COLLABORATION OF THE WEATHER AND CLIMATE COMMUNITIES TO ADVANCE SUBSEASONAL-TO-SEASONAL PREDICTION

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Progress in long-range prediction depends on coordination of research: in multimodel ensembles, in tropical convection and its interaction with the global circulation, in data assimilation, and in socioeconomic applications.

The Observing System Research and Predictability Experiment (THORPEX) is the leading component within the World Weather Research Programme (WWRP). THORPEX aspires to accelerate improvements in the accuracy of 1-day to 2-week forecasts of high-impact weather and in the use of this information to benefit society. Meanwhile, the World Climate Research Programme (WCRP) is charged with determining the predictability of climate and the effect of humans on climate. Thus, WWRP and WCRP (both sponsored fully or in part by the United Nations) share the responsibility of advancing scientific knowledge and infrastructure to provide information, including accurate predictions, to reduce losses related to weather, climate variability, and change.

As scientists associated with WWRP and WCRP, we feel that increased collaboration between the two programs is timely because of recent advances in observing technologies, field and laboratory process studies, data assimilation techniques, and coupled numerical models of weather and climate prediction, as discussed by Shapiro et al. (2010). The challenge is to leverage these advances to develop and apply new forecast and diagnostic products and to increase their societal applications. The next generation of climate and weather prediction systems, based on coupled ocean–land–atmosphere and Earth-system models, will greatly benefit from this effort. The four main areas of the WWRP–WCRP collaboration described in this paper are as follows:

i) Seamless weather/climate prediction, including ensemble prediction systems (EPSs).
ii) Multiscale organization of tropical convection and its two-way interaction with the global circulation.
iii) Data assimilation (the process of fitting numerical prediction models to observations) for coupled models as a prediction and validation tool for weather and climate research.

iv) Utilization of subseasonal and seasonal predictions for social and economic benefits.

These are particularly promising areas of research that will greatly accelerate realizing the common goals of WWRP and WCRP and in turn any Earth-system prediction initiative that would embrace our research (Nobre 2010; Shapiro et al. 2010; Shukla et al. 2010). The advance of predictive skill of weather/climate EPSs, promoted by the first of the four areas of collaboration, will depend crucially on progress in the other three areas. These are the most pressing issues to solve before achieving optimal utilization of EPSs and their applications. Because they lie at the intersection of weather and climate, these research priorities require the multidisciplinary, collaborative approach promoted by an Earth-system prediction initiative.

SEAMLESS WEATHER/CLIMATE EPSS. A fundamental principle of seamless prediction is that the Earth system[1] exhibits a wide range of dynamical, physical, biological, and chemical interactions involving spatial and temporal variability continuously spanning all weather/climate scales. The traditional boundaries between weather and climate are artificial (Shapiro et al. 2010).

As explained in Hurrell et al. (2009), for example, the slowly varying planetary-scale circulation preconditions the environment for the "fast acting" microscale and mesoscale processes of daily high-impact weather and regional climate. As an example, there is evidence that natural climate variations, such as ENSO and the North Atlantic Oscillation (NAO)/northern annular mode, significantly alter the intensity, track, and frequency of extratropical and tropical cyclones and also affect decadal variability in tropical cyclones and the multidecadal drought in the Sahel region. Conversely, small-scale processes have significant upscale effects on large-scale circulation and on the interactions among the components of the global climate system.

The challenge facing our scientific community is to improve the prediction of the spatial–temporal continuum of the interactions among weather, climate, and the Earth system. The most important aspect of the challenge is the chaotic nature of weather and climate predictability that needs to be characterized with probabilistic information.

