An Object-Based Approach for Quantification of GCM Biases of the Simulation of Orographic Precipitation. Part I: Idealized Simulations

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ABSTRACT

An object-based evaluation method to quantify biases of general circulation models (GCMs) is introduced using the National Center of Atmospheric Research (NCAR) Community Atmosphere Model (CAM). Idealized experiments with different topography are designed to reproduce the spatial characteristics of precipitation biases that were present in Atmospheric Model Intercomparison Project simulations using the CAM finite volume (FV) and CAM Eulerian spectral dynamical cores. Precipitation features are identified as “objects” to understand the causes of the differences between CAM FV and CAM Eulerian spectral dynamical cores. Three different mechanisms of precipitation were simulated in idealized experiments: stable upslope ascent, local surface fluxes, and resolved downstream waves. The results indicated stronger sensitivity of the CAM Eulerian spectral dynamical core to resolution. The application of spectral filtering to topography is shown to have a large effect on the CAM Eulerian spectral model simulation. The removal of filtering improved the results when the scales of the topography were resolvable. However, it reduced the simulation capability of the CAM Eulerian spectral dynamical core because of Gibbs oscillations, leading to unusable results. A clear perspective about models biases is provided from the quantitative evaluation of objects extracted from these simulations and will be further discussed in part II of this study.

1. Introduction

All atmospheric general circulation models (GCMs) have systematic errors in their simulation of the present climate. These systematic errors (i.e., biases like continental precipitation, tropical mean state, etc.) are resistant to improvements in model formulation. It has proved difficult to isolate cause and effect: that is, linking model formulation or model components to the presence or absence of a particular bias. For example, a common experimental approach is to change some model component (e.g., the convective parameterization or dynamical core) and evaluate the impact of the change on the global climate. Improvements are sometimes realized and other times they are not; there is an ambiguous mix of results.

This study is motivated by the hypothesis that there is a subset of the biases in climate simulations that are at the mechanistic level; that is, the bias is the manifestation of a poor representation of quasi-local mechanisms rather than the residue of global inadequacies of, for instance, model parameterizations. Deterministic weather predictions are often validated with feature-by-feature comparison (Davis et al. 2006; Ebert and McBride 2000; Marzban and Sandgathe 2006; Micheas et al. 2007; Posselt et al. 2012; Wernli et al. 2008; Xu et al. 2005). Probabilistic weather forecasts and climate projects are evaluated with statistical methods (Airey and Hulme 1995). We seek to develop model evaluation strategies that identify similar “objects”: coherent systems with an associated set of measurable parameters (Douglass 2000). This makes it possible to evaluate processes in models without needing to reproduce the time and location of, for example, a particular observed cloud system. Process- and object-based evaluation preserves information in quantitative analyses by avoiding the need for extensive spatial and temporal averaging. Of particular interest in our research is the interaction of the dynamical core (Williamson 2007) and the physical parameterizations and how the interaction changes as resolution is increased. We investigate the representation of the orographic precipitation (Roe 2005) by spectral and finite volume dynamical cores (McGuffie and Henderson-Sellers 2005, 170–174; Neale et al. 2010).
We focus on the wintertime western U.S. orographic precipitation. This phenomenon is easy to isolate and has known physical mechanisms and sufficient observational data. The map of our study domain is given in Fig. 1.

The area in the red circle is the California Coast Ranges along the shore and the Sierra Nevada, with the Central Valley in between. During winter, synoptic-scale storms propagate from the Pacific Ocean and the lift from the topography causes precipitation on the upslope of the mountain ranges, with far less precipitation in the Central Valley.

Section 2 gives theoretical information about orographic precipitation and the object-based approach we aim to implement. Section 3 introduces the idealized test case setups, the models used and their simulation of orographic precipitation. The discussion of results is given in section 4, and section 5 contains the conclusions.

2. Orographic precipitation and object-based analysis

a. Orographic precipitation

Orographic precipitation is a complex phenomenon because of the physical mechanisms involved, encompassing fluid dynamics, thermodynamics, microscale cloud processes, and topographical structure, as well as its dependence on the larger-scale patterns of the atmospheric general circulation (Roe 2005). In addition to the problematic representation of the cloud microphysics by GCMs due to the finescale of occurrence of these processes, orography introduces complexity regarding the dynamics of the flow like the stable upslope ascent and the partial blocking of the air mass. Other typical finescale mechanisms include lee-side convergence, convection triggered by solar heating, and convection due to the lifting above the level of free convection. The stable upslope ascent is a straightforward mechanism of orographic precipitation and has been utilized in many modeling studies of this variable (Roe and Baker 2006; Smith 2003; Smith and Barstad 2004). Figure 2 shows a typical precipitation response to a stable upslope ascent (Roe and Baker 2006).

