BAMS Article

The Ongoing Need for High-Resolution Regional Climate Models

Process Understanding and Stakeholder Information

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ABSTRACT: Regional climate modeling addresses our need to understand and simulate climatic processes and phenomena unresolved in global models. This paper highlights examples of current approaches to and innovative uses of regional climate modeling that deepen understanding of the climate system. High-resolution models are generally more skillful in simulating extremes, such as heavy precipitation, strong winds, and severe storms. In addition, research has shown that fine-scale features such as mountains, coastlines, lakes, irrigation, land use, and urban heat islands can substantially influence a region's climate and its response to changing forcings. Regional climate simulations explicitly simulating convection are now being performed, providing an opportunity to illuminate new physical behavior that previously was represented by parameterizations with large uncertainties. Regional and global models are both advancing toward higher resolution, as computational capacity increases. However, the resolution and ensemble size necessary to produce a sufficient statistical sample of these processes in global models has proven too costly for contemporary supercomputing systems. Regional climate models are thus indispensable tools that complement global models for understanding physical processes governing regional climate variability and change. The deeper understanding of regional climate processes also benefits stakeholders and policymakers who need physically robust, high-resolution climate information to guide societal responses to changing climate. Key scientific questions that will continue to require regional climate models, and opportunities are emerging for addressing those questions.

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Regional climate modeling has been developed to understand processes affecting climate that are not resolved well by global models, particularly those that may be important for climate change in regions. A further motivation has been to provide policymakers and other stakeholders information about changing climate for their specific regions that is salient, credible and legitimate (Cash et al. 2003). High-quality simulation of regional processes is vital for satisfying this need. The scale of targeted regions is generally subcontinental, such as an agricultural or water-resource region (i.e., a few tens of kilometers).

Although global models can (and have) been run at resolutions fine enough to simulate regional processes, with grid spacings of a few to tens of kilometers, the cost of performing extensive simulation and experimentation with different assumptions about forcing scenarios and relevant Earth system processes has been prohibitive. Knowledge about the scientific value of high-resolution global modeling is emerging, but it is expected to evolve slowly given unprecedented data storage and analysis requirements, and lingering issues with model tuning and validation at unfamiliar scales; intuition for such issues is more easily drawn from regional benchmarks.

Beside computational considerations, one can tailor regional models to focus on climatic processes that are especially germane to a targeted region, such as sea ice in the Arctic or mesoscale convective systems where they prevail. Several such climatic processes that are highly relevant in the context of regional modeling are depicted in Fig. 1. With fine resolution, users of regional models can also exploit high-spatial-resolution observations to evaluate and refine the model performance.

There are several approaches to producing regional climate information. Obtaining regional climate from numerical models is often referred to as "dynamical" because the climate dynamics are explicitly simulated. Limited-area numerical models derived from forecast models or developed ab initio have yielded regional climate models (RCMs; Giorgi and Mearns 1991; Wang et al. 2004; Giorgi 2019), which are the focus of this article. Other numerical-model approaches have used global climate models (GCMs), either with uniform finescale grid spacing (Zhao and Held 2012; Bacmeister et al. 2014) or with variable resolution that has finescale grid spacing over a targeted region (Fox-Rabinovitz et al. 2008; Zarzycki et al. 2014; Sakaguchi et al. 2015). Here, finescale refers to resolutions of 50 km grid spacing or smaller as grid spacing of 100–150 km is still common for GCMs used in historical simulations and long-term projections. Statistical approaches under the general descriptor of empirical statistical downscaling (ESD) have also provided regional information. ESD covers a wide range of methods; Maraun and Widmann (2018) assess these approaches. Finally, hybrid approaches combine dynamical and statistical approaches to expand (Mearns et al. 2013), refine (Walton et al. 2015), or bias-correct (Wood et al. 2004) the output from numerical simulations.

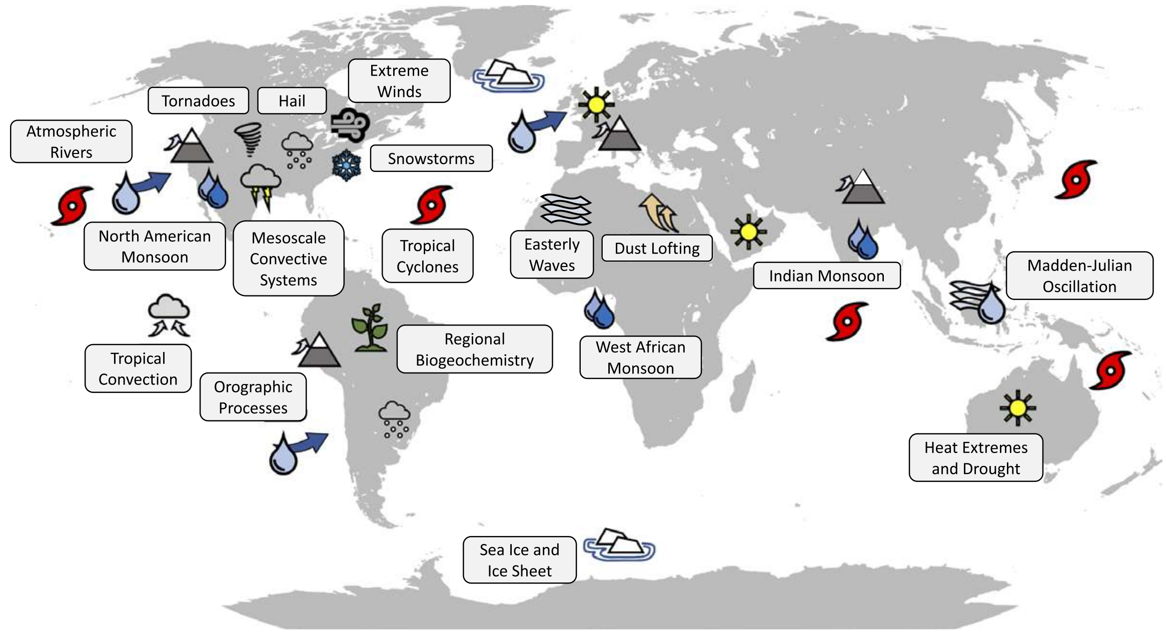

Fig. 1. Key features of the climate system where finescale regional climate modeling will likely be important for advancing our understanding.

As computing power has increased, the resolutions used by both global and regional models have tended to increase, though other simulation goals have also competed for the increased power, such as producing ensembles of simulations or adding more processes (carbon cycle, ecosystems, etc.) to make models more representative of Earth's climate system. For RCMs, the advances in computing power have allowed climate simulations at grid spacings of 1–4 km, for which a parameterization of atmospheric deep convection is no longer used, simulations termed "convection permitting" (see Prein et al. 2015, and references therein). These simulations cross a threshold into direct simulation of a process heretofore parameterized, and they show advantages over RCM simulations at coarser resolution (e.g., Yang et al. 2017). Higher resolution in RCMs permits better representation of key climate processes and features, as depicted in Fig. 2.