EPSs are widely used for weather and environmental (e.g., hydrological) prediction by operational services. Ensemble forecasts offer not only an estimate of the most probable future state of a system, but also a range of possible outcomes. Assessing how climate subseasonal-to-seasonal variations may alter the frequencies, intensities, and locations of high-impact events is a high priority for decision making. Many users are risk averse—more concerned with the probability of high-impact events than with the most probable future mean state. This makes the

[1] In this context, the Earth system is understood to mean the atmosphere and its chemical composition; the oceans, sea ice, and other cryosphere components; the land surface, including surface hydrology, wetlands, and lakes; and short-time-scale phenomena that result from the interaction between one or more components, such as ocean waves and storm surge. On longer (e.g., climatic) time scales, the terrestrial and ocean ecosystems, including the carbon and nitrogen cycles, and slowly varying cryosphere components, such as the large continental ice sheets and permafrost, are also considered to be part of the Earth system.

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development and use of ensemble-based modeling a requirement to improve estimates of the likelihood of high-impact events a central scientific issue.

In general, a multimodel ensemble prediction system (MEPS) approach provides more useful probability density functions (PDFs) than those obtained from a single EPS when using EPSs of equivalent skill. Moreover, the MEPS approach identifies which outcomes are EPS independent and hence likely to be robust.

While a goal of weather and climate EPS is to produce model outputs that are unbiased—together with ensemble forecasts that properly account for uncertainty—models have biases, and atmospheric ensemble predictions only partially account for the true uncertainty. It is a nontrivial task to characterize statistically these deficiencies and to utilize the information to process model output for seamless forecast applications, which have a wide range of time horizons. The common model output statistics (MOS) approaches are very useful but only partially meet the needs of users, because the skill and uncertainty of weather and climate forecasts are highly space and time-scale dependent. Accounting for this dependency is critical for many EPS applications that are sensitive to the space–time variability of weather and climate. Evaluating MEPS biases and forecasting skill on the subseasonal time scale will require hindcast experiments.

It is well recognized that subseasonal and seasonal predictions must realistically represent day-to-day weather fluctuations and their statistics. Collaboration of the WCRP Climate Variability and Predictability (CLIVAR) Climate-system Historical Forecast Project (CHFP) and the THORPEX Interactive Grand Global Ensemble (TIGGE) would help bridge the gap between daily and seasonal forecasting and develop a MEPS that spans from weeks to seasons. As an example, Palmer et al. (2008) indicate that the statistics of dynamical and physical processes, like the atmospheric response to sea surface temperature, in seasonal forecasts based on a MEPS can be utilized to assess the reliability of climate projections done with the same MEPS.

Operational weather forecast systems provide our best representation of synoptic and mesoscale weather events. However, these short-to-medium-range (~10 days) forecast models have not traditionally addressed key interactions, for example, at the air–sea–ice interface. We know that this is problematic on time scales beyond two weeks; modeling and predicting seasonal climate anomalies requires a realistic treatment of the effects of sea surface temperature, sea ice, snow, soil wetness, vegetation, stratospheric processes, and chemical composition. The lack of such components of the Earth system in current prediction models may well be an impediment to improving forecasts on shorter time scales, particularly for high-impact weather. For example, the ocean mixed layer can precondition the atmosphere–ocean interface for subsequent extratropical and tropical storms. Seasonal prediction systems, on the other hand, typically include such coupled interactions, yet they fail to adequately resolve mesoscale weather systems. There is a wide range of scale interactions to be considered within the context of improving EPSs.

Scale interactions are essential to ENSO prediction, and much progress has been achieved in operationally predicting ENSO with coupled models in the last two decades. These coupled models now give good guidance on the evolution of SST up to six months in advance in the Pacific. However, there are still profound gaps in our prediction capabilities, in part due to large systematic errors in the coupled models in other regions. These mean state errors and errors in the evolution of climate anomalies have been addressed semiempirically to improve physical parameterizations in the models and to allow for imperfect models in EPSs and MEPSs (Hurrell et al. 2009).

The seamless prediction approach raises another problem: that current climate models poorly represent the statistics of weather events for which there is predictive skill. The typical assumption for subgrid-scale parameterization is to assume that the statistics of subgrid-scale processes can be parameterized in terms of the grid-scale variables. An alternative strategy is to increase the grid resolution of the model and to explicitly represent key dynamical/thermodynamical processes. While this approach has yielded some improvements, it is limited by the available computing capacity and incomplete explicit representations. Moreover, the specification of accurate initial conditions has an effect on the skill of daily-to-seasonal prediction. The issue then becomes: What are the important physical processes and data assimilation aspects crucial for better-coupled model initialization? We will discuss these two issues in the following two sections.