![Orographic Precipitation Diagram](image)
In Fig. 2, the moist air moves from left to right and is lifted by the elevation on the windward side of the mountain. This causes the air column to be cooled, resulting in condensation and precipitation. The peak precipitation occurs at a distance before the mountain peak. The air continues its movement over the mountain peak, leaving a significant portion of the moisture as precipitation, and the descent on the leeward side of the mountain results in warming, which leads to suppression of the precipitation. This forms the classic rain shadow, which is observed in the study region (Fig. 1). The rain shadow phenomenon is both observed and is consistent with underlying theory and understanding. This link between observation and theory and how realistically it is simulated drives our analysis.

b. Object-based analysis

Object-based analysis combines our theory-based mechanistic understanding of a meteorological feature, with weather-scale observations describing the feature, and the morphology of how models represent the feature. These features are weather, and weather features are represented in climate models. The dynamics of the weather features organize the flow and hence precipitation. We define features such as fronts, rainbands, clouds in deep convection, etc., as objects (Posselt et al. 2012; Xu et al. 2005). These features can be composed of clusters of small-scale processes in finer scales or they can aggregate to form features that are observed in the larger scale (Barros and Lettenmaier 1993). The presence of small-scale structure in weather observations provides powerful information on model performance that is both quantitative and qualitative. A focus on these as objects and how the objects relate to simulated and observed underlying structure allows us to look at similar features in models and observations. This approach supplements the grid-level and grand-mean comparisons that are exemplified by many forecast evaluation techniques. These comparisons suffer from inadequacies such as loss of information on local biases since the information is crunched to single numbers (Gilleland et al. 2009). Here we identify features or objects that are representative of orographic precipitation by two configurations of a GCM. We then pose an idealized numerical experiment to investigate these features.

The identification of features consists of both subjective (theory of orographic precipitation) and objective input. The 21-yr (1979–2000) January-mean precipitation of two configurations of the Community Atmosphere Model (CAM) (Bala et al. 2008) exhibits such features (Fig. 3). The configurations of the model in Fig. 3 differ by the dynamical core, with one configuration using a finite volume (FV) core and the other using an Eulerian spectral dynamical core. These dynamical cores are described in detail in the CAM model documentation (Neale et al. 2010). The two simulations are plotted along with the Global Precipitation Climatology Centre (GPCC) observations (limited to land) over our domain of interest (Rudolf et al. 2005; Schneider et al. 2013).

The CAM FV model and GPCC observations in Fig. 3 have ~0.5° horizontal grid spacing, and the CAM Eulerian spectral model has a T170 (~0.7°) triangular truncation. The color scale of the CAM Eulerian spectral model plot is reduced in order to show the structure of precipitation features better. The observed precipitation is concentrated on the coastline and closely linked to the mountain ranges on the western edge of the continent. Closer examination of the observations shows similarities with the simple description of orographic precipitation in Fig. 2. The rain is on the windward side of the mountains,
associated with the moisture flux from the west. To the eastward (leeward) side of the mountains there is a rain shadow. In much of the western United States, the land to the east of the mountains is semiarid or desert.

The area in Fig. 3 (white circle) is the California Coast Ranges and the Sierra Nevada, with the Central Valley in between. In this region, the rain shadow is observed in both the Central Valley and to the east of the Sierra Nevada. The highest point in the area is Mount Whitney in the Sierra Nevada with an elevation of 4421 m, and the average width of the mountains is 105 km (including the valley between the mountains). The California Coast Ranges provide the orographic lift to the impinging moist air leading to precipitation. As a result of the smaller-scale dynamical and physical mechanisms taking place in between two mountain ranges, the remaining moisture (if any) undergoes a second lift over the Sierra Nevada, which is on average higher than the California Coast Ranges. The CAM Eulerian spectral dynamical core in Fig. 3 created a big blob of precipitation with the precipitation over the mountain ranges combined into a single large precipitation feature. On the other hand, the CAM FV model produced a narrow band of precipitation over the mountain range with a higher peak value (10 mm day$^{-1}$) than that of the CAM Eulerian spectral model (8.5 mm day$^{-1}$). This “spread out” effect in the CAM Eulerian spectral model was also discussed by (Bala et al. 2008). The precipitation feature produced by the CAM FV model visually represents the observations better than the CAM Eulerian spectral model: it looks more realistic. The monthly-mean plots (not shown) illustrate that this type of behavior for the CAM FV and CAM Eulerian spectral models is typical throughout the 21-yr period. As a result, the precipitation over the California Coast Ranges and Sierra Nevada is a good candidate for further analysis.

