1. Introduction

As a result of coarse grid resolution and inadequate model physics, general circulation models (GCMs) are currently unable to produce reliable climate information on the scale needed to assess regional climate change impacts and variability. To assess the possible societal impacts of climate change, many regional climate models (RCMs) have been developed and used to provide projections of regional-scale climate for guiding policies in economy, ecosystem, water supply, agriculture, human health, and air quality (Giorgi et al. 1994; Leung and Ghan 1999; Leung et al. 2003; Liang et al. 2004b; Duffy et al. 2006). Although many regional climate features have been successfully captured in RCMs, obvious biases in simulated precipitation remain, particularly a wintertime wet bias commonly seen in West Coast mountain regions (Leung et al. 2003; Kim 2004; Duffy et al. 2006; Caldwell et al. 2009, hereafter C09). Precipitation bias in coastal ranges has historically also been large mainly because of inadequate grid resolution.

The strong interaction at many scales between atmospheric circulation, ocean, and topography in the western United States provides a challenging test bed for RCMs. Within this region, California is especially important not just because it has the largest population in the nation, but also because it has one of the most sophisticated water collection and distribution systems in the world. Adapting California’s water management systems to climate change presents significant challenges. Therefore, a credible regional modeling capability is essential...
for understanding and preparing for the impacts of climate change on the temporal and spatial scales that are critical to California.

Currently, one of the most popular methods for obtaining such regional climate prediction is to run a numerical weather prediction model forced at the lateral boundaries and sea surface with predictions from a GCM. This is known as dynamical downscaling and is reviewed in many recent studies (Wang et al. 2004; Fowler et al. 2007; Solomon et al. 2007). Forecast errors in these coupled modeling systems can arise from several different sources, such as the quality of the GCM forcing and problems with RCM physics and numerics. Additionally, errors in the measurement datasets used for validation can strongly affect the apparent size of model bias. Therefore, it is difficult to detect the primary sources of RCM bias. To this end, we present both short-range (several days) and long-range (multiple years) Weather Research and Forecasting (WRF) simulations to explore the possible sources of California wintertime precipitation bias.

In this study, short-range simulations driven by reanalysis data are designed to address three objectives: 1) to gauge the sensitivity of model precipitation to standard parameterization options for each physical process, 2) to examine how the choice of observational datasets impacts the apparent model bias, and 3) to test the robustness of microphysics and cumulus parameterizations to grid resolution changes. The objectives of long-range simulations driven by both reanalysis and GCM data are to assess the impacts of the GCM forcing and measurement uncertainties on the RCM precipitation bias. The model setup, test cases, experiment design, and measurement datasets used to validate the model are presented in section 2. Section 3 shows the results for both short-range and long-range simulations. A summary and discussion follow in section 4.

2. Model description and test cases

a. Model setup

The model used is the Advanced Research WRF (ARW) modeling system version 3.0.1. The ARW is nonhydrostatic and fully compressible. It uses the sigma pressure coordinate in the vertical to better simulate airflow over complex terrain. The model has a flux form set of governing equations for better numerical conservation of mass and scalars. The model physics contains cumulus convection, microphysics of cloud processes and precipitation, long- and shortwave (LW and SW) radiation, turbulence and diffusion, a planetary boundary layer (PBL) scheme, a surface layer parameterization, and soil layer representations. There are a variety of choices for each of the physical processes. The WRF model takes sea surface temperature (SST) as an input rather than predicting it. In this study, SST is given from either reanalysis data or GCM outputs and updated from the forcing model every 6 h throughout all simulations. The reader is referred to Skamarock et al. (2008) for further details on WRF.

In this study, a small-area fine-resolution domain is nested within a coarser, large-area domain in order to minimize the impact of outer lateral boundary conditions (LBCs) on the model solution. Seth and Giorgi (1998) found that small RCM domains produce spurious LBC dynamic effects and cause the RCM to generate unrealistic responses to internal forcing. To make our domain large enough to avoid these problems while maintaining reasonably high resolution and model outputs, our low-resolution simulations are based on a two-way nested 12-km domain over California within a 36-km West Coast domain. To ensure smooth solutions, outer-domain grid cells closer than 10 cells from an outer boundary (in either the x or y direction) are nudged toward the imposed large-scale forcing (from either reanalysis data or GCM outputs) following Davies (1976). In this study, cells on the outer boundary of the domain are completely specified by the large-scale and nudging strength decreases exponentially with a five gridcell e-folding length toward the interior of the domain. The nudging zone boundaries are illustrated in Fig. 1a. In our experience, these changes from the WRF default (a five-layer zone with linear decreasing nudging strength) improve model performance for long-range simulations.