Because of the relatively small scale of many events, there will be an ongoing need to improve model resolution and to develop alternative downscaling techniques, for example, for specific applications such as hydrology. The requirements for both ensemble prediction methods and greatly increased spatial resolution imply a need for substantial improvements in computational power and data storage, as advocated in Shukla et al. (2010).

Both TIGGE and CHFP are planning multimodel multi-institutional numerical experiments using state-of-the-art models and computing systems. The sharing of the resulting datasets from both retrospective and near-real-time subseasonal-to-seasonal forecasts requires a common and seamless framework for comparison and diagnosis to bridge the respective goals of TIGGE and CHFP for improving subseasonal and seasonal forecasts. In particular, a small number of data archive centers need to be identified, and they need to support the scientific and user communities. These databases will require unprecedented storage capacity (TIGGE is already providing such support for MEPS, but it is limited to two-week forecasts).

TROPICAL CONVECTION AND ITS TWO-WAY INTERACTION WITH THE GLOBAL CIRCULATION. The tropics are where the net solar energy input to the Earth occurs. Solar energy is received mostly at the land and ocean surfaces, with a small amount being absorbed within the atmosphere. This heat energy is distributed throughout the troposphere by convection. The clouds formed as a result of moist convection release of latent heat whereas the evaporation of precipitation has a cooling effect. Clouds interact with short- and longwave radiation that feeds back to affect the cloud properties and the vertical distribution of heating. Besides its thermodynamic implications, atmospheric convection has important dynamical effects. For example, surface gustiness associated with convection enhances the surface–atmosphere exchange, and the vertical transport of horizontal momentum and convectively generated gravity waves affect the atmospheric circulation directly.

Tropical convection exhibits a remarkable variability and organization across space and time scales, ranging from individual cumulus clouds to mesoscale cloud clusters to superclusters (families of mesoscale clusters) to synoptic-scale disturbances, and even to planetary-scale circulations. The synoptic disturbances are often associated with equatorially trapped atmospheric waves (Wheeler et al. 2000; Yang et al. 2007), which, in turn, organize tropical convection. This hierarchy constitutes a highly nonlinear continuum of scale interaction. It follows that forecast skill in the tropics—on time scales of days, weeks, and beyond—is dependent upon both equatorial waves and convective organization, which contemporary weather and climate prediction models do not realistically represent. This low skill is usually attributed to inadequacies in parameterizations of moist physical processes. Organized tropical convection is an important part of this deficiency, since it is neither represented by contemporary convective parameterizations nor adequately resolved in global models, especially climate models.

An excellent example of the multiscale convective organization in the tropical atmosphere is the Madden–Julian oscillation (MJO), where precipitating convection organizes into coherent structures (convective clusters) up to 1,000 times larger than an individual cumulonimbus. In turn, the MJO excites Rossby wave trains that propagate into the extratropical Pacific, North America, and the North Atlantic, disrupting the midlatitude storm tracks and sometimes causing high-impact weather. Conversely, midlatitude weather and climate variability affect the tropics. For example, Lin et al. (2009) show a two-way connection between the NAO and the MJO (see Table 1). The MJO may be linked to a change of upper zonal wind in the tropical Atlantic associated with the NAO. The MJO is also considered a

Table 1. Lagged probability composites of the NAO index with respect to each MJO phase. Lag *n* means that the NAO lags the MJO of the specific phase by *n* pentads, while lag −*n* indicates that the NAO leads the MJO by *n* pentads. Positive values are for the upper tercile, while negative values are for the lower tercile. Values shown are only for those having a 0.05 significance level according to a Monte Carlo test (Lin et al. 2009).