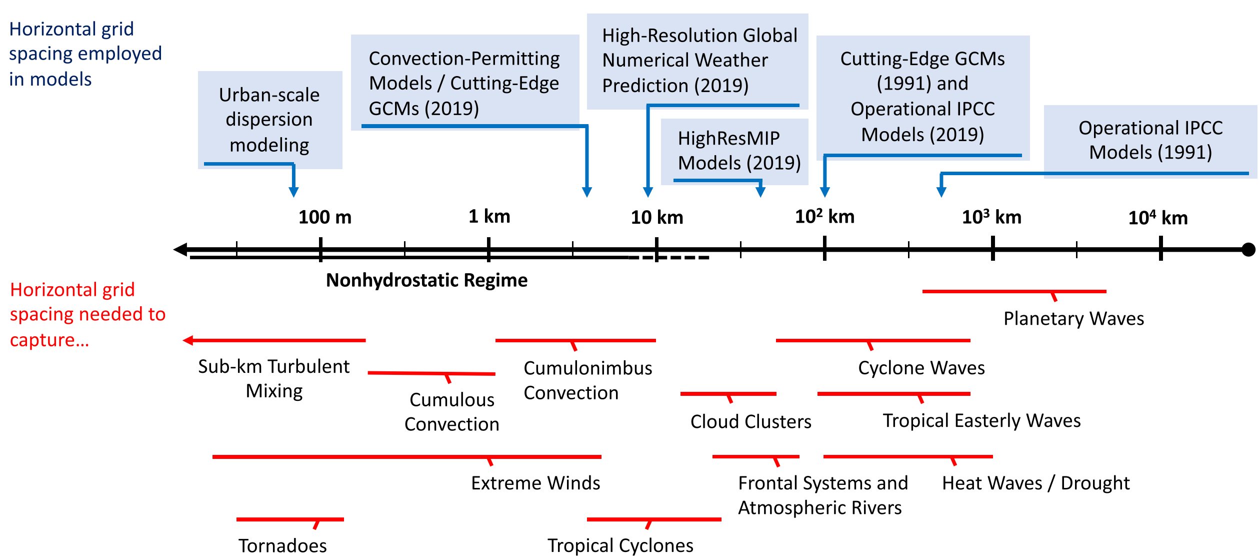

Fig. 2. The horizontal grid spacing employed in regional and global atmospheric models and the approximate horizontal grid spacing required to capture key atmospheric features. Regional climate modeling has the greatest potential to improve our understanding of processes where grid spacing less than 50 km resolution is needed.

RCM simulation relies on good input data for its boundary conditions, and so it can be sensitive to GCM biases. As resolutions for GCMs have increased, they have demonstrated potential for improving boundary conditions for RCM simulations (Roberts et al. 2018). The increase in supercomputer performance over the past 30 years has been approximately exponential, with performance doubling every 1.2 years (TOP500 2019), facilitating increased GCM resolution. However, the cost of global simulation can be substantial as resolution increases. Assuming model complexity and vertical resolution are held constant, the growth in computing performance would correspond to a feasible doubling of horizontal resolution every 3–4 years. The actual rate has been closer to 8–10 years (e.g., Cubasch et al. 2013), partly because of the other uses of increased computing power identified above. In fact, since the fourth IPCC assessment report was published in 2007, the nominal GCM resolution has remained at ~1°, although 0.25° simulations are now being conducted as part of the HighResMIP program (Haarsma et al. 2016). With this past experience in mind, it is expected that nominal grid resolution for GCM production simulations will be on the order of tens of kilometers for at least the next decade. This resolution places them clearly in the hydrostatic regime (typically grid spacing greater than 10 km).

Roberts et al. (2018) discuss the current and future capabilities of global high-resolution climate simulation, especially in the context of assessing climate risks associated with the hydrological cycle. This paper complements Roberts et al. (2018) in highlighting current capabilities of high-resolution climate modeling for regions by RCMs and pointing a direction for future development that complements and adds value to high-resolution GCM simulation. Although there is substantial RCM activity around the world (Giorgi and Gutowski 2015), we focus here primarily on North America in order to use a succinct set of regional processes for illustrating the benefits of high-resolution regional simulation of climate.

Overview of experimental designs and scientific questions addressed

RCMs have played an important role over the past three decades in advancing regional climate science for several reasons: 1) their low computational cost, relative to uniform-resolution GCMs; 2) their high level of configurability, which permits selection of physics options and calibration of model parameters to focus on domains and regional phenomena of interest and reduce regional climate biases; and 3) the unique experimental designs enabled through manipulation of lateral boundary conditions. The low computational cost arises simply because they operate over a limited area of the globe, with areal coverage—and therefore their computational cost relative to GCMs—typically not exceeding approximately 15% of the global surface area (e.g., the area of a quadrangle bounding a continent). This efficiency enables long integrations on university-scale computing clusters, and even desktop computers, worldwide (Schaller et al. 2018). For a fixed level of computational resources, RCMs thus enable higher model resolution, model complexity, and ensemble size (Fig. 3).

RCMs typically offer a higher level of atmospheric and land model configurability than GCMs. This is partly because RCMs, such as the Weather Research and Forecasting (WRF) Model, often offer a wide variety of parameterization choices. In addition, a regional model's flexibility in domain size and location can allow it to target specific regional processes (and choose appropriate parameterizations as needed). Further, the regional models' smaller domains and the grid nesting they often contain allow substantial flexibility in grid-spacing choices. This flexibility has important implications for regional climate-science experiments, as one can configure RCM experiments from a suite of subgrid parameterizations to ensure that processes important for regional phenomena are well represented in a given simulation: for example, cloud–radiation–turbulence interactions for coastal clouds (O'Brien et al. 2013; Jousse et al. 2016) and microphysics for mesoscale convective systems (MCSs; Squitieri and Gallus 2016; Feng et al. 2018). In addition to WRF's potential for optimizing parameterization choices for regional climate, WRF has spawned specialized variants, such as WRF-Chem (Grell et al. 2005), WRF-Hydro (Gochis et al. 2013), WRF-Parflow (Maxwell et al. 2011), and Polar WRF (Hines and Bromwich 2008).

There are three broad classes of experimental design that make RCMs a unique and invaluable tool for building our understanding of regional climate, which we describe below: lateral boundary condition modification experiments, dynamical downscaling experiments, and pseudo-global-warming experiments.

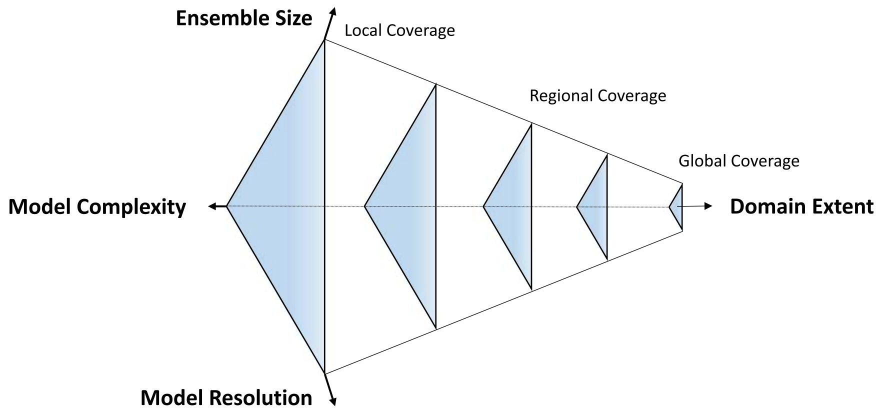

Fig. 3. A depiction of the allowed state space for modeling experiments given a prescribed limit on computational resources. Reducing the domain extent allows for more options for model resolution, ensemble size, and model complexity.

Lateral boundary condition modification. Regional climate models require prescribed lateral boundary conditions (LBCs). The LBCs are a controllable constraint on the simulation, providing an opportunity for unique experimental designs. Regional models are thus well suited for performing hypothesis-driven, mechanistic experiments to understand how transient wave activity propagating from one region can influence downstream atmospheric phenomena and climate. For example, experiments in which the midlatitude storm track was seeded by high-frequency atmospheric waves through the LBCs have demonstrated relationships between wave breaking and the North Pacific storm track (Orlanski 2005) and the North Atlantic Oscillation (Rivière and Orlanski 2007). This approach has also unraveled the causality between Atlantic tropical cyclones (TCs) and their typical precursor, African easterly waves (AEWs), on seasonal time scales. By designing a regional domain that included the TC genesis region and excluded the AEW genesis region, and applying a 2–10-day filter to the LBCs to remove any AEWs, Patricola et al. (2018) demonstrated that seasonal Atlantic TC number is not limited by AEWs.