We use idealized GCM runs to provide analogs to the features to be investigated. For this purpose, a modification to the mountain Rossby wave test case (Jablonowski et al. 2008) was implemented to create suitable conditions of wind, moisture flux, and topography. The simpler—and controlled—experiments reveal relationships between the simulation of orographic precipitation and the components of GCMs, including sensitivity to the dynamical core, the numerical representation of topography, and the complexity of the topography. We leave quantitative descriptions of the simulation differences to part II of this study (Yorgun and Rood 2014, manuscript submitted to J. Climate).

3. Idealized test cases

The idealized cases are the second step of our object-based approach and link the representation of orographic precipitation in the Atmospheric Model Intercomparison Project (AMIP) runs to GCM structure. GCMs are composed of multiple components that are connected together yielding a highly complex system. The two main components of a GCM are the physical parameterization suite and the dynamical core. In this study, we focus on the dynamical core component of the National Center for Atmospheric Research (NCAR) CAM versions 3.0 (Collins et al. 2006) and 5.0 (Neale et al. 2010). The dynamical core can be defined as the “resolved fluid flow” component of the model (Williamson 2007). CAM serves as the atmospheric component of the Community Earth System Model, which supports several dynamical cores, including the two used here. The two dynamical cores under analysis—namely, CAM FV and CAM Eulerian spectral—were run in two different resolutions for each dynamical core: that is, 1$^\circ$ and 0.5$^\circ$ for CAM FV and T85 and T170 for CAM Eulerian spectral. The two dynamical cores were coupled with a reduced moist parameterization suite (“Simple Physics”) that was used to test the simulation of tropical cyclones by GCMs and the effect of the dynamical core (Reed and Jablonowski 2012). CAM allows us to couple a simpler version of physics parameterization with a dynamical core in order to assess the capabilities of each dynamical core and compare them to each other in terms of simulation of orographic precipitation.

a. CAM Eulerian spectral

In spectral models global basis functions are used to describe the spatial structure of the variables and hence information from both upstream and downstream influences a particular point in space. Computational flow of a spectral GCM proceeds as the data fields are transformed to grid space at every time step via fast Fourier transforms and Gaussian quadrature (a form of numerical integration) and back to spectral space via Legendre transforms and Fourier transforms (McGuffie and Henderson-Sellers 2005, 170–174). Vertical discretization is achieved via finite differences on a hybrid coordinate system (Neale et al. 2010). Spectral harmonics are susceptible to Gibbs oscillations, and spectral models are prone to produce unrealistic oscillatory results especially when dealing with sharp gradients (e.g., orographic precipitation). Models employ different forms of dissipation/diffusion to mitigate these effects together with other numerical noise generated by dispersion errors or computational modes. Explicit diffusion with varying coefficients (such as second-, fourth-, or higher-order coefficients) is widely used to remove Gibbs oscillations in spectral models (Jablonowski and Williamson 2011). Relevant to our study, models also apply a terrain filter, which is an adoption of a monotonic
filter (Bala et al. 2008), to get a smoother topography, thus damping the gradients to reduce Gibbs oscillations. These filters, useful in removing noise, create a trade-off between numerical artifacts, accuracy, and physical realism, which will be discussed in section 4, where the results of our idealized test cases are presented.

b. CAM FV

Lin (2004) developed a multidimensional flux-form semi-Lagrangian transport, finite volume method, which is a generalization of one-dimensional (1D) FV schemes to multiple dimensions combined with an efficient algorithm to reduce the stringent time step stability requirements. The algorithm aimed to conserve mass without a posteriori restoration, compute fluxes based on the subgrid distribution in the upwind direction, generate no new maxima or minima, preserve linear tracer correlations, and be computationally efficient in spherical geometry (Lin and Rood 1996, 1997) The resulting multidimensional scheme is free of the Gibbs oscillations (with the optional monotonicity constraint), mass conserving, and stable for a Courant number greater than one in the longitudinal direction, which made the scheme competitive for the intended application on the sphere. The vertical discretization is Lagrangian with a conservative remapping, which essentially makes it quasi-Lagrangian (Neale et al. 2010). Rasch et al. (2006) compared the tracer transport properties of spectral, semi-Lagrangian, and FV numerical methods in CAM3.0. They found that the FV core is, unlike spectral and semi-Lagrangian, conservative and less diffusive. It also accurately maintains the nonlinear relationships (required by thermodynamic and mass conservation constraint) among conserved and nonconserved variables that are influenced by adiabatic and nonadiabatic processes.

c. Physics parameterization

As previously mentioned, the physical parameterization is set to a simplified moist parameterization suite called Simple-Physics suite (Reed and Jablonowski 2012) for both CAM FV and the CAM Eulerian spectral dynamical core. The suite allows physical processes that are important for orographic precipitation (i.e., large-scale condensation, boundary layer turbulence of horizontal momentum, temperature, and specific humidity) and surface fluxes of horizontal momentum, evaporation (specific humidity), and sensible heat (temperature) from the surface to the lower atmosphere.