Phase	1	2	3	4	5	6	7	8
Lag −5		−35	−40			+49	+49	
Lag −4						+52	+46	
Lag −3		−40					+46	
Lag −2						+50		
Lag −1								
Lag 0				+45				−42
Lag 1			+47	+45				−46
Lag 2		+47	+50	+42		−41	−41	−42
Lag 3		+48				−41	−48	
Lag 4						−39	−48	
Lag 5				−41				

significant aspect of ENSO through its forcing of the equatorial ocean (e.g., Kutsuwada and McPhaden 2002).

At the synoptic scale, energy originating at high latitudes, in upper-level westerly flow in the Pacific and Atlantic storm tracks, propagates into the tropics through Rossby wave dispersion. Such wave trains frequently excite convection within the intertropical convergence zone (ITCZ), transporting moisture from the tropical boundary layer into the upper troposphere and transporting it poleward, extending it into the extratropics of both hemispheres (Knippertz 2007). Moisture transport between the tropics and extratropics is enhanced during synoptic-scale "atmospheric river" events (Neiman et al. 2008). Moist intrusions from the tropics may lead to sustained heavy precipitation and flooding in Australia, Europe, and North and South America. Other aspects of subseasonal variability within the extratropical storm tracks that pose problems for both weather and climate models are the initiation and maintenance of atmospheric blocking (sustained anticyclones) and wave–mean flow interactions. These contribute to variability in teleconnection patterns such as the NAO and the Pacific–North America (PNA).

In contemporary convective parameterizations, subgrid-scale processes are approximated in terms of the resolved (grid scale) variables. An alternative strategy now being used is to increase the resolution of the model to *explicitly simulate* organized convection and hence quantify the upscale cascade of energy associated with convective organization. This is achieved by cloud-resolving models (CRMs) at a horizontal grid spacing of 1 km or finer. Present computer capacity precludes cloud-resolving representations of moist convection in global subseasonal-to-seasonal deterministic prediction models and EPSs. Therefore, it is also essential in the meantime to accelerate the improvement of traditional convective parameterizations.

To accelerate parameterization improvement, the following potential projects have been identified (many of them at the March 2006 joint WCRP–WWRP/THORPEX workshop in Trieste, Italy; see Moncrieff et al. 2007):

i) Develop metrics/description of the daily, subseasonal, and seasonal characteristics of the MJO and organized tropical convection.
ii) Promote collaborative numerical weather prediction (NWP) experiments that explore error growth in simulations of the MJO and other modes of organized convection associated with two-way interaction between tropical and extratropical weather and climate.
iii) Plan a collaborative and integrative research project or a "virtual field campaign" with an emphasis on organized tropical convection and its interaction with the global circulation. Such a project is now underway in the form of the WCRP–WWRP/THORPEX Year of Tropical Convection (YOTC). Described in more detail online (www.ucar.edu/yotc), YOTC consists of three components: high-resolution operational global models' analysis and forecasts; satellite, in situ, and field campaign measurements; and cloud-resolving modeling and theory.
iv) Contribute to field studies of organized convection fields guided by high-resolution modeling. Tropical field campaigns have been undertaken in the Indian Ocean and others at the planning stage, with an emphasis on processes (e.g., moisture transport) that are important for the onset of the MJO.
v) Use operational global prediction systems to experimentally hindcast with mesh size 10–15 km to emphasize meteorological phenomena involving organized tropical convection that challenge the global prediction system, for example, MJO and convectively coupled waves. Develop a strategy for the demonstration and assessment of socioeconomic benefits and applications arising from advanced knowledge and predictive skill of multiscale tropical weather and climate events.

These five studies will require high-performance computing (HPC) centers to enable efficient numerical modeling, advance experimental design, and improve data processing, distribution, and analysis (Shukla et al. 2010). Another important requirement is to maintain existing and implement planned satellite missions that observe tropical clouds and precipitation and provide long-term capability for process studies, data assimilation, and prediction.