Although LBCs provide opportunities for mechanistic experiments, they can pose a hindrance for addressing some types of scientific questions. The tropical-channel model is another configuration option, which uses periodic zonal LBCs, prescribed meridional LBCs, and a domain covering at least the entire tropical band. It is therefore well suited for understanding teleconnections between ocean variability and the weather and climate within the tropics, as the model design allows the atmospheric response to ocean forcing to propagate throughout the tropics uninhibited by zonal lateral boundary constraints. The tropical-channel configuration of the WRF Model has been used to understand MJO initiation (Ray et al. 2011) and the influence of the spatial patterns and magnitude of El Niño events on TC activity (Patricola et al. 2016). It is unique in demonstrating skill at representing interannual TC variability across Northern Hemisphere basins and the MJO (Fu et al. 2019).

Dynamical downscaling. Most uses of RCMs can be classified as dynamical downscaling. However, here we refer to "dynamical downscaling experiments" as experiments whose primary purpose is to produce high-resolution climate information from low-resolution boundary conditions. A large body of literature exists describing individual and coordinated (multimodel) downscaling experiments, such as the Coordinated Regional Downscaling Experiment (CORDEX; Giorgi and Gutowski 2015, and references therein). There are two main applications of dynamical downscaling: downscaling of output from atmospheric reanalyses, and downscaling of output from GCM simulations. With reanalysis-driven RCM simulations, synoptic state information from the LBCs, and possibly from scale-selective "spectral nudging" over the simulation domain (e.g., Kanamaru and Kanamitsu 2007a), drives the RCM such that its time-evolving synoptic state approximates the observed synoptic state. There is good evidence that this approach effectively allows an RCM simulation to be used like a regional reanalysis, achieving higher resolution than would otherwise be practical via global reanalysis (Kanamaru and Kanamitsu 2007b). For example, a 27 km WRF simulation with lateral boundary conditions prescribed from 2.5° reanalysis can reproduce the characteristics of atmospheric rivers compared with a reanalysis at ~0.5° resolution (Patricola et al. 2020); see Fig. 4 and the associated animation ES1 in the online supplemental material (https://doi.org/10.1175/BAMS-D-19-0113.2). Reanalysis-driven RCM simulations are also commonly used in configuring and assessing a model with respect to the mean climate and phenomena of interest in a region (e.g., Booth et al. 2018).

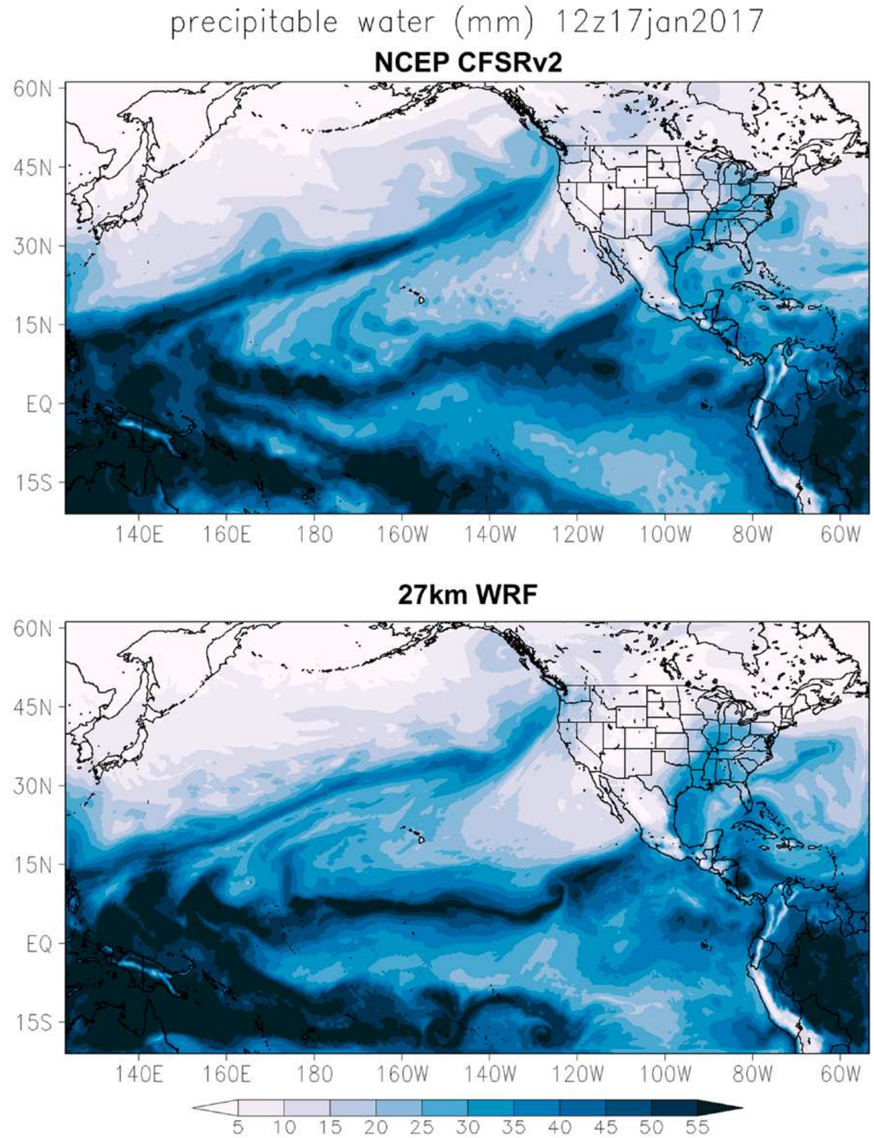

Fig. 4. An atmospheric river as shown by precipitable water (shaded; mm) at 1200 UTC 17 Jan 2017 from (top) the NCEP CFSRv2 (Saha et al. 2014) and (bottom) a 27 km resolution WRF simulation (Patricola et al. 2020). Lateral boundary conditions for the WRF simulation were prescribed from the 6-hourly 2.5° × 2.5° NCEP-II reanalysis. (See animation ES1 for an animation of this event.)

Reanalysis-driven simulations, often referred to as hindcasts, are often a preparatory step for GCM-driven experiments (Fig. 5). These experiments typically involve boundary conditions from GCM simulations of both historical climate and climate projections based on scenarios of future climate forcings. The former serves as a method for revalidating the RCM simulation and as a baseline for future climate simulations. Evaluating the performance of the historical GCM-driven RCM simulations is also important for assessing large-scale biases that the RCM may inherit from the driving GCM that can compromise results from accompanying climate change simulations. The biases could include, for example, incorrect midlatitude jet stream position or sea surface temperature (Giorgi and Gutowski 2015). The GCM-driven RCM simulations of future climate are then examined relative to their historical counterparts to understand how regional climate, and associated regional phenomena, might change with future climate forcing.

