The Intermediate Complexity Atmospheric Research Model (ICAR)

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(Manuscript received 21 August 2015, in final form 9 December 2015)

ABSTRACT

With limited computational resources, there is a need for computationally frugal models. This is particularly the case for atmospheric sciences, which have long relied on either simplistic analytical solutions or computationally expensive numerical models. The simpler solutions are inadequate for many problems, while the cost of numerical models makes their use impossible for many problems, most notably high-resolution climate downscaling applications spanning large areas, long time periods, and many global climate projections. Here the Intermediate Complexity Atmospheric Research model (ICAR) is presented to provide a new step along the modeling complexity continuum. ICAR leverages an analytical solution for high-resolution perturbations to wind velocities, in conjunction with numerical physics schemes, that is, advection and cloud microphysics, to simulate the atmosphere. The focus of the initial development of ICAR is for predictions of precipitation, and eventually temperature, humidity, and radiation at the land surface. Comparisons between ICAR and the Weather Research and Forecasting (WRF) Model for simulations over an idealized mountain are presented, as well as among ICAR, WRF, and the Parameter-Elevation Regressions on Independent Slopes Model (PRISM) observation-based product for a year-long simulation over the Colorado Rockies. In the ideal simulations, ICAR matches WRF precipitation predictions across a range of environmental conditions with a coefficient of determination $r^2$ of 0.92. In the Colorado Rockies, ICAR, WRF, and PRISM show very good agreement, with differences between ICAR and WRF comparable to the differences between WRF and PRISM in the cool season. For these simulations, WRF required 140–800 times more computational resources than ICAR.

1. Introduction

The sophistication of modern weather and regional climate models has enabled many scientific advancements; however, this sophistication comes with a cost of added complexity, which has hindered their application in studies of more than a small number of simulations in relatively small domains. In particular, more complex models are
extremely computationally expensive, thus limiting the number, duration, resolution, and spatial domain of simulations performed with such models, particularly regional climate model simulations (Mearns et al. 2013; Kotlarski et al. 2014; Rasmussen et al. 2014; Rummukainen 2010). Similarly, the length and complexity of the source code in these models, often on the order of millions of lines of code, limits the ability of users to understand why the model behaves the way it does. These limitations create hurdles for both scientists and end users and potentially reduce insight into physical processes.

For climate downscaling, the computationally frugal alternative is the use of statistical downscaling methods. These methods include those based on directly rescaling climate model output for the variable of interest (Wood et al. 2002; Maurer et al. 2010; Stoner et al. 2013; Pierce et al. 2014), statistical techniques based on atmospheric circulation patterns (Bárdossy and Pegram 2011; Clark and Hay 2004; Langousis and Kaleris 2014; Wilby 1998), and weather generators (Vrac et al. 2007; Clark et al. 2004). Because the rescaling techniques are most often based directly on climate model precipitation, they have relatively strong assumptions of stationarity imposed on them that may not be reasonable in a changing climate (Gutmann et al. 2012; Chen et al. 2015). In addition, many of these methods introduce statistical artifacts even in their simulations of current climate (Gutmann et al. 2014; Maraun 2013), though more recent advances in this field have reduced those artifacts (Pierce et al. 2014). The techniques based on circulation patterns in the climate model are believed to require fewer stationarity assumptions, but they have other limitations: 1) they still require a consistent relationship between broad circulation patterns and local precipitation, 2) they can be affected by changes in the frequency of occurrence of these circulation patterns (Hertig and Jacobeit 2013), and 3) they do not permit a physically based interaction between atmospheric variables derived from first principles. Finally, because statistical methods require training on observed datasets, they are less useful in data-sparse regions of the world, and they may not be able to simulate events outside of the range of current observations, for example, more extreme precipitation.

Here we present the Intermediate Complexity Atmospheric Research model (ICAR) to serve as an intermediate point in the complexity continuum among statistical methods, highly idealized physical models (Smith and Barstad 2004, hereafter SB04), and fully nonhydrostatic numerical weather prediction models such as the Weather Research and Forecasting (WRF) Model (Skamarock and Klemp 2008). ICAR is designed to serve multiple purposes: 1) as a fast, quasi-dynamical model that can be used for downscaling multiple climate model realizations for long time periods and over large areas; 2) as a simplified model for analysis of atmospheric features such as orographic precipitation; 3) for uncertainty characterization in which a large number of simulations may be performed with perturbed physics parameterizations; and 4) as a simplified model having additional relevance to outreach and education, particularly for students who may lack access to high-performance computing.

ICAR is not the first effort to approach the problem from a more physically based perspective, though it is by far the most comprehensive approach short of a full numerical weather prediction model. Previous work focused almost entirely on orographic precipitation with highly idealized homogenous conditions. Early work on simple orographic precipitation models dates back to the models of Sarker (1966) and Rhea (1978), which both used a simple orographic lifting model to improve prediction of orographic precipitation in weather forecasts. More recent work (Barros and Lettenmaier 1993; Sinclair 1994; Georgakakos et al. 2005) developed more sophisticated models of orographic precipitation, though these models are still highly idealized and require many assumptions, not the least of which being that of spatial and temporal homogeneity in the atmosphere. In addition, they used simplified microphysics and limited dynamic formulations. From a more theoretical perspective, SB04 developed a model of precipitation using linear theory for atmospheric dynamics (Sawyer 1962; Smith 1979) but which, like previous work, required assumptions of homogeneity and used simple microphysical processes. Despite these limitations, the model of SB04 was used by Crochet et al. (2007) and Jarosch et al. (2012) in application to reanalysis and climate model data with ad hoc approaches to mitigate problems due to the required assumptions, for example, by masking out results from locations that are not saturated in the input dataset. None of these previous models approach a more general atmospheric model as developed here, but they illustrate the continuing urgent desire within the community for computationally frugal, physically based downscaling capabilities.

