra* data along the Sierra Nevada's windward side and slightly lower SCF east of the Sierra Nevada. WRF snow cover also persists longer during the melt season, with

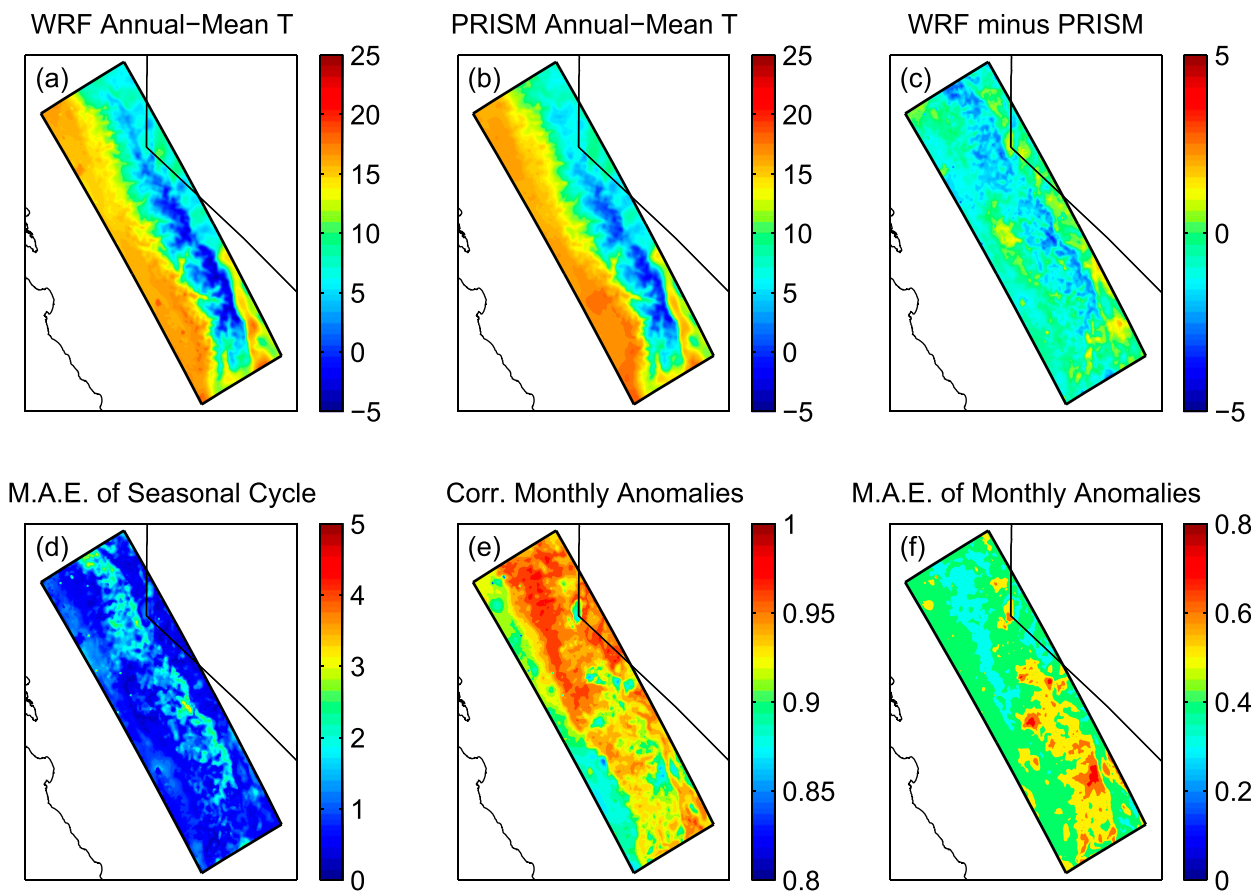


FIG. 3. Comparison of WRF and PRISM temperatures ($^{\circ}\text{C}$), for 1981–99. PRISM temperatures are interpolated to the WRF 3-km grid and adjusted based on a lapse rate of $6.5^{\circ}\text{C km}^{-1}$ to correct for the mismatch between WRF elevations and the interpolated PRISM elevations. Shown are the annual-mean T climatologies for (a) WRF, (b) PRISM, and (c) WRF minus PRISM. (d) MAE between the composite seasonal cycles (12 monthly values) of WRF and elevation-corrected PRISM. (e) Correlations of monthly temperature anomalies (relative to composite 1981–99 seasonal cycle). (f) MAE of monthly temperature anomalies.

higher May and June SCF values than MODIS/Terra data. These biases have an important effect on WRF's simulation of SAF. In areas where WRF produces unrealistically high SCF values in the historical simulation, there is potential for larger snow cover reductions and thus larger warming enhancements due to SAF. We discuss in detail how biases in temperature and snow cover affect our final results in section 5.

c. WRF climate changes

The WRF climate changes, calculated by differencing the climates of the five future simulations and the climate of the 1991–2000 subperiod of the historical simulation, are the basis for the hybrid dynamical–statistical model used to downscale all GCMs. (Recall that these changes represent a downscaling of GCM-simulated changes in climate between 2081–2100 and 1981–2000 under RCP8.5.) The WRF warming patterns are compared to those produced by two commonly used

statistical downscaling methods: bias correction and constructed analogs (BCCA; Hidalgo et al. 2008; Maurer and Hidalgo 2008) and bias correction with spatial disaggregation (BCSD; Wood et al. 2002; Wood et al. 2004; Maurer 2007). The BCCA and BCSD projections were obtained from the archive of downscaled CMIP3 and CMIP5 climate and hydrology projections (available at http://gdo-dep.ucllnl.org/downscaled_cmip_projections/; Reclamation 2013). BCCA bias-corrects the GCM using a transformation that constrains the GCM's historical period daily temperature distribution to match that of $1^{\circ} \times 1^{\circ}$ coarsened observations. Then, the constructed analog step consists of approximating the low-resolution pattern for the target day as a linear combination of low-resolution patterns in the historical record. The same linear combination is then applied to the corresponding high-resolution historical patterns to generate the approximate high-resolution pattern for the target day. BCCA projections are available for daily maximum and

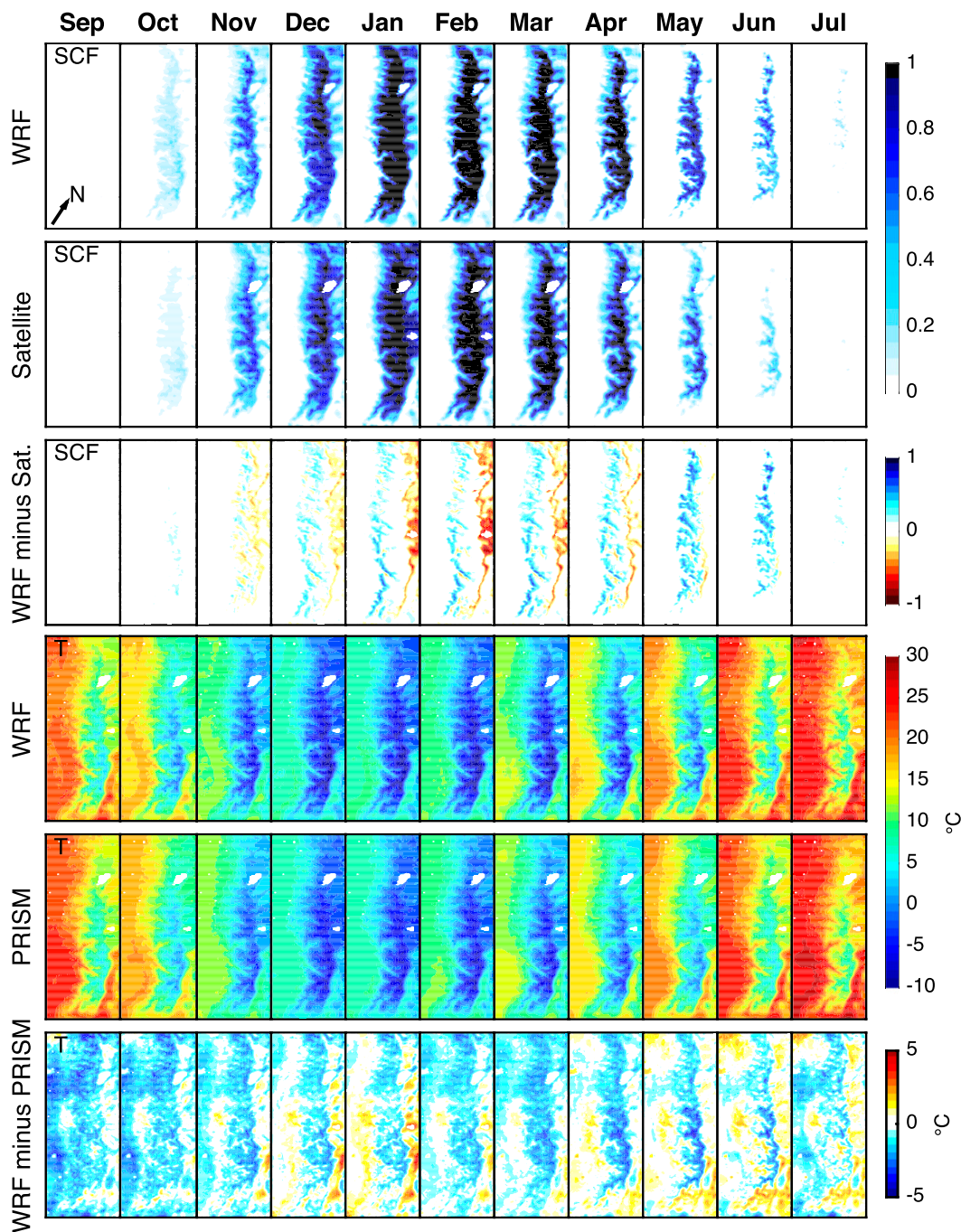


FIG. 4. (top)–(bottom) Monthly snow-covered fraction climatology (using data from April 2000 to December 2006) for WRF, MODIS/Terra data, and WRF minus MODIS/Terra data; and monthly temperature climatology (°C) for the period 1981–99 for WRF, PRISM, and WRF minus PRISM. MODIS/Terra and PRISM data have been linearly interpolated to the 3-km WRF grid.

