14 Coupled special-applications models

14.1 Background

Sometimes the standard dependent variables of NWP and climate models are all that are required for making decisions. But, frequently these meteorological variables influence some other physical process that also must be simulated before a weather-dependent decision can be made. As we will see, there are myriad examples of such situations. These models that are coupled with the atmospheric model may be referred to as special-applications models or secondary models. Examples include the following.

- Air-quality models
- Infectious-disease models
- Wave-height models
- Agricultural models
- River-discharge, or flood, models
- Wave-propagation models – sound and electromagnetic
- Wildfire-behavior and -prediction models
- Electricity-demand models
- Dust-elevation and -transport models
- Ocean-circulation models
- Ocean-drift models
- Aviation-hazard models – turbulence, icing, visibility

Sometimes the secondary model is embedded within the code of the atmospheric model, and the coupled system is run simultaneously. And, sometimes there are two distinct model codes that are run sequentially. When the code that represents the secondary process is run within the atmospheric model, the secondary process may interact with the atmospheric simulation. Or, the flow of data may be in one direction only, where the atmospheric variables are used in the secondary model without feedback. There are some secondary-model processes that have strong feedbacks to the atmosphere, and for their prediction there is of course a greater need to have a two-way exchange of information between the atmospheric and secondary models. Examples include dust models wherein the dust influences the atmospheric radiation budget, wildfire behavior models where the fire modifies the atmospheric circulation, atmospheric-chemistry models where gases and particles that are involved in reactions influence the radiation budget, and wave-height models where the waves influence the evaporation rate and roughness length. These coupled models are applied on time scales of daily weather prediction, seasonal prediction, and multi-decadal climate prediction.

Even though it is implied above that the coupling is between two models, the atmospheric model and the application model, there are some situations in which more models are involved in the process. For example, assume that a disease pathogen is released into the atmosphere.

- *Atmospheric model* – The atmospheric model will define the transport winds, boundary-layer turbulence, humidity, etc.
- *Plume model* – A plume model will calculate the transport and diffusion of the aerosol, and the dosage (time-integrated concentration) or human exposure footprint at ground level.
- *Disease models* – A disease model can simulate the spread of a disease in an organism (humans or agricultural livestock) or among organisms (e.g., human beings) in a population.
- *Treatment models* – These define an optimal course of treatment based on many factors including the time since exposure, the size of the exposed organism, etc. This will most likely be a simple protocol that is based on previously run pharmacokinetics (how the drug moves around the organism) models and pharmacodynamics (how the drug acts on the organism) models.

The secondary and tertiary (etc.) processes or variables may be defined using physically based equations, such as chemical reactions in air-quality models or ocean currents in ocean-circulation models. Or, the secondary model may simply be a set of statistical or empirical algorithmic relationships that relate the predicted atmospheric state to some other variable. The simpler relationships are often call translation algorithms because they translate atmospheric conditions to the state of some other quantity. Thus, a hierarchical ranking of coupled models, from the simplest to the most sophisticated approaches, is as follows.

- *Type 1: Decision-Support Systems (DSSs)* – These can be simple or complex systems that formalize a decision-making process, using meteorological and other input data. Even though it can be argued that these are not models at all, DSSs nevertheless do post process model output, interpreting the large amount of data to allow decisions to be made in an intelligent and repeatable way. As shown below, these DSSs can be used to interpret atmospheric-model or coupled-model output.
- *Type 2: Translation algorithms* – These are simple physical equations or statistical relationships that use, as input, the variables predicted by the atmospheric model to define ancillary, sometimes nonmeteorological, variables that are required. An example would be algorithms that calculate atmospheric visibility or radio refractive index based on model output.
- *Type 3: One-way coupled models* – Even though the above translation algorithms do not feed information back to the atmospheric model, and are therefore one-way coupled, they are sufficiently simple that it can be argued that they should be distinguished from codes that are larger in size and might actually be considered a model in a traditional

sense. Examples of one-way coupled models are codes that model the spread of infectious diseases, some dust elevation and transport models that do not feed back, and some flood models.

- *Type 4: Two-way coupled models* – These are generally large pieces of code that may be embedded in the atmospheric model, for example as a subroutine. An example may be an ocean-wave model or an ocean-circulation model.
- *Type 5: Specialized atmospheric models* – Sometimes an atmospheric model is merged with specialized-applications codes in such an extensive way that the entire modeling system becomes specialized. For example, some atmospheric-chemistry models involve a thorough merger of the atmospheric and chemistry codes to produce an integrated, specialized model (e.g., WRFChem).

Because the coupled, secondary models are typically employed in order to provide information that can be used to make practical decisions, the secondary-model output is often used as input to a formal DSS. This DSS translates the data provided by the secondary model, and perhaps the driving atmospheric model, into a decision about whether to take an action – protect an agricultural crop against freezing, apply an anti-icing agent to a highway or an aircraft, vaccinate a population against an infectious disease, or evacuate a town that is threatened by flooding. The DSS may include an analysis of the relative benefit versus cost of taking alternative actions. This sequence of software components is summarized in Fig. 14.1.

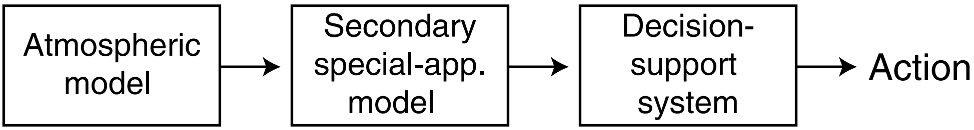

Fig. 14.1 Sequence of software components that are involved in providing the basis for a decision (action) that is weather dependent.

There is a hierarchy of methods for verification of coupled modeling systems, and this is illustrated in Fig. 14.2. First, it is reasonable to want to verify the accuracy of the atmospheric model alone, in the context of the geographic area and atmospheric variables of interest. In the figure, this is referred to as a Type-1 verification, where archived cases are used and the model retrospective forecasts are compared with meteorological observations or reanalyses. A Type-2 verification would again involve the use of historical cases, but the full coupled model (the atmospheric model and the end-user, or secondary, model) would be employed to produce a forecast of the secondary variable. This would be compared with a forecast from the secondary model that used meteorological input from observations or analyses. This tests the coupled system, but no observations of the secondary variable are used for verification, so the veracity of the secondary model is not evaluated. For the Type-3 verification, the coupled model is used for a retrospective forecast, but the forecast secondary variable is compared with observations.

This chapter will not provide a detailed discussion of the coupled models themselves. Rather, the focus will be on how the coupled modeling systems or algorithms are used to address practical problems. References will be cited for additional reading.