DATA ASSIMILATION FOR COUPLED MODELS IN RESEARCH. Fundamental issues related to data assimilation at different scales must be addressed before we can design "seamless" Earth-system prediction systems. Historically, data assimilation research and applications have focused mostly on the requirements of short-to-medium-range operational forecasting. As operational forecasting has extended into subseasonal prediction, improved data assimilation in the tropics, ocean, upper atmosphere, and other aspects of the Earth system have become necessary. The return on the investment in existing and new observations will be significantly increased by advances in data assimilation systems. A unified forecasting and data assimilation system will accelerate the improvement of weather/climate models and applications.

Data assimilation allows the diagnosis of errors while they are still small, before they interact significantly with other fields. This established NWP approach is also proving beneficial for climate models, through application in centers where climate and NWP modeling is unified (e.g., the Met Office) and by the international Working Group on Numerical Experimentation (WGNE) Transpose Atmospheric Model Intercomparison Project (AMIP), which seeks to run climate models in NWP mode. The method permits direct comparison of parameterized variables, such as clouds and precipitation, with synoptic observations and satellite and field campaign measurements.

It will not be possible, with foreseeable computers, to develop one data assimilation method for an Earth-system model with the complexity required for seamless prediction. What is possible is a composite system, applying different assimilation steps to different scales and components of the total Earth-system model. These can be based on the methods currently used in specialized systems, such as NWP. Recent attempts to build such a composite system use a two-way interaction model for the forecast step; however, they apply assimilation to each component of the Earth system separately (Stammer et al. 2002; Galanti et al. 2003; Sugiura et al. 2008). Ideally, the assimilation should be coupled so that observed information in one component is used to correct fields in the other coupled component. One of the few attempts to do this is coupled land–atmosphere assimilation, where soil moisture is corrected based on errors in atmospheric forecasts of near-surface temperature and humidity (Mahfouf 1991; Bélair et al. 2003; Drusch and Viterbo 2007; Mahfouf et al. 2009). Yet, many land surface modelers distrust such soil moisture analyses, which assign compensating errors to soil moistures to reduce atmospheric forecast errors. As a result, the analyses produce soil moisture values that do not correspond to actual values or conserve the water budget. Coupled data assimilation must be accompanied by a much better characterization of the errors and biases in components (e.g., atmosphere, upper ocean) of a coupled model. Only then can we successfully correct the components as part of the data assimilation process.

Another challenge in seamless prediction is the fact that assimilation methods attempt to estimate only a certain range of scales (temporal and spatial). For example, all current operational implementations of 4D variational assimilation compare measurements to model forecasts over a fixed assimilation window and assume that the flow evolution is weakly nonlinear during this window. This implies that temporal and spatial scales for which this is true can be resolved well if those same scales are observed. Thus, for the global NWP assimilation problem, with an assimilation window of 6 or 12 h, synoptic-scale flow can be estimated since it is observed well. Similarly, a high-resolution cloud-scale model with a very short assimilation window can resolve fine scales if they are observed, for example, by Doppler radar.

However, when a model can simulate a very wide range of scales of motion, this method of assimilation can be limiting. Thus, for a global model with extremely high resolution, synoptic-scale flow has a nonlinear time scale commensurate with the assimilation window but convective-scale motions do not. In addition, convective-scale motion is not completely observed over the whole globe. Thus, 4D variational assimilation methods currently rely on the fact that larger scales can generate smaller scales through nonlinear interactions. The final analysis of the global model with extremely high resolution will contain finescale features that are developed during the nonlinear forecast. However, these features may not match the observed flow on these fine scales.

An ensemble of global forecasts generates an ensemble of possible finescale structures. In this case, it would be useful to know not only which ensemble members are most accurate but also whether observations can help constrain the range of the ensemble in terms of the power at scales that are not completely observed. In other words, how can assimilation methods make use of information about power on these scales? Such information might come directly from satellite images or indirectly from measurements of eddy fluxes—for instance, from observations of large scales of the MJO, plus an understanding of the convection necessary to drive them; or from estimates of an eddy flux needed to give the observed ocean state; or from measurements of the age of stratospheric air and the Brewer–Dobson circulation plus an understanding of the vertical eddy fluxes that drive this circulation. Part of the problem with these types of indirect measurements is that they contain information about time scales that are much longer than those resolved by current assimilation schemes. Thus, a major challenge will be to build a composite assimilation system for the Earth system capable of dealing with a wide range of time scales, from atmospheric to oceanic time scales.