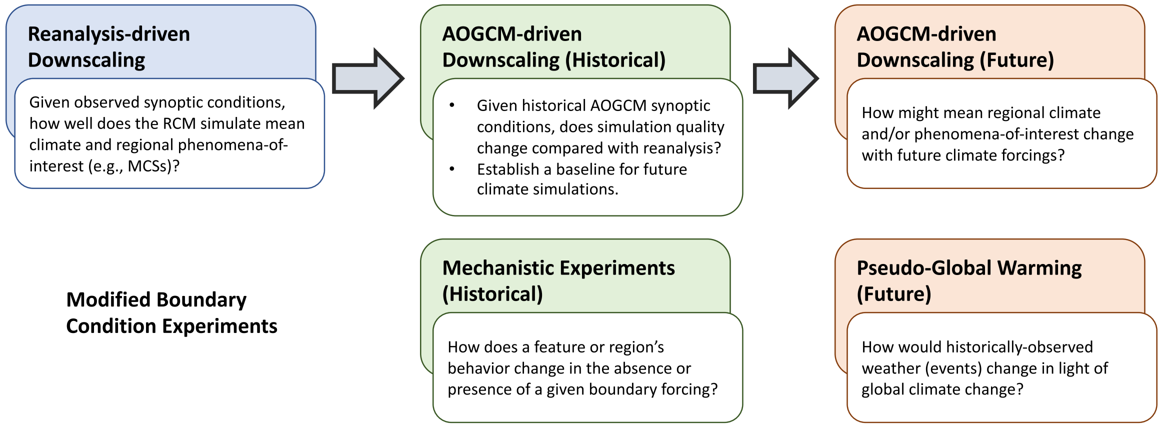

Fig. 5. Relationships among common RCM experimental designs and their associated scientific questions.

The historical GCM-driven simulations also allow assessing the added value from improved resolution of a region's climate processes that the RCM simulation contributes to the GCM output (Di Luca et al. 2016; Rummukainen 2016). For example, Bukovsky et al. (2017) noted that an ensemble of RCM simulations at 50 km grid spacing over North America produced improved baseline simulations and projected more consistent future summer drying in the central United States than their GCM counterparts. The drying was traced to mechanistically credible processes involving strengthening of the North American monsoon high, an earlier springtime poleward shift of the upper-level jet, strengthening of the Great Plains low-level jet converging moisture poleward, and land–atmosphere interactions that amplify the drying initially set up by the large-scale and mesoscale circulation changes.

Pseudo global warming. An alternate approach to direct dynamical downscaling of GCMs is pseudo global warming (PGW; Schär et al. 1996; Kimura and Kitoh 2007). The PGW approach utilizes reanalysis-driven RCM simulations as a baseline. Future climates are represented by modifying greenhouse gas concentrations, aerosols, and/or landcover in the regional model and using initial, surface, and lateral boundary conditions from reanalysis, with adjustments to add a mean climate change signal estimated from one or more GCMs. The synoptic and interannual variability from the present climate is maintained in these experiments. In addition, this treatment of surface and lateral boundary conditions attempts to mitigate any GCM biases (e.g., Richter 2015; Zuidema et al. 2016) that would be prescribed in the direct downscaling method and that can substantially degrade the quality of simulated extreme events such as tropical cyclones (e.g., Hsu et al. 2019).

The PGW approach can be applied for both continuous, decades-long simulations and event-scale experiments. It is particularly useful for addressing how climate change could influence the magnitude of specific historical events, conditional on the occurrence of similar synoptic or seasonal–interannual conditions in different climate scenarios. However, the approach is unable to inform changes in the frequency of events. An additional limitation of the approach is that it does not consider changes in transient eddy activity that may occur, for example, with changes in the midlatitude storm track. Nonetheless, the configurability provided by regional models is advantageous for producing simulations of historical events under conditions altered by climate change. The PGW approach has been used to quantify the influence of climate change (from preindustrial to present to future) on extreme synoptic events, including floods (Pall et al. 2017), extreme precipitation and convective storms (Prein et al. 2017a,b), and tropical cyclones (Patricola and Wehner 2018; Wehner et al. 2019), as well as multiyear drought (Ullrich et al. 2018).

Highlights of accomplishments to date

The finescale simulation provided by RCMs has allowed them to support the goal of advancing understanding of regional processes and their role in regional climate and climate change impacts. This success derives from their ability to resolve finescale atmospheric phenomena and finescale heterogeneity of surface properties, adding value not only by producing more spatial detail, but, more important, improving the overall simulation quality and enabling investigation of the role of finescale atmospheric phenomena and finescale surface heterogeneity in regional climate variability and change.

Finescale atmospheric phenomena. RCMs provide significant capabilities in resolving finescale atmospheric phenomena that are too computationally expensive to resolve in GCMs. Especially important examples of finescale atmospheric phenomena are different types of convection ranging from isolated and organized mesoscale convection to severe convective storms and hurricanes. Cumulus parameterizations have been a major source of uncertainty in climate modeling, with consequential impacts on many aspects of climate simulations through their direct influence on clouds, precipitation, and water vapor, and their indirect effects on radiation and atmospheric circulation.

Mesoscale convective systems (MCSs), for example, contribute over 50% of warm season precipitation in the central and midwestern United States. Failing to simulate MCSs, most GCMs exhibit dry and warm biases in those regions, accompanied by errors in the precipitation diurnal cycle and intensity (Lin et al. 2018; Van Weverberg et al. 2018). In contrast, convection-permitting RCMs with grid spacing of a few kilometers are able to simulate MCS behavior, allowing investigations of how large-scale environments and convection–circulation interactions may influence MCS characteristics such as lifetime and propagation (Yang et al. 2017; Feng et al. 2018), as in Fig. 6 (animated in animation ES2). By tracking and compositing MCSs that are explicitly simulated by a climate model, one can evaluate changes in storm characteristics to advance scientific understanding and provide important user-relevant information. Consistent with the observed changes in MCSs (Feng et al. 2016), MCSs in future warming scenarios produce a 15%–40% increase in maximum precipitation rates that also spread over larger rain areas (Prein et al. 2017a). Furthermore, as warming increases both the convective available potential energy (CAPE) and convective inhibition (CIN), convection-permitting RCM simulations project a shift of convective storms from weak-to-moderate convection to more frequent intense convection (Rasmussen et al. 2020). Global warming may also influence the characteristics of hazardous convective weather (HCW) such as hail, tornado, lightning, and strong winds. While resolving these processes requires modeling at subkilometer grid spacing, a model proxy based on the simulated updraft helicity and radar reflectivity factor has been used to study tornado characteristics in convection permitting simulations (e.g., Hoogewind et al. 2017). Future projections of hazardous convective weather may also be diagnosed from predictors such as wind shear, CAPE, freezing-level height, and storm relative helicity for hail (Prein and Holland 2018) and microphysical processes for lightning (Wilkinson 2017) in high-resolution simulations.

While decadal convection-permitting simulations can provide more robust statistics of signal to noise for analysis of climate response, their computational cost has limited their use to a relatively small number of studies (e.g., Rasmussen et al. 2011; Kendon et al. 2014; Prein et al. 2017a,b; Hoogewind et al. 2017). An alternative to continuous dynamical downscaling is to composite severe storms in short initialized simulations of specific storm events. This approach has been used to study storms in the present climate (e.g., Trapp et al. 2011; Robinson et al. 2013) and their future changes (e.g., Mahoney et al. 2013). Focusing on hailstorms in the Rocky Mountains, Mahoney et al. (2013) found that future warming may increase the height of the melting level, leading to a reduction in hail reaching the surface during the warm season.

Patricola and Wehner (2018) used a PGW approach to evaluate anthropogenic influence on major tropical cyclones. Comparing an ensemble of short RCM convection-permitting simulations of 15 major tropical cyclones in the historical record with and without anthropogenic forcing, they found that in 11 of the tropical cyclones simulated, future anthropogenic warming would robustly increase the storms' wind speed and rainfall. Convection-permitting resolution was necessary to reproduce the observed category 5 intensity of Hurricane Katrina (Fig. 2d of Patricola and Wehner 2018), and it captures finer-scale storm characteristics compared with 9 and 27 km grid spacing; see Fig. 7 and the associated animation in animation ES3.