The vertical axis contains 31 levels with 20-m resolution near the ground and gradually coarser spacing aloft. The domain top resides at the height of 100 hPa. Static fields (e.g., land use, terrain, and soil type) with a resolution of 30 arc s (~1 km) are used to initialize simulations. Positive-definite advection (PDA) is turned on for moisture variables. Hahn and Mass (2009) indicated that PDA plays an important role in WRF to avoid artificial moisture creation and to reduce overprediction of precipitation near topography. Third-order Runge–Kutta time splitting is also adopted with sound waves treated explicitly in the horizontally and implicitly in the vertical on shorter substeps. The fifth- and third-order schemes are used for the horizontal and vertical advection, respectively.

b. Test cases

C09 showed California precipitation overprediction is worst for the strongest storms, which suggests that simulating and evaluating a collection of individual storms may be the most useful means to understand West Coast wet bias. In this study, we analyze eight major precipitation
events chosen as representatives of California wintertime precipitating storms. We choose two storms from each of the four types of large-scale conditions that bring rain to California. These storm types include the Pineapple Express, El Niño, La Niña, and the synoptic cyclone (see Table 1). Because climatology is just the collection of individual events, if we can identify a consistent source of bias in our eight storms, we will likely have found the cause of the climatological bias identified in C09 and elsewhere. Descriptions of these storms and their aftermath can be seen in Dettinger (2004), Dettinger et al. (2004), and Null (2004). Six of these events caused floods and severe local damage in portions of California.

Durations of short-range simulations for these selected storms range from 3 to 11 days. The initial and lateral boundary conditions of these simulations are based on the National Oceanic and Atmospheric Administration (NOAA) National Climatic Data Center’s North American Regional Reanalysis (NARR) data (more information is available online at http://nomads.ncdc.noaa.gov) at a spatial resolution of 32 km and an output resolution of 6 h. Reanalysis data provide more realistic large-scale forcings, which allow us to focus on the WRF model bias.

Long-range simulations are performed for 10 consecutive California winters with two sets of large-scale forcings: 1) NARR and 2) the National Center for Atmospheric Research (NCAR) Community Climate System Model 3.0 (CCSM3) outputs (Vertenstein et al. 2004). Both datasets (from November to March 1990–2000) are available at a 6-h interval. The difference in RCM simulations from both sets of large-scale forcings can be used to quantify the impact of the GCM forcing on the model precipitation bias. In this study, T85 CCSM3 data (more information is available online at http://www.earthsystemgrid.org) are given from the twentieth-century run (b30.030e ending at December 1999) along with three additional months from the beginning of the twenty-first-century run for the A2 scenario (b30.042e).

c. Experiment design

Because of computational constraints, the impacts of model physics options and grid resolutions on the precipitation bias are evaluated only in short-range simulations. Table 2 lists the model physics options used in short-range simulations. Because of its direct influence on cloud and precipitation processes, extra effort is

<table>
<thead>
<tr>
<th>Storm type</th>
<th>Occurrence period</th>
<th>Remarks</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pineapple Express</td>
<td>10–20 Feb 1986</td>
<td>PE1</td>
</tr>
<tr>
<td></td>
<td>30 Dec 1996–4 Jan 1997</td>
<td>PE2</td>
</tr>
<tr>
<td>El Niño</td>
<td>7–11 Mar 1995</td>
<td>EN1</td>
</tr>
<tr>
<td></td>
<td>18–24 Feb 1998</td>
<td>EN2</td>
</tr>
<tr>
<td>La Niña</td>
<td>6–10 Mar 1989</td>
<td>LN1</td>
</tr>
<tr>
<td></td>
<td>3–7 Mar 2001</td>
<td>LN2</td>
</tr>
<tr>
<td>Synoptic cyclone</td>
<td>10–12 Dec 1995</td>
<td>SC1</td>
</tr>
<tr>
<td></td>
<td>29–22 Feb 1996</td>
<td>SC2</td>
</tr>
</tbody>
</table>
focused on microphysics schemes. Five microphysics schemes are tested in 12-km simulations: Lin (Lin et al. 1983), WRF Single-Moment 5-Class Microphysics scheme (WSM5; Hong et al. 2004), Goddard 3ICE scheme with graupel (Tao et al. 2003), Thompson (Thompson et al. 2008), and Morrison (Morrison et al. 2005). All microphysics options are single-moment schemes except Morrison (a two-moment scheme). Other physics module choices include cumulus parameterization from Kain–Fritsch (Kain 2004), Grell–Devenyi (Grell and Devenyi 2002), soil layer modules of Noah (Chen and Dudhia 2001), the Rapid Update Cycle (RUC; Smirnova et al. 2000), PBL physics including Yonsei University (YSU; Hong et al. 2006), Asymmetric Convective Model, version 2 (ACM2; Pleim 2007), and radiation choices of the Rapid Radiative Transfer Model (RRTM) LW/Dudhia SW (Mlawer et al. 1997; Dudhia 1989) or the Community Atmosphere Model (CAM) LW/SW (Collins et al. 2004). The Noah soil layer scheme used in this study has additional snow albedo and deep soil temperature updates, as in ARW version 3.1. We compare parameterization choices against a control configuration consisting of Morrison microphysics, Grell–Devenyi cumulus, Noah land soil module, YSU PBL, and CAM radiation. We choose this control configuration because it provides a reasonable match to observations for all storms (as documented in section 3a).