Besides obtaining an initial condition for launching a weather forecast, data assimilation methodology can also be used for parameter estimation. Since the largest uncertainties in climate and weather models are associated with their physical parameterizations, improvements in these schemes may reap great benefits. This process has been used in the NWP context, but it is relatively new for climate models. It is simple enough to determine uncertain parameters for a given parameterization scheme [such as gravity wave drag (GWD) or convective schemes]. However, if the scheme is not adequate (i.e., it has too few or too many parameters, or it is missing processes), then the results of assimilation may not lead to useful parameter estimates. Nonetheless, the failure of the assimilation process could provide an indication of the inappropriateness of a given scheme without directly indicating how it should be improved.

The coupled seamless prediction system requires unified data assimilation and model development. This already occurs for NWP, but it is less common for climate models. The trend toward unified weather/climate models should help solve this problem. For example, there is a need to test "climate modelling in a deterministic prediction mode," as advocated by Morel (2007). Thus, close collaboration between data assimilation and model developers is needed to interpret assimilation results and address flaws in specific schemes. Environmental monitoring initiatives have already linked assimilation with models of atmospheric composition, and deterministic forecasts have been used to better understand middle atmosphere climate models in the context of the WCRP Stratospheric Processes and their Role in Climate (SPARC) program. As an example, Fig. 1 shows that a GWD scheme can provide the dominant forcing in the mesosphere for some phenomena (here, a stratospheric sudden warming). If the zonal-mean mesosphere is sometimes slaved to the stratosphere through GWD, then this raises the prospect of using data assimilation of mesospheric observations to constrain GWD parameters.

There is also the problem of forecasting initial conditions in the stratosphere. The stratosphere has more intrinsic memory than the troposphere, with significant intraseasonal memory (during winter) in the polar regions and interannual memory in the tropical winds. Thus, correct stratospheric initial conditions, and realistic retention of those conditions in the model, are required for accurate subseasonal and seasonal prediction.

New resources would accelerate the development of seamless coupled model and data assimilation systems discussed earlier (Shapiro et al. 2010; Shukla et al. 2010). One mechanism to achieve this (also promoted by Trenberth 2008) is through the various reanalysis projects that provide a historical record for climate studies. In the past these projects have been based on operational NWP systems; most of the resources were directed toward gathering and controlling the quality of the observations and performing the assimilation. Next-generation developments can no longer rely on operational forecast systems, now requiring an interdisciplinary research program on data assimilation methodologies, as advocated by Shapiro et al. (2010).

SOCIOECONOMIC APPLICATIONS. The primary rationale for pursuing a seamless prediction

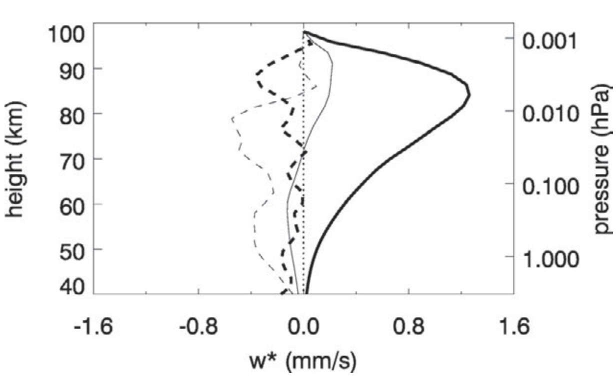

Fig. 1. Residual vertical velocity w^* induced by the resolved waves (dashed line) and nonorographic GWD parameterization (solid line) in the steady, "downward control" limit. The calculation is area-weighted and averaged over the polar cap (60°–90°S) and during the period 25 Sep–1 Oct 2002, for an ensemble of three forecasts that capture (thick curves) or miss (thin curves) the 2002 stratospheric sudden warming in the Southern Hemisphere. Positive (negative) w^* is associated with cooling (warming). The GWD parameterization is responsible for the mesospheric cooling (upwelling) around 80 km in the forecast "hits" (thick solid curve). For the forecasts that miss the stratospheric warming (thin solid curve), the upwelling and associated cooling due to parameterized waves are much smaller. In these experiments, observations were only assimilated below 50 km, so the mesospheric response occurs entirely through the model dynamics. If this mesospheric cooling is not verified by observations, then the GWD parameterization needs adjustment (Ren et al. 2008).