ICAR permits atmospheric simulations ranging in complexity from highly simplified formulations to a fully three-dimensional model with transient and spatially variable boundary conditions and wind fields and a sophisticated microphysics parameterization. Because ICAR is a general atmospheric model, maintaining a complete three-dimensional grid of pressure, wind, temperature, humidity, and various microphysical species, it is possible to include any of the physics packages used in a state-of-the-art regional climate model such as WRF. Even with this physical sophistication, ICAR can
greatly decrease the required computational time compared to WRF; this makes ICAR more suitable for a large class of problems, particularly those for which many model runs are required. In addition, the simplified nature of the model permits a more intuitive understanding of model simulations, thereby enabling both a greater number of and more tightly controlled idealized research experiments than can be performed with models such as WRF.

In this paper we describe the design and implementation of ICAR and provide some basic analysis of skill in idealized simulations as well as in a 1-yr simulation over a real domain. First, the model dynamics and physical parameterizations are described in an overview. Next, descriptions of two datasets to be compared to ICAR are presented, the Parameter-Elevation Regressions on Independent Slopes Model (PRISM) gridded observational dataset (Daly et al. 2002, 2008) and a high-resolution WRF simulation (Rasmussen et al. 2014). This is followed by two-dimensional ideal test cases comparing separate versions of ICAR having multiple levels of complexity to the linear model of SB04 and to WRF. Next, a year-long simulation over the Colorado Rockies is presented and compared with the PRISM dataset and a WRF simulation. Finally, a summary of the paper is presented along with a brief discussion of planned future model enhancements and applications.

2. Model description
   a. Overview

ICAR is a simplified three-dimensional atmospheric model. ICAR advects heat and moisture based on a transient three-dimensional wind field. This wind field is calculated from the combination of linear mountain wave theory with the circulation field from a forcing dataset such as the output from an earth system model (ESM) or a coupled atmosphere–ocean general circulation model (AOGCM) from the Coupled Model Intercomparison Project (CMIP; Meehl et al. 2005). ICAR uses a microphysical scheme to calculate precipitation and other hydrometeorological and thermodynamic tendencies. A simplified flowchart for the model is presented in Fig. 1. ICAR operates on a staggered Arakawa C grid with terrain-following coordinates. The primary simplification in ICAR is in the solution for the wind field; this permits ICAR to avoid directly solving the Navier–Stokes equations of motion, which form the numerical core of a traditional atmospheric model.

The input requirements for ICAR are the same as those of a regional climate model (RCM): three-dimensional time-varying temperature, pressure, humidity, and wind fields. However, unlike a traditional RCM, ICAR uses the three-dimensional fields of pressure and wind from the driving low-resolution model throughout the domain, while temperature and humidity are only applied at the boundaries of the model as in a traditional RCM (Fig. 1). ICAR can also use a spatially constant forcing dataset as from an atmospheric sounding. Low-resolution fields are linearly interpolated to the ICAR high-resolution grid, and pressure is adjusted for the change in elevation between the interpolated input grid and the ICAR grid, as shown in Fig. 1 (top). If other relevant fields, such as cloud water or ice, are available from a forcing dataset, these fields can also be input at the boundaries. These forcing data are read in for each available input time and linearly interpolated in time to match the internal model physics time steps. However, the linear wind perturbations (described below) are only calculated at each input time and are likewise linearly interpolated in time. The internal model state is updated with an explicit time-stepping scheme by alternately...
performing microphysical calculations and advection calculations, as shown in Fig. 1 (bottom).

The grid dimensions and input forcing time step may be specified at run time, as in other regional climate models. The internal time step in ICAR is calculated for each input wind field to satisfy the Courant–Friedrichs–Lewy (CFL) condition (Courant et al. 1928), with an upper bound that can be set to maintain stability in the physics schemes. As currently implemented, ICAR assumes a spatially uniform $x$ and $y$ grid size, specified at run time. Similarly, the vertical discretization of the model assumes a fixed vertical thickness as a function of $x$ and $y$, but the vertical thickness is allowed to change as a function of elevation above the terrain.

b. Dynamics

Linear theory predicts mountain wave formation using a linearized Boussinesq approximation (Smith 1979; Sawyer 1962), and a detailed overview of the dynamics derivation and calculations for the three-dimensional wind field is presented in Barstad and Gronas (2006). The solution to the equation is performed in frequency space, and in the following equations the Fourier transform to the equation is performed in frequency space, is presented in Barstad and Gronas (2006). The solution to the equation is performed in frequency space, and in the following equations the Fourier transform to the equation is performed in frequency space, is presented in Barstad and Gronas (2006). The solution to the equation is performed in frequency space, and in the following equations the Fourier transform to the equation is performed in frequency space, is presented in Barstad and Gronas (2006). The solution to the equation is performed in frequency space, and in the following equations the Fourier transform to the equation is performed in frequency space, is presented in Barstad and Gronas (2006).