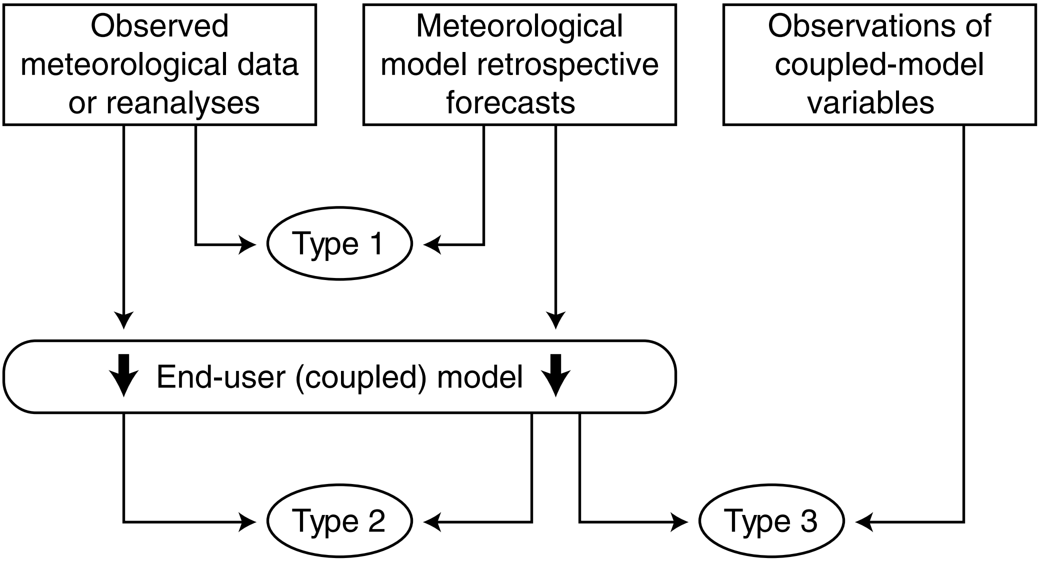

Fig. 14.2 Three types of verification for coupled modeling systems. See the text for details. Adapted from Morse *et al.* (2005).

14.2 Wave height

There are various practical and modeling-related reasons for wanting to model the properties of wind-driven waves that exist on oceans and other water bodies.

- Heights of waves and swells impact the safety of recreational and commercial maritime activities, and therefore must be forecast. In the extreme, it would also be desirable if the probability of "freak" or "rogue" wave occurrences might be predictable.
- Wave action in littoral zones can be used to generate electricity, and thus wave forecasts are related to power forecasts.
- Evaporation of spray from waves releases aerosols into the atmosphere, which can influence cloud microphysical processes that are parameterized in a model.
- The albedo of the water surface is a function of wave activity, and is needed in the calculation of the ocean's energy budget.
- The evaporation rate is a function of the amount of sea spray, and this affects atmospheric temperatures.
- The roughness of the ocean surface that is experienced by the atmospheric-model's surface layer is a function of wave properties.
- Wave activity is associated with vertical mixing in the upper layer of water, which influences the water temperature at the lower boundary of the model atmosphere.

One or more of the above effects of waves on the atmosphere can be individually parameterized directly in the atmospheric model, or the predicted atmospheric variables can be used as input to a separate model that diagnoses wave properties. Wave-height predictions can be verified against buoy observations, as can the near-surface wind predictions that are

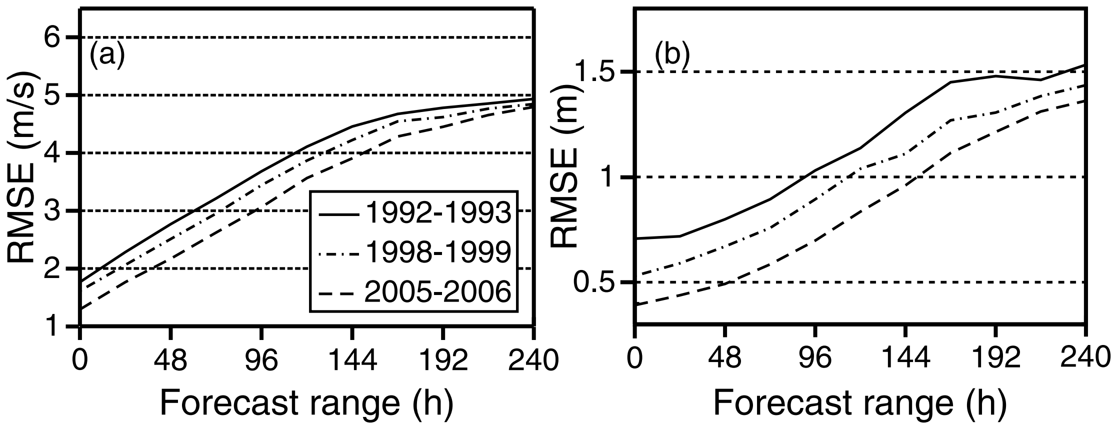

Fig. 14.3 Accuracy of wind-speed (a) and wave-height (b) forecasts, based on ECMWF global-atmospheric and wave-height models. Statistics are shown for three years during a 13-year evolution of the models. The wave model employed wind predictions from the atmospheric model. Verification of both variables used buoy observations during October through March. Adapted from Janssen (2008).

used in the wave models. Indeed, wind-prediction accuracy is critical to wave-height prediction. For example, Fig. 14.3 shows the improvement in the accuracy of ECMWF wave predictions over a 13-year period, as well as the associated improvement in the prediction of the near-surface wind speed. Janssen (2008) calculated that 25% of the improvement in the wave-height forecasts, whose accuracy is shown in this figure, resulted from improvements in the wave model itself. The rest of the improvement was a consequence of more-accurate wind predictions. Growth in the wave-height RMSE was approximately linear between about 48 h and 168 h, with the error beginning to saturate after that. For additional discussion of wave-model verification, see Bidlot *et al.* (2002) who compare buoy observations with ocean-wave forecasts from a number of operational centers.

Note that wave heights are a function of wind gustiness as well as of the mean wind that is predicted by Reynolds-averaged model equations. The previously mentioned concept of a weather generator can be used here to infer gustiness based on air–sea temperature differences, where the gustiness metric can be used in the wave model (Abdalla and Cavaleri 2002).

14.3 Infectious diseases

The atmosphere can influence the spread of human and agricultural infectious diseases through a few different mechanisms, which are summarized in Fig. 14.4.

- *Health of the pathogen* – The health of the disease organism may be related to atmospheric variables such as temperature, relative humidity, the intensity of ultraviolet radiation, and precipitation.