We perform two sets of short-range nested-grid simulations. Durations of short-range simulations are shown in Table 1. The first set (referred as low resolution) has two nested grids with resolutions of 36 and 12 km, respectively, and is primarily used to study the sensitivity of forecast precipitation to all model physics and storm types. The other simulations (hereafter high resolution) are conducted using three levels of nested grids at 18, 6, and 2 km, respectively. Comparison of low- and high-resolution simulations is used to assess the robustness of microphysics and cumulus parameterizations to grid resolution changes. Because of computational constraints, we only perform high-resolution simulations for four storm events (PE2, EN1, LN1, and SC1: one for each large-scale condition) and three microphysics schemes (Lin, Goddard, and Morrison). Only the results from the innermost domain (100 × 130 and 544 × 712 grids in the x and y axes, respectively) of low- and high-resolution simulations are shown in this study. Time steps for the model domains of 2- and 12-km resolutions are 6.67 and 40 s, respectively. Figure 1 shows model terrain and domain coverage for both low- and high-resolution simulations. The topography in the high-resolution run clearly shows finer structure and larger magnitude in mountain areas and coastal ranges (Figs. 1b,c).

In long-range simulations, only the low-resolution nested grids and the control configuration of physics options are used. The primary focus of long-range simulations is to evaluate the influence of the GCM forcing on the model wet bias. Following C09, we prevent our long-range simulations from drifting by reinitializing from large-scale forcings on a monthly basis. This method has the additional benefit that it allows us to simultaneously run simulations for multiple months, significantly increasing our throughput. It also circumvents the problem that WRF—like most RCMs—was not designed for long runs since it may drift from reality.

d. Measurements for validation

The model–observation comparisons performed here are an attempt to clarify the skill of model predictions over California. Because the exact positioning of individual storms is not very relevant to the model’s climatological biases, we focus on regional-average statistics rather than metrics geared toward evaluating spatial and temporal structure. An additional advantage of this approach is that spatial and temporal averaging increases the statistical robustness of our approach. A limitation to this methodology is that we may miss some feature (such as mountain overprediction because of insufficient coastal rainout), which could provide a physical explanation for our results. To avoid this problem, we break California into four climate regimes for validation: the coast, central valley (C_Valley), mountains (Mtn), and Southern California (S_Cal) as shown in Fig. 1.

In this study, we use three gridded observational precipitation datasets to assess the sensitivity of model precipitation bias to observations in both short-range and long-range simulations. Because of the large size difference between RCM gridcell and point observation, we focus on gridded datasets because RCM output represents gridcell averages, which can bear little resemblance to point observations, particularly in areas of complex terrain. The gridded observations we use
involve more data points and utilize more sophisticated techniques for turning point data into area averages than we could achieve on our own. Because this process is very challenging, we compare three different gridded datasets to get a sense of observational uncertainty. The goal of our model–observation comparison is to determine reasonable model configurations for California regional model simulations using WRF.

The first of these three gridded datasets is from NOAA with a spatial resolution of 0.25°. The other two are from the University of Washington (UW) with a grid resolution of 0.125°. These gridded precipitation data are derived from rain gauge measurements through a spatial interpolation scheme, NOAA data using a simple Cressman scheme (Cressman 1959), and UW data using the synergraphic mapping system algorithm (Shepard 1984). The NOAA dataset contains more rain gauge stations than UW data, but UW’s datasets have topography adjustment to match that of the Parameter-elevation Regressions on Independent Slopes Model (PRISM) dataset (Maurer et al. 2002). In addition to terrain correction, one of the UW datasets includes additional adjustment for temporal heterogeneities following Hamlet and Lettenmaier (2005), which makes it more appropriate for long-term trend analysis. We call the UW data with temporal correction UW2 and the nontrend adjusted version UW1. Note that for the LN2 case, only UW2 measurements are available for validation.

3. Results

a. Short-range simulations

1) Sensitivity of model precipitation to WRF physics

Precipitation is a very important variable for climate studies, so lowering precipitation bias is an important goal for regional climate simulations. As described in the introduction, many factors can contribute to forecast bias. Given the driving large-scale conditions, the success of RCM forecasts depend strongly on the accuracy of model physics representations and the interactions between physical processes. This subsection describes a series of experiments at 12-km resolution to examine the sensitivity of simulated precipitation to individual model physics.