Moreover, tests shown later in this paper suggest that these effects are of second-order importance. The Brunt–Väisälä frequency is computed in one of two different ways depending on whether the atmosphere is saturated or not; the dry $N_d$ and moist $N_m$ frequencies are computed as follows:

$$N_d^2 = \frac{g}{\theta} \frac{d\ln(\theta)}{dz}$$

and

$$N_m^2 = \frac{g}{T} \left( \frac{dT}{dz} + \Gamma_m \right) \left( 1 + \frac{Lq_s}{RT} \right) - \frac{g}{q_w} \frac{dq_w}{dz},$$

where $g$ is the acceleration due to gravity, here treated as a constant 9.81 m s$^{-2}$; $\theta$ is the potential temperature; $T$ is the sensible temperature; $\Gamma_m$ is the moist adiabatic lapse rate; $L$ is the latent heat of vaporization; $R$ is the ideal gas constant for dry air; $q_s$ is the saturation mixing ratio; and $q_w$ is the total water mixing ratio including both $q_s$ and the liquid water mixing ratio (Durrant and Klemp 1982). When the air is unsaturated, the dry Brunt–Väisälä frequency is used, and when the air is saturated, the moist Brunt–Väisälä frequency is used. Hereafter, references to the Brunt–Väisälä frequency refer to the squared form ($N^2$). The practical aspects of the calculation of the linear wind field, including the Brunt–Väisälä frequency, are discussed next.

Because of the use of the Fourier transform in the solution, care must be taken in the treatment of topography at the boundaries. In particular, the Fourier transform of the terrain assumes an infinitely repeating surface in $x$ and $y$. To prevent edge effects when one side of the domain is substantially higher or lower than the other, a buffer of 200 km is added to all sides of the domain prior to the solution of the linear equations. The terrain in this buffer is interpolated and progressively smoothed between the two edges of the domain so that there is no discontinuity in the effective terrain surface. This approach is similar to that taken when analyzing spatial frequencies, which may smooth the outer edges of the domain for this same purpose (Denis et al. 2002).

The use of a Fourier transform also means that all points in space are calculated simultaneously; however, the use of a spatially variable background wind field and high-resolution Brunt–Väisälä frequency requires that the linear solution be recomputed at every point. To prevent this from creating an excessive computational burden, a lookup table (LUT) is precomputed once at the beginning of the simulation. This LUT provides the linear solution for all combinations of a range of background wind speed and direction values and a range of Brunt–Väisälä frequencies. The values in this table are trilinearly interpolated to the exact $U$, $V$, and $N^2$ value.
of a given grid cell. The range and discretization of this table is left as an option for the user; typically, only 36 directions (0–2\(\pi\) rad), 7 speeds (0–30 m s\(^{-1}\)), and 10 logarithmically spaced stability values (from \(1 \times 10^{-7}\) to \(6 \times 10^{-4}\) s\(^{-1}\)) are used. Conditions outside of these ranges use the endpoint of the LUT. Sensitivity tests suggest that the exact discretization used does not have a very large effect. Such an LUT requires a large amount of random access memory (RAM).

Linear theory provides an estimate for the idealized steady-state mountain wave that would develop over topography; however, the atmosphere is rarely in steady state. The linear wind field can also be treated as developing over time within ICAR, in which case only a fraction of the linear wind field calculated at the current input time step is added to the background wind field. In this case, a point that changes background environmental conditions rapidly would not develop a strong mountain wave above it, while a point that maintains a more constant background environment would progressively develop a stronger mountain wave. The time constant used for this transient formulation of the linear perturbation can be specified at run time. For the simulations that are presented here, this time constant is set to zero, that is, instantaneous. Future work will investigate the sensitivity of this parameter. Not present in the current version of ICAR is the closely related issue of partially blocked flow, for which the effective lifting produced by the terrain may be worked out from the theory used in gravity wave drag algorithms, more specifically, in calculating the blocked-flow drag (e.g., Lott and Miller 1997).

Finally, because ICAR lacks a full dynamical solution, which would integrate out any spatial imbalance in the wind field, the wind fields must be properly defined to conserve mass and thus prevent numerical problems. To do this, vertical winds are calculated to balance the convergence in the density-weighted horizontal winds by continuity [Eq. (9)]:

\[
\frac{\partial \rho w}{\partial z} = \frac{\partial \rho u}{\partial x} + \frac{\partial \rho v}{\partial y},
\]

where \(\rho\) is the density of the air on the staggered \(u, v,\) and \(w\) grids, respectively. Density can optionally be fixed at 1.0 in this step and in the advection calculation, to match the Boussinesq approximation of the linear theory. This calculation is done starting at the first model level assuming no flow in and out of the terrain. Each successive model level takes the horizontal convergence (divergence) and adds (subtracts) that field from the \(w_{i-1/2}\) field to calculate the \(w_{i+1/2}\) field, where the subscript on \(w\) represents the vertical level. Note that the \(w\) field is horizontally centered on the mass grid cell, but vertically offset to fall between two mass layers, as in previous work (e.g., Smolarkiewicz and Margolin 1998; Skamarock and Klemp 2008). Alternatively, the same model stability could be achieved through modifications to the density field, though this is not explored in the current paper.