Finescale heterogeneity of surface properties. Finescale heterogeneity in surface properties is another key source of spatial variability in weather and climate unresolved by GCMs. Elevation fluctuations in regions of complex topography are one important source of this finescale heterogeneity. Regional models have demonstrated added value over GCMs in resolving the significant spatial variations in temperature, circulation, and precipitation in such regions.

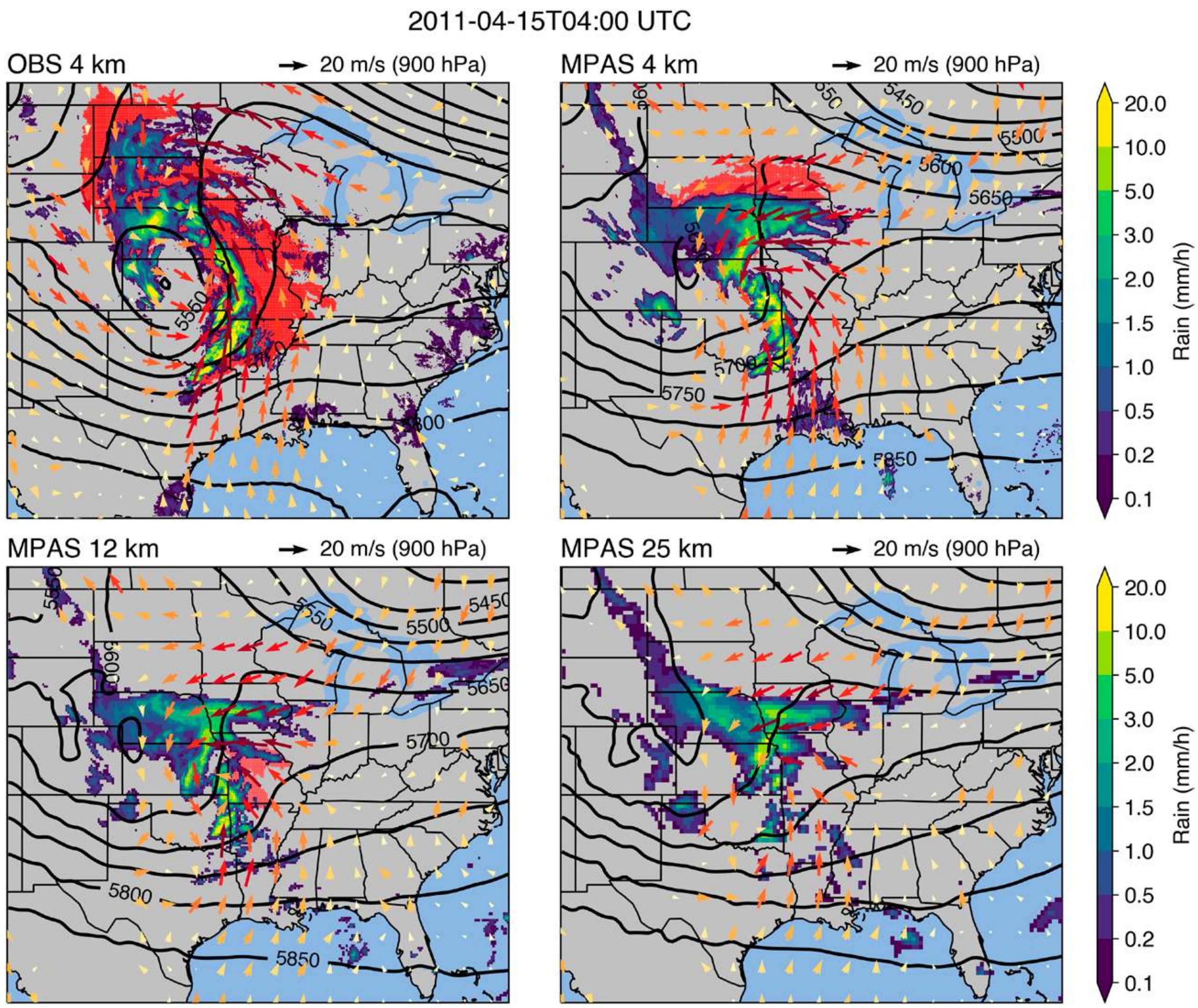

Fig. 6a. An MCS and its large-scale environment at ~0400 UTC 15 Apr 2011 from (top left) observations and three MPAS simulations at grid spacing of (top right) 4 km, (bottom left) 12 km, and (bottom right) 25 km in a regionally refined domain over the United States. The MCS is depicted by its cloud shield (red shading, defined as a contiguous area with brightness temperature <241 K; Feng et al. 2018) and precipitation (color shading varying from yellow to dark blue). The MCS large-scale environment is indicated by the 500 hPa geopotential height (black contours) and 900 hPa wind vectors (vectors with color shading). At 4 km grid spacing, the MCS developed under the strong baroclinic forcing of a frontal system. MPAS produced the most realistic simulation compared to observations. (See animation ES2 for an animation of this event.)

