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Future Research Outlook: Challenges and Opportunities

Y. Liu

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Environmental and Climate Sciences Department

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Future Research Outlook: Challenges and Opportunities

Yangang Liu[1] and Pavlos Kollias[1,2]

ABSTRACT

This chapter synthesizes the recent cross-cutting advances and overarching trends across the various topics discussed in this book, highlights new challenges confronting further developments, and presents new opportunities for future research.

18.1. RECENT ADVANCES

In addition to the significant progresses of the various topics elucidated in the preceding chapters, several, worth highlighting, advancements in cross-cutting research areas are mentioned here. First, fast physics parameterizations have been gradually advancing from being primarily practical fix for individual fast processes to deep theoretical underpinning of stochastic scale interactions, and process interactions within the complex "4M-2N" system (recall Figure 3 in Chapter 1). These advancements are schematically illustrated in Figure 18.1 as three levels of development. Second, several different approaches/ideas have been proposed to unify the representation of distinct processes and their interactions. Third, the importance and necessity of top-down approaches have been increasingly recognized and ideas in other disciplines, such as statistical physics and chaos theory, have found valuable applications in atmospheric and climate sciences. Fourth, the essential role of organic integration of numerical models of different types, synthesis of measurements from different observing platforms, and effective evaluation of various parameterizations has been increasingly emphasized for further development. The growing interest of a systematic, process-oriented model-measurement synthesis further reinforces the pressing need for interdisciplinary research. Fifth, with the advancement in computer technology and growing computational power, model resolutions have been continually increasing, along with the development of unstructured or resolution-adaptive meshes. Finally, more physical processes that were ignored in early studies have started to be considered, for example, turbulent entrainment-mixing processes detailed in Chapter 4.

18.2. CHALLENGES AND OPPORTUNITIES FOR FUTURE RESEARCH

The material presented in the previous chapters—especially the recent advances—reveal new challenges and opportunities for future research. Below we highlight 12 points with a focus on those relevant to more than one physical process/phenomenon.

First, for developing unified parameterizations that consider a variety of different processes together and address process interactions, new issues likely emerge that differ fundamentally from parameterizing individual processes, e.g., self-consistency between different physical

[1] *Department of Environmental and Climate Sciences, Brookhaven National Laboratory, Upton, NY, USA*

[2] *School of Marine and Atmospheric Sciences, Stony Brook University, Stony Brook, NY, USA*

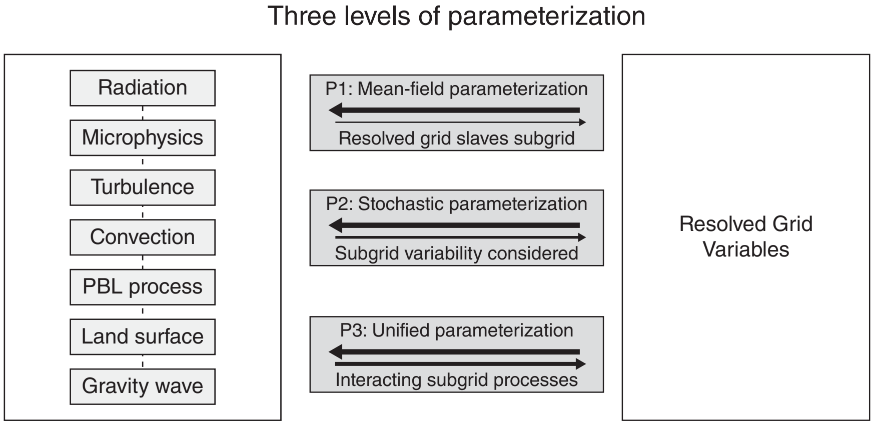

Figure 18.1 Schematic to illustrate the three levels of fast physics parameterizations. The left box lists the main subgrid processes, with the dotted vertical lines to indicate the fact that the interactions among subgrid processes have not been well represented in existing parameterizations. The three boxes in the middle show the three levels of parameterizations (P1, P2, and P3), respectively, from the top to the bottom. The thickness of the left-to-right arrow indicates the strength of considering the subgrid process couplings/interactions.

processes/variables (Liu & Daum, 2008; Park et al., 2017; Shaw and Shepherd, 2009).