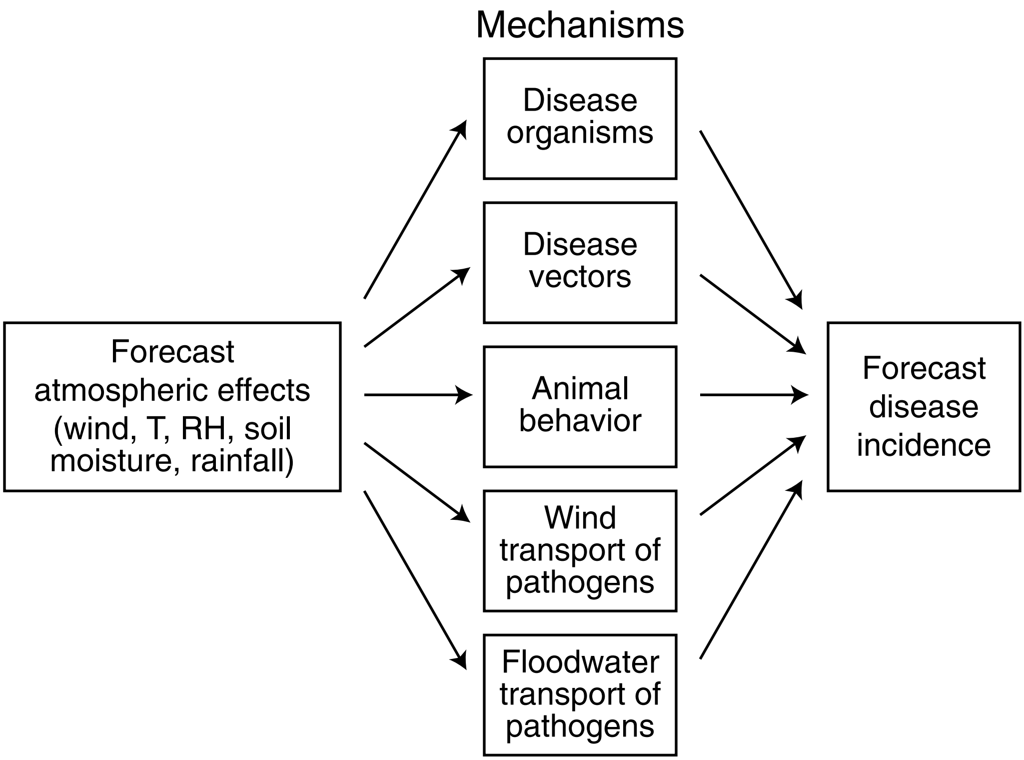

Fig. 14.4 Mechanisms by which atmospheric processes influence the spread of infectious diseases. The implication is that predictions for the atmosphere can be translated into predictions of disease emergence and spread.

- *Disease vectors* – The disease may spread through vectors such as fleas, mosquitoes, or rodents, and the number and health of the vectors can depend on temperature, relative humidity, vegetation greenness, and soil moisture.
- *Animal behavior* – Animal behavior is related to atmospheric conditions (e.g., for humans, the amount of time spent indoors in proximity to other people), and this behavior can influence the spread of disease.
- *Wind transport* – The wind can transport disease organisms and expose new populations.
- *Flooding* – This can increase the incidence of many diseases as a results of the compromise of fresh-water supplies, forced migration, and the production of a favorable environment for disease vectors.

Through knowledge of the statistical or physical relationships between disease incidence, for example outbreaks, and weather or climate conditions, it is possible to translate predictions of the atmosphere into predictions of disease spread or incidence. Medium-range forecasts of 7–10 days can allow redistribution of vaccines and medical personnel to locations that will be in greatest need. And interseasonal forecasts, e.g., of the ENSO cycle, can provide long-lead-time information for disease early-warning systems, which can guide the manufacture of vaccines and inform aid agencies about future requirements (Thomson *et al.* 2006). Because of the existence of complex physical, biological, and societal aspects to the links between atmospheric conditions and disease, correlations used for prediction are sometimes employed without a good knowledge of the underlying mechanisms. Given that some period of time exists between the occurrence of atmospheric conditions that are related to disease incidence, and the response of the incidence itself, lagged correlations can be used to develop statistical relationships for prediction.

14.3.1 Human infectious diseases

The following major infectious diseases have been shown to have some relationship to atmospheric conditions (weather or climate). The meteorological and other factors can be temperature, relative humidity, wind speed and direction, precipitation, sea-surface temperature, and vegetation-canopy density and health.

- West Nile virus
- Dengue Fever (DF)
- Dengue Hemorrhagic Fever (DHF)
- Valley fever
- Rift Valley fever
- Malaria
- Meningitis
- Cholera
- Typhoid fever
- Leptospirosis
- Hepatitis A

For human infectious diseases, there is an especially strong potential connection between weather or climate and human activities that can spread pathogens. For example, drought can cause migrations. Windy, dusty, rainy, or cold conditions can cause humans to congregate inside and spread diseases through contact. Thus, disease-spread prediction models must incorporate societal/behavioral factors as well as physical and biological processes.

An example of a success at establishing correlations between weather factors and human disease is described in Fuller *et al.* (2009), who explain 83% of the variance in weekly DF/DHF cases in Costa Rica from 2003 to 2007 using a simple regression model that incorporates lagged ENSO-related SST and MODIS vegetation indices. Another example involves the production of retrospective forecasts of malaria. The atmospheric model simulations were produced by seven institutions in Europe that participated in the DEMETER project (Palmer *et al.* 2004). The output from these models was used in a Malaria Transmission Simulation Model (MTSM, Hoshen and Morse 2004). The DEMETER-MTSM system was verified using the Type-2 method described earlier (Fig. 14.2), where ERA-40 gridded analyses (see Chapter 16) served as the atmospheric verification data set. The malaria predictions were shown to be skillful for the 1-month lead seasonal predictions, and for the 4–6-month lead for the seasonal malaria peak. Other discussions of the use of seasonal weather predictions for anticipating malaria outbreaks are found in Thomson *et al.* (2000) and Thomson and Connor (2001). Reviews of the overall potential for predicting human infectious diseases using weather and climate forecasts can be found in Kuhn *et al.* (2005) and NRC (2001).