c. Advection

Advection in ICAR is handled using an unsophisticated first-order scheme (Courant et al. 1952). This scheme is positive definite and computationally efficient, but is known to be highly diffusive. In the future, more sophisticated schemes, such as Multidimensional Positive Definite Advection Transport Algorithm (MPDATA; Smolarkiewicz and Margolin 1998) or third-order Adams–Bashforth (Durran 1991), will be implemented, but in the initial version of the model, simplicity and speed were deemed higher priorities. The fundamental advection equation is as follows:

\[
\frac{\partial q}{\partial t} = \frac{\partial Uq}{\partial x} + \frac{\partial Vq}{\partial y} + \frac{\partial Wq}{\partial z},
\]

where \(q\) is the scalar conserved quantity to be advected; \(U, V,\) and \(W\) are the wind speeds in the horizontal \(x\) and \(y\) and vertical dimensions, respectively, multiplied by the air density \(\rho\) on their respective grids. The scalars advected in ICAR are potential temperature, and mixing ratios of water vapor, cloud water, cloud ice, rain, snow, and, if present, graupel, and number concentrations of rain and cloud ice. Number concentrations do not include density in the advection term.

d. Microphysics

Microphysical calculations can be handled in one of two ways at present. First, a simplified microphysics scheme comparable to that in the linear model of SB04 is employed. This permits us to compare ICAR results to the linear model, with the primary difference being in our numerical discretization of the problem. Second, we have incorporated the Thompson microphysics scheme (Thompson et al. 2008). This scheme is a sophisticated, double moment in cloud ice and rain, microphysical scheme, which is prognostic for mixing ratios of water vapor, cloud water, rain, cloud ice, snow, and graupel. The Thompson microphysics scheme is not described further here, and the code used in ICAR comes directly from the WRF, version 3.5.1, codebase with only minor modifications for parallelization within the ICAR framework.

The simple microphysics scheme, based on SB04, assumes all humidity in excess of saturation is immediately transformed to cloud water, and this cloud water is converted into precipitable hydrometeors with a time
constant $\tau_c$, $O(500)$ s for rain in SB04. These hydrometeors reach the ground with a time constant $\tau_f$, $O(500)$ s for rain in SB04, based on the assumption of a $10 \text{ m s}^{-1}$ terminal velocity for rain. In SB04, cloud water and rain evaporation occurs instantaneously in subsaturated air, though if the quantity of rain to be evaporated exceeds the vertically integrated saturation deficit, rain can reach the ground even in the lee of the terrain. In the simple microphysics option implemented here we retain a time constant for the conversion from cloud water to rain of $500$ s and from cloud ice to snow of $2000$ s, but we implement the fall speed explicitly as $10 \text{ m s}^{-1}$ for rain and $2 \text{ m s}^{-1}$ for snow, to be consistent with the physical representation in SB04 and the numerical discretization in ICAR.

3. Evaluation data

a. WRF

The WRF Model is used to evaluate ICAR for both ideal and real test cases. WRF is a compressible, non-hydrostatic, atmospheric weather model (Skamarock and Klemp 2008; Klemp et al. 2007) used both for numerical weather prediction and regional climate modeling. The ideal test cases use WRF, version 3.5.1, with the Thompson microphysics (Thompson et al. 2008). For the real test cases, the model output from Rasmussen et al. (2014) was used. Rasmussen et al. (2014) used WRF with the Noah land surface model (Chen and Dudhia 2001), Thompson microphysics, Yonsei University planetary boundary layer (Hong et al. 2006), and Community Atmosphere Model (CAM) longwave and shortwave radiation (Collins et al. 2006). Additional descriptions of the domain and forcing data used for these simulations are given later in the description of the real test case.

b. PRISM

The PRISM monthly gridded dataset (Daly et al. 2002, 2008) is used as an observational dataset to compare with ICAR for the real test case. PRISM is derived from station measurements interpolated to a high-resolution grid and adjusted for elevation changes. These adjustments vary spatially by regional topographic aspect attributes and are further refined based on expected orographic effectiveness of local terrain as defined by subgrid topography statistics. While gridded precipitation datasets have their weaknesses (Lundquist et al. 2015; Gutmann et al. 2012), the PRISM dataset often serves as a benchmark for comparison because it represents a best guess based on observations. The monthly PRISM dataset is produced on a $0.04167 \degree$ grid ($\sim 4 \text{ km}$).

4. Evaluation

a. Idealized hill experiment

A series of ideal cases are presented to compare ICAR with WRF and the linear model of SB04. In these cases, ICAR is run once with the Thompson microphysics, once with the simple microphysics, and once with the Thompson microphysics but with the linear wind calculations turned off, leaving only the background wind field. This enables linked evaluations of the effect of the choice of microphysics, the effect of discretization in ICAR as compared to SB04, the effect of the linear wind calculations, and the effect of the simplification from WRF to ICAR.

The ideal cases are all based on homogenous flow over a two-dimensional, 1-km-tall mountain (Fig. 2). The shape of this mountain is defined as follows:

$$Z(x) = \frac{H_m}{1 + \left(\frac{x - x_m}{w_m}\right)^2} - H_0,$$

where $Z$ is the land surface elevation, $H_m$ is the height of the mountain (1000 m), $x$ is the horizontal position, $x_m$ is
Plots of precipitation rate averaged from 8 to 12 h into the simulation are shown in Fig. 3 for a subset of environmental parameter combinations. These plots show that ICAR, run with the linear solution and the Thompson microphysics (ICAR$_L$), produces a similar spatial pattern of precipitation as WRF. There are some differences between WRF and ICAR, in the location and amount of the precipitation rates, but differences are typically less than 0.2 mm h$^{-1}$. This shows that the simplifications within ICAR are reasonable across a range of environmental conditions, at least as compared to a much more complex representation of the physics in a fully dynamic atmospheric model.