process is that the resulting information will influence decisions that contribute to objectives such as protection of life and property, enhancement of socioeconomic well-being, and sustainability of the environment.

Weather forecasts have been proven useful for short-term decision making in many economic sectors, and the number of applications to longer-term operational and planning decisions—including those related to climate change—is growing. However, there is considerable evidence of underutilization of weather and climate information that may be rooted as much in a lack of understanding of the decision-making context as in the accuracy or precision of atmospheric predictions. A variety of constraints make it difficult for decision makers to benefit fully from scientific information and for the science to satisfy users' needs (Jasanoff and Wynne 1998; Morss et al. 2005; Rayner et al. 2005). Extending the concept of "seamless prediction," as introduced earlier in the paper, may help resolve this problem if the process explicitly incorporates social science together with users' knowledge and experience.

Take public health, for example (Fig. 2). Decisions cover a wide range of temporal scales, each influenced by weather, climate, and even climate change predictions, but only in combination with other pieces of information (e.g., expected disease outbreak patterns, available medical supplies, poverty indicators) that more directly relate to health outcomes. In this sense the term *seamless* extends beyond the realm of atmospheric predictions to include the consideration of biophysical, medical, and socioeconomic factors pertinent to successful decision making (Shapiro et al. 2010). Potential benefits are greatest in developing nations, especially in Africa, where at least 30 climate-sensitive diseases pose a major threat to the lives and livelihoods of millions of people. More than 500 million Africans live in regions endemic with malaria, which is highly correlated with the seasonal climate, and a further 125 million people live in regions prone to epidemic malaria, which is correlated with climate anomalies (Connor and Thomson 2005). About 350 million Africans are also at risk for meningococcal meningitis, a disease linked to the dusty conditions prevalent during the dry season in sub-Saharan Africa. In each of these diseases, the response time to a particular outbreak or epidemic is greater than one week and often much longer.

Collaboration with medical and social scientists permits the development of these environmental prediction tools and decision support across time scales of NWP and seasonal forecasting. In addition to working across disciplinary boundaries, an enriched concept of seamless prediction within WWRP/WCRP also demands active involvement of service providers and users/decision makers (Morss et al. 2008).

Fortunately, these elements have been successfully embodied in several projects that serve as demonstrations for future activities. Many projects are focused on shorter-term applications [e.g., many client-based activities of the Met Office (www.metoffice.gov.uk/services/)] or have been developed to help decision makers across a range of sensitive sectors (e.g., water management, agriculture, coastal management, tourism) to understand and to begin to consider adaptations to the effects of climate change (see IPCC 2007). Others target the seasonal-to-subseasonal scales. For example, sand and dust research is already incorporated into studies such as the Meningitis Environmental Risk Information Technologies (MERIT) project (http://merit.hc-foundation.org/), which is user-driven and led by the World Health