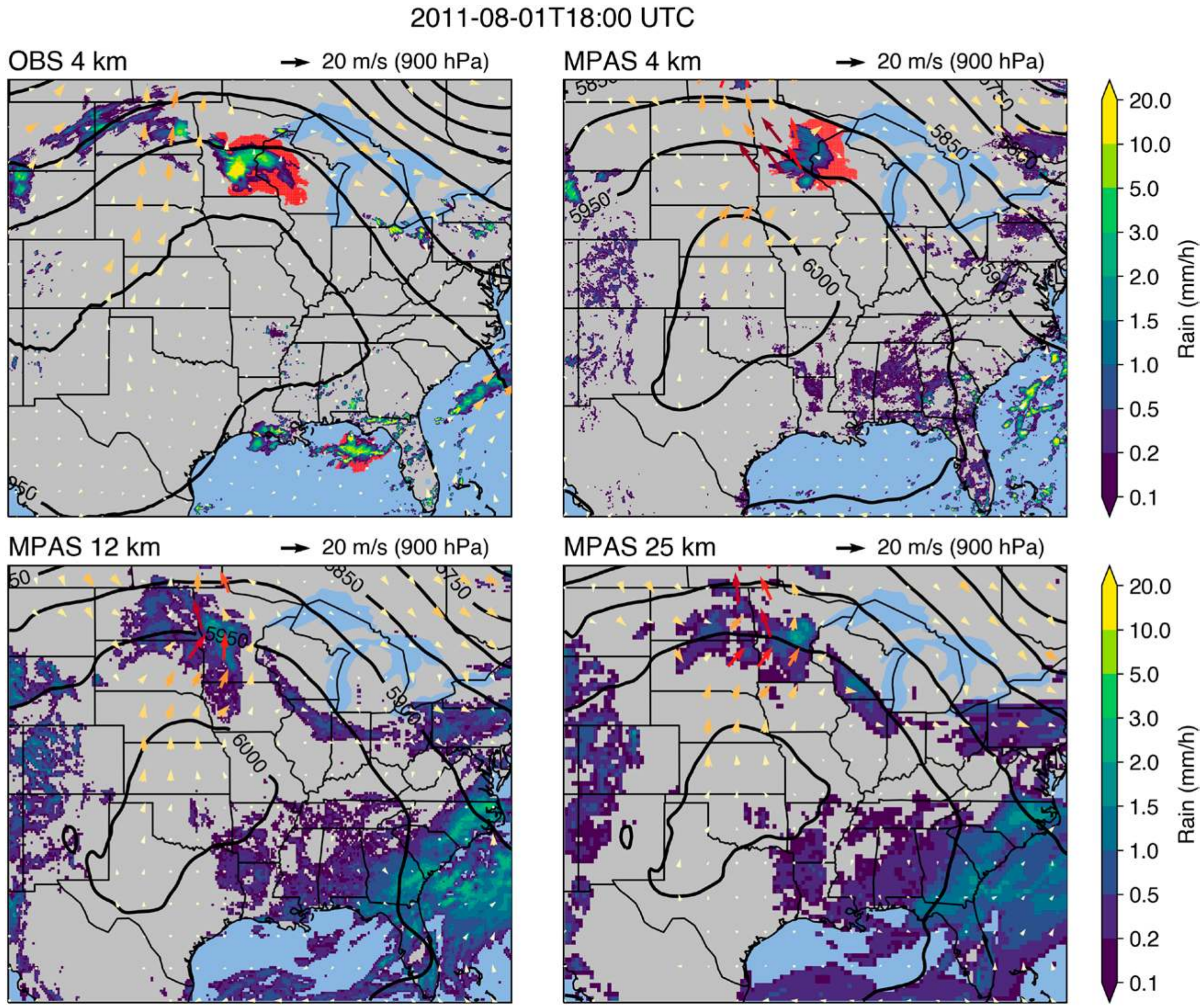

Fig. 6b. As in Fig. 6a, but for an MCS and its large-scale environment at ~1800 UTC 1 Aug 2011. The MCS developed under weak forcing associated with midtropospheric short waves on the poleward fringes of a high pressure system over the central United States. Only the simulation at 4 km grid spacing captured the MCS, despite being weaker than observed. (See animation ES3 for an animation of this event.)

Complex topography produces variations in temperature simply because of lapse rate effects, and when regional models such as WRF are driven by reanalysis, they reproduce these variations with a reasonable degree of realism (e.g., García-Díez et al. 2013; Walton et al. 2017). In addition, topography produces temperature anomalies due to the nighttime pooling of cool, dense air masses in valleys and other depressions. Reanalysis-driven regional models, with appropriate boundary layer modeling, can simulate the phenomenon realistically (Zängl 2005; Pagès et al. 2017). In climate change experiments using regional models, resolution of the snow line in areas of complex topography produces credible localized intensification of warming due to snow albedo feedback. This phenomenon has been demonstrated in many regions, including the U.S. Rocky Mountains (Letcher and Minder 2015; Minder et al. 2016), the U.S. Pacific Northwest (Leung et al. 2004; Salathé et al. 2008), California's Sierra Nevada (Walton et al. 2017), the Canadian Rockies (Pollock and Bush 2013), and the European Alps (Winter et al. 2017). In contrast, global models often put the snow–albedo–feedback warming in the wrong place because of a poorly resolved and often displaced snow line (Walton et al. 2017). This affirms the need for regional modeling techniques to produce credible warming projections in regions of complex topography.

Regional models can also resolve the intricate circulation patterns prevalent in areas of complex topography. For example, a reanalysis-driven regional model simulated the influence

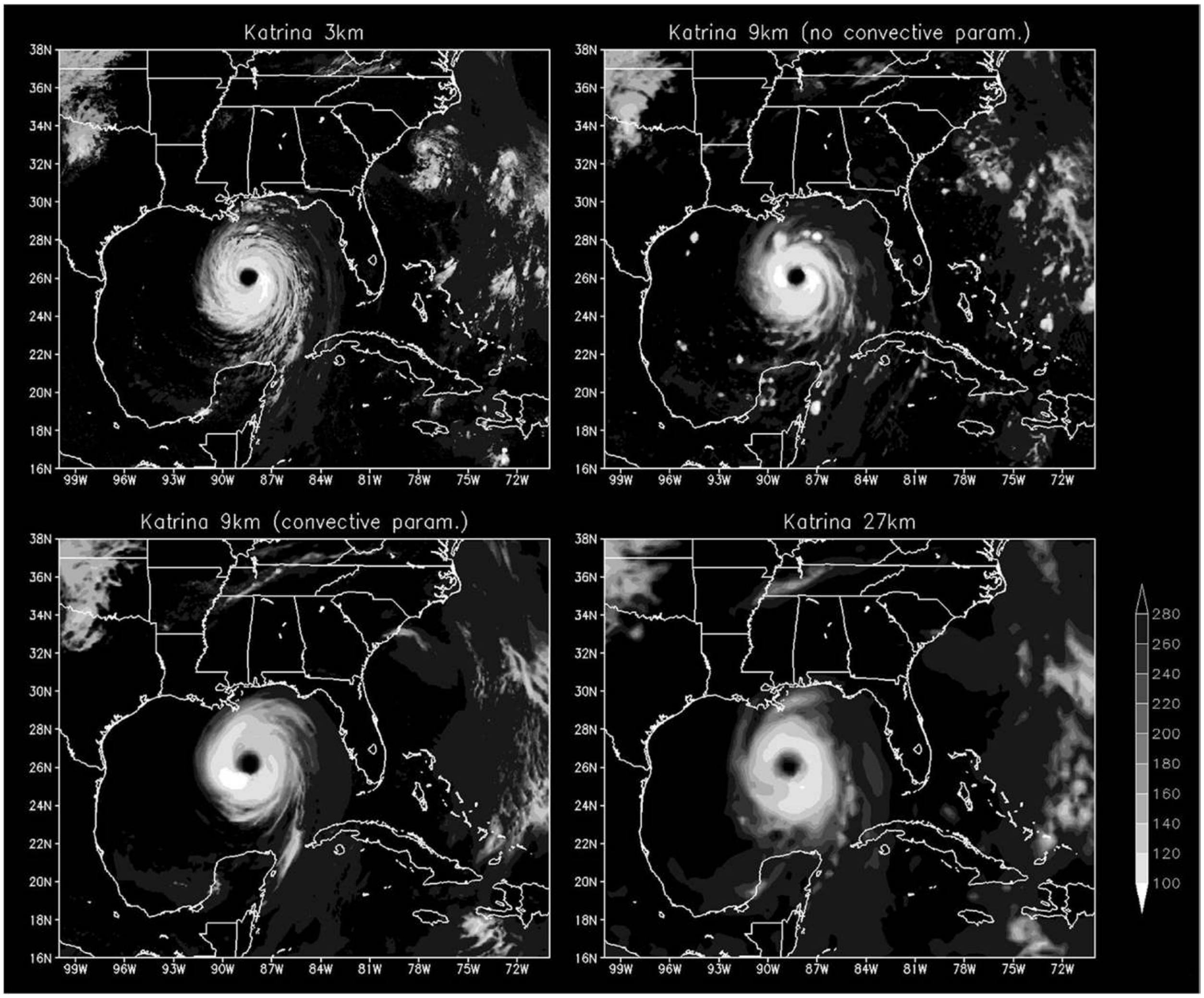

Fig. 7. Hurricane Katrina as shown by outgoing longwave radiation (shaded; W m^{-2}) at 1600 UTC 28 Aug 2005 from hindcasts simulated with WRF at (a) 3 km resolution, (b) 9 km resolution without cumulus parameterization, (c) 9 km resolution with cumulus parameterization, and (d) 27 km resolution (Patricola and Wehner 2018). (See animation ES4 for an animation of this event.)