minimum temperature with native resolution of $1/8^\circ$, which are averaged to produce monthly average temperatures and are linearly interpolated to the 3-km WRF grid. Similar processing was applied to BCSD data (only monthly BCSD data are available). BCSD uses a similar bias

correction step to BCCA. Then, to determine the high-resolution temperature pattern corresponding to the bias-corrected GCM temperature pattern, the GCM anomaly pattern is linearly interpolated and added to the high-resolution observed climatology. Finally, we also include

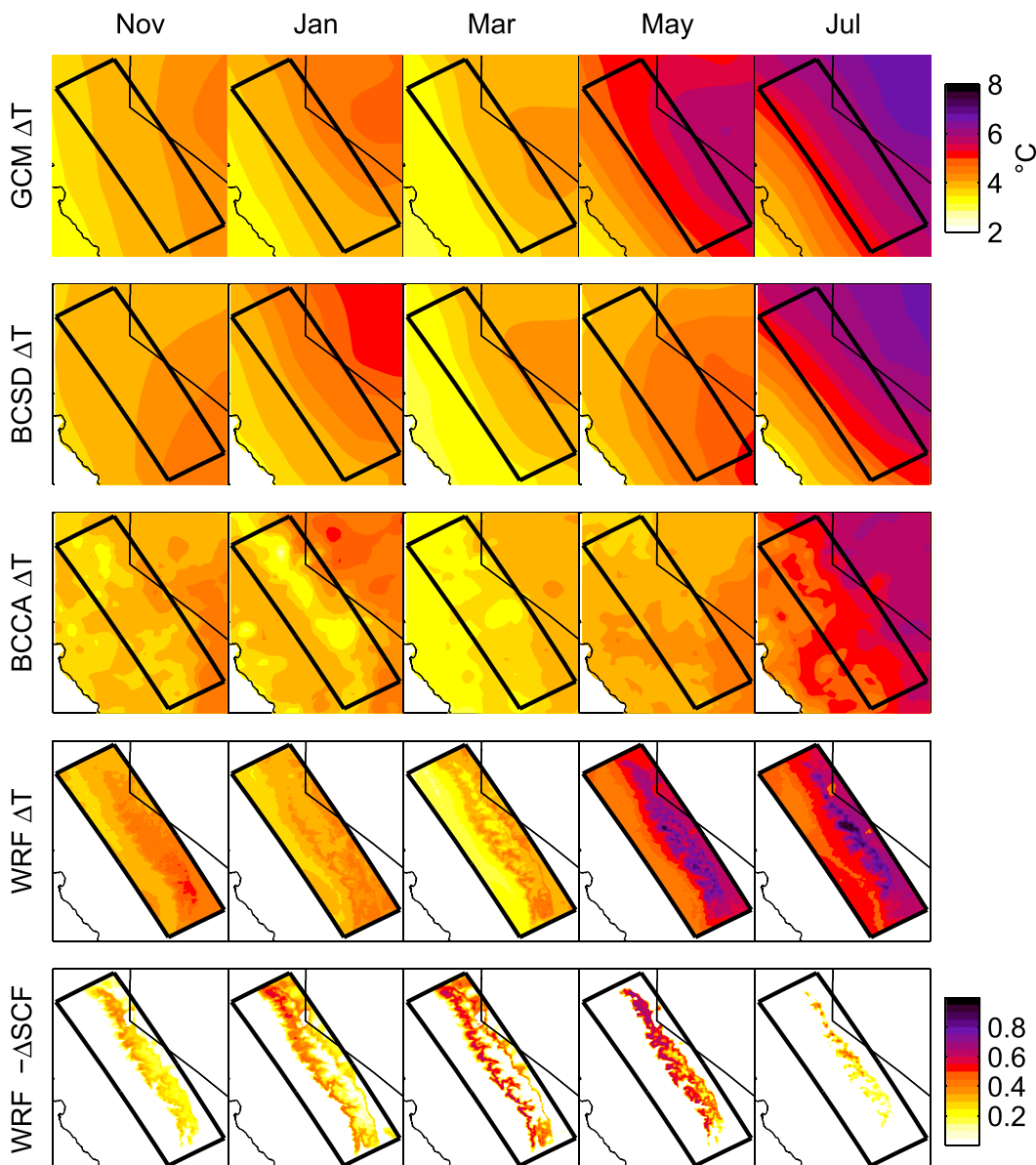


FIG. 5. Changes between 1981–2000 and 2081–2100 in temperature climatologies ($^{\circ}\text{C}$) averaged over five GCMs downscaled multiple ways: (top)–(bottom) linear interpolation, BCSD, BCCA, the hybrid statistical model, and WRF. (bottom) Decreases in WRF SCF are also shown. The innermost WRF domain is outlined in black.

simple linear interpolation of the GCM output as the most naïve possible method for downscaling, representing a standard measure of minimal downscaling skill against which the other methods can be compared.

All downscaling methods produce climate change patterns exhibiting reduced warming closer to the coast and higher warming inland of the Sierra Nevada (Fig. 5). This gradient is a common large-scale feature of GCM warming patterns. It arises from the warming contrast between the continental inland interior and adjacent ocean (Manabe et al. 1991; Cubasch et al. 2001; Braganza et al. 2003, 2004;

Sutton et al. 2007; Joshi et al. 2008; Dong et al. 2009; Fasullo 2010). The Sierra Nevada's high peaks create a formidable topographic barrier that likely inhibits mixing of marine and high desert air masses and their accompanying properties. Because WRF resolves this effect, it produces warming patterns with a sharper and more physical coastal–inland warming gradient than the other methods. This effect is most apparent in summer, when the GCMs' land–sea warming contrast is greatest.

Only the WRF warming patterns exhibit finescale amplification in regions of snow cover loss. To verify

that SAF is responsible for these warming anomalies, we perform an analysis of changes to the surface energy budget (Fig. 6). A primary effect of snow cover loss is a surface albedo reduction, increasing absorbed surface shortwave radiation (SWnet). This effect is largest in May, when large snow cover losses coincide with high insolation, as ΔSWnet is as high as 60 W m^{-2} . Spatial variations in SAF strength also arise from insolation gradients. Although the northern and western Sierra Nevada generally experience the largest snow cover reductions, they receive less insolation, so they have much smaller SWnet increases than the southern and eastern Sierra Nevada. Snow reductions also affect the surface energy budget in other important ways. Melting snow can offset the warming by absorbing extra heat [see increases in the flux into the soil/snowpack (GRDFLX) at high elevations in January–May]. However, once snow completely disappears, it can no longer absorb heat (see decreases in GRDFLX in middle elevations in May and middle and high elevations in July). In this case, extra heat that would have gone toward melting snow must be offset by increases in sensible heat flux (HFX) and longwave radiative flux (LWUP) associated with a further rise in temperature.

SAF is the key contributor to local enhancement of warming in WRF, yet the other statistical downscaling methods show no such effect (Fig. 5, top three rows). It is not surprising that linearly interpolating the GCM warming misses this effect. BCSD produces very similar warming patterns to the linear interpolation, consistent with the fact that BCSD temperature patterns are generated by adding the linearly interpolated bias-corrected GCM temperature anomaly to the high resolution ($1/8^\circ$) observed climatology. Thus, BCSD also misses local SAF. BCCA should, in theory, better capture effects of SAF in its warming patterns, if patterns associated with its relatively high-resolution ($1/8^\circ$) historical analogs are sufficiently shaped by SAF. However, warming patterns produced by BCCA show no apparent effects of SAF. It is difficult to see how WRF could be qualitatively wrong in its prediction that SAF is a key process shaping warming patterns in the Sierra Nevada. Thus, the warming patterns produced by these statistical downscaling techniques lack a vital element of physical realism. To make projections for a full GCM ensemble and that capture the effects of SAF, we use hybrid downscaling, as explained in the next section.