As another illustration of how atmospheric-model reanalyses and predictions can be used to make decisions about infectious-disease management, consider the problem of meningitis in the Sahel of Africa. Even though the mechanisms are unclear, meningitis outbreaks tend to occur as the relative humidity decreases in the winter season, when harmattan winds bring dry, dusty air from the Sahara. When the relative humidity increases with the beginning of the Guinea monsoon, the number of cases decreases. Forecasting the spatial pattern of the seasonal rise in relative humidity is important to allow the appropriate distribution of the remaining vaccine. We begin by defining a somewhat arbitrary threshold for cessation of meningitis susceptibility as the first occurrence of five continuous days of relative humidity of at least 40% for any point on a grid. Those areas of the Sahel for which this threshold is reached at times that vary considerably from year to year could benefit from forecasts. If there is little year-to-year departure from the climatological date when this condition is met, the climatology can be used. Figure 14.5 shows a map of the standard deviation of the date on which this criterion is first met, based on the NCEP-NCAR Reanalysis Project archive (NNRP, Section 16.2, Kalnay *et al.* 1996) for

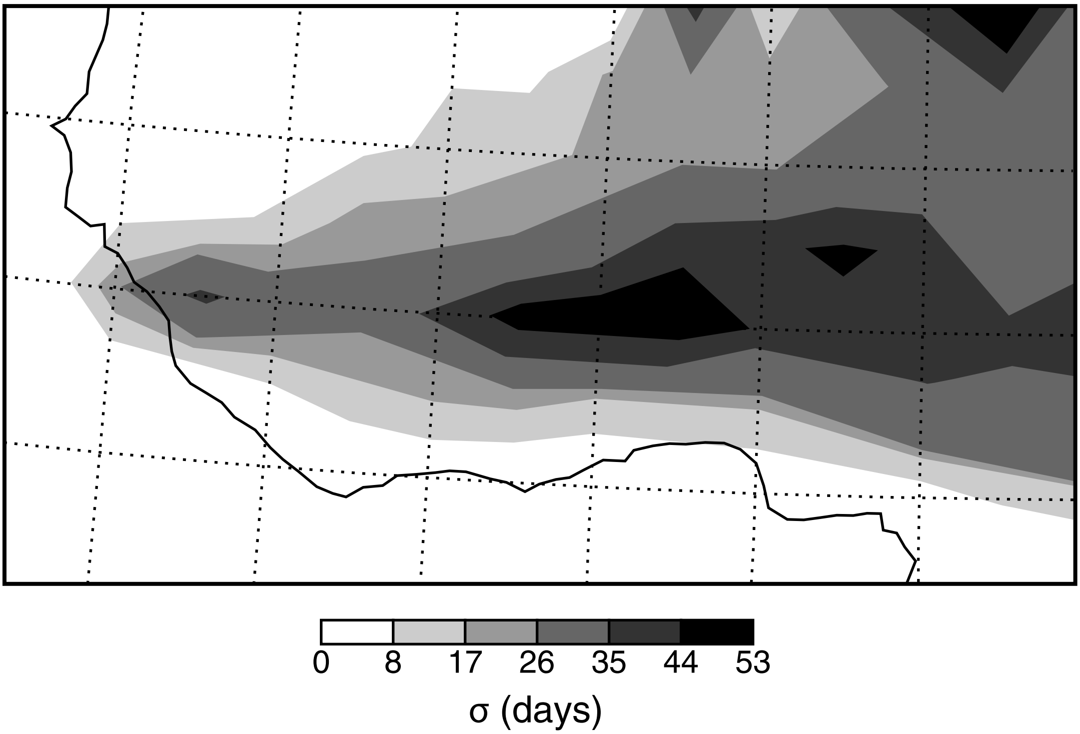

Fig. 14.5 The standard deviation in the date on which five continuous days of relative humidity of at least 40% first occur in the Sahel, based on 50 years of the NNRP reanalysis. Provided by Thomas Hopson, NCAR.

1949 through 2009. The standard deviation approaches or exceeds a month over a significant area of the central Sahel, indicating where forecasts of this threshold, or a similar one, would be useful.

14.3.2 Agricultural diseases

Many agricultural diseases are related to atmospheric conditions, so models for disease probability or spread use NWP forecasts or analyses as input. Examples of plant-disease forecasting systems used by the US Department of Agriculture for diagnosis and prediction of insect pests, fungal diseases, mildew, etc., are NAPPFAST (Magarey *et al.* 2007) and ipmPIPE (Isard *et al.* 2006). These are interactive web-based systems that generate a number of weather-dependent crop and disease maps and other graphical products that allow farmers to save money by targeting mitigation strategies (e.g., pesticide applications) only where and when they are needed. Also, some plant and livestock diseases are spread by aerosols (e.g., spores, bacteria, viruses) that are carried by the wind, so the plume models discussed in Section 14.5.1 can be used with input from NWP-model analyses or forecasts to track the movement of these pathogens. Similarly, insect pests are carried by wind from regions where they begin their life cycle to regions where they can impact agriculture, so plume-type models can predict these processes as well. Many different systems that employ atmospheric-model products have been developed to address the specific needs of agriculture, worldwide.

14.4 River discharge, and floods

Operational river-discharge[1] models, flood models, and flash-flood models often use precipitation estimates from radars and rain gages as input. However, the forecast lead time for flooding at a particular location on a river is thus limited to the time it takes the rainwater (and possibly resulting snowmelt) to travel along the water course. This may allow insufficient time to respond, whether the forecast information is being used to warn or evacuate people near the water course, or to release water from a downstream dam. A solution is to use atmospheric-model forecasts of precipitation as input to the discharge/flood-prediction model, thus providing much additional lead time for the response.

Discharge models have a wide range of complexities, and the partitioning between those aspects of the surface hydrologic cycle that are treated in the atmospheric model and those that are represented in a separate discharge model varies considerably. Many current-generation NWP models employ a simple representation of the hydrologic cycle in their land-surface model; they partition some water as runoff in each grid cell, but they do

[1] Discharge is the volume of water flowing in a river or stream channel, and is generally defined in cubic meters per second.

not route or track the water from grid cell to grid cell through channels across the land surface, and thus they cannot explicitly predict discharge. This would need to be accomplished by a coupled runoff/discharge model. Obviously, the processes represented in coupled discharge and atmospheric models need to be compatible, and collectively define the entire surface-hydrologic system. Alternatively, some atmospheric models represent the entire process, including surface routing and calculation of discharge.