In contrast, the linear model of SB04 produces a somewhat different spatial distribution of precipitation. The precipitation maximum is farther upwind in SB04 than in WRF; precipitation typically begins much farther upwind than in WRF and ends more abruptly just downwind of the mountain top. ICAR with the microphysics from SB04 (ICAR$_S$) produces a very similar structure to that of SB04, showing that the differences between SB04 and WRF are primarily due to the microphysics formulation. However, ICAR$_S$ is able to adjust for subsaturated air and, as a result, has less precipitation for the 75% relative humidity cases. In addition, because ICAR$_S$ can simulate saturated air near the surface even when the total column is not saturated, ICAR$_S$ produces more precipitation downwind of the topographic peak than the linear model, seen most clearly in the 15 m s$^{-1}$, 270 K, 99% humidity case and the 20 m s$^{-1}$ cases (not shown). This shows that differences due to the assumptions of homogeneity and saturation in the linear model are also problematic.

Simulations without the linear perturbation (ICAR$_{L}$) show how the decrease in the upward air motion, shown in Fig. 2, reduces the total precipitation substantially. This is most prominent in the 5 m s$^{-1}$ cases in Fig. 3, in which precipitation is more than tripled without the linear wind solution, though it is also evident in the faster wind speed cases and in real domain tests (not shown). The location of the precipitation also tends to be shifted slightly downwind when the linear wind solution is not used. This may be due to lifting occurring at higher levels in the atmosphere, which can allow precipitation to be carried farther downwind before it reaches the ground. This is particularly true for snow, which has a terminal velocity 2–10 times slower than the background wind speeds used in these simulations.

To summarize results across the full range of environmental combinations in Table 1, we simplify the data to show only the precipitation rate averaged over the domain using ICAR run with the Thompson microphysics and linear dynamics. Average precipitation from

<table>
<thead>
<tr>
<th>Variable</th>
<th>Options</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wind speed (m s$^{-1}$)</td>
<td>5, 10, 15, and 20</td>
</tr>
<tr>
<td>Relative humidity (%)</td>
<td>75, 90, and 99</td>
</tr>
<tr>
<td>Surface temperature (K)</td>
<td>260, 270, and 280</td>
</tr>
</tbody>
</table>

the location of the center of the mountain (the middle of the domain), $w_m$ is the half-width of the mountain (20 km), and $H_0$ is the value of the first half of the expression at the edge of the domain to set the boundaries to an elevation of zero. The models are run multiple times with all combinations of varying surface temperature, wind speed, and relative humidity: options for each variable are presented in Table 1, and all 36 possible combinations are used. These environmental conditions were selected because we wish to focus initially on cool-season, nonconvective precipitation events. In all cases, the temperature profile was specified with a constant increase in potential temperature with height (3 K km$^{-1}$) corresponding to an environmental lapse rate of $-6.8$ K km$^{-1}$. This is equivalent to a dry Brunt–Väisälä frequency of $1 \times 10^{-4}$ s$^{-2}$, but a variable moist Brunt–Väisälä frequency. The moist frequency varies with altitude; it is approximately $1 \times 10^{-4}$ s$^{-2}$ at altitudes above 6500 m in all cases, and at altitudes less than 1000 m, it varies with the base temperature from $1 \times 10^{-4}$ s$^{-2}$ when the base temperature is 260 K to $1 \times 10^{-7}$ s$^{-2}$ when the base temperature is 280 K. In both cases, it increases with elevation. Because we are most interested in precipitation, and thus moist dynamics, we use a Brunt–Väisälä frequency of $3 \times 10^{-5}$ s$^{-2}$ for the ideal simulations. For the ideal cases we chose not to vary the Brunt–Väisälä frequency within the domain to be consistent with the model of SB04, and this does not appear to substantially decrease the skill in comparison to WRF because the value selected is representative of the lower atmosphere where precipitation is forming. Adjusting this value in space and time might improve the simulations with respect to WRF but would complicate the interpretation relative to the model of SB04, and the current simulations already perform very well in comparison to WRF. Background wind speed and relative humidity were specified as constant with height. The vertical components of the wind fields are presented in Fig. 2 for the 20 m s$^{-1}$, 260 K, 75% humidity case as modeled by WRF and ICAR using a Brunt–Väisälä frequency of $1 \times 10^{-4}$ s$^{-2}$. Note that the vertical component of the wind in ICAR without the linear wind solution is simply the background wind speed multiplied by the slope of the topography and is constant with height.
ICAR is plotted against the corresponding WRF simulation in Fig. 4. These results illustrate that, across a broader range of environmental conditions, ICAR matches WRF precipitation rates. Upon examination of the WRF wind fields from each simulation, we found that WRF exhibited some convection in a few simulations, and the simulations with convection present on the upstream side of the mountain are marked as black squares in Fig. 4. These simulations corresponded to the 99% relative humidity, 280 K cases with wind speeds less than 20 m s\(^{-1}\) and the 90% relative humidity, 280 K cases with wind speeds less than 15 m s\(^{-1}\), five simulations total. In these simulations, ICAR typically underpredicts precipitation as compared to WRF. This is not surprising, as the current version of ICAR has no convective scheme. Including all results, the correlation between the WRF and ICAR simulations has a coefficient of determination \(r^2\) of 0.92; after removing the cases for which WRF exhibited substantial convection, the \(r^2\) increases to 0.96. If the statistical outlier at 0.5 mm h\(^{-1}\) is also removed, the \(r^2\) only drops to 0.93.