3. Statistical downscaling

In this section, we build a statistical model that can be applied efficiently to all CMIP5 GCMs. This statistical model (referred to as StatWRF) is designed to ingest any

GCM's warming pattern and produce a high-resolution warming pattern that mimics what WRF would produce had dynamical downscaling been performed. First, we explain how WRF's warming patterns can be decomposed into components corresponding to regional physical processes and GCM parameters associated with those processes. These components are the building blocks of StatWRF. StatWRF scales each component up or down commensurate with the magnitude of the GCM parameters to generate the high-resolution warming pattern.

a. Decomposing the WRF warming patterns

Analysis of the WRF climate change signal (section 2c) revealed that the east–west warming gradient, strongly shaped by the Sierra Nevada divide, and additional warming due to SAF were two key features of the warming for this domain. In this section, we describe how we decompose the warming pattern into components corresponding to these features.

First, we quantify the additional warming due to SAF, a local feature determined by WRF. To diagnose SAF strength, we regress historical local temperature anomalies against snow cover, as follows: For a given calendar month, we first calculate the historical monthly temperature and snow cover anomaly time series. This is done for each grid cell in the domain. The time series of anomalies, denoted T' and SCF' , each have length 20, since there are 20 instances of a given calendar month in the 20-yr historical simulation. Likewise, we calculate the domain-average anomaly time series for temperature, denoted $\langle T' \rangle$, for that calendar month. The values $T' - \langle T' \rangle$ tell us how much warmer the anomaly at this particular grid cell is than the domain-average anomaly. We then linearly regress $T' - \langle T' \rangle$ onto SCF' . The slope of this relationship a represents the additional local warming we would expect per change in SCF. To fully utilize the information content of the WRF simulations, we also include the time series of future anomalies in our calculations of a . (Future anomalies are calculated relative to the future climatology of each downscaled GCM.) Thus we regressed the concatenated time series $[T'_{\text{hist}} - \langle T'_{\text{hist}} \rangle, T'_{\text{fut1}} - \langle T'_{\text{fut1}} \rangle, \dots, T'_{\text{fut5}} - \langle T'_{\text{fut5}} \rangle]$ onto $[\text{SCF}'_{\text{hist}}, \text{SCF}'_{\text{fut1}}, \dots, \text{SCF}'_{\text{fut5}}]$. Each time series has length 70 since there are 20 instances of a given calendar month during the historical simulation and 10 instances of that month in each of the five future simulations.

The local SAF strength a varies seasonally and spatially (Fig. 7). In most months, the western and northern Sierra Nevada have weaker SAF strength because of lower insolation. Winter months have low insolation, with a values generally between 1° and 3°C . (An a value of 1°C means that a grid cell that goes from being completely snow covered to completely snow free would experience an

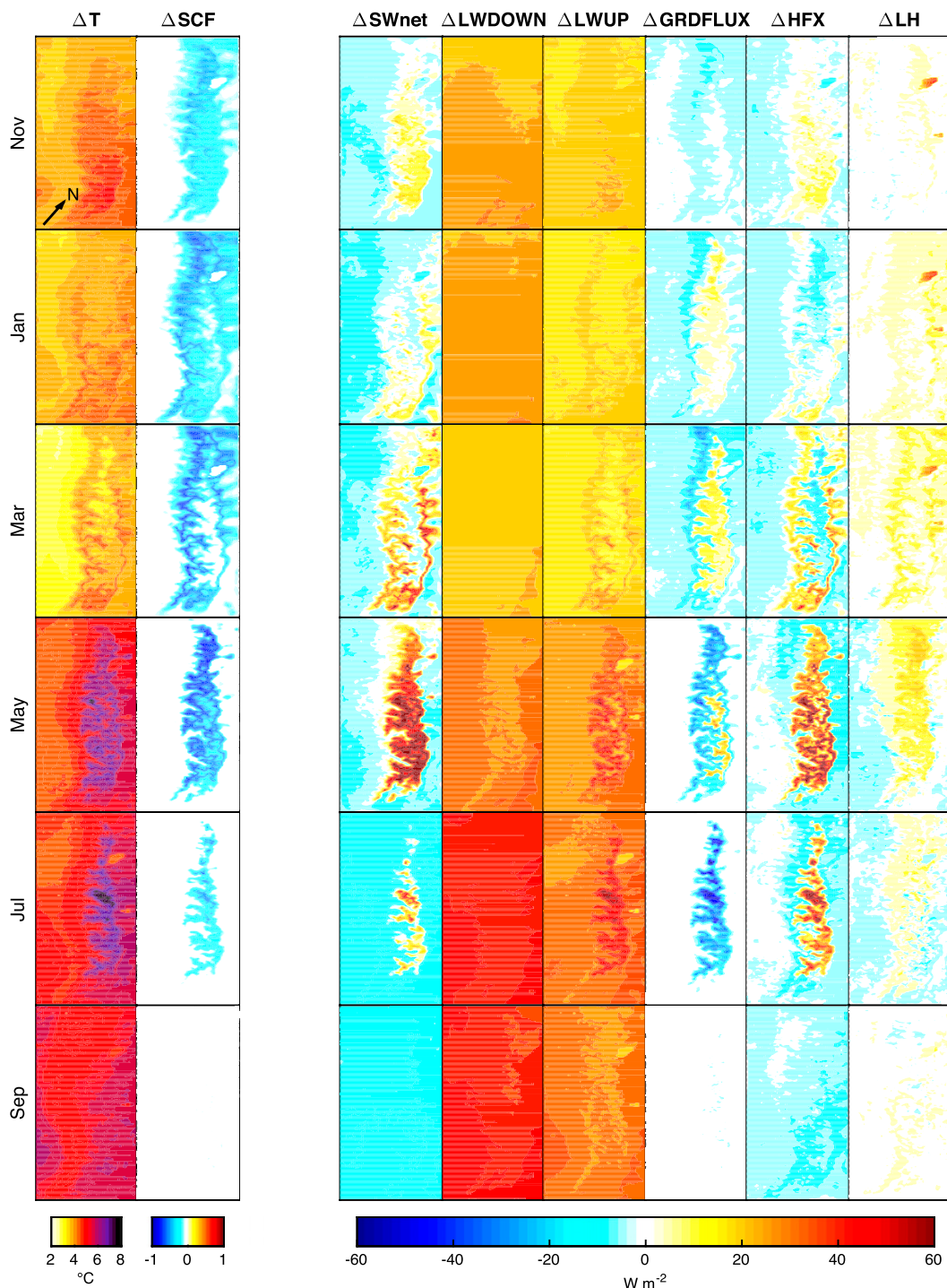


FIG. 6. Climate changes (representing differences between 1981–2100 and 2081–2100) computed as the difference between the average of the five future WRF simulations and the historical WRF simulation. The left two columns show ΔT ($^{\circ}\text{C}$) and ΔSCF respectively. The remaining columns from left to right show changes in the surface energy balance (W m^{-2}): net shortwave radiation (ΔSWnet), downward longwave radiation (ΔLWDOWN), outgoing longwave radiation (ΔLWUP), flux into the soil/snowpack (ΔGRDFLX), sensible heat flux (ΔHFX), and latent heat flux (ΔLH).