Flash floods are defined as events wherein the water goes from base-flow to flood level in less than 6 hours, they are most common in complex orography, they are typically caused by convective–precipitation events, and they take a significant number of lives because of the short warning time available. Unfortunately, for a variety of reasons, radar estimates of precipitation are often unreliable or nonexistent in areas of complex terrain. And, rain gages are sparse in mountains, and their estimates are not representative of a larger area. Thus, a useful degree of predictability of flash floods in mountainous terrain, if that is attainable, may have to rely on precipitation forecasts with convection-resolving atmospheric models that accurately represent local orographic and other landscape forcing. There have been occasional successful simulations in research settings that give us hope for possible eventual operational predictability in such situations. For example, Nair *et al.* (1997) describe a successful model simulation of the convective storm that produced the severe 1972 Black Hills flash flood in a mountainous area of South Dakota, USA. Also for an area in the USA with complex orography, Fig. 14.6 shows a discharge simulation from a coupled mesoscale LAM (MM5) and a discharge model (Precipitation-Runoff Modeling System, PRMS, Leavesley *et al.* 1983) for a convection-related flash-flood event (Yates *et al.* 2000, Chen *et al.* 2001). The simulations were part of a research study to estimate the effects of a recent wildfire on the severity of the flood. Shown are discharge calculations from PRMS based on the use of radar-estimated and model-simulated precipitation, and for land-surface parameters in MM5 and PRMS that were defined with the burn area (fire) and with the pre-burn natural vegetation (no fire). Also shown is the discharge calculated by simply totaling the amount of model-simulated rainwater that is partitioned to runoff, where no routing through the stream channels is calculated. The discharge estimated from the high-water marks along the water course is indicated. Discharge was calculated accurately by PRMS using the radar-estimated rainfall (with the fire, solid line), but the use of MM5-simulated precipitation in PRMS underestimated the peak discharge by a factor of three (dotted line). However, the base flow for the stream was normally only a few meters per second, so a significant event was still predicted. The direct-MM5 discharge peak was earlier than the observed peak because the time required for the rainwater to flow to the location of the verification was ignored. And, no water was lost to infiltration during overland flow, so the peak discharge was greater than that produced by PRMS. Thus, the reasonably accurate value of this peak was probably obtained for the wrong reason.

As an example of the use of this type of coupled system for larger scales (continental USA) and longer lead times (to 8 days), Clark and Hay (2004) evaluated discharge forecasts for four study basins, based on the PRMS model coupled with the NCEP MRF model. The MRF precipitation forecasts showed considerable error in many regions, so the temperature and precipitation forecasts were corrected using MOS (Chapter 13). The

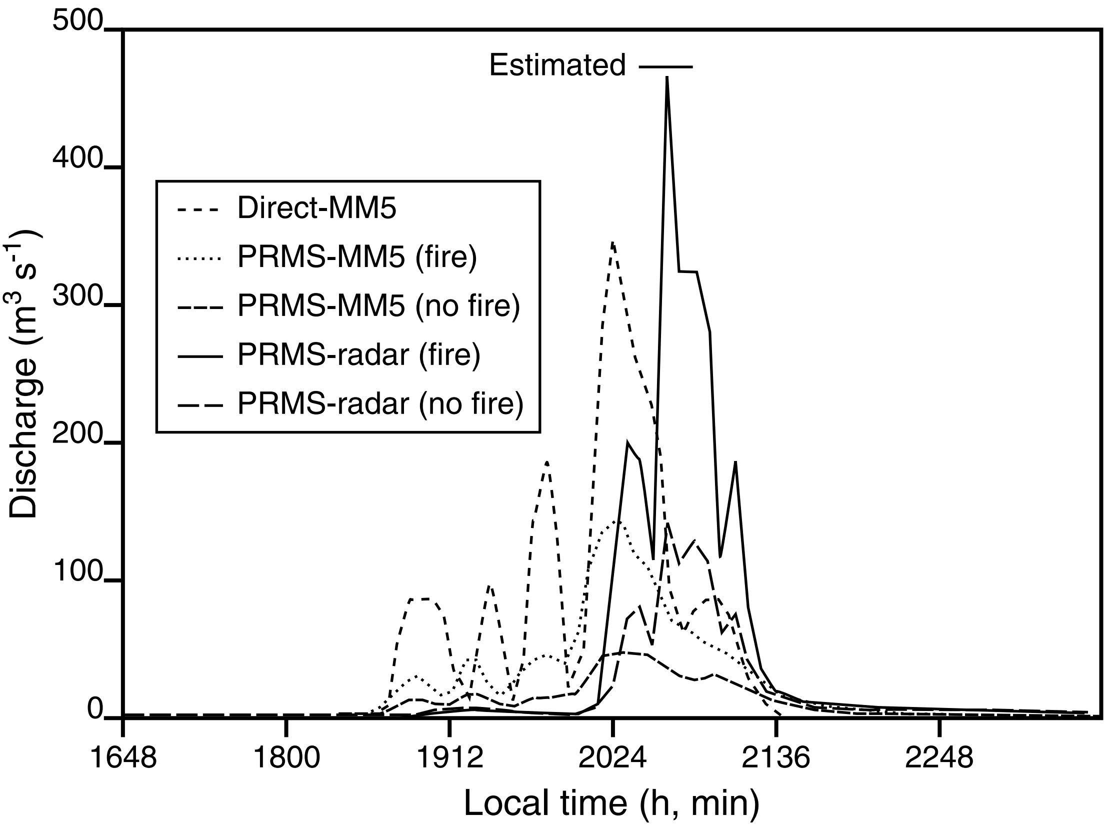

Fig. 14.6 Discharge simulation from a coupled mesoscale LAM (MM5) and a discharge model (PRMS) for a convection-related flash-flood event. Shown are discharge calculations from PRMS based on the use of radar-estimated and model-simulated precipitation, and for land-surface parameters in MM5 and PRMS that were defined with the burn area and with the pre-burn natural vegetation. Also shown is the "discharge" calculated by simply totaling the amount of model-simulated rainwater that is partitioned to runoff, where no routing through the stream channels is calculated. See text for details. Adapted from Yates *et al.* 2000.

MOS correction of systematic error provided improved discharge forecasts in only the snowmelt-dominated river basins because the MOS was only able to improve temperature and not precipitation forecasts.

The predictive skill of discharge forecasts from coupled atmospheric–discharge models is obviously no better than that of the precipitation forecasts. And, of course we know that precipitation forecast skill has shown the slowest benefit, relative to other dependent variables, as a result of improvement in all aspects of atmospheric-modeling systems. On the convective scale, operational models have virtually no skill at deterministically predicting precipitation events – i.e., correctly locating individual convective cells. Thus, referring to the convective events that commonly lead to flash flooding, even though a mesoscale model may be able to routinely predict the general area and severity of the convection, there is relatively little hope of using the forecasts as a basis for evacuating residents when the watersheds are of small to modest size.

Discharge models are often used in conjunction with global or regional climate models in order to couple the hydrologic cycles over land and over the ocean. In addition, there is a need to assess changes to the hydrologic system associated with future-climate scenarios (e.g., Bell *et al.* 2007, Bronstert *et al.* 2007, Charles *et al.* 2007, Fowler *et al.* 2007).