Overall, the performance of ICAR in the ideal simulations shows that it matches the output of a far more sophisticated atmospheric model and that the improvements in ICAR relative to previous simplifications can clearly be traced to the improved microphysical representation and the ability to simulate variably saturated air made possible by the spatial discretization of ICAR. The skill ICAR shows in simulating changes in precipitation comparable to that of WRF suggests that its representation of changes in precipitation due to

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**Fig. 3.** Precipitation over an idealized hill (centered at 100 km; dotted line) with various environmental conditions. Wind speeds are (top) 15 and (bottom) 5 m s\(^{-1}\). Shown are relative humidity values of (a),(b) 75% or (c),(d) 99%; and base temperatures of (a),(c) 260 or (b),(d) 270 K. Lines show precipitation from the linear model of SB04 (red); ICAR with the microphysics from SB04 (orange); ICAR with the Thompson microphysics (green); ICAR with the Thompson microphysics, but with the linear solution turned off (blue); and WRF with the Thompson microphysics (black).

**Fig. 4.** Scatterplot of ICAR and WRF precipitation rates (mm h\(^{-1}\)) averaged across the 200-km-wide domain centered on the ideal hill for all ideal cases. Each point represents a model run with a different set of environmental conditions. Square points are runs identified as being convectively unstable in WRF. A one-to-one line is also plotted.
climate change may be comparable to those in WRF, at least for orographic precipitation. Indeed, the differences between WRF and ICAR are less than the differences that would occur between two WRF simulations with different microphysics parameterizations of equivalent sophistication (e.g., Liu et al. 2011), and initial climate change simulations with ICAR show a change signal closer to that of WRF than to various statistical downscaling methods (not shown).

b. Colorado Rockies experiment

A single real case is presented to compare ICAR with observations and WRF for a fully three-dimensional simulation over the domain of Rasmussen et al. (2014). In this case, ICAR is only tested using the Thompson microphysics and with variations in the linear dynamics. A map of the domain is shown in Fig. 5; covering this domain with 4-km-wide grid cells results in a grid that is 318 and 264 grid points in the x and y dimensions, respectively. The WRF domain used 44 vertical layers ranging in thickness from 36 m at the surface to greater than 500 m at higher altitudes. The top of the WRF domain was specified at 100 hPa, approximately 16 km above sea level. The ICAR domain used 14 vertical layers ranging in thickness from 60 m at the surface to 500 m at higher altitudes. The top of the ICAR domain was specified as 5.64 km above the land surface, which is 7.4 km above sea level on average over this domain.

The boundary conditions for these model simulations were derived from the North American Regional Reanalysis (NARR), which has a 32-km grid spacing (Mesinger et al. 2006). These simulations were performed beginning on 1 October 2000 and ending on 30 September 2001. To simplify the processing, ICAR was forced with the output from a 36-km WRF simulation that covered the same domain; the 36-km WRF simulation was also forced with the NARR boundary conditions. The 36-km WRF simulation does not add substantially to the computational cost, because it also runs over 700 times faster than the equivalent 4-km WRF simulation, though ICAR can be run directly with output from a climate model, reanalysis product, or other relevant atmospheric dataset. In addition, a 4-km WRF simulation would also typically utilize a lower-resolution simulation as an outer nest when applied to downscale a climate model directly. ICAR simulations are performed with the full linear solution of SB04 for the wind field perturbations and the Thompson microphysics. While the previous ideal simulations illustrated the importance of the microphysical calculations and the linear wind solution, these simulations test the ability of ICAR to simulate a transient simulation in the real world in comparison to observations.

1) Spatial comparisons

The cool-season total precipitation amounts from ICAR and WRF are shown in Fig. 6. We emphasize cool-season (from 1 October to 1 May) totals because we are initially focused on stratiform orographic precipitation processes rather than convective processes; this season is particularly relevant for water management in this and other similar domains because cool-season precipitation forms the mountain snowpack, the natural reservoir crucial to meeting human and ecological water demands. Compared to the WRF simulation (Fig. 6a) and PRISM data (Fig. 6c), the ICAR simulation (Fig. 6b) has a very similar precipitation distribution over most mountain ranges, with a slight overestimate in the San Juan Mountains and a slight underestimate in the Park Range and in the valleys.

Interestingly, the ICAR simulations are actually closer to the PRISM observations than the WRF simulations are in some areas, particularly near the southern and western boundaries, including as far north as the southern San Juan Mountains. These boundaries are where most flow enters the domain, and the WRF output may still be influenced by boundary artifacts, up to 36°N. In contrast, ICAR matches the PRISM spatial distribution after only a few grid cells into the domain.
Because of this, we exclude a large border area (50 grid cells see Fig. 5) when making quantitative comparisons between WRF and ICAR. This is approximately the distance to the 36°N line, north of which is where WRF agrees best with PRISM.