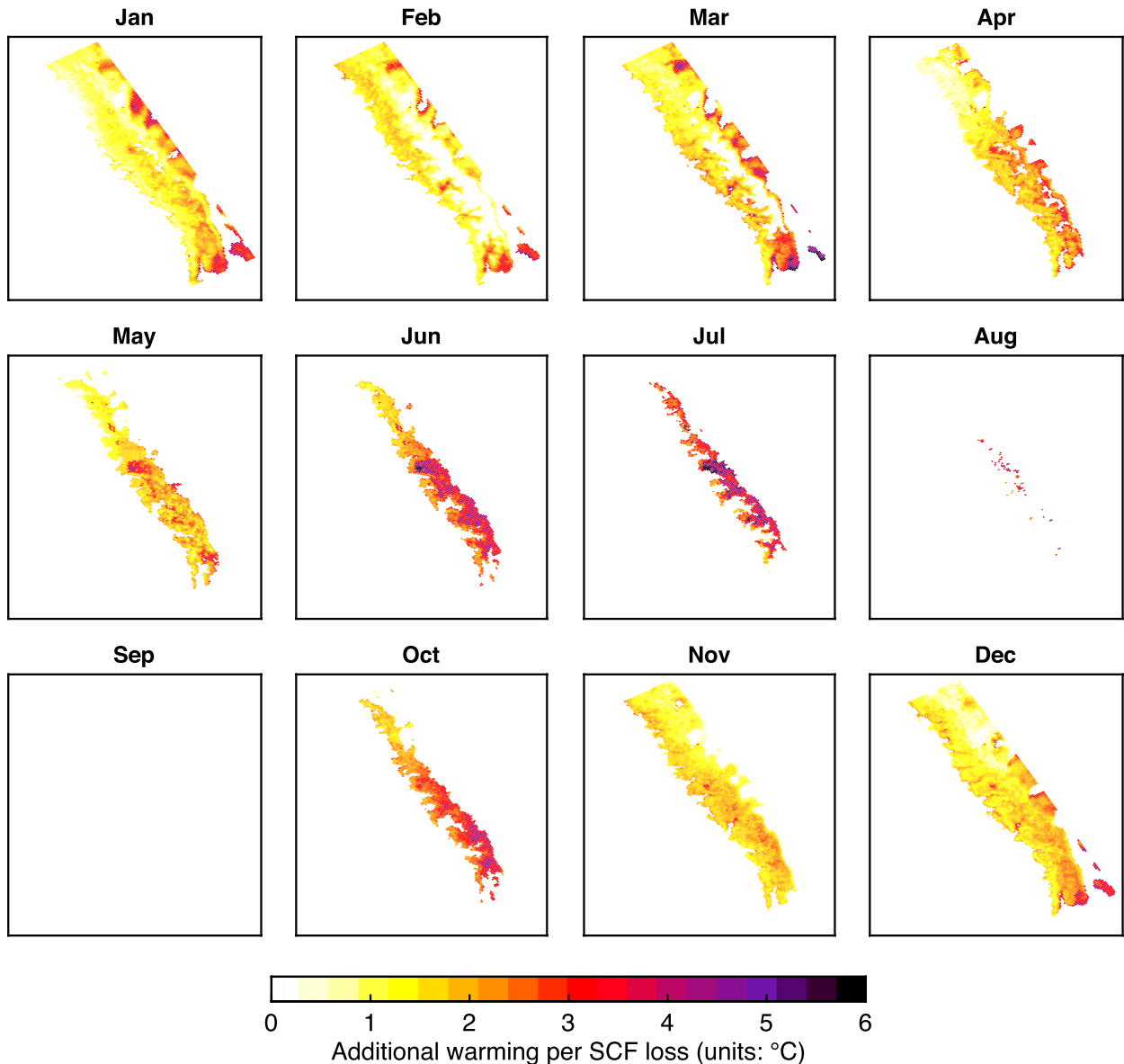


FIG. 7. Additional warming per loss of SCF (°C) due to SAF [i.e., negative a in Eq. (1)]. This quantity is calculated by regressing temperature anomalies onto snow cover anomalies as described in section 3a.

additional 1°C in warming.) Summer a values are higher, with typical values in June and July ranging from 2° to 5°C.

Knowing the local SAF strength a , we can now remove the additional warming attributable to local SAF, allowing us to diagnose a “background warming” ΔT_{back} :

$$\Delta T_{\text{back}} = \Delta T - a\Delta\text{SCF}. \quad (1)$$

The value of ΔT_{back} is an estimate of what the warming would be without local SAF. Computing the background warming is necessary because it is this component of WRF’s warming pattern that we expect to be most physically relatable to GCM warming patterns, which

do not include the effect of local SAF. Thus in the construction of the final statistical model our aim is to use the GCM warming to predict the background warming, and then add in a local warming enhancement due to local SAF.

It is worth emphasizing that the local SAF component of the warming $a\Delta\text{SCF}$ is only the local contribution to the warming resulting from local snow cover loss. There is also nonlocal or regional-scale warming resulting from the regional-scale snow cover loss. Previous studies have demonstrated that atmospheric circulation diffuses energy away from locations experiencing SAF, thereby

increasing the warming nonlocally (Letcher and Minder 2015). Thus a grid cell can experience additional warming as a result of its proximity to other grid cells experiencing SAF. Of course, this warming is traceable to SAF in a physical sense. But since it is not a result of snow cover loss at that particular grid cell, in our framework it is lumped in with the background warming.

Background warming patterns are calculated for each of the five future simulations, using Eq. (1). The next step is to decompose the background warming patterns into components that are physically relatable to GCM parameters. As in previous work (Walton et al. 2015), two components are enough to almost fully characterize the background warming patterns: the regional-mean warming and the dominant mode of spatial variability identified via principal component analysis. For each month, PCA is performed on the five background warming patterns, following Walton et al. (2015). For every month, a single principal component (PC1) accounted for the overwhelming majority of the spatial variance ($>77\%$ of the variance in every month, $>90\%$ for 8 of the 12 months). Without exception, PC1 in each month is characterized by an east–west contrast with a sharp gradient corresponding to the crests of the Sierra Nevada. Thus an east–west warming contrast pattern is the dominant source of spatial heterogeneity in any downscaled GCM once the local SAF effect is removed. The final component of the background warming is the regional-mean warming, calculated as the average warming over the innermost domain. It varies only by month and by downscaled GCM.

b. Generating warming patterns for any GCM

StatWRF takes a GCM warming pattern as input, and produces a warming pattern over the Sierra Nevada that approximates what WRF would produce. StatWRF samples the GCM warming to determine the regional-mean warming and the east–west warming contrast, and then adds in further warming due to local SAF.

The first component to be predicted is the regional-mean warming. Selecting the optimal predictor of the regional-mean component is not trivial. A first guess is to use the interpolated GCM warming averaged over the innermost domain. This predictor is adopted for May through November, where it works well, but it performs poorly from December through April. During these winter and spring months, GCM grid cells in the region experience SAF. The resulting warming enhancement varies widely across GCMs, possibly due to the large range of SAF strengths in GCMs (Qu and Hall 2014). Information about each GCM's SAF warming enhancement is not passed to WRF, because WRF

receives the GCM's climate change signal at the ocean surface, through nudging above the boundary layer in the outermost domain, and at the outermost domain's boundaries. Instead, WRF adds in its own SAF. Thus, the GCM warming sampled over the Sierra Nevada may not be an ideal as a predictor of WRF warming over the Sierra Nevada. To determine a better predictor for December–April, we linearly interpolate GCM warming patterns to our outermost 27-km WRF grid and determine the grid point that minimizes the root-mean-square error (RMSE) between the GCM warming and the WRF regional-mean warming. The grid point at $35^{\circ}11'N$, $119^{\circ}03'W$, just southwest of the Sierra Nevada range in the southern part of California's Central Valley, is found to be the best predictor of the WRF warming averaged over the Sierra Nevada. This makes physical sense: The point is close to our innermost domain, yet is southwest of the GCM grid cells that experience widely varying SAF warming enhancements.

We also seek locations to sample the GCM warming pattern to determine the appropriate scaling of the other component of the background warming, PC1. Since PC1 represents an east–west warming gradient, we assume a good predictor can be found by differencing GCM warming sampled at two locations. We start by linearly interpolating GCM warming patterns to the 27-km outermost WRF domain, and differencing the warming at each pair of grid cells. Linear regression is then used to determine the value of β that appropriately scales the GCM warming differences to approximate PC1 loadings, while minimizing error. The intercept in this regression is set to zero, corresponding to the physical constraint that if the GCM-sampled warming difference were zero, the resulting background warming would have zero east–west gradient. The two grid cell locations giving the least error are located over the high desert east of the Sierra Nevada ($35^{\circ}37'N$, $116^{\circ}16'W$) and over the coastal ocean ($30^{\circ}47'N$, $120^{\circ}02'W$). Note that this location pair is consistent with our physical interpretation of the origins of the PC1 pattern.

The background warming is approximated as the sum of the GCM prediction of the regional-mean warming and the GCM prediction of the east–west gradient multiplied by PC1:

$$\Delta T_{\text{back}}(x, y) = \Delta T_{\text{RgMean}} + \beta(\Delta T_{\text{East}} - \Delta T_{\text{West}})\text{PC1}(x, y). \quad (2)$$

For May–November, ΔT_{RgMean} is the interpolated GCM warming averaged over the innermost domain. For December–April, ΔT_{RgMean} is the interpolated GCM warming at the location just southwest of the Sierra

Nevada noted above. For each month, $\Delta T_{\text{East}} - \Delta T_{\text{West}}$ is the difference in the GCM warming between high desert and coastal ocean locations noted above.