(i) Microphysics schemes

Figure 2 illustrates the spatial distribution of convective (parameterized) and stratiform (resolved) surface precipitation simulated with five different microphysics...
schemes from a California wintertime synoptic cyclone case (SC1). All simulations show that heavier stratiform precipitation primarily appears in the high-elevation mountain region while stronger convective rain is mainly located in the coastal region. The principal result from this figure is that overall patterns of convective and stratiform precipitation are less influenced by microphysics schemes (either single or two moment). Instead, the primary impact of microphysics schemes on simulated precipitation is in the magnitude. Magnitude change is also major effect of varying microphysics schemes for the other storms (not shown). The narrow simulated stratiform precipitation band found in the Morrison (two moment) scheme for California wintertime storms is at odds with the results of Morrison et al. (2009) for summertime squall-line (multicell type) storms with a distinct tilting structure of convective cores; they found the two-moment scheme to cause wider spread of surface stratiform precipitation as a result of weaker evaporation of rainwater below the melting layer.

As compared to the statistics of midlatitude squall-line environment (Bluestein and Jain 1985), the vertical structure of the prestorm environment in Case SC1 near the northern California coast exhibits very weak convective available potential energy (CAPE; 555 m² s⁻² vs 2820 m² s⁻²) and almost no vertical wind shear in the lowest few kilometers. Earlier studies also indicated that the low-level wind shear intensity plays an important role in the formation of tilting convective cores, and its resulting horizontal transport of hydrometeors from deep convective cores (Weisman and Klemp 1984; Fovell and Ogura 1988; Chin 1994; Chin et al. 1995). Therefore, the weaker convective instability and low-level wind shear of this California winter storm lead to upright convective cores (not shown), which results in a narrow surface stratiform precipitation band.

The impact of microphysics schemes on simulated surface total precipitation in individual regions of California for all selected storms is described in Fig. 3, which compares spatially and temporally averaged precipitation between simulations and observations. In addition to the sensitivity of model results to microphysics schemes, observations from different sources of gridded measurements differ markedly. This discrepancy leads to high sensitivity of simulated precipitation bias to validation datasets (elaborated in Tables 3, 4, and 5). The difference between UW1 and UW2 datasets is due to the inclusion of long-term trend adjustment in UW2, which clearly weakens precipitation over all regions in California for all storms. In low-elevation regions, such as Southern California and central valley, UW1 and NOAA datasets agree better. In mountain regions, topographical adjustment (not included in NOAA dataset) becomes important resulting in larger differences between UW1 and NOAA datasets.

Generally speaking, model forecast skill for surface precipitation depends strongly on storm type and geographic location. All microphysics schemes exhibit considerable overestimation of surface precipitation for the La Niña type of storms over all regions of California except the coast. A recent study indicates that during La Niña, storm systems tend to take a more northeastward track, and there is an additional leak of wave energy from the central Pacific toward the eastern equatorial Pacific, thus reducing incidence of storm systems moving into California and the southwest of the United States (Seager et al. 2010). Thus, California normally receives less winter precipitation in La Niña years. For the rest of the storm types, these schemes show better agreement with observations (in particular with UW1) in mountain and Southern California regions. Noticeable underestimation appears in the coastal region and considerable overestimation occurs in the central valley region.

Tables 3, 4, and 5 summarize forecast biases for short-range simulations (with respect to UW1, UW2, and NOAA datasets, respectively) in terms of the mean absolute error (MAE) of model surface precipitation. These errors are averaged with equal weight over all available storms except for LN2 because of the absence of UW1 and NOAA datasets. Results indicate that the magnitude of precipitation biases exhibits strong dependence on measurement sources and geographic zones; dependence on microphysics schemes appears to be weaker. Although the impact of microphysics schemes on forecast biases is weak, they clearly exhibit their preference with the geographic locations: Lin and WSM5 schemes works better at the coast, Goddard and Thompson are skillful at C_Valley and S_Cal regions, and Morrison is favored in the mountains.

As a whole, bias compared to the UW1 dataset is smaller for all regions except the coast, where the simulations show better forecast skill with respect to the UW2 dataset. Within California subregions, the largest precipitation bias appears in the central valley for all microphysics schemes although this bias is substantially reduced for the synoptic cyclones (see the parentheses in Table 3). This precipitation bias is even worse with the UW2 or NOAA datasets. A better representation of climatological precipitation bias can be obtained by weighting the bias with the occurrence frequency of storm types. This analysis suggests that long-term forecasts may be better than suggested by equal weighting (elaborated in section 3b).