Large-scale condensation is parameterized to occur when the atmosphere becomes saturated. The atmospheric profiles of moisture, temperature, and winds are not relaxed to specified states; therefore, they are allowed to evolve throughout the model runs. The eddy turbulence surface momentum fluxes, evaporation of water vapor at the surface, and kinematic eddy sensible heat fluxes are approximated by the bulk formulas. The boundary layer is defined as all the levels with pressure values greater than 850 hPa and the effect of boundary layer diffusion is tapered to zero above the 850-hPa level. There is no parameterized convection scheme. The details of these parameterizations can be found in Reed and Jablonowski (2012). The surface flux of evaporation especially is an effective process in creating precipitation over the mountains. Because our test cases are on an aquaplanet setting (Neale and Hoskins 2000), the mountains are covered with water, and this leads to the reinforcement of the moisture in the lower atmosphere via surface fluxes. This is analogous to a well-known phenomenon called precipitation recycling, which is the contribution of evaporation within a region to precipitation in that same region (Bosilovich et al. 2003; Eltahir and Bras 1996). This is observed in all cases in this study and gives valuable insight as to how it is simulated by different dynamical cores with varying resolution. All experiments were conducted using 26 hybrid vertical model levels. The physics and dynamics time steps for CAM Eulerian spectral model are identical, and they are 1800 and 300 s for T85 and T170, respectively. For the CAM FV model, the physics time steps are 1800 and 600 s and the dynamics time steps are 180 and 60 s for 1° and 0.5°, respectively. The total model run was for 30 days.

d. Test case setup

The initial conditions are similar to the mountain-induced Rossby wave train test case (Jablonowski et al. 2008), which are similar to initial conditions by Tomita and Satoh (2004). The main difference is the derivation of the surface pressure for hydrostatic conditions. The simulation starts from smooth isotermal initial conditions that are a balanced analytic solution to the primitive equations.

The horizontal wind components are prescribed as

\[ u(\lambda, \phi, \eta) = u_0 \cos \phi \quad \text{and} \quad v(\lambda, \phi, \eta) = 0 \text{ m s}^{-1}, \]

where \( \lambda, \phi, \) and \( \eta \) are longitude, latitude, and hybrid model level, respectively, and \( u_0 \) is a constant 20 m s\(^{-1}\) for all experiments. The meridional wind is set to zero initially. The experiments were run on an aquaplanet setting where the temperature is isothermal given by \( T(\lambda, \phi, \eta) = T_0 = 288 \text{ K} \). This yields the constant Brunt–Väisälä frequency (\( N \))
The test cases are set up to progress from simple to more complex to observe the evolution of complexity in the simulation of orographic precipitation by different models. The first case with a single mountain represents stable upslope ascent precipitation on the windward side of the mountain as well as the rain shadow on the leeward side. The baroclinic waves induced by the mountain also create precipitation after some distance. The second case has a second mountain peak of the same height in front of the first one to observe the smaller-scale dynamics and the distribution of precipitation between the two peaks. The third (“realistic”) case contains two mountains; however, the altitudes resemble those of the California Coast Ranges and the Sierra Nevada.

The surface pressure field balances the initial conditions. For hydrostatic primitive equation models, it is given by

\[ N = \sqrt{\frac{g^2}{c_p T_0}} \approx 0.0182 \text{ s}^{-1}, \] (3)

where \( g \) is the gravitational acceleration and \( c_p \) is the specific heat at constant pressure. The vertical temperature profile is also isothermal thus the atmosphere has a zero lapse rate. The waves are triggered by idealized Gaussian bell-shaped mountains. The mountains has a zero lapse rate. The waves are triggered by idealized Gaussian bell–shaped mountains. The mountains induce the disturbance to the initial conditions to create baroclinic waves in the leeward side. The idealized Gaussian bell mountain is introduced via surface geopotential (\( \Phi_s \)),

\[ \Phi_s(\lambda, \phi) = g z_s = g h_0 \exp[-(r/d)^2], \] (4)

where \( z_s \) is the surface height, \( h_0 \) is the peak height of the mountain, and \( d \) is the half-width of the Gaussian mountain profile. The term \( r \) is defined as the great circle distance,

\[ r = a \arccos[\sin \phi_c \sin \phi + \cos \phi_c \cos \phi \cos(\lambda - \lambda_c)], \] (5)

where \( a \) is Earth’s radius and \( \phi_c \) and \( \lambda_c \) are center points in latitude and longitude, respectively. The mountain specifications for each setup are given in Table 1.