14.5 Transport, diffusion, and chemical transformations of gases and particles

There are a few types of models that are used operationally and for research to track the transport, turbulent diffusion, and chemical transformation of particulates and gases in the atmosphere. These types of models are summarized in the sections below. Note that there can be considerable overlap in the purpose, numerical approaches, and processes represented in the different types of models. Dust elevation and transport models are used to simulate or predict the elevation of mineral dust from the surface, and the consequent dust storms that result. Volcanic-ash models also track dust, but specifically the material that is ejected forcefully into the troposphere and stratosphere from a volcano. Air-quality models are specialized or general models that simulate gases or particles whose concentrations are often regulated for environmental or human-health reasons, where the sources can be numerous and distributed over a large area (e.g., an entire city). Plume models tend to be used for single sources of contaminants, or perhaps a few sources.

14.5.1 Plume models

A plume is a volume of air, containing particles or gases that have been released into the atmosphere, that spreads horizontally and vertically from its source. Models that simulate plumes are generally Type-3 models, which do not feed back to the atmospheric model that provides them with time-dependent winds, thermal properties, humidity, precipitation, and possibly turbulence intensity. All of these meteorological variables can influence plumes in different ways. Plume models can have either an Eulerian or Lagrangian framework. With an Eulerian approach, the gaseous or particulate contaminant is released in a grid box within a three-dimensional array of points, and the model calculates the transport of the material from the source to downwind grid boxes through transport by the mean wind and turbulence. In contrast, with Lagrangian methods, puffs or particles of material released from the source are tracked, where their size or concentration, and location, are again controlled by atmospheric processes. Thus, Eulerian methods are grid-centric and Lagrangian methods are plume-centric. In either case, the plume model essentially solves a continuity equation for the gas or particles released.

Plume models have a variety of practical applications, including predicting

- the impact of smoke from wildfires;
- the movement of hazardous chemical, biological, and radiological material that has been accidentally released (an industrial or transportation accident) or intentionally released (a terrorist attack) into the atmosphere; and

- the airborne movement of insects or naturally occurring pathogens that are related to human or agricultural infectious diseases.

If the atmospheric model produces a forecast, the plume evolution is a forecast. If model-based reanalyses are used as input to the plume model, the simulated plume can be viewed as a reconstruction of a real or hypothetical historical event. The plume-modeling process involves a few steps. First, the atmospheric variables must be predicted by a model or diagnosed by a data-assimilation system. Then the source of the material being tracked needs to be estimated in terms of the amount of material released (instantaneously or continuously) and the location of the source (moving or stationary). The plume-model equations, in Eulerian or Lagrangian form, are then integrated in order to calculate the downwind advection and diffusion of the plume.

14.5.2 Air-quality models

Air-quality models typically represent (1) multiple sources and species of contaminants, (2) chemical reactions among contaminants, and between them and naturally occurring gases and particles, (3) transport and diffusion, and (4) interactions of contaminants with cloud, precipitation, and radiation. They are used for research, regulatory purposes, and forensic analysis. Research applications attempt to improve knowledge of physical and chemical processes associated with the existence of pollutants in the atmosphere. Regulatory applications take a number of forms, where an example is the use of the model to assess the impact on air quality of a proposed new source of pollution, where the results of the study would serve as the basis for a decision about whether to permit the source to operate. A forensic analysis could involve the use of a model to establish a source–receptor relationship between a region that produces pollutants and regions that are impacted by them. Air-quality models can be of Type 3, 4, or 5. Examples and brief discussions of each type of air-quality model application are provided in the following sections. Summaries of these models, and extensive reference lists are provided in the review papers by Russell and Dennis (2000) and Carmichael *et al.* (2008), and the text by Jacobson (1999).

Research applications

Research applications are likely to use model Types 4 and 5, because complete interaction among the various physical and chemical processes is desirable. An example of a Type-5 model is the WRFChem LAM system (Grell *et al.* 2005) that is based on the integration of chemistry into the framework of the community WRF atmospheric model. When used with some type of urban-canopy parameterization, it is applicable for research studies of atmospheric, physical, and chemical processes in urban areas. For example, Jiang *et al.* (2008) used WRFChem to estimate the impact on surface ozone of climate change related to greenhouse gases and urban growth in Houston, USA for the 2050s. And, Zhang *et al.* (2009) applied the model for Mexico City for the period of the MILAGRO field campaign, and verified chemical-species concentrations against special observations.

An example of a global air-quality system is the Model for Integrated Research on Atmospheric Global Exchanges (MIRAGE, Easter *et al.* 2004), which is designed to study the impacts of anthropogenic aerosols on the global environment. The MIRAGE system consists of a chemical transport model coupled with the Community Climate Model, Version 2 (CCM2). Zhang (2008) summarizes the history, current status, and outlook for coupled atmospheric and chemistry models, and includes the MIRAGE and WRFChem models in the discussion. The Community Multiscale Air Quality (CMAC) model is an example of a Type-3 coupled system that is used for research.

Operational applications

Air-quality models are used to provide operational next-day predictions of various measures of air quality, such as ozone concentration, in order to inform the public about the need for possible avoidance of exposure. Such models are used worldwide, and address the specific local air-quality issues. An example is the US National Air Quality Forecast Capability (NAQFC), which utilizes the NCEP Eta meteorological model coupled with the CMAQ modeling system (Byun and Schere 2006). Others are the MM5-CMAQ-based system, which is employed for Europe (San José *et al.* 2006) and the Australian Air Quality Forecasting System, which is applied to the regions of Melbourne and Sydney (Cope *et al.* 2004).

Forensic analysis

Forensic studies can take a number of forms, and can be viewed as research investigations that have a specific practical objective (in contrast to improving our knowledge of processes). For example, if a particular geographic region experiences poor air quality in terms of some chemical species or aerosol, perhaps not attaining the minimum standards prescribed by government, air-quality models can be used to help estimate whether the contaminant is being transported into the area from external sources, or how different local mitigation strategies will improve the air quality. The above noted CMAQ model is often used for such studies, where models or reanalyses provide the input meteorological variables.

14.5.3 Dust elevation and transport models

For both research and operational-prediction applications, it is important to be able to model processes that involve mineral dust that has been elevated into the atmosphere by high winds. Because dust has strong influences on atmospheric short- and longwave radiation, and it affects cloud microphysical processes that in turn influence precipitation, its effects should be represented in weather- and climate-prediction models. An example of this importance is that aerosols of Saharan origin have been shown to affect the development of tropical cyclones and hurricanes in the Atlantic Ocean (Karyampudi and Pierce 2002). In addition, dust elevated into the atmosphere has numerous environmental consequences that are important to represent in coupled-modeling systems. These include contributing to climate change; modifying local weather conditions; producing chemical and biological changes in the oceans that can lead to blooms of toxic algae and coral-reef mortality; transporting bacteria and other pathogens over long distances; and affecting soil formation, air quality, surface water and groundwater quality, and crop growth and survival. Societal impacts include disruptions to air, land and rail traffic; interruption of radio services; the effects of static-electricity generation; property damage; and health effects on humans and animals.