In addition to the influence of storm types, the large overprediction in the central valley (major agricultural area) is likely caused by several additional factors, such
as coastal terrain and local aerosol effects. The southern portion of C_Valley and S_Cal are locations in the rain shadow of California coastal ranges (Whiteman 2000). The underpredicted precipitation in the coastal region and overpredicted rainfall in the central valley may reflect insufficient rain shadowing due to inadequate grid resolution or smoothing by the terrain-following coordinate system. Use of an alternative gridding technique, known as an immersed boundary method, has demonstrated its skill in alleviating coordinate transformation errors and eliminating restrictions on terrain slope in mesoscale models (Lundquist et al. 2010). The representation of local aerosol effects on cloud condensation nuclei (CCN) number might also be underestimated. For example, the CCN number in the Thompson scheme is set by default to 100 cm$^{-3}$. CCN concentrations over land are likely much

Fig. 3. Area- and daily-averaged surface (stratiform and convective) precipitation (mm day$^{-1}$) for all simulated storms (horizontal axis): the Pineapple Express (PE), El Niño (EN), La Niña (LN), and synoptic cyclone (SC): (a) coast, (b) mountain, (c) S_Cal, and (d) C_Valley. Simulations at 12-km resolution with five different microphysics schemes (top five colors on color bar) and the control configuration for the other model physics are compared with three sets of observations (bottom three colors).
larger, which would slow down the autoconversion of rainwater (Rosenfeld et al. 2001). The default setting of graupel density in the Thompson scheme is specified at 0.4 g cm\(^{-3}\), but observations show it to range between 0.1 and 0.85 g cm\(^{-3}\) (Pruppacher and Klett 1997). Lower graupel density can lead to smaller fall velocity (Khain et al. 2001), which could reduce the growth of precipitation. Horizontally uniform microphysics properties used in all microphysics schemes may be another cause of the degraded model performance in the inland regions.

(ii) Cumulus parameterizations

The Kain–Fritsch (KF) and Grell–Devenyi (GD) schemes are chosen for this study because they outperformed other cumulus parameterizations in earlier modeling studies (e.g., Kerkhoven et al. 2006). The major difference between these two parameterizations is the treatment of entrainment/detrainment mixing of convection. The KF scheme assumes this mixing occurs throughout the whole depth of the convective layer while the GD scheme only allows entrainment/detrainment at the cloud top. Liang et al. (2004a) demonstrated that the GD scheme is very responsive to large-scale forcing, while the KF scheme is more influenced by boundary layer forcing. Liang et al. (2004b) indicated that the partition between parameterized and resolved precipitation is very sensitive to the cumulus scheme, a feature also found in this study (not shown).

Figure 4 illustrates the impact of cumulus parameterizations on simulated total (convective plus stratiform) precipitation. As compared to the grid scheme, the KF scheme acts to enhance surface total precipitation for all microphysics schemes over all regions. Larger precipitation in the KF scheme than in the GD scheme was also reported by Liang et al. (2004b) for a summertime East Coast case. One exception occurs in the central valley for the LN2 case, where KF precipitation is weaker for all microphysics schemes. Since coastal precipitation is generally underpredicted and precipitation in other regions is generally overpredicted, the KF scheme improves coastal precipitation forecasts, but the GD scheme remains a better choice in the other portions of California. Therefore, we choose the GD cumulus scheme for our control configuration. As found in previous studies, cumulus parameterization has an impact on precipitation prediction rivaling that of the microphysics parameterization. It is, however, beyond the scope of this study to determine what aspects of the parameterizations cause the differences in precipitation prediction.

(iii) Other physics

PBL, soil layer, and radiative transfer play indirect roles in cloud–precipitation processes by changing the atmosphere’s thermodynamic structure. Interactions between the surface and the atmosphere have been the focus of modeling studies on a wide range of time and spatial scales (e.g., Pielke 2001; Koster et al. 2004). Soil moisture and temperature have an important effect on the determination of surface sensible and latent heat fluxes, and therefore have a profound influence on the development of clouds, the PBL, and surface energy budgets particularly for longer time scales (Small and Kurc 2001).

The impact of model physics other than cloud processes on simulated surface precipitation is depicted in Fig. 5. Our results indicate that this impact is weaker

### Table 3. Area-averaged mean absolute errors of surface precipitation (with respect to UWI observations, %). These errors are computed from 12-km resolution short-range simulations with different microphysics schemes for all storms except for LN2. The values in parentheses are the errors for the cases of synoptic cyclones.