The surface pressure field balances the initial conditions. For hydrostatic primitive equation models, it is given by

\[ p_s(\lambda, \phi) = p_{s0} \exp \left[ -\frac{a N^2 u_0}{2g^2 \kappa} \left( \frac{u_0}{a} + 2\Omega \right) (\sin^2 \phi - 1) \right] - \frac{N^2}{g^2 \kappa} \Phi_s(\lambda, \phi), \] (6)

where \( \kappa \) is the ideal gas constant for dry air (\( R_d \)) divided by specific heat at constant pressure (\( c_p \)) and is \( \gamma \approx \frac{7}{5}; \Omega = 7.292 \, 12 \times 10^{-5} \text{ s}^{-1} \) (Earth’s angular velocity); and \( p_{s0} \) denotes the surface pressure at the South Pole, which is set to 930 hPa. The moisture, which triggers the orographic precipitation, is initialized via specific humidity calculated as

\[ q = \frac{q_{s0} \rho}{p_{s0}}, \] (7)

where \( q \) is the specific humidity, \( \rho \) is a pressure level, \( p_{s0} \) is a reference surface pressure (1000 hPa), and \( q_{s0} \) is the specific humidity at the surface when the relative humidity equals 80%.

### 4. Discussion of idealized setup results

#### a. Case 1: Single mountain

Figure 4 shows the surface geopotential overlaid by 30-day-mean precipitation for CAM Eulerian spectral T85 and T170 and CAM FV 1° and 0.5° resolutions. Surface geopotential contours (topography) are \( 5 \times 10^2, 2 \times 10^2, 5 \times 10^2, \) and \( 11 \times 10^2 \text{ m}^2 \text{ s}^{-2} \) throughout all plots. Stable upslope ascent precipitation features are observed in all simulations on the northward and windward side of the mountains. The large-scale precipitation is initiated at the start of the simulation, moves northward, and loses intensity as the simulation continues. The intensity of the precipitation feature simulated by CAM Eulerian spectral T85 is significantly lower than that of other runs. This is mostly due to the spectral filtering applied to the topography: the effect of which will be discussed in the next section (case 2). The intensity for CAM Eulerian spectral T170 is lower than that of both CAM FV models. The simulation is almost identical for CAM FV 1° and 0.5° resolutions in terms of

<table>
<thead>
<tr>
<th>Case No.</th>
<th>Center point in longitude (( \lambda_c ))</th>
<th>Center point in latitude (( \phi_c ))</th>
<th>Peak height (( h_0 ) m)</th>
<th>Half-width (km)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>97°E</td>
<td>30°N</td>
<td>1500</td>
<td>1500</td>
</tr>
<tr>
<td>2</td>
<td>90°E</td>
<td>30°N</td>
<td>1500</td>
<td>1500</td>
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<tr>
<td>3</td>
<td>90°E</td>
<td>30°N</td>
<td>500</td>
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both the shape and the intensity of the features. This difference in intensity between spectral and FV cores was observed in AMIP runs (Fig. 3). This idealized simulation also indicates the high sensitivity to resolution for spectral models.

Examining a daily precipitation plot (Fig. 5) reveals information about the types of simulated features: some of which are not apparent in the monthly-mean plot. These feature types (as indicated by their corresponding numbers in Fig. 5d) are as follows:

1) large-scale features due to stable upslope ascent;
2) small-scale features due to local evaporation and leeside convergence; and
3) features due to leeward baroclinic waves.

The picture in Fig. 5 is different than Fig. 4, where the stable upslope ascent precipitation features (type 1) lost intensity and moved northward, the small-scale features (type 2) started to emerge (around day 18), and the features due to baroclinic waves (type 3) started to appear periodically as the simulation went on. These three feature types are all different in their origin and thus present valuable insight in terms of their difference between each dynamical core as they point toward a different aspect of models. Coarser-resolution models (CAM Eulerian spectral T85 and CAM FV 1°) do not simulate the small-scale features, although some very low intensity precipitation can be observed for CAM FV 0.5° model on the mountain peak. The finer-resolution models simulate these features, but with the difference of CAM Eulerian spectral T170 simulating them with larger spatial extent and higher intensity when compared to that of CAM FV 0.5°. This sensitivity to intensity is contrary to what is observed with the large-scale stable upslope ascent features. All models produced the features due to baroclinic waves (CAM FV 1° seems to have missed them in Fig. 5; however, they appear in other days because of the periodic nature of this phenomenon).
To understand these differences, it is essential to understand the genesis and evolution of these features. Vertical pressure velocity ($\omega$), moisture flux convergence (MFC), and zonal winds were plotted for the lowest model level and are given in Fig. 6.

Diagnostics for CAM FV 0.5° are chosen to explain the evolution of features because it has all the features simulated. There is negative pressure velocity, upward motion (Fig. 7b), on the windward side of the mountain, where the large-scale precipitation feature is observed. This is consistent with the stable up-slope ascent process and the subsequent condensation/precipitation explained in section 2a (Fig. 2).