The final step is to compute the total warming by adding in the local effect of SAF. The additional warming increment due to local SAF is $a\Delta\text{SCF}$. However, to compute this quantity we must determine ΔSCF ; ΔSCF is constrained by the fact that the change in snow cover at a particular grid cell must be consistent with the combined warming (ΔT) coming from all sources (i.e., both the background warming and the additional warming due to local SAF). We can easily diagnose this equilibrium relationship between ΔSCF and the ΔT from WRF output. [ΔSCF also depends on precipitation changes (ΔP), but ΔT explains most of the variance, and including ΔP in the model did not improve the results.] To determine this equilibrium relationship at a given grid cell, we use the climate states spanned by the historical and five future simulations. Thus for a given month, at a grid cell P , there are six pairs of SCF and T values: one pair from the historical simulation, and five pairs from the future simulations. Generally, as T becomes large, SCF approaches zero. As T decreases, SCF approaches 1. Therefore, we fit a logistic function of the form

$$\text{SCF}(T) = \frac{1}{1 + \exp[c(T - T^*)]} \quad (3)$$

to the data, where c and T^* are constants computed via logistic regression. An example is shown for a grid cell at 1760-m elevation for January (Fig. 8). Equation (3) can be rewritten to express ΔSCF in terms of ΔT :

$$\Delta\text{SCF} = \frac{1}{1 + \exp[c(\Delta T + T_{\text{hist}} - T^*)]} - \text{SCF}_{\text{hist}} \quad (4)$$

Now Eqs. (1) and (4) form a system of two equations and two unknowns (ΔT and ΔSCF) that can be solved iteratively, starting with initial guesses $\Delta\text{SCF}_0 = 0$ and $\Delta T_0 = \Delta T_{\text{back}}$, and by following

$$\Delta\text{SCF}_n = \frac{1}{1 + \exp[c(\Delta T_{n-1} + T_{\text{hist}} - T^*)]} - \text{SCF}_{\text{hist}}$$

and

$$\Delta T_n = \Delta T_{\text{back}} + a\Delta\text{SCF}_n.$$

The final values of ΔT and ΔSCF returned by StatWRF are values of ΔT_n and ΔSCF_n after five iterations, which is sufficient to get them to within 1% of their limits. In the next section, we evaluate the skill of StatWRF in approximating WRF ΔT and ΔSCF values.

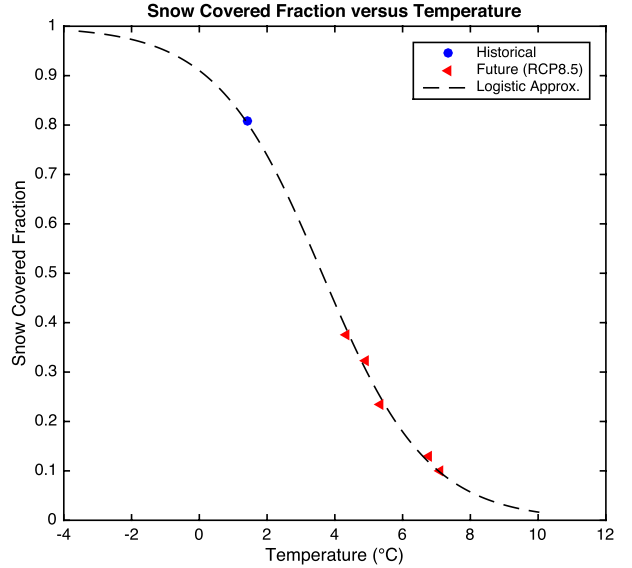


FIG. 8. Logistic function fit to SCF and T ($^{\circ}\text{C}$) climate states at an example grid cell (1760-m elevation) for the month of January. Data are shown for the historical simulation (blue dot) and future simulations (red triangles).

c. Evaluation of StatWRF

To evaluate how similar StatWRF's warming projections are to those of WRF, we employ leave-one-out cross validation (LOOCV). Under LOOCV, we rebuild StatWRF from scratch using only four of the five dynamically downscaled GCMs, and apply it to the remaining GCM. The resulting StatWRF warming pattern can be compared against the corresponding WRF warming pattern to test StatWRF's predictive ability. This procedure is repeated five times, with each GCM taking its turn being left out. As an example, Fig. 9 shows the March StatWRF-predicted patterns for each left-out GCM. Note that this cross-validation procedure underestimates StatWRF's skill, since for the purposes of making actual projections StatWRF is trained on five dynamically downscaled GCMs, not four.

StatWRF's predictive ability is judged against BCSD, BCCA, and linear interpolation of the GCM warming. Figure 10 shows the mean of the absolute differences between the WRF warming patterns and those produced by each statistical downscaling method (top four rows). StatWRF has lower errors in nearly all months and all locations. StatWRF's MAE calculated for all grid points, for all months, and for all five GCMs is 0.45°C , while the MAE for BCCA, BCSD, and linear interpolation is 0.80° , 0.78° , and 0.59°C , respectively. This includes locations not experiencing SAF, where other statistical methods are more likely to have skill comparable to StatWRF. StatWRF adds more value at locations experiencing large snow cover losses. At locations

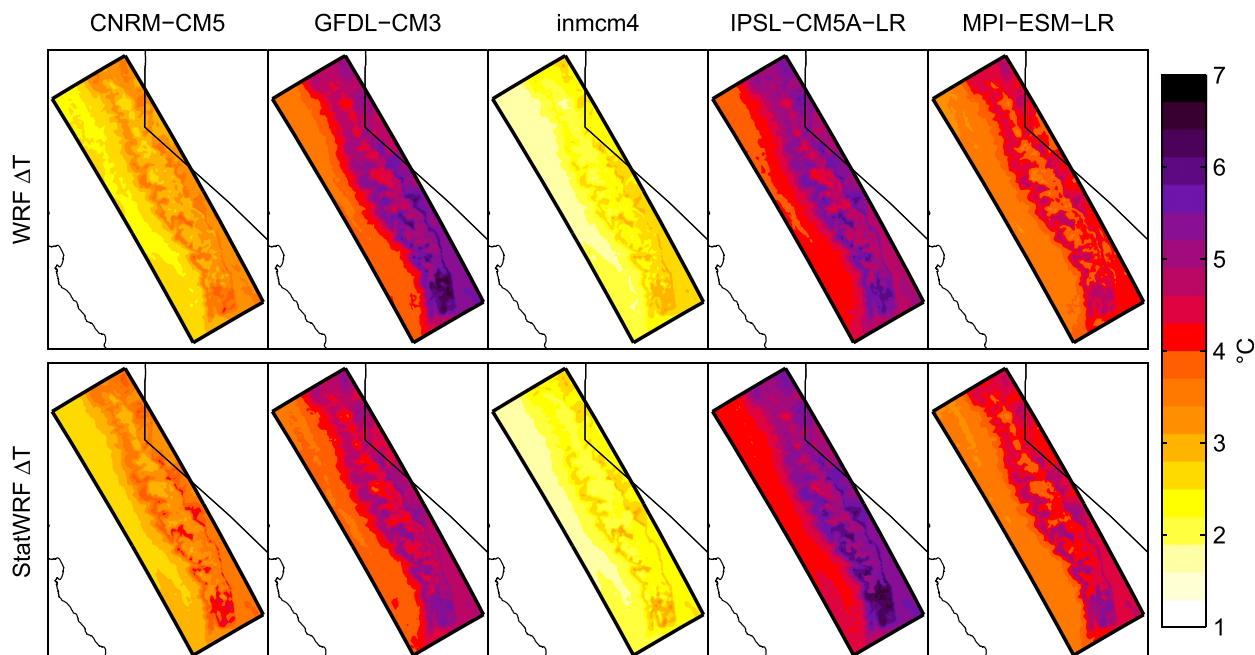


FIG. 9. (top) WRF March warming patterns (°C). (bottom) StatWRF March warming patterns for the left-out GCM produced in cross validation. Warming patterns represent a downscaling of GCM temperature changes between the 1981–2000 and 2081–2100 periods.

where $\Delta\text{SCF} < -0.25$ in WRF, the errors for the left-out GCM are 0.53°C for the StatWRF, 1.3°C for BCCA, 1.0°C for BCSD, and 0.82°C for linear interpolation.

We also evaluated StatWRF's ability to predict the ΔSCF in the left-out dynamically downscaled GCM over all locations and months for which $|\Delta\text{SCF}| > 0.01$ in WRF. The resulting MAE is 0.04. To put this into context, the average WRF value of $|\Delta\text{SCF}|$ over those locations and times is 0.23.

4. Ensemble climate change projections

Here we examine StatWRF downscaled temperature and snow cover changes between the 1981–2000 and 2081–2100 periods for CMIP5 GCMs from multiple scenarios (see Table 1 for GCM details). We start by addressing results for RCP8.5 and then broaden our scope to all scenarios. Figure 11 shows GCM ΔT , StatWRF ΔT , StatWRF additional warming due to SAF, and StatWRF ΔSCF averaged over 35 GCMs run under RCP8.5. StatWRF projects September and October domain-average temperatures to warm the most ($\sim 6^{\circ}\text{C}$), whereas February and March warm the least ($\sim 4^{\circ}\text{C}$). Months in the late spring and early summer warm about 5°C , and exhibit large spatial variations due to SAF and coastal–inland contrast. In May–July, the warming enhancement due to SAF is especially strong, with additional warming due to SAF exceeding 2°C in some locations. The presence of such large warming

enhancements due to SAF reaffirms the importance of capturing this effect.

Regardless of GCM, warming generally increases with height and is enhanced by SAF in a characteristic elevation range that varies monthly. From December through April, only the low-to-middle elevations (~ 1000 – 3000 m) are vulnerable to snow cover loss, while high elevations (> 3000 m) are relatively unaffected (Fig. 11, fourth row from top). This results in narrow bands of additional warming ringing the Sierra Nevada (Fig. 11, third row from top). At the beginning of the snow season (October–November) and the end (May–July), baseline temperatures are warm enough that snow cover at all elevations is vulnerable to loss.