of coastal mountains and capes on the spatial structure of nearshore winds crucial for upwelling (Boé et al. 2011; Renault et al. 2016; Patricola and Chang 2017) and coastal circulation (Steele et al. 2015). Hughes and Hall (2010) demonstrated that a regional modeling framework is necessary to produce the critical offshore wintertime flow pattern known as the Santa Ana winds in Southern California that is due to topographic pooling of desert air masses and downslope channeling of the winds through mountain passes to the coast. Mountain–valley circulations, characterized by thermally driven upslope flow during the day and downslope flow at night, are also very realistically simulated by regional models (e.g., Jin et al. 2016; Junquas et al. 2018)

Topographically induced variations in both temperature and circulation lead to a variety of climatologically important effects, such as orographic uplift yielding precipitation, rain shadows, and barrier jets. The skill of regional models in simulating these signals has been recognized for more than two decades through studies on multiple continents (e.g., Marinucci et al. 1995; Leung and Qian 2003, 2009; Insel et al. 2010; Cardoso et al. 2013). Improving the representation of orographic forcing also improves simulations of extreme precipitation in mountains, such as that induced by atmospheric rivers (e.g., Leung and Qian 2009; Chen et al. 2018). In fact, in mountainous regions, well-configured regional models may produce better estimates of total annual rain and snow than current observational estimates (Lundquist et al. 2019) and improve understanding of processes driving surface hydrologic extremes associated with landfalling atmospheric rivers in mountainous areas (Chen et al. 2019).

Regional models are also capable of simulating more subtle orographic precipitation effects, such as the blocked flows that develop parallel to mountain chains on the windward side in low Froude number flow configurations. Such blocked flows produce more gradual forced ascent in advance of the topographic barrier. The corresponding reduction in precipitation gradients normally associated with orography on the windward side has been successfully simulated for California (Hughes et al. 2009) and the Andes (Viale et al. 2013). On the lee side, where rain shadows are found, regional models have also demonstrated the inverse relationship between the static stability of the large-scale flow and rain shadow intensity (Lorente-Plazas et al. 2018). Finally, regional models have been used to illustrate the interannual mesoscale precipitation signals that result when ENSO cycles drive systematic changes in the orientation of moist flows. This shifts the mountainsides driving orographic uplift (Leung et al. 2003).

Variations in surface properties themselves (apart from elevation) also produce spatial variability in weather and climate variables. These variations include transitions from open water to land along complex coastlines and around lakes, and variations in land cover and land use. Thus, regional models can simulate land–sea breezes and lake breezes with a high degree of realism, along with the localized suppression of the land–water temperature gradient in the coastal zone that results (Hughes et al. 2007; Vishnu and Francis 2014). Regional models also provide much more realistic distributions of "lake effect" precipitation through resolution of local coastlines and topography than is possible with global models (e.g., Wright et al. 2013). Finally, when given urban–rural land-use differences, regional models can simulate urban heat island impacts on local energy flows and atmospheric circulation (Sharma et al. 2017; Hai et al. 2018). These capabilities underscore the relevance of regional modeling techniques for credible climate change projections in regions where surface properties vary significantly.

Future promise and directions

Continued advances in computing and algorithms for regional climate modeling have the potential to greatly advance understanding of key processes and features in the Earth system. Upcoming major changes in GPU-enabled supercomputing capacity have the potential to be transformative for cloud-resolving simulations (Fuhrer et al. 2018). However, new hardware architectures do require a substantial rethinking of traditional model design, with more computation needed per memory access or parallel exchange (e.g., a convection superparameterization applied on one compute node per grid point). Similarly, machine-learning emulation of turbulent physics (Brenowitz and Bretherton 2018; O'Gorman and Dwyer 2018) could be transformative, especially if it can be made robust and stable (Rasp et al. 2018). Further, by pursuing traditional strategies like limiting the geographic extent of the high-resolution region, computational resources can be better leveraged to enhance model complexity, local resolution, simulation length and ensemble size. Growth in conventional computing power has already enabled several promising approaches for modeling at regional scales, including further development of regional convection-permitting and finer scale modeling, use of unstructured meshes, and regional integrated assessment modeling. In this section, we focus on the value of these approaches, while also noting briefly several other promising pathways for modeling at regional scales, all of which could enable the development of more valuable models for scientific discovery.

Regional climate modeling at convection-permitting and smaller scales. As discussed above, MCSs are an important part of the water cycle, and improving their representation in models has implications for many stakeholders. Simulations at resolutions of 1–4 km, far from the scale employed by GCMs for decadal simulations, can unlock some of the critical questions posed by MCS research. For example, how do cloud microphysical processes, surface fluxes, and convection–circulation interactions influence MCS properties and life cycle? How do MCS precipitation impact the surface water balance, surface temperature, and runoff? Even at convection-permitting resolutions, convective updraft characteristics can be artificially constrained as a result of insufficient resolution to resolve entrainment effects from turbulent motions (Lebo and Morrison 2015). There also remains a reliance on parameterization of subkilometer turbulent mixing, which requires even finer scales to resolve well (~5–100 m). Such scales of turbulence matter. They are key, for example, to recent understanding of vegetation-induced drying in the Amazon (Kooperman et al. 2018; Langenbrunner et al. 2019), in which ecophysiological responses to CO_2 force the PBL through repartitioning of sensible and latent heat fluxes. Likewise, near-surface eddies on subkilometer scales sustain stratocumulus dynamics (Wood 2012), including turbulence-induced transitions between various forms of low-level cloud organization that impact their mean optical properties.

Parameterizations of processes at the smallest scales, such as cloud microphysics, also strongly impact the structure and lifetime of MCSs (Feng et al. 2018), but these sensitivities can be small relative to natural variability (Elliott et al. 2016), necessitating multiyear simulations. Investigation across all relevant scales, in the context of natural variability, thus presents a computational challenge that regional modeling can approach through technical advances (GPU computing and machine learning), creative solutions for complexity tradeoffs (embedded cloud-resolving models and variable resolution), and explicit large-eddy simulation models.

Unstructured meshes for targeted studies in RCMs. Downscaling via RCMs can build on efforts in the global modeling community to use unstructured grids (Abiodun et al. 2008; Tomita 2008; Walko and Avissar 2011; Zarzycki et al. 2014; Skamarock et al. 2018). One way this has been implemented is via a GCM with relaxation of the far-field atmospheric state to a specified driver, such as a reanalysis (Kooperman et al. 2012; Tang et al. 2019). The strong advantage of unstructured grids within RCMs is that the transition between typical RCM resolutions (10–50 km) to much finer resolution in targeted regions is seamless in terms of model column physics, though it does require careful consideration of parameterizations' resolution dependency, such as for cloud and convection processes.

RCMs with an unstructured grid can attain much finer resolution in targeted regions to resolve coupling of land–atmosphere or ocean–atmosphere process where surface and atmosphere features vary on scales of kilometers. For example, studies have demonstrated the importance of subsurface processes such as groundwater table dynamics in regulating land–atmosphere interactions (e.g., Gutowski et al. 2002; Maxwell and Kollet 2008). Finescale heterogeneity in surface fluxes induced by finescale heterogeneity in topographically modulated subsurface processes may influence atmospheric boundary layer processes and cloud formation (Rihani et al. 2015). Such tight coupling at extremely high resolution, becoming achievable in regional models, has opened the door for modeling finescale effects of irrigation and water management, and their feedback to local and regional atmospheric and water cycle processes.

Regional integrated human–Earth system modeling. There has been extensive growth in the development of integrated human–Earth system models (IHESMS), which incorporate representations of both the physical system and multisector dynamics, and scenarios of future emissions and land-use changes (O'Neill et al. 2017). These developments have included increased regional resolution, increased process detail, and increased coupling with detailed subsystem models, such as models of marine and terrestrial ecosystems or water resources management (Monier et al. 2018; Weyant 2017). Nonetheless, many outstanding research questions remain that can be addressed by this new generation of models (Calvin and Bond-Lamberty 2018).