<table>
<thead>
<tr>
<th>Microphysics region</th>
<th>Lin WSM5</th>
<th>Goddard</th>
<th>Thompson</th>
<th>Morrison</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coast</td>
<td>11.3 (13.2)</td>
<td>15.1 (16.5)</td>
<td>19.6 (25.3)</td>
<td>17.0 (16.9)</td>
</tr>
<tr>
<td>Mountain</td>
<td>21.3 (19.0)</td>
<td>23.3 (14.5)</td>
<td>16.7 (5.5)</td>
<td>14.7 (4.5)</td>
</tr>
<tr>
<td>Central valley</td>
<td>76.2 (32.5)</td>
<td>54.2 (19.8)</td>
<td>44.8 (21.7)</td>
<td>44.3 (17.9)</td>
</tr>
<tr>
<td>Southern California</td>
<td>24.0 (30.1)</td>
<td>26.0 (35.3)</td>
<td>21.6 (26.6)</td>
<td>19.7 (14.9)</td>
</tr>
</tbody>
</table>

### Table 4. As in Table 3, but using UW2 observations.

<table>
<thead>
<tr>
<th>Microphysics region</th>
<th>Lin WSM5</th>
<th>Goddard</th>
<th>Thompson</th>
<th>Morrison</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coast</td>
<td>11.4</td>
<td>8.8</td>
<td>13.8</td>
<td>12.3</td>
</tr>
<tr>
<td>Mountain</td>
<td>48.0</td>
<td>45.3</td>
<td>37.2</td>
<td>35.0</td>
</tr>
<tr>
<td>Central valley</td>
<td>123.1</td>
<td>93.4</td>
<td>77.9</td>
<td>81.2</td>
</tr>
<tr>
<td>Southern California</td>
<td>38.1</td>
<td>38.7</td>
<td>34.3</td>
<td>31.1</td>
</tr>
</tbody>
</table>

### Table 5. As in Table 3, but using NOAA observations.

<table>
<thead>
<tr>
<th>Microphysics region</th>
<th>Lin WSM5</th>
<th>Goddard</th>
<th>Thompson</th>
<th>Morrison</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coast</td>
<td>12.6</td>
<td>9.3</td>
<td>11.3</td>
<td>10.3</td>
</tr>
<tr>
<td>Mountain</td>
<td>63.6</td>
<td>60.7</td>
<td>52.2</td>
<td>49.3</td>
</tr>
<tr>
<td>Central valley</td>
<td>62.8</td>
<td>42.9</td>
<td>37.6</td>
<td>34.7</td>
</tr>
<tr>
<td>Southern California</td>
<td>24.2</td>
<td>25.3</td>
<td>26.4</td>
<td>27.7</td>
</tr>
</tbody>
</table>
than that of microphysics and cumulus parameterizations for all studied storms. Part of this low sensitivity is due to the fact that noncloud processes have relatively long response times that may not be captured in short-range simulations. Therefore, these processes could be an issue in long-range simulations even though they have little effect here. Because the YSU PBL, Noah soil layer, and CAM radiation parameterizations generally perform slightly better than the others, we chose them for our control configuration.

2) IMPACT OF GRID RESOLUTIONS ON MODEL PRECIPITATION

The impact of horizontal grid resolution on short-range numerical weather predictions has been extensively studied in the past two decades. Mass et al. (2002) provided a detailed overview of resolution dependence for a variety of atmospheric phenomena with different spatial scales. Most existing microphysics schemes were originally designed for use in cloud-resolving models.
with higher horizontal grid resolutions (~1 km or less). However, these microphysics schemes have been widely used in RCMs for regional climate research. Therefore, it is of importance to assess how parameterization performance changes with grid resolution. In addition, the comparison of low- and high-resolution simulations can be used to evaluate whether the RCM needs higher horizontal resolution for adequate performance.

Figure 6 exhibits comparison of the spatial distribution of total (convective plus stratiform) precipitation from both high- (2 km) and low-resolution (12 km) simulations using control physics options for four selected storms from different large-scale conditions. Note that the cumulus parameterization is turned off in the high-resolution experiments. Results indicate that the simulated precipitation pattern exhibits strong similarity...
between both sets of simulations. The primary difference is on more intense precipitation, particularly in the mountain region of higher-resolution runs. Similar results also appear in simulations with different microphysics schemes (not shown). Increasing precipitation with higher horizontal resolution was also reported in many other studies (Mass et al. 2002; Leung and Qian 2003; Colle et al. 2005).

Area-averaged statistics of high- and low-resolution simulations show that higher grid-resolution improves surface precipitation forecast in the coastal region, particularly with the Morrison (two moment) scheme (Fig. 7a). Although the precipitation processes in this region may involve complex scale interactions among atmospheric circulation, ocean, and topography, the stronger model resolved orographic lifting associated with higher-resolution grids (see Figs. 1b,c) certainly plays some role in enhanced coastal precipitation. Similar forecast improvement of coastal precipitation with increasing horizontal grid resolutions was also found over the Pacific Northwest (Mass et al. 2002); however, the finer-resolution grids of this earlier study did not cover a wide enough area to include the high-elevation mountains for direct comparison with our study. Colle et al. (2005) also demonstrated the importance of higher grid resolution on improved precipitation forecast over a narrow mountain range. Unfortunately, our high-resolution simulations increase overestimation of surface precipitation in Mtn and C_Valley regions (Figs. 7b,d). In contrast, this resolution impact is small in the S_Cal region (Fig. 7c). The enhanced precipitation in the C_Valley region by increasing grid resolution suggests that the grid resolution has little influence on the rain shadow effect of California coastal ranges.