MFC is a prognostic quantity for forecasting convective initiation, with an emphasis on determining the favorable spatial location(s) for such development (Banacos and Schultz 2005). In our study, we use this quantity as a diagnostic to understand the behavior of the small-scale features appearing on the peak of our mountains. MFC can be derived from the conservation equation for water vapor using the material derivative and the continuity equation on generalized vertical coordinates (Collins et al. 2006),

$$\frac{\partial}{\partial t} \left( \frac{\partial p}{\partial \eta} \right) = - \frac{1}{a \cos \theta} \left[ \frac{\partial}{\partial \lambda} \left( uq \frac{\partial p}{\partial \eta} \right) + \frac{\partial}{\partial \phi} \left( vq \frac{\partial p}{\partial \eta} \cos \phi \right) \right] - \frac{\partial}{\partial \eta} \left( q \frac{\partial p}{\partial \eta} \right) + (E - P) \frac{\partial p}{\partial \eta},$$

where $q$ is the specific humidity, $E$ is evaporation, and $P$ is precipitation. The term $\eta$ represents the model level, $\dot{\eta}$ is $d\eta/dt$, $\nabla_{\eta}$ is the horizontal velocity vector, $V$ is the two-dimensional gradient on constant $\eta$ surfaces, and $\partial p / \partial \eta$ is the hybrid vertical coordinate pseudo density. This equation is an expression of the moisture budget of an air parcel. All terms in this equation are divided by $g$ (gravitational acceleration); thus, the MFC unit is $\text{kg m}^{-2} \text{s}^{-1}$. The first, bracketed term in the right-hand...
side of the above equation is the MFC and is plotted in Fig. 6c. We calculated the surface MFC on the lowest hybrid model level. The second term is the vertical MFC. MFC has traditionally been calculated as a vertically integrated quantity (Frankhauser 1965; Hudson 1970); however, Newman (1971) calculated the surface MFC to be able to make use of high-resolution temporal and spatial observations of the lower-level atmosphere. The majority of the studies computed surface, not vertically integrated, MFC since then. Given the variable of interest being total precipitation on the surface in our study, we also calculated surface MFC to be able to have a sensible diagnosis.

The small-scale precipitation features (type 2) in Fig. 5 have complex and multiple underlying causes. The location of peak convergence of moisture flux in Fig. 6c (on the mountain peak) is where the small-scale precipitation is observed. Previous studies also showed a strong relationship between surface MFC and the precipitation (Becker et al. 2011; Bhushan and Barros 2007; Holman and Vavrus 2012). This convergence can have multiple reasons, such as moisture transport from the moist air impinging on the mountain and local evaporation over the mountain peak where precipitation is observed. These small-scale features, unlike the large-scale stable upslope ascent features, remain stationary after their inception. However, there is a convergence of zonal wind (Fig. 6d) around the mountain toward the leeward side. This convergence of the zonal winds transport moisture to this area representing another mechanism of orographic precipitation: that is, lee-side convergence (Roe 2005). Also, additional model runs were made with varying the surface temperature of the aquaplanet setting, which showed increased intensity of these small-scale precipitation features with increasing temperature. Reducing the surface temperature led to the disappearance of these features. This sensitivity of the surface flux parameterization in the simple physics suite to temperature demonstrates the role of local evaporation. Therefore, these small-scale features are labeled as features due to local evaporation and lee-side convergence.

As summary for this initial case, we were able to observe and identify causes and evolution of orographic precipitation features observed in AMIP runs in Fig. 3. The small-scale precipitation features (type 2) were lost

![Fig. 6. Day-23 (a) total precipitation, (b) vertical pressure velocity (ω), (c) MFC, and (d) zonal velocity (U) overlaid by surface geopotential for case 1 simulated by CAM FV 0.5°.](image-url)
via averaging in Fig. 3; however, the large-scale upslope features (type 1) were apparent. The features due to the baroclinic waves (type 3) were inherent to the setup we created and do not have easy analogs in the AMIP runs we examined.

b. Case 2: Double mountain

Figure 7 shows the surface geopotential and 30-day-mean total precipitation (as in Fig. 5) for case 2, two mountains of the same size. The large-scale stable upslope ascent precipitation features appear in this case as separate features on the windward side of each mountain. The features in front of the eastward, downstream peak are lower in intensity and smaller in extent as the moist air precipitates at the first peak. Daily precipitation plots (not shown) exhibit these features appearing in front of the peaks on day 1 with high intensity. They then move northward and lose intensity every day. The large-scale features simulated by CAM Eulerian spectral T85 are similar to CAM FV; however, there is a higher amount of merging between the two features simulated by CAM Eulerian spectral T170. There is almost a total merge in CAM Eulerian spectral T85 with relatively low peak intensity (1 mm day$^{-1}$), whereas features of the other three simulations have peak intensities at around 1.7 mm day$^{-1}$.