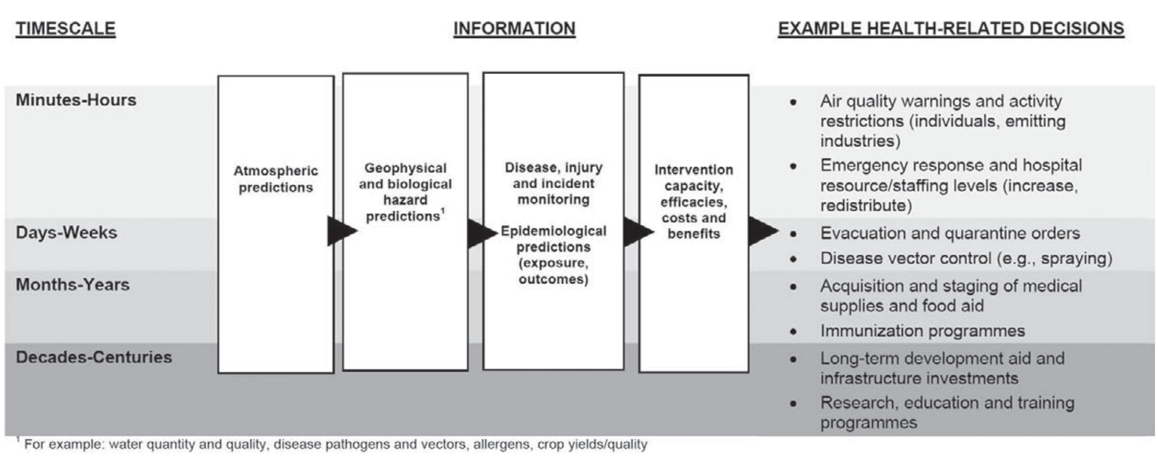

Fig. 2. Simplified set of public health–related decisions and supporting information.

Organization. Such studies are leading the way in demonstrating the need for the integration of environmental information with social, economic, and health risk factors to develop timely and geographically specific warnings of disease outbreaks. MERIT is a decadal-long operational research project that was conceived in response to a specific need identified by the health sector. The health community was aware of the importance of the environment for the outbreak of meningitis, but it lacked the capacity to address the issue alone. The result was a team of about 30 research institutions and country health services working together to build a predictive model of disease risk that appropriately incorporates environmental prediction and assessment into the health decision process.

In part by building and learning from formal evaluations of projects such as MERIT, social science research can contribute to a seamless prediction system by identifying effective and sustainable mechanisms for generating and communicating decision-relevant weather and climate information; assessing the use and value of this information in decision making, making refinements as needed; and transferring knowledge and experiences to other regions. A practical first step is to determine where within each country or region the greatest potential for use of subseasonal-to-seasonal forecasts exists, and where the largest social benefit and biggest buy-in can be realized. Inevitably, this will vary by region and involve trade-offs; it may be easier to develop a successful relationship with representatives of the electricity sector to enhance supply, demand, and delivery efficiencies, but it is more important to work with an initially less familiar and less receptive set of decision makers responsible for public health and safety issues. The necessary infrastructure (e.g., near-real-time hospital patient data) may be in place in some regions to develop an operational weather-related hospital admissions forecast but not in others. Whatever priorities emerge, they can then be used as a focus for articulating requirements. In the longer term, it will be critical to develop and expand the pool of scientists and practitioners that can perform or at least dialogue seamlessly across disciplinary, scale, and applied-academic boundaries. Toward this end, collaborations with programs such as Weather and Society*Integrated Studies (WAS*IS; Demuth et al. 2007), Global Change System for Analysis, Research, and Training (START; www.start.org), and Dissertations Initiative for the Advancement of Climate Change Research (DISCCRS; www.disccrs.org/) will be particularly helpful.

CONCLUSIONS. Collaboration between climate and weather communities has always existed, as these scientists are in front of problems with great similarities. A more formal and reinforced collaboration between WWRP and WCRP is timely because of the technological advances and the much-increased interest in subseasonal-to-seasonal ensemble prediction systems (Shapiro et al. 2010). This is a problem that both communities can effectively collaborate on to better tackle shared critical issues: i) the modeling problems of tropical convection and two-way interaction with the global circulation; ii) data assimilation for coupled models; and iii) the understanding of weather/climate information and utilization. We promote the fact that weather, climate, and Earth-system prediction services will greatly benefit worldwide from this joint effort.

The success of this endeavor will depend, of course, on the collaboration, commitment, excellence, and strength of the weather, climate, Earth system, and social science research communities (Nobre 2010; Shapiro et al. 2010; Shukla et al. 2010). On this point, the twentieth-century track record provides a solid base for confidence.

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