The cause of the degraded performance of high-resolution simulations in the high-elevation mountain region remains unclear. Further understanding of this cause is beyond the scope of this study. However, more effort is needed to clarify whether this issue is caused by a numerical problem in handling steep terrain by the
sigma pressure coordinate model, or by insufficiency of
the microphysics schemes for handling the geographic
location in this study.

Based on our short-range simulations, our results sug-
gest that two approaches can be used to improve RCM
simulations: 1) improving cumulus schemes to increase
precipitation in the coastal region and 2) amending terrain
treatment or microphysics schemes to reduce precipi-
tation in finer-grid applications. Because of the con-
siderable computational costs of the second approach,
the former approach may be more practical for RCM
applications.

b. Long-range simulations

The primary goal of long-range simulations in this
study is to assess the sensitivity of the GCM forcing and
measurement uncertainties to the model wet bias, rather
than to study the impact of climate variability, which
requires datasets several decades in length. This section
presents two sets of WRF long-range simulations driven

![Fig. 7. As in Fig. 3, but for comparisons of both high- (2 km) and low-resolution (12 km) simulations with three sets of observations.](image-url)
by NARR (the best available proxies for observations) and CCSM3 data, respectively. These simulations are evaluated using monthly area-averaged statistics for 10 consecutive winters (Fig. 8). This figure indicates that the temporal evolution of RCM-simulated monthly precipitation forced by NARR data fairly agrees with observations in most parts of California. In contrast, the long-range simulations driven by CCSM3 data exhibit a clear phase error at the timing of seasonal maximum for all regions; maxima fall one or two months earlier than observations. Similar phase error was also found in our recent 40-yr WRF simulations driven by Lawrence Livermore National Laboratory's CCSM3 data (C09). As a result, the GCM forcing tends to greatly overpredict surface precipitation in the early winter in all regions of California— with the worst prediction in December and moderate overestimation of surface precipitation in the later winter in most parts of California— while this feature does not appear in our earlier 40-yr WRF-CCSM simulations. This contrast suggests that this difference may arise from insufficient simulation length.

As in short-range averaged measurements, long-range observations also indicate that the long-term adjustment of UW2 data acts to weaken precipitation in all parts of California as compared to the UW1 dataset (Fig. 8). Similarly, NOAA long-range measurements are substantially weaker in the areas with terrain, such as coastal and mountain regions. The geographic variations of these measurement sources thus have some impact on apparent model wet biases.

Table 6 shows seasonal means of monthly percent errors of RCM surface precipitation biases with respect to UW1, UW2, and NOAA measurements. The impact of measurement uncertainty on the long-range model wet bias is similar to its counterpart in short-range simulations; the model compares best to UW2 measurements in the coastal region where the model wet bias is generally small, and the NOAA dataset provides the most pessimistic view of mountain-region precipitation. As a whole, forecast biases are lowest in California if one trusts the UW1 dataset. The error induced by switching to GCM-forced runs, however, dwarfs the differences between observational datasets. RCM simulations driven by the GCM forcing strongly increase model wet bias in Mtn, C_Valley, and S_Cal regions (ranging from 30% to 50%) but give lower model bias in the coastal region (~5%–10%). Such large model bias mainly arises from the phase error of the GCM forcing in the earlier winter, particularly December. This study suggests that further understanding of such phase error in CCSM3 would help reduce RCM precipitation bias for the projection of future regional-scale climates and provide better water management policies to prepare for the impact of climate change.

4. Summary and discussion

The ARW modeling system version 3.0.1 was used in this study to explore California wintertime model wet bias. This work was motivated by the existence of large wet bias in the western United States found in earlier RCM studies. Major effort was placed on assessing the impacts of WRF physics options, measurement quality, and horizontal grid resolution on short-range simulations, and evaluating the influence of measurement uncertainties and GCM forcing on long-range simulations.

For short-range simulations, we chose eight California wintertime storms from four major types of large-scale conditions: the Pineapple Express, El Niño, La Niña, and synoptic cyclones. We tested the forecast skill of physics configurations (e.g., microphysics, cumulus parameterization, planetary boundary layer, soil layer, and radiation transfer) against three sets of gridded observations (NOAA, UW1, and UW2). We divided California into four regions for validation: Coast, C_Valley, Mtn, and S_Cal. Control simulations were conducted with 12-km grid spacing to study the sensitivity of forecast precipitation to all model physics options and storm types. Additional experiments were performed at 2-km resolution to gauge the robustness of microphysics and cumulus parameterizations in coarser-grid applications.