Second, the feedbacks between different processes remain poorly understood and understudied, so is the numerical dynamics-physics coupling (Keyes et al., 2013; Gross et al. 2018). As the representation errors associated with each individual model component decrease, the correlated errors introduced by the component coupling will eventually dominate. Furthermore, the calling order of different process parameterizations in the conventional splitting treatment was recently found to affect not only current-climate behavior but also the model's prediction of climate sensitivity, suggesting that process ordering should be considered carefully during model development and that optimizing the order of calling different processes should be explored together with proper parameter tuning (Donahue & Caldwell, 2018).

Third, fast physics parameterizations will continue to be major sources of uncertainty in weather and climate prediction models. In particular, those associated with sub-LES scale processes fraught with significant knowledge gaps will likely become more acute as the resolutions of weather and climate models increase, including adequate representation of shallow convection, turbulent entrainment-mixing processes, and turbulence-microphysics interactions. Using process modeling studies for parameterization development is essential because it ensures that increased knowledge on processes can be incorporated into models in a physically realistic way. Particle-resolved direct numerical simulation models that can resolve the smallest turbulent eddies and follow individual cloud particles and its integration with LES models hold great potential in this area (Gao et al., 2018; Wang et al., 2011).

Fourth, as for cloud microphysics and aerosol-cloud interactions, several areas of research warrant more attention in future, including aerosol-cloud interactions in the updraft-limited regime, multimoment schemes that consider the roles of spectral shape of hydrometeor size distributions (Milbrandt & Yau, 2015a, 2015b), droplet size distributions (Chen et al., 2016, 2018; Liu et al., 2023), and wet removal of aerosols due to ice processes. Adequately coupling entrainment/detrainment and turbulent mixing processes with cloud microphysics and turbulence representation merits further investigation (Xu et al., 2022). Also moving to the forefront is the issue of aerosol-cloud continuum and transitional zone between clouds and aerosols (Charlson et al., 2007; Marshak et al., 2021), which calls for further unification of aerosol processes, cloud microphysics, and those processes expecting to significantly affect cloud edges such as entrainment-mixing and radiative effects on cloud microphysics (Zeng et al., 2022).

Fifth, most fast physics parameterizations remain essentially one dimensional in the vertical direction; such 1D representation will likely experience a shift to more realistic 3D representation for processes such as radiative transfer, gravity waves, and turbulence. This shift will pose new challenges not only to representing individual processes in question but more so to considering the process interactions (e.g., gravity-turbulence interactions) and coherent structures (Dritschel, 2013; Penner et al., 2018). Results from high-resolution 3D numerical simulations and machine learning modeling are expected to play growing roles in addressing such challenges. For this, improving high-resolution models (e.g., LES models) is crucial in view of their existing deficiencies, for example, in representing fractal-like spatial structures of cloud microphysical properties (Witte et al., 2022).

Sixth, as open systems in general, atmospheric phenomena or the fast processes to be parameterized often need to confront the issue of equifinality because the final state may be reached from different initial conditions and in different ways (von Bertalanffy, 1950). The same concept is particularly amenable to parameterizations with multiple empirical parameters constrained by uncertain observations and/or knowledge gaps. Many different sets of parameters can lead to equally good fit to the observational data, and these equally good models/parameterizations may lead to widely divergent model results under new conditions (Tang & Zhuang, 2008). The barrier of equifinality likely conspires with the curse of parameter dimensionality to present challenges to constraining models with observations, and to conducting model evaluation and parameter calibration (Mülmenstädt et al., 2020). Without a direct way of measuring key quantities in fast physics parameterizations, tuning parameters have been often estimated indirectly. Such an exercise implicitly assumes that errors from other parts of the model including the dynamical core and other parameterizations are negligible, and that the mathematical form of the parameterization to be tuned is correct. However, these assumptions are generally not valid, which results likely in the occurrence of error compensations or correct results for wrong physical reasons. Somewhat related are the use of emergent constraints to reduce the uncertainty in climate sensitivity (Caldwell et al., 2018; Eyring et al., 2019) and the use of known physical relationships to improve data-driven machine learning forecast models (Liu et al., 2021, 2022). All these potential issues together call for rigorous uncertainty quantification of observational data, modeling results, and the parameters to be calibrated. Again, machine learning models hold tremendous potential(s) in these areas.