The push toward a higher-resolution representation of atmospheric, oceanic and land processes in RCMs opens a pathway for parallel and concerted effort in the IHESM community for two major reasons. First, changes in climate are local as are many human-system processes. To adequately capture human responses to those changes, higher resolution IAMs are needed. For example, changes in water availability may vary from one grid cell to the next (Hanasaki et al. 2013). Without sufficient regional resolution, those changes may be averaged away, obscuring their implications for energy and land use (Hejazi et al. 2015; Cui et al. 2018). Second, the local and regional climate is strongly influenced by land management practices that impact land characteristics like albedo, surface roughness, and soil moisture. For example, irrigation practices (Lobell and Bonfils 2008; Qian et al. 2013) and land-use change (Brovkin et al. 2013; Hallgren et al. 2013) can influence land–atmosphere fluxes, impacting local and regional temperature and precipitation patterns. For these reasons, a coordinated effort between the regional climate modeling and the integrated assessment modeling communities can explore regional and local implications of coupling between human decisions, climate evolution, and impacts.

Further opportunities for regional modeling. In addition to the opportunities for RCMs discussed above, there are several further important pathways for advancing RCM applications; we describe some briefly here.

1) *Better simulation of finescale processes and their interactions*: There are extensive, ongoing efforts to build comprehensive, fully coupled regional models that contain not only atmosphere, land, and ocean models, but fully integrated ocean surface, hydrology, and ecosystem models with sophisticated physics, chemistry, and biology. For example, coupling regional models of atmosphere, land, ocean, and waves (e.g., Chen and Curcic 2016) may improve their representation of tropical storm climatology by accounting for the impacts of hurricane winds on the cold wakes that modulate the surface enthalpy flux, a major energy source for hurricane intensification. Adding wave models to an atmosphere–ocean RCM (e.g., Warner et al. 2010) is also important for improving the modulation of surface winds by ocean waves and for assessing hurricane-induced storm surges. Shallow-water polar ocean eddies, sea ice deformation, and dust lofting over the Sahara, all critical to broader climate, are areas that would benefit from reduced assumptions of how scale interactions in the momentum budget occur in the planetary boundary layer. Such issues are currently slave to unrealistic assumptions of eddy isotropy in both GCMs and RCMs and an ideal focus of RCM process study to improve modeling of coupled processes at regional scale.
2) *Addressing questions of uncertainty*: Climate models hold great promise to inform decisions and increase our understanding of fundamental processes but also have known or unknown errors and biases from various sources such as uncertain parameters, structure, initial and lateral boundary conditions (e.g., Qian et al. 2016, 2018). RCMs offer a promising framework for identifying and quantifying these errors and their sources, ultimately improving both RCMs and GCMs (e.g., Yang et al. 2012). For example, Xu et al. (2019) used RCMs with observation-based boundary conditions and a wide range of GCMs to separate regional-scale errors from large-scale errors, quantify how the large-scale errors propagated to regional scales, and map regional errors back to their upstream drivers. One can also conduct climatic parameter-sensitivity tests at process level (e.g., different cloud regimes) and develop new parameterizations of local-to-regional-scale phenomena

at the native scales of those phenomena (Yan et al. 2014). Further, climate measurements and observations at local scales and the process level can be more appropriately utilized for model validation and calibration.

3) *Subseasonal to seasonal (S2S) forecasting*: Credible forecasts on S2S time scales are of growing value to a wide range of stakeholders. In regions where global S2S forecasting systems are skillful at capturing large-scale teleconnection modes [e.g., the NCEP Climate Forecast System version 2 (CFSv2)], dynamical downscaling, especially at convective-permitting resolutions, may improve forecasts. Efforts such as the Multi-RCM Ensemble Downscaling (MRED) project demonstrated that RCMs are highly relevant to forecasting on these time scales. Advances in modeling at convection-permitting scales can provide an improved representation of storm-scale structures and have the potential to substantially improve S2S forecasts, which have historically performed on par or worse than climatology (Castro et al. 2016). Further, ongoing RCM-centric efforts to evaluate and compare modeling approaches, develop scale-aware physical parameterizations, and simulate at nonhydrostatic scales will be essential in improving forecast quality (Leung and Gao 2016).
4) *Ensembles and climate variability*: The relatively low computational cost of regional models enables development of large ensembles at resolutions capable of capturing finescale processes (e.g., Mearns et al. 2017) and their role in internal climate variability (Nikiéma et al. 2018, and references therein). Given that the challenges and costs associated with convection-permitting models are still high, ensembles of regional simulations at moderately high resolutions (~10 km) will remain relevant and useful in the future. At these scales, models have demonstrable value over coarser resolutions in, for example, complex terrain (Torma et al. 2015); can perform equally as well as convection permitting simulations where convection is not forced by the boundary layer; and may project similar futures in precipitation regimes where changes are primarily forced by the large scale (e.g., Fosser et al. 2017).

Assessing internal variability in RCMs requires acceptable LBCs and sea surface temperatures that are broadly sampled from large-scale, low-frequency drivers (e.g., PDO, AMO) that future high-resolution GCM simulations are expected to provide (Roberts et al. 2018). In addition, an increasing number of single-GCM large ensembles now allow RCM ensembles to address the uncertainty that results from natural variability (e.g., von Trentini et al. 2019). Multiple realizations are also relevant for studying extreme events, which are rare by definition.

Concluding remarks

Regional and global climate modeling have been simultaneously advancing toward higher resolution along complementary paths. These advancements have provided—and will continue to provide—a deeper understanding of the processes that govern climate and its change in a region. The ability of higher resolution GCMs to provide improved representation of processes, such as storm tracks, that feed into boundary conditions for RCMs, allows better simulation by the RCMs of targeted regions (Roberts et al. 2018). Together, the two approaches can cross thresholds in simulating climate for regions, opening the door to potentially transformative advances such as convection-permitting regional modeling. The opportunities provided by the complementary development of both modeling approaches argues for developing seamless models, as occurring at the Hadley Centre (Lewis et al. 2018; Williams et al. 2018) and developing at NCAR (NCAR 2019). Such efforts would support the development of modeling tools that can be tailored for targeted problems, for example, high-resolution GCMs for studying storm tracks, in conjunction with finer-resolution RCMs for climatological study of mesoscale convective systems with cloud-permitting dynamics and local coupling of land–atmosphere hydrologic processes.

The configurability of RCMs allows for a wide range of studies that help disentangle the local climatic response to global versus regional processes. By better resolving land surface heterogeneity stemming from complex topography, land use and coastlines, regional models capture critical phenomena such as orographically influenced variations in precipitation, wind, and surface energy balance, as well as details of other regional phenomena such as irrigation, atmospheric aerosols, and urban heat islands. Regional models are thus indispensable tools for understanding drivers of regional climate variability and change in complex terrain, including hydrologic response; they can demonstrate when and where regional climate response to finescale forcing is significant.

Finally, regional models can show substantial skill in simulating extreme events such as heavy precipitation, tropical storms and strong winds, including their spatial and temporal variability, by virtue of their ability to represent regional atmospheric behavior, such as atmospheric circulation, orographic uplift, atmospheric instability, vertical and horizontal gradients, etc. Extreme events, in particular, have substantial societal impact. Insights gained from regional modeling can and will continue to provide stakeholders important information about changing climate in their regions of interest that satisfies the need for information that is salient, credible, and legitimate.

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