The large ensemble of downscaled projections also allows for meaningful estimates of spread resulting from intermodel variations, typically a large uncertainty source in regional climate projections (Giorgi and Francisco 2000). Unsurprisingly, warming over the Sierra Nevada is highly dependent on GCM (Fig. 12, left). Warming projections in the 5th and 95th percentiles typically have a spread of 3° – 4°C , with a smaller spread at lower elevations, and a larger spread (sometimes reaching 5°C) at the highest elevations. SAF generally enhances warming spread, as a GCM with more warming has larger SCF losses and additional warming when downscaled. In contrast with the StatWRF ensemble-mean warming, the linearly interpolated GCM

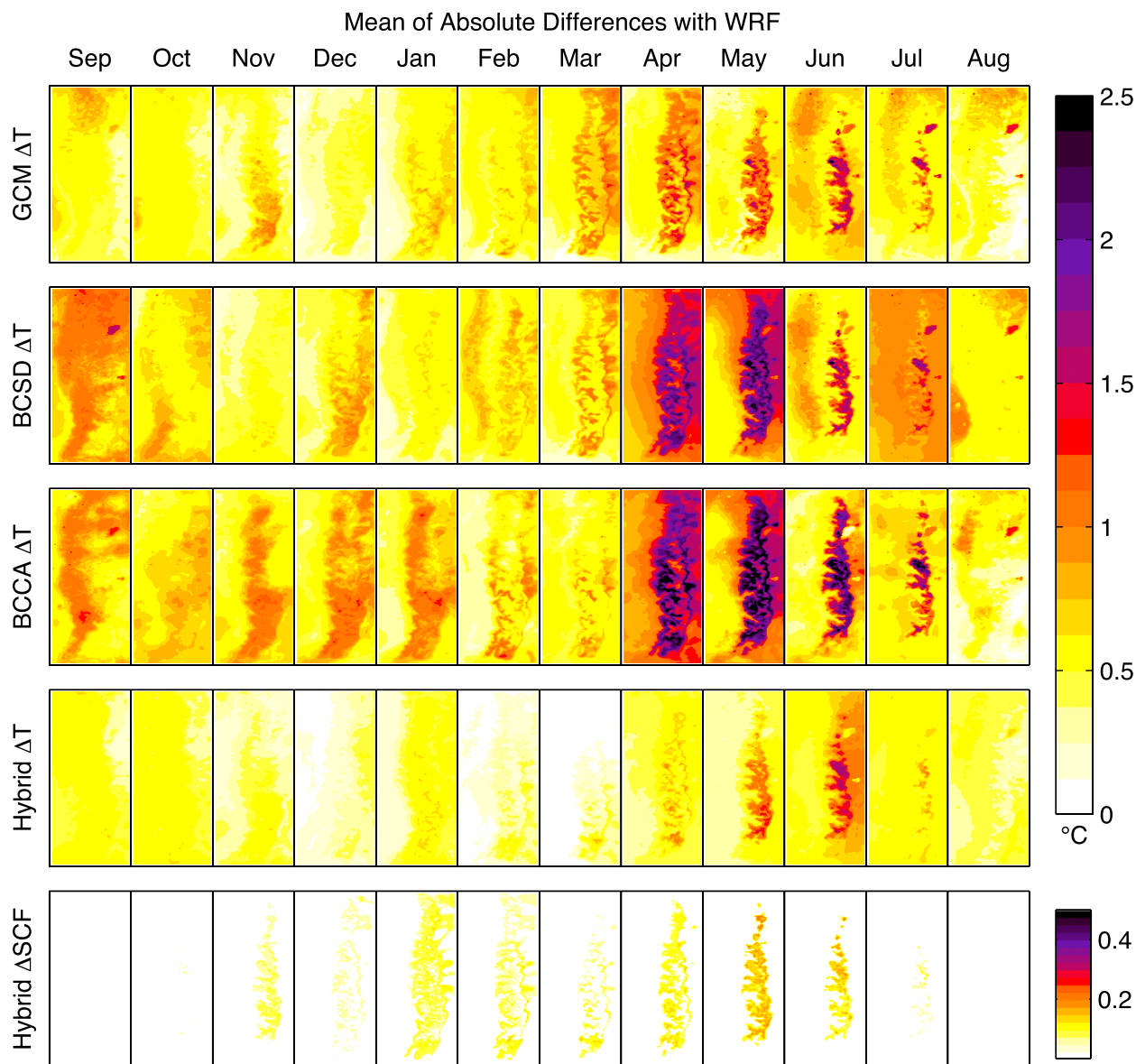


FIG. 10. Comparison of the results of cross validation of StatWRF to other statistical methods. Mean absolute differences ($^{\circ}\text{C}$) between the five WRF warming patterns for (left)–(right) each month and (top)–(bottom) the linearly interpolated GCM warming patterns, BCSD warming patterns, BCCA warming patterns, and StatWRF warming patterns for the left-out GCM produced via cross validation, respectively. (bottom) Mean absolute differences between the five WRF ΔSCF patterns and corresponding StatWRF ΔSCF pattern produced via cross validation. Climate change patterns represent a downscaling of GCM climate changes between the 1981–2000 and 2081–2100 periods.

ensemble-mean warming profile (dashed green line) exhibits little variation with height. Differences between the two profiles are largest at high elevations at the beginning and end of the snow season.

Despite the large warming spread, all projections indicate substantial snow cover losses (Fig. 12, center). Early (October–February) and late (May–July) in the snow season, all elevations see SCF reductions, regardless of GCM. Meanwhile, during March and April, the

highest elevations remain nearly completely snow covered for all GCMs. Intermodel spread is the largest at middle elevations (1500–3000 m). For example, in March, the baseline SCF in the 2000–2200-m band is 0.64, with end-of-century values ranging between 0.14 and 0.41 (5th–95th percentile).

Total snow-covered area (SCA) is also projected to decline substantially (Fig. 12, right). The largest percentage SCA drop occurs at the beginning and end of