In some other regions, ICAR is more similar to the WRF simulation than to PRISM. In some of these regions, both ICAR and WRF may simply suffer from similar problems. In a few locations, however, most notably in the La Garita Mountains, WRF has been shown to have a better representation of annual precipitation than PRISM because of a lack of measurements with which to constrain the PRISM data (Gutmann et al. 2012). Here ICAR is also able to represent the decrease in atmospheric moisture downwind of the San Juan Mountains, and thus, like WRF, ICAR predicts precipitation totals more accurately than PRISM.

In addition to season total precipitation, it is notable that ICAR matches much of the spatiotemporal variability in a month-to-month comparison with WRF and PRISM (Figs. 7, 8). During the cool season, ICAR, WRF, and PRISM display very similar month-to-month variations, with more precipitation in October, particularly in the southern half of the domain, and less precipitation in November–January, followed by an increase in precipitation again in February and April that is more centrally located in the domain. Finally, in May, both models predict more precipitation on the northeastern side of the mountains; however, WRF shows a large amount of precipitation over the eastern Great Plains driven by convection in the model throughout the warm season. WRF actually overestimates this convective precipitation when compared to PRISM. Because the current version of ICAR does not represent convection, it is unable to simulate these processes, although the amount it underestimates this precipitation is comparable to the overestimate in WRF. This convection-dominant feature continues through September, although there remains some signal in the ICAR simulation, for example, less precipitation in June than in July and August, particularly in the mountains.

2) QUANTITATIVE COMPARISONS

Quantifying the comparison between WRF and ICAR winter precipitation totals shows somewhat mixed results. Scatterplots of cool-season total precipitation are shown in Fig. 9. The scatterplots are color coded by the density of the number of points in each region, with each point representing one grid cell in the model domain. While the spatial correlation between the ICAR simulation and the WRF simulation has a seemingly low $r^2$ value of 0.72, this is actually comparable to what might be expected for
FIG. 7. Monthly precipitation totals (mm) over the domain (October–March) from (left) WRF, (center) ICAR, and (right) PRISM.
FIG. 8. Monthly precipitation totals (mm) over the domain (April–September) from (left) WRF, (center) ICAR, and (right) PRISM.
different RCMs. For example, the spatial correlations between cool-season precipitation totals from different North American Regional Climate Change Assessment Program (NARCCAP) models (Mearns et al. 2013) in this region have $r^2$ values that range between 0.22 and 0.91 with a mean of 0.65. In addition, scatterplots comparing ICAR and PRISM, and WRF and PRISM, are also shown in Fig. 9. The $r^2$ value for the correlation between ICAR and PRISM is 0.63; between WRF and PRISM, it is 0.78.

When comparing ICAR to WRF, various features are apparent in Fig. 9. First, ICAR can clearly be seen to have a low bias on average over the domain; this stands out as a shift in the location of the scatterplot, particularly for lower values. Second, the previously mentioned low bias in ICAR precipitation over the Park Range stands out in the scatterplot, with most of the points above 650 mm in WRF and less than 600 mm in ICAR coming from the Park Range. In addition, the high bias in ICAR relative to WRF in the San Juan Mountains leads to the slight high bias for points greater than 500 mm in ICAR. ICAR has less bias in this region relative to PRISM, and WRF is biased low compared to PRISM over the San Juan Mountains.

Next, subdomain averaged monthly precipitation time series from WRF, ICAR, and PRISM are evaluated quantitatively. For this comparison, we neglect the eastern plains and set the eastern edge at 105°W, because this region will not be simulated well until convection is included in ICAR. For the cool season, the correlation between subdomain average monthly total precipitation from ICAR and WRF has an $r^2$ value of 0.85, between ICAR and PRISM the $r^2$ is only 0.56, and between WRF and PRISM the $r^2$ is only 0.82. When including the warm-season months up until 1 July, the $r^2$ value remains reasonably high (ICAR–WRF = 0.50, ICAR–PRISM = 0.55, and WRF–PRISM = 0.82), but drops substantially when including the entire year (ICAR–WRF = 0.20, ICAR–PRISM = 0.25, and WRF–PRISM = 0.86) because of the poor representation of convection in the later summer months.

Finally, the intensity distributions of daily cool-season precipitation events are shown for ICAR and WRF in Fig. 10. No comparison to PRISM is possible because PRISM is a monthly product. Figure 10 shows that the low bias in ICAR seen in Fig. 9 is distributed roughly evenly across the range of precipitation intensities. However, ICAR does not produce as many of the largest-magnitude events (>50 mm day$^{-1}$) as WRF does. ICAR also does not produce excessive drizzle when compared to WRF. For the warm season, ICAR will have more problems reproducing extreme events until convection is better simulated, though convection remains a problem for most regional climate models.

3) REAL SIMULATION DISCUSSION

The initial evaluation of ICAR for cool-season precipitation is promising; however, more work needs to be done to improve the model, most notably to account for convection. In the future, such improvements to the physical realism of ICAR will increase our confidence in the model results in current and future climate. However, even without such improvements, ICAR already offers a new approach to downscaling climate data that is more based on fundamental physics than any of the statistical methods currently in use. There are many facets of ICAR that could be explored in the future as well. For example, the relatively low model top in ICAR means that high clouds will not be simulated. This could affect the current simulations through the lack of high seeder clouds, and future work simulating convection or radiation could also be affected.
Analysis of the contribution of individual model components to errors in different subregions within the domain may also shed light on the physical processes controlling precipitation over each mountain range. Although a similar analysis can be done to some extent within the framework of a more sophisticated model such as WRF, it is often difficult to completely disentangle various competing parameterizations in such a model, making it difficult to tease apart the interrelationship between different processes. While an analysis performed purely with ICAR would also be incomplete, ICAR adds an additional tool to permit researchers to study atmospheric processes, for example, the ability to vary or turn off the linear solution; to use spatially or temporally constant wind, temperature, or humidity fields; and to test many changes in the microphysics, all without incurring excessive computational expenses.