Physical processes that must be simulated by a dust model include the lifting of the dust from the surface, which requires accurate representation of the near-surface wind speeds, including the parameterization of gustiness. Correct calculation of this source term also relies on the use of a good land-surface model for predicting soil moisture, and the correct estimation of the density and size of vegetation that can shield the surface from high winds. Winds aloft must also be simulated well by the meteorological model in order to accurately estimate the distance and direction of the horizontal transport. Lastly, the size distribution of aerosol particles needs to be estimated in order for settling velocities and surface deposition to be accurately calculated.

There are numerous dust models used for research and operational prediction worldwide. Examples of Type-4/5 models include (1) the US Navy Aerosol Analysis and Prediction System (NAAPS), which is a global operational aerosol model that involves a coupling of the Navy Operational Global Atmospheric Prediction System (NOGAPS) meteorological model and a dust-transport model (Westphal *et al.* 2009) and (2) a companion LAM, the Coupled Ocean–Atmosphere Mesoscale Prediction System (COAMPS) with an embedded dust-modeling capability (Liu *et al.* 2007). Type-3 models are the Community Aerosol and Radiation Model for Atmospheres (CARMA, Toon *et al.* 1988, Barnum *et al.* 2004, Su and Toon 2009) and the DUst-emission MOdule (DuMo, Darmenova and Sokolik 2007). Lastly, the Barcelona Supercomputing Center operates the Type-3 Dust REgional Atmospheric Model (DREAM, Nickovic *et al.* 2001), which uses meteorological input from the NCEP Eta model.

14.5.4 Volcanic-ash models

Contemporary volcanic-ash models are based on atmospheric models coupled to special transport and diffusion models. Their use is motivated by the need to evacuate populations because of the negative health effects of the dust (called tephra) immediately downwind. And, the dust can seriously damage aircraft engines, so commercial airline flights must be rerouted to avoid the dust plumes. The need for ensuring aircraft safety has motivated most of the historical model applications. One of the earliest examples of the operational use of such a coupled modeling system employed NCEP (then NMC) regional and global models to provide input to the Volcanic Ash Forecast Transport And Dispersion (VAFTAD) model (Heffter and Stunder 1993). Operational products included relative ash concentrations in three aircraft flight layers. Other operational plume-tracking systems are used by the Canadian Meteorological Centre (CMC). The simplest is a three-dimensional trajectory model (see Section 11.2.2) that uses input from the CMC global data-assimilation and forecast systems. The second capability is the CANadian Emergency Response Model (CANERM), which is a three-dimensional Eulerian model for calculating the medium- to long-range transport of pollutants (volcanic ash, radioactive plumes, etc.) in the atmosphere (Pudykiewicz 1988). It uses the same operational CMC global modeling system for meteorological input. More recent coupled models have focussed on predicting tephra impacts and accumulations at the surface. For example, the

RAMS atmospheric model coupled with the HYbrid Particle And Concentration Transport (HYPACT) model was used to simulate the ash dispersal from the 1995 and 1996 eruptions of Mount Ruapehu, New Zealand (Turner and Hurst 2001). More recently, Byrne *et al.* (2007) verified simulations from the MM5 atmospheric model used with trajectory and particle-fall models against observed tephra accumulations for the Cerro Negro, Nicaragua, volcano.

14.6 Transportation safety and efficiency

14.6.1 Aviation

Airport ground operations, the routing of aircraft by traffic controllers, and real-time pilot decisions are all affected by weather, and in many cases DSSs are employed to translate weather observations and forecasts into decisions. The example topics below focus on weather impacts on in-flight safety, and discuss associated coupled models.

Turbulence

Turbulence that impacts aviation safety results from a variety of meteorological situations, such as convection and wind shear. Models that diagnose the probability of turbulence use forecasts from NWP models as well as pilot reports of turbulence as input. The resulting fields are used by dispatchers and pilots for turbulence avoidance. Graphical products displaying turbulence potential are available on the web for different flight levels. See Sharman *et al*. (2006) for a description of one such turbulence diagnostic model. This is a Type-3 coupling.

In-flight icing

Aircraft icing, which results from flight through supercooled liquid water, is a significant cause of aircraft accidents. An example of an operational system for predicting the likelihood of aircraft icing is the Current Icing Product (CIP) algorithm (Bernstein *et al.* 2005), which combines analyses and very-short-range forecasts from the RUC model (Benjamin 2004a) with real-time satellite, radar, surface, lightning, and pilot-report observations to create an hourly three-dimensional diagnosis of the potential for the presence of supercooled large droplets and icing. First, the volume of atmosphere that is occupied by clouds and precipitation is estimated. Then, fuzzy-logic methods use temperature, relative humidity, vertical velocity, pilot reports of icing, and explicit model fields of supercooled liquid water to estimate the presence of icing. A Future Icing Product (FIP) system produces forecasts of icing based on longer-lead-time RUC products. Resulting icing-advisory and icing-severity maps are available on the web, as are flight-path tools that define conditions along a prescribed flight track. This is a Type-3 coupling.

Cloud ceiling and visibility

Cloud ceiling and visibility must be predicted for a couple of reasons. Airport capacity, in terms of the minimum spacing of aircraft on approach and departure, is generally a function of the prevailing visibility. And, noncommercial pilots with only "visual-flight-rules" certification must avoid flight within clouds and in low-visibility situations. To obtain ceiling and visibility from model-simulated, state-of-the-atmosphere variables, Stoelinga and Warner (1999) developed a translation algorithm based on empirical and theoretical relationships between model hydrometeor characteristics and light extinction. This is a Type-2 coupling.

14.6.2 Surface transportation

Weather affects highway and rail traffic in almost as many ways as it does air travel. Forecasts from NWP-models have been used as input to algorithms and DSSs that are employed for

- deployment and prepositioning of snow-removal equipment in advance of a winter storm;
- evacuation of the public in advance of a hurricane;
- estimating regions where rail lines and highways will flood as a result of heavy precipitation;
- defining the amount and type of chemicals to be applied to highways to melt ice and snow; and
- deployment and prepositioning of electrical and communications workers in advance of a natural disaster such as a hurricane or midlatitude winter storm.