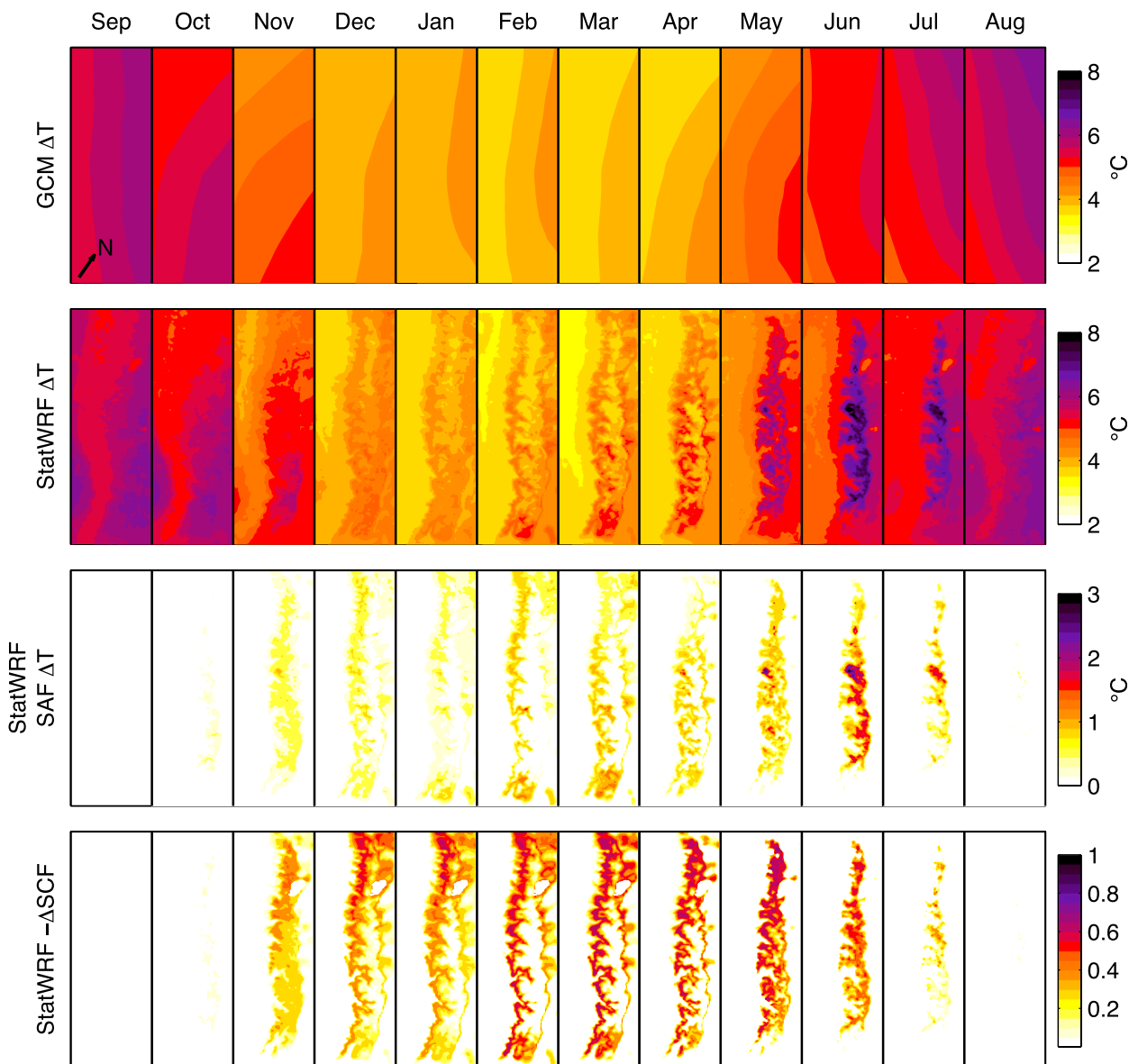


FIG. 11. (top) Linearly interpolated GCM ΔT ($^{\circ}\text{C}$) averaged over 35 RCP8.5 GCMs for 2081–2100 minus 1981–2000. (middle top) As in (top), but for StatWRF ΔT ($^{\circ}\text{C}$). (middle bottom) As in (top), but for StatWRF additional warming ($^{\circ}\text{C}$) due to local SAF, which is equal to $\alpha\Delta\text{SCF}$. (bottom) As at (top), but for StatWRF SCF loss ($-\Delta\text{SCF}$). Grids have been rotated to vertical from their original orientation (see north arrow in the top-left panel).

the snow season. In July, average SCA is projected to decrease 75% by 2100, with an uncertainty envelope of 60%–96% (5th–95th percentile). For November, the ensemble-mean projection is a 66% SCA loss, with a 40%–85% range. Thus there is some uncertainty as to whether months at the beginning and end of the snow season will experience a nearly complete SCA loss or if the reductions will merely be large. Months in the middle of the season also experience large reductions. April SCA is expected to decline 47%, with a range of 30%–60%. Although these uncertainty ranges are

considerable, it is clear that substantial reductions in SCA are likely even for GCMs predicting lower overall warming.

Another large source of spread in StatWRF projections is due to scenario (Fig. 13). For example, April domain-average ensemble-mean temperature changes range from 1.4 $^{\circ}$ (RCP2.6) to 4.1 $^{\circ}\text{C}$ (RCP8.5). April SCA losses are somewhat mitigated in lower emission scenarios. Ensemble-mean SCA totaled over the Sierra Nevada decreases by 48% under RCP8.5, but only by 17% under RCP2.6. The smaller losses in snow cover in

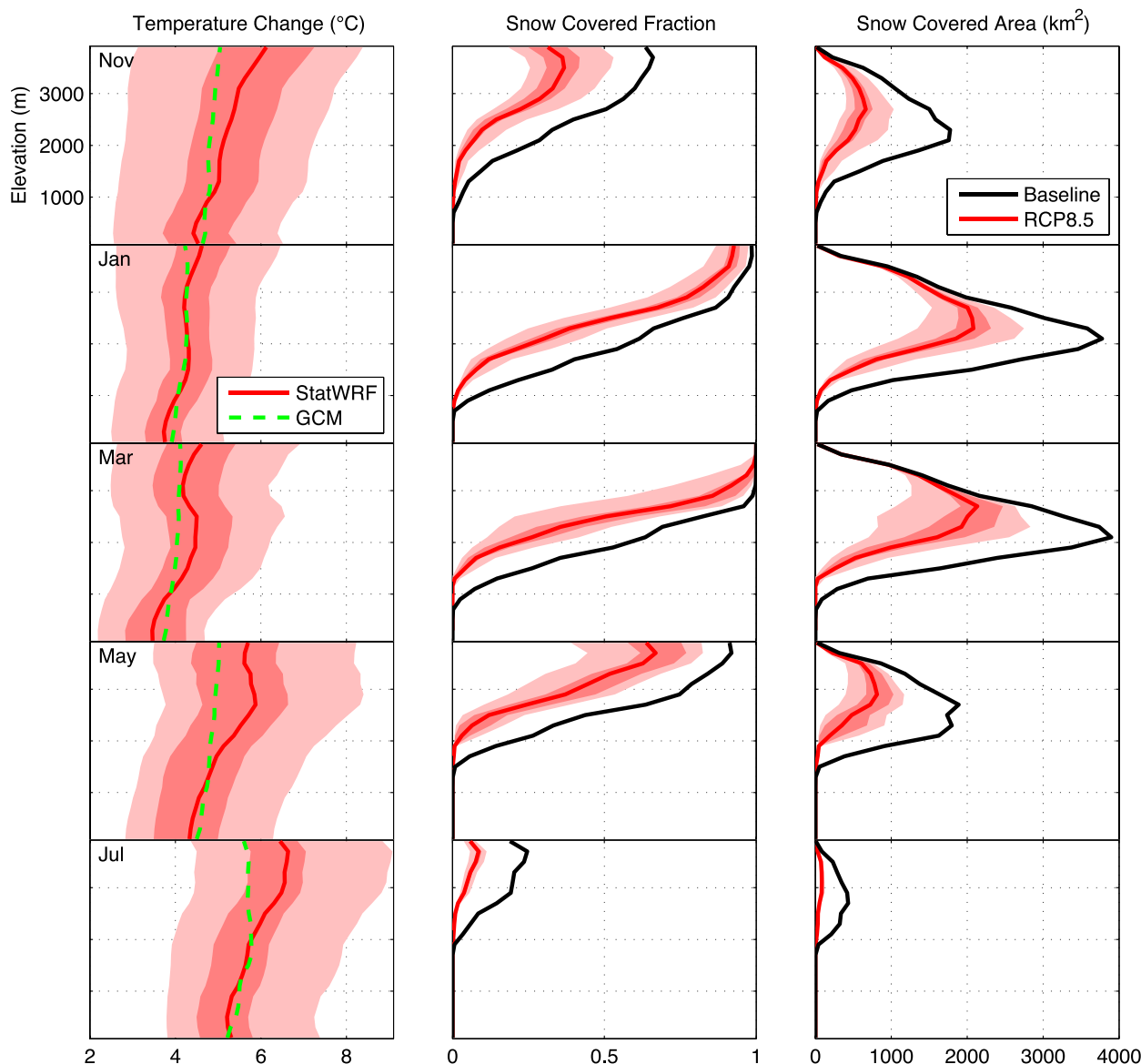


FIG. 12. (left) Elevation profiles of StatWRF warming ($^{\circ}\text{C}$). (center) WRF baseline and StatWRF future snow-covered fraction. (right) WRF baseline and StatWRF future snow-covered area (km^2). Changes shown represent a downscaling of GCM climate changes between the 1981–2000 and 2081–2100 periods. The RCP8.5 ensemble mean (red line) is shown along with 25th–75th percentiles (light red shading) and the 5th–95th percentiles (pink shading). The ensemble-mean warming profile of the linearly interpolated RCP8.5 GCMs is shown for reference (green dashed line). For snow-covered fraction and snow cover, the historical climatology is shown by the black line. A bin size of 200 m was used to create the elevation profiles. Bin midpoints are used to draw curves.

the lower emissions scenarios are associated with less additional warming due to SAF. This leads to warming elevation profiles with smaller variations.

5. Discussion

StatWRF's credibility is based partly on the ability of WRF and the Noah-MP land surface model to realistically simulate regional climate, and in particular processes shaping SAF. Based on our evaluation of the

baseline simulation, WRF simulates slightly more snow cover than MODIS/*Terra* near the snow line of the Sierra Nevada's western slopes and less to the east of the mountain range. Since snow cover in both areas is highly susceptible to loss, it is likely that if WRF had more accurate snow cover, it would produce smaller warming enhancements along the snow line of western slopes and larger enhancements to the east of the Sierra Nevada than projected here. We also noted that WRF's simulated snow cover persists longer than observed,