For the purposes of this paper, the output of WRF has been considered as a validation target, although it should be pointed out that neither WRF nor PRISM is correct. Indeed, three different regional climate models will result in three different precipitation maps, in no small part because of variations in the subgrid-scale physics parameterizations used. Part of the goal of ICAR is to provide the ability to test the effect of many different physics parameterizations for long simulations, a goal that is computationally infeasible for a more complex atmospheric model such as WRF. In addition, WRF simulations have been shown to be more accurate than some gridded observational products for season total precipitation over some mountain ranges (Gutmann et al. 2012); as such, they make as good a target as the PRISM data do, at least in some regions.

5. Computational requirements

The real test case described above provides an excellent example of the reduction in computational requirements of ICAR (Fig. 11). These tests were all performed on the NCAR Yellowstone supercomputer (Computational and Information Systems Laboratory 2012), which uses 2.6-GHz Intel Xeon E5-2670 (Sandy Bridge) processors with 16 cores per node. For this test case, WRF required approximately 43 000 core hours for 1 year of simulation. Core hours are defined as the number of wall-clock hours times the number of processor cores used as tested on a cluster of 16-core 2.6 GHz Intel Sandy Bridge systems.
The speed of ICAR comes from a variety of sources. Most obviously, the lack of requirement to solve the Navier–Stokes equation reduces the required computation substantially; however, that alone would not provide the speedup seen here. Additionally, the lower model top and decreased vertical resolution have the effect of decreasing the number of grid cells that need to be processed and increasing the allowable time step substantially. Both of these changes have less effect on ICAR output than they would in a fully dynamic simulation because they do not directly affect the dynamics. Similarly, the speedup from turning off the linear wind solution is primarily due to a slower typical domain maximum wind speed; as a result, ICAR uses a longer time step. For very short runs the model speed will be hindered by the time required to generate the linear wind lookup table (10 min), although this could simply be loaded from a disk if the same simulation needs to be performed multiple times. It is the combination of all of these factors that results in the significant decrease in model simulation times exhibited here.

6. Conclusions

We have shown that an intermediate complexity model of the atmosphere, which runs over 100 times faster than a traditional numerical weather model, can produce estimates of precipitation that reproduce 92%–96% of the variability from a fully nonhydrostatic numerical weather prediction model for ideal orographic cases, as well as 72% of the spatial variability and 85% of the month-to-month variability for real simulations of cool-season precipitation (October–April). We have also illustrated the importance of using a sophisticated microphysics package and of the representation of the atmospheric flow fields over topography within such a model.

It should be stressed that ICAR is not a complete representation of atmospheric physics, nor is it meant to be. Indeed, no atmospheric model is a truly complete representation of physics either; even large-eddy simulation (LES) models have subgrid turbulence and internal physics parameterizations. ICAR provides another step along the continuum of complexity that will enable new scientific endeavors primarily with respect to downscaling climate model output, though it may provide an opportunity to test some atmospheric hypotheses in a way that is not possible within either the original linear model framework or within a model such as WRF. It is important to note that the differences between ICAR and WRF are smaller than the differences between multiple climate model realizations (e.g., Deser et al. 2012; Kay et al. 2014; Sriver et al. 2015); as such, it may be more important to run many ICAR simulations with multiple climate models than it is to run one or a few WRF simulations.

This initial version of ICAR has been evaluated most thoroughly for orographic precipitation, but because it is a more general atmospheric model, it will be possible to simulate many other phenomena. In particular, the inclusion of large-scale convergence allows ICAR to produce precipitation in the absence of topography in the same way that a regional climate model with a convective parameterization would. The future inclusion of a convective scheme in ICAR is likely to substantially improve ICAR’s representation of precipitation in the warm season, and the inclusion of a land surface model will permit the representation of land–atmosphere interactions, which are of particular importance in reproducing surface temperature.

Future work will investigate the portrayal of climate change signals using ICAR as compared to a limited-duration simulation from WRF, and compared to statistical downscaling methods of varying complexity. We will also develop a version of ICAR that includes a convection scheme, land surface model, radiation scheme, and planetary boundary layer scheme in a future publication. Other areas that could be examined are the possibility of adding a bogus vortex to the wind and pressure fields to represent hurricanes, or squall lines derived from a limited set of high-resolution RCM simulations. The model source code is freely available at https://github.com/NCAR/icar.

Acknowledgments. This work was funded in part through a contract from the U.S. Army Corps of Engineers and a cooperative agreement with the U.S. Bureau of Reclamation. The authors thank Levi Brekke and David Raff for early feedback on the utility of such an approach, Andrew Newman and Andreas Prein for helpful discussions on atmospheric dynamics, and Justin Minder for prompting us to think about spatial variations in the linear wind field early on. All data and models used in this work are freely available.

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