We find that the choice of validation datasets has a significant impact on the magnitude of model precipitation bias, particularly in the mountain region. For both short- and long-range simulations with the control physics configuration, our results indicate that UW1 observations give smaller forecast bias than UW2 and NOAA datasets in most parts of California, except in the coastal region where the UW2 dataset results in slightly smaller bias than UW1.

Our short-range results suggest that the model precipitation forecast skill depends strongly on geographic location and storm type. In low-resolution (12 km) simulations, Lin and WSM5 microphysics parameterizations and the Kain–Fritsch cumulus scheme have better forecast skill in the coastal region while Goddard, Thompson, and Morrison microphysics parameterizations, and the Grell–Devenyi cumulus scheme perform better in the rest of California. Precipitation prediction is particularly bad for both of the La Niña storms in all regions except the coast. The impact of planetary boundary layer, soil layer, and radiation physics on precipitation is weaker than their counterparts in microphysics and cumulus processes in short-range low-resolution simulations.
Of note is the large wet bias from all microphysics schemes in the central valley region. Reasons for this are not clear. An overly weak coastal–mountain rain shadow due to insufficient resolution is an obvious candidate, but this does not seem to be the cause as simulations at 2-km resolution actually show increased C_Valley overprediction. Other potential causes for this error are model errors in the representation of aerosol effects on cloud–precipitation processes.

Coastal precipitation tends to be unresolved (convective) at 12-km resolution, which suggests that model underprediction of coastal precipitation in both the Kain–Fritsch and Grell–Devenyi cumulus schemes is due to the deficiencies in the convective parameterizations. Precipitation in this region is improved by increasing model resolution to 2 km, suggesting that higher resolution is needed to properly simulate precipitation in this region. Because 2-km resolution is currently too computationally expensive to use for long climate runs, a more effective path toward improvement of coastal precipitation might be to focus on cumulus parameterization development. It is interesting that except in the coastal region, increasing resolution did not improve model performance. This suggests that there may be little benefit to moving toward ultrahigh resolution.

Conclusions from our reanalysis-forced long-range simulations closely match those of our single-storm simulations, giving us confidence that our short-range

![Fig. 8. Monthly variations of simulated and measured surface precipitation rates (mm day$^{-1}$): (a) the coast, (b) mountains, (c) Southern California, and (d) central valley. These area-averaged quantities are derived from 10 consecutive winters using low-resolution (12 km) WRF simulations driven by NARR and CCSM3 data.](image_url)
Table 6. Area-averaged seasonal means of monthly percent errors of simulated surface precipitation with respect to three sets of observations. These errors are computed from 12-km resolution long-range simulations driven by NARR and CCSM3 data 10 consecutive winters.

<table>
<thead>
<tr>
<th>Simulation region</th>
<th>NARR_UW1</th>
<th>NARR_UW2</th>
<th>NARR_NOAA</th>
<th>CCSM_UW1</th>
<th>CCSM_UW2</th>
<th>CCSM_NOAA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coast</td>
<td>7.5</td>
<td>4.8</td>
<td>10.2</td>
<td>18.9</td>
<td>16.1</td>
<td>15.8</td>
</tr>
<tr>
<td>Mountain</td>
<td>16.8</td>
<td>22.5</td>
<td>38.7</td>
<td>45.3</td>
<td>52.8</td>
<td>72.3</td>
</tr>
<tr>
<td>Central valley</td>
<td>14.6</td>
<td>25.1</td>
<td>12.5</td>
<td>46.3</td>
<td>56.5</td>
<td>36.5</td>
</tr>
<tr>
<td>Mountain</td>
<td>16.8</td>
<td>22.5</td>
<td>38.7</td>
<td>45.3</td>
<td>52.8</td>
<td>72.3</td>
</tr>
<tr>
<td>Southern California</td>
<td>17.6</td>
<td>11.7</td>
<td>20.0</td>
<td>64.1</td>
<td>58.1</td>
<td>66.9</td>
</tr>
</tbody>
</table>

Simulations provide useful guidance for climate parameterization. It also worth noting that the effect of switching from reanalysis-derived lateral boundary conditions to GCM-based conditions causes a greater increase in model precipitation bias than the differences from switching between observational datasets. This emphasizes the fact that regional models are only as good as the data used to drive them. It is also noted that a large portion of the GCM-induced bias is due to a phase shift in the seasonality of California precipitation in GCM—an effect worthy of future research.

Reducing the biases identified in this study is critical to improving regional climate prediction, and our study is a first step toward this goal. The fact that none of our parameterization combinations fixed this problem suggests that improvements to the parameterizations themselves are needed to truly bring California regional climate modeling forward.

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REFERENCES