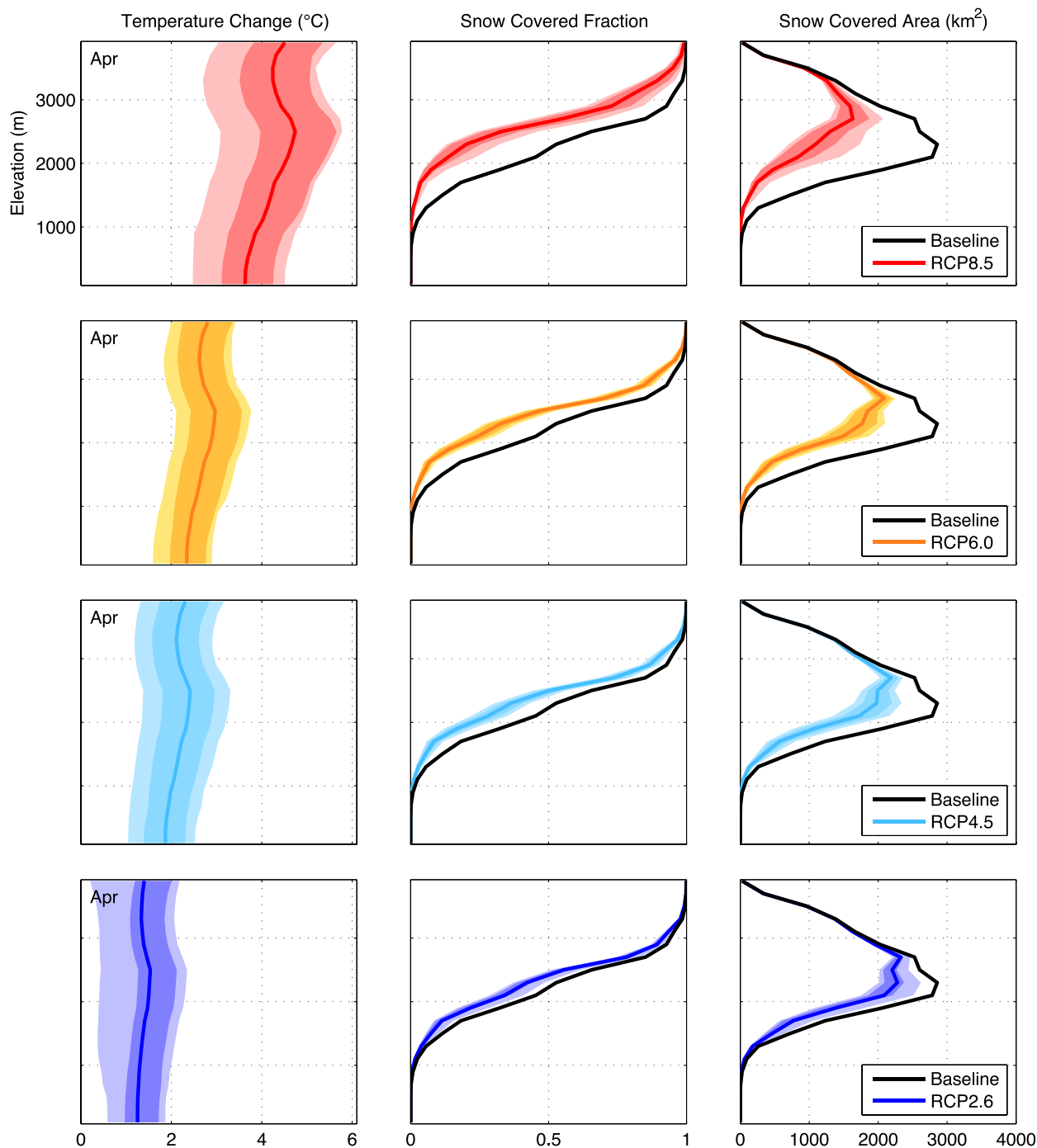


FIG. 13. April StatWRF elevation profiles of (left) ΔT ($^{\circ}\text{C}$), (middle) future SCF, and (right) SCA for (top)–(bottom) RCP8.5, RCP6.0, RCP4.5, and RCP2.6. Changes shown represent a downscaling of GCM climate changes between the 1981–2000 and 2081–2100 periods. The ensemble mean is represented with dark color lines, with lighter shading marking the 25th–75th percentile, and the lightest shading marking the 5th–95th percentile. A bin size of 200 m was used to create the elevation profiles. Bin midpoints are used to draw curves.

especially in May, June, and July. Since there is somewhat less snow during these months in reality, less can be lost under climate change, and the associated extra warming should also be less than what WRF predicts. On the other hand, if snow cover is not persisting as long

in reality, then it must be disappearing earlier in the season. This could indicate that actual snow cover is more sensitive to temperature than is indicated by WRF in the earlier months such as March, April, and May. If this is the case, then the SAF-induced warming

enhancement should be larger than that simulated by WRF in these months.

Other factors also influence the SAF-induced warming in these projections. SAF strength depends on treatment of snow albedo processes, snow-free surface albedos, and the vegetation masking effect (Qu and Hall 2007). Future work could explore the sensitivity of the local SAF strength a to these parameters in the land surface model. It is also worth noting that StatWRF only explicitly addresses SAF resulting from reduction in snow cover, although SAF also occurs because of reduction in snow albedo from snow metamorphosis. However, the snow metamorphosis effect is typically smaller in comparison (Qu and Hall 2007), and the parameter a is influenced by the metamorphosis effect, so StatWRF includes it implicitly.

6. Conclusions

Here we have presented projections of temperature and snow-covered fraction change for the 2081–2100 period over California's Sierra Nevada. These projections were produced with StatWRF, a hybrid statistical model that emulates WRF. StatWRF explicitly incorporates SAF, which plays a key role in creating spatial variations in the climate change signal. Snow cover losses amplify the warming up to 3°C under RCP8.5, with lower-emission scenarios seeing less warming. The SAF-induced warming is generally confined to an elevation band near the snow line that varies seasonally. During the middle of the snow season, from January to April, this amplification happens in roughly the 1500–3000-m elevation range. At the beginning and end of the snow season (October–December and May–July), the warming amplification extends from the historical snow line up to the mountain peaks.

Ensemble projections for RCP8.5 with the StatWRF indicate large intermodel spread (3°–5°C) in the warming. However, even projections corresponding to GCMs experiencing the least warming show dramatic snow cover losses under this scenario. Most is lost at the middle elevations (1500–3000 m), where there is substantial baseline snow cover and temperatures are close enough to freezing that warming affects S/P and snowmelt greatly. Snow cover losses are somewhat mitigated under the lower-emission scenarios, but all models predict some snow cover loss, even under the lowest scenario.

SAF influences the spatial structure of warming in the Sierra Nevada profoundly, yet the other downscaling methods (BCSD, BCCA, and linear interpolation) miss its effects entirely. It is clear that BCSD and linear interpolation fail in this regard because their climate

change patterns contain no high-resolution information. It is less clear why BCCA—which uses high-resolution historical analogs—shows no sign of SAF. We hypothesize that the problem stems from the use of daily analogs. BCCA essentially approximates a day in warmer future climate with a linear combination of analogous warm days in the historical period. A historical warm day is likely to reflect only day-to-day temperature fluctuations. However, snow cover may only be weakly correlated with day-to-day temperature fluctuations. Instead, it is shaped by the integrated history of snowfall and melt over the entire snow season up to that point. Thus, analogous warm historical days selected by BCCA are unlikely, on average, to capture the dramatic snow cover losses that would occur in a future climate in which the entire snow season is substantially warmer. Therefore, BCCA temperature patterns generated from these analog days do not contain any warming enhancement due to SAF.

The technique presented here is region dependent, so it would need to be modified if applied elsewhere. In the case of the Sierra Nevada, SAF and the east–west warming gradient have been identified as the two main contributors to spatial variations in the warming. In a different region, other factors may be important. For example, if Colorado were the domain of interest, then SAF would also likely be an important factor modulating the warming (Letcher and Minder 2015). However, it is unclear what other processes might be important. An investigation into the region-specific underlying causes of spatial variations in the WRF climate change pattern is needed in order for StatWRF to be grounded in physical principles.

The formulation of StatWRF presented here is only one way to construct a WRF emulator. It is certainly possible to imagine other statistical downscaling techniques trained on the WRF output. For example, if a machine-learning technique were applied to build StatWRF, StatWRF might still emulate WRF to high degree of accuracy. However, it is unlikely in this case that StatWRF would be an easily interpretable physically based model that adds to our understanding of climate change in that region.

The hybrid method presented here represents one route for capturing local SAF effects: emulation of an RCM. Future research could calculate local SAF strength directly from observational datasets. This would avoid relying on computationally expensive RCM simulations and their results, which do not always perfectly replicate the actual climate. Future research in other mountain ranges with seasonal snow cover would likely benefit from using a downscaling technique that includes SAF effects.

Snow cover loss and its associated amplification of warming have implications for water resources. Sierra Nevada snowpack plays an important role in California's hydrology by storing water during wet winter months and releasing it in late spring and summer, when little precipitation falls. In the current climate, snowmelt recharges human-built reservoirs throughout spring and into summer. Dramatic projected snow cover loss strongly indicates that this runoff would be exhausted much sooner. A snow cover retreat may also lead to enhanced evaporative water loss at snow margins, diminishing water that would reach reservoirs. Statistically downscaled future projections using BCCA (Pierce and Cayan 2013) suggest that, as a whole, the Sierra Nevada is likely to experience significant decreases in total 1 April snow water equivalent by end of century. Future work—using the high-resolution dynamical simulations and statistical projections developed here—will allow for a detailed analysis of projected snowpack and runoff changes. This analysis will include the effect of SAF, which may be important for accurate characterization of elevation-dependent outcomes in these variables.

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