The main reason for the difference at the spectral resolutions is the spectral filtering applied to the topography for the spectral model. To understand the effect of topographic filtering, additional model runs were made with CAM Eulerian spectral T85 and T170 without the topographic filtering (Fig. 8).

The filtering reduces the peak height of CAM Eulerian spectral T85 by 243 m, which is 16% of the total height of the mountain (the reduction is 42 m for CAM Eulerian spectral T170). The spectral filtering for smoothing the topography in CAM5.0 is a two-dimensional filter applied to the Fourier and Legendre coefficients equally and is only a function of the total wavenumber. Such filters are effective, but they are shown to result in strong smoothing and do not guarantee shape preservation of the horizontal features.

![Fig. 7. The 30-day-mean total precipitation (mm day$^{-1}$) and surface geopotential for case 2 simulated by (a) CAM Eulerian spectral T85, (b) CAM Eulerian spectral T170, (c) CAM FV 1°, and (d) CAM FV 0.5°.](image-url)
The effect of removing the spectral filtering is especially apparent in CAM Eulerian spectral T85 precipitation plot (Fig. 8a; cf. Fig. 7a), where the mountains are more structured and two the large-scale features in front of each mountain are more distinct in the case of unfiltered topography. However, these features still have relatively low intensity when compared to other three simulations. The peak precipitation values of the two large-scale features for CAM Eulerian spectral T170 (Fig. 8b) increased with the steeper topography. The change in the topography of CAM Eulerian spectral T85 as a result of filtering can also be observed via the surface geopotential plot (Fig. 9).

The orographic precipitation simulated by CAM Eulerian spectral T170 strongly resembles CAM FV models due to the setup of the case 2, which is not observed in the AMIP runs given in Fig. 3. The mountains in case 2 are larger than the real topography and the related precipitation due to impinging airflow is easily resolvable for a fine-resolution spectral model. The separation distance between the two mountains is another parameter affecting the distribution of precipitation. The first mountain is located at 90°E and the second is located at 97°E, which allows a 10 gridpoint distance between them for CAM Eulerian spectral T170 and a 5 gridpoint distance for CAM Eulerian spectral T85. Having 10 grid points for CAM Eulerian spectral T170 allows for better resolution, so it was able to simulate the dryer region.

As the simulation proceeds, smaller precipitation features start to form after day 10 for all models except CAM Eulerian spectral T85 (they are not as apparent for CAM FV 1° because of their relatively lower values thus being lost in the 30-day-mean plots). These features start to form at the peak points of the mountains as apparent in Figs. 7b,d. The second mountain leads to small-scale dynamics, especially in between the two mountains (Fig. 10d).

Figure 10 shows diagnostic measures as in Fig. 6. The more structured manifestation of smaller-scale features compared to case 1 (Fig. 5), over both mountain peaks is apparent in Fig. 10a. A similar manifestation can also be observed in MFC in Fig. 10c, because of the smaller-scale local dynamics. In addition to the surface flux parameterization of the simple physics suite feeding moisture back to the atmosphere, turbulence can also play a role in making the smaller-scale features more structured. Houze and Medina (2005) showed that, even if a stable flow impinges on the mountains, it can

(Navarra et al. 1994).
organize itself to produce a layer of smaller-scale cellular overturning because of either shear-induced turbulence or buoyancy oscillations in the shear layer that are forced by the lower terrain.

Case 2 revealed that the size and the grid spacing between the two mountains significantly affect the simulation of orographic precipitation as well as the treatment of topography (i.e., the spectral filtering). We have yet to see the merging of the large features due to stable upslope ascent in front of each mountain peak for CAM Eulerian spectral T170. However, as we move toward less resolvable scales (case 3) that are more resembling of California Coast Ranges and the Sierra Nevada region, the differences between CAM FV and CAM Eulerian spectral models become more apparent.

c. Case 3: Realistic

In this case the differences between CAM FV and CAM Eulerian spectral models are much more apparent (Fig. 11). Both CAM FV model resolutions were able to simulate the dry region between the mountains, whereas there is a merge between two precipitation features in the cases of CAM Eulerian spectral T85 and T170. Both CAM FV resolutions were able to create distinct mountains separated from each other. The CAM Eulerian spectral T170 has connected the two mountains, leaving 5 grid points between peaks and CAM Eulerian spectral T85 merged the mountains into one (geopotential contours in Figs. 11a,b). This shows that, as the topography gets smaller and structured, the ability of all models to simulate orographic precipitation is reduced. The CAM FV dynamical core represents the spatial structure and relationship with underlying topography more realistically than the CAM Eulerian spectral dynamical core (Fig. 3).