Seventh, the climate or atmospheric system can be seen as a forced and dissipative nonequilibrium thermodynamic system (Lucarini et al., 2014; Wu & Liu, 2010) and generating entropy via a variety of irreversible processes. Subgrid-scale processes have long been known to be a critical issue when attempting to provide an accurate climate entropy budget. The consistency with the second law of thermodynamics has been understudied and needs further attention (Akmaev, 2008; Gassmann, 2018; Gassmann and Herzog, 2015; Kleidon and Lorenz, 2005; Kunz et al., 2008). An important question to address is whether the standard model equations and physical parametrizations are already compliant with the second law. It may also be useful to analyze other processes and their parametrizations from the perspective of compliance with the second law and overall entropy inventory.

Eighth, this book also demonstrates the complementarity of different observational platforms, including space-based remote sensing, surface-based remote sensing, aircraft-enhanced field campaigns, distributed observational networks, and laboratory experiments with well-controlled conditions. The next decade will bring major advancements in our measurement capabilities thanks to the rise of CubeSats and the development of data-driven dynamical observing systems (Kollias et al., 2020). Multiple lines of developing trends are anticipated, including multiangular sampling or scanning, multiwavelength, polarization, and 3D tomography for remote sensing; and high-resolution 3D holographic in situ sampling. These measurements are collected at different sampling scales and rates, and for disparate variables, and thus adequate data synthesis and integration will be needed to generate multiscale scale and 3D data sets readily available for process study and evaluation of various model types with different grid spacing and domain sizes. Such big-data tasks will be daunting and can benefit from advances in artificial intelligence and machine learning.

Ninth, another challenge we need to address to optimize atmospheric science experiments is the "valley of death" between modeling requirements and observational capabilities. Often scientists involved in the design of experiments to test theory and models have limited understanding of the real information content of measurements provided by a particular field experiment. We advocate for the development of open access, comprehensive Observing System Simulation experiment (OSSE) software packages that will generate in-silico versions of field experiments. The "digital twin" of an observational campaign will allow atmospheric scientists to evaluate proposed measurements before the experiment is conducted. It will simulate the effects of observing system design decisions (i.e., type of radar, sampling strategy, and drone-sampling strategy) on measurement data (Oue et al., 2022; Sanchez et al., 2022) and their downstream ability to constrain and improve model predictions. Developing digital twins presents a tremendous opportunity to transform the indispensable integration of measurements and models across multiple scales (Bauer et al., 2021)

Tenth, the problem of modeling weather and climate can generally be organized in terms of seven dimensions: resolution, complexity, integration length, ensemble size, data assimilation, parameter calibration, and measurements, each of which competes for computational resources (Navarra et al., 2010). The inevitable resource limitation necessitates the need to strike an optimal balance among the various tasks associated with these dimensions, for example, having better fast physics representation vs. assimilating more quality measurements or high model resolutions. The growing use of ML models is anticipated in such endeavors.

Eleventh, the continual increase of model resolutions and development of unstructured or resolution-adaptive meshes present new requirements for parameterization development. For example, the need for representing coupled subgrid variabilities and developing scale-aware parameterizations will become increasingly important. The resolution-dependent partitioning between resolved and subgrid contributions is also part of the scale-awareness solution as the weather and climate models move toward the gray zone of "terra incognita" (Malavelle et al., 2014; Schneider et al., 2007; Wyngaard, 2004).

Last but not least, despite the growing recognition of atmospheric sciences in improving prediction of weather, climate, and renewable sources of energy, the sizes of related communities are relatively small, which is particularly true for the parameterization development community (Jakob, 2010). The lack of sufficient manpower remains a serious issue to our society as a whole in view of the high benefit-to-cost ratio of the fields. New efforts to inspire and expand the next-generation workforce are desirable, including training of multidisciplinary scientists and outreach to the public.

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