In case 2, there was the suggestion that topographical filtering adversely affects the simulation of orographic precipitation. In case 3, the CAM Eulerian spectral core run without the filter, introduced significant amounts of noise due to Gibbs oscillations, thus producing smaller-scale precipitation features that dominate the entire field in a short period of simulation time. Therefore, without the topography filter, the simulation is not realistic.

In case 3, there are significant differences between two resolutions of the CAM FV model. In both CAM FV simulations, a precipitation feature occurs at the peak of the first, westward, mountain, which is lower than the
second mountain. On the second mountain, two separate precipitation features are observed over both the north and south ends of the Gaussian bell shape. The features simulated by CAM FV 1° are significantly lower in intensity when compared to CAM FV 0.5°. This separation of large-scale stable upslope ascent features into two is not observed in either CAM Eulerian spectral simulation; there is one large-scale feature related to each mountain peak as in the previous cases. These large-scale features are connected to the ones simulated over the first mountain peaks, creating a wet region between the mountains in both CAM Eulerian spectral simulations as opposed to the dry region in the CAM FV models. To understand these differences, total precipitation, vertical velocity, and MFC are plotted for both CAM FV 0.5° and CAM Eulerian spectral T170, for day 3.

The negative vertical pressure velocity (upward motion) at the windward side of the first mountain of CAM FV 1° simulation leads to the large-scale stable upslope ascent precipitation (Fig. 12c). This is not the case for CAM Eulerian spectral T170 (Fig. 12d); there is no precipitation over the first mountain but it is apparent over the second mountain, creating the single large precipitation peak observed in Fig. 12b. The reason we do not observe such single precipitation feature for CAM FV simulation (Fig. 12a) is the structured manifestation of both vertical velocity and the MFC (Fig. 12e) over the second mountain. Both stable upslope ascent and surface fluxes contribute to the organization of the precipitation for the CAM FV model, and both convergence/divergence boundaries and the negative vertical velocities occur at both tails of the second mountain, producing precipitation features over that area.

5. Conclusions

In this study, we aim to identify the local biases inherent to GCMs, with a focus on dynamical cores, by qualitatively assessing and comparing their performance in simulating orographic precipitation. We used observations and results of AMIP runs over a specific local area that
introduces challenging conditions for GCMs (California Coast Ranges and Sierra Nevada) as reference simulations of orographic precipitation to be tested via idealized setups with CAM Eulerian spectral and CAM FV dynamical cores in varying resolutions using a simple physics parameterization. Our conclusions can be summarized as follows:

- We were able to reproduce the large-scale stable upslope ascent precipitation features present in observations and simulated in AMIP runs (Fig. 3). The simulation of small-scale features was also observed in the idealized experiments. We were able to identify the origins of these features via orographic precipitation theory and diagnostic measures and classify them as 1) large-scale features due to stable upslope ascent, 2) smaller-scale features due to local surface fluxes, and 3) leeward side features due to baroclinic waves.
- Examination of the differences in simulation of these features by CAM FV and CAM Eulerian spectral dynamical cores with varying resolutions led to deeper understanding about the sources of biases related to GCM structure and how the biases evolve with varying resolution. CAM FV model simulations resembled observations, producing precipitation consistent with underlying topography as well as the dry regions. The fine-resolution CAM Eulerian spectral model exhibited similar behavior, when the mountains were well separated and the same height (cases 1 and 2). The CAM Eulerian spectral simulation developed biases similar to the AMIP simulations when the mountains were of different height and closer together (case 3). It was also noted that the effect of resolution is much more pronounced for CAM Eulerian spectral models compared to CAM FV models, because the improvement of results from T85 to T170 was significant while CAM FV 1° and 0.5° consistently produced similar results.
- The merger of two large-scale stable upslope ascent features observed in AMIP runs for CAM Eulerian spectral T170 were not observed in case 2, where mountains were well separated. Furthermore in case 2,
the removal of the spectral filtering applied to topography improved the results (especially for CAM Eulerian spectral T85). However, the merger was apparent in the realistic case 3 and the removal of spectral filtering gave unacceptable results for both CAM Eulerian spectral T170 and T85. We conclude that the performance of CAM Eulerian spectral dynamical core and the improvement capability of spectral filtering depend on both the scales of the topography and the scales of the features to be simulated. These scales are in a dynamic relationship with each other; thus, it is challenging to produce a specific solution of when and/or how to apply any limitation (e.g., filtering) to spectral models. Application of more flexible filters such as exponential filters (Navarra et al. 1994), scale-selective filters (Webster et al. 2003), or a variational filtering method (Rutt et al. 2006) can potentially improve the spectral model simulations by making it more adaptable to local spatial scales.

- The characterization of features observed in AMIP runs and our test cases is a crucial step toward application of our object-based bias quantification (which is the subject of part II of this study), as identification and isolation of these features will depend on the underlying conditions that create them as well as their size, shape, location, etc.

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