Visibility is a hazard that surface and air transportation have in common. Some models now have sufficient skill to enable them to predict visibility, based on impairments from aerosols and fog. For example, Clark *et al.* (2008b) and Haywood *et al.* (2008) report on the operational version of the UKMO Unified Model in terms of its ability to predict visibility. This would be a Type-4 modeling system.

14.7 Electromagnetic-wave and sound-wave propagation

Electromagnetic (EM) energy is refracted through, primarily, vertical gradients of temperature and moisture. This is a practical issue because it is important, for various applications of radars, to know from where in space a reflection originates. This requires knowledge of the refraction, obtained through the use of a propagation model. An example of an EM propagation model that simulates this refraction, based on atmospheric variables provided by a model, is the Advanced Refractive Effects Prediction System (AREPS). The AREPS is a complete suite of software modules that can be applied for a wide range of propagation applications over sea and land.

Sound propagation through the atmosphere is sensitive to vertical profiles of meteorological variables as well as the nature of Earth's surface, so predictions of the sound intensity at various distances and azimuths can be produced using input from an NWP model. Practical applications of such coupled modeling systems include the timing of explosions associated with military testing or commercial excavation, such that the resulting sound will have minimal impact on surrounding structures and personnel. Another application could involve mitigation of the impact of aircraft-engine noise on developed areas around airports. An example of a prediction from a coupled sound-propagation model and a mesoscale NWP model is shown in Fig. 14.7. The sound propagation model is the Noise Assessment Prediction System (NAPS), where the physical basis for the model and references can be found in Sharman *et al.* (2008).

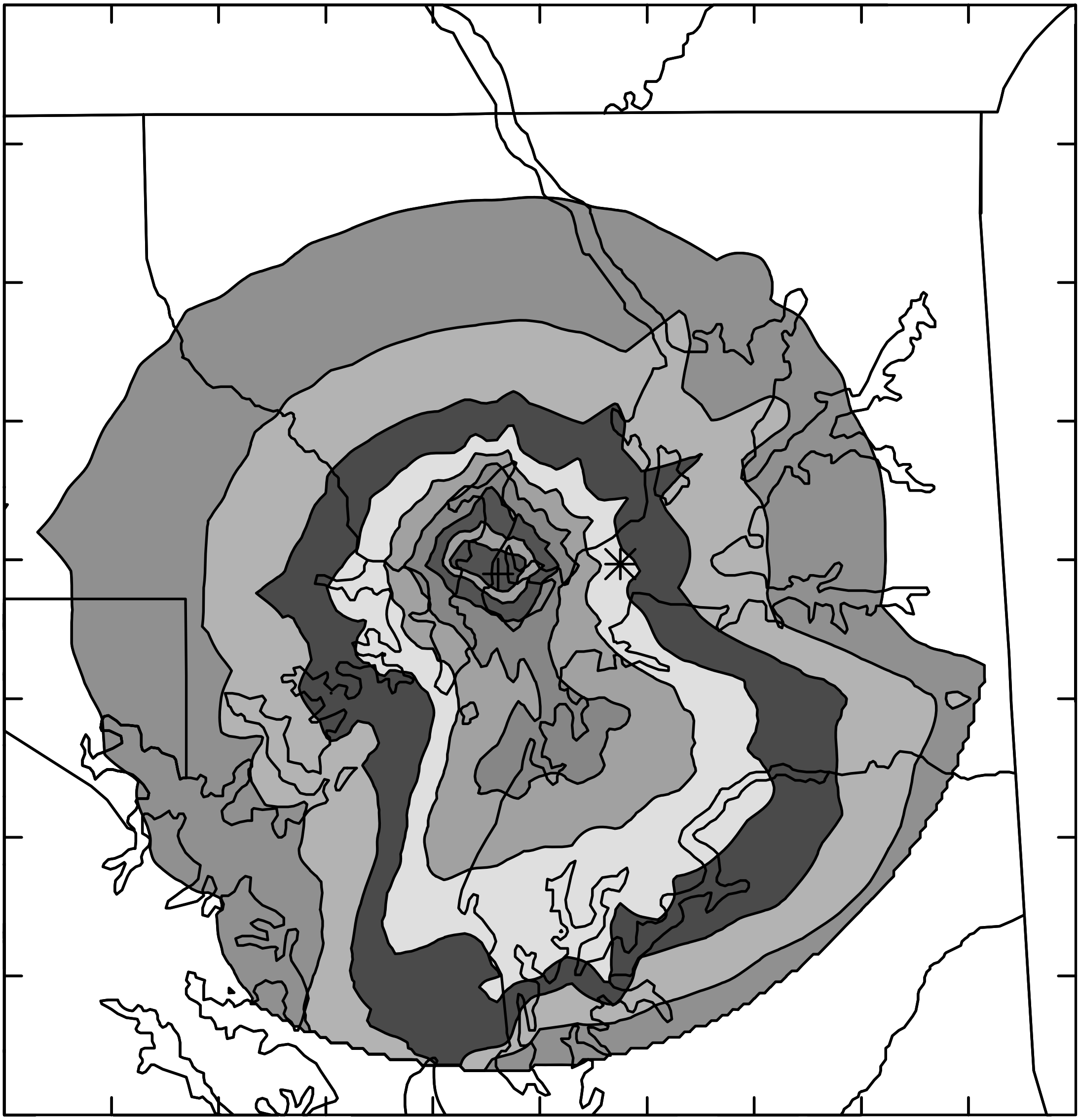

Fig. 14.7 Predicted sound intensity from an explosion in a coastal area in the eastern USA. Output from the MM5 LAM was used as input to the Noise Assessment Prediction System. The sound intensity in the outer shaded band is 100–105 dB and for the innermost band it is 140-145 dB. Adapted from Sharman *et al.* (2008).

14.8 Wildland-fire probability and behavior

The probability that a wildland fire will occur in a particular region depends on many factors, but one of the most important is the amount of moisture in the natural fuel (live and dead vegetation). This fuel-moisture level is a function of antecedant temperature, relative humidity, wind speed, and rainfall. In order to supplement *in-situ* and remotely sensed estimates, specially adapted high-resolution land data-assimilation systems (see Section 5.4.2) can be used to provide continuous gridded fields of fuel-moisture estimates. Or atmospheric-model forecasts can provide the input variables. An example of the latter approach is described in Fiorucci *et al.* (2007), wherein the atmospheric variables predicted by the LAM described in Doms and Schättler (1999) are used as input to an operational Italian dynamic wildfire-danger assessment system. Analogous wildfire-danger assessment systems in the USA and Canada employ observed meteorological conditions. The resulting fire-threat assessment can be used in a DSS that optimizes the location of fire-fighting assets such that they will be available quickly in the event of a fire.

Models that directly simulate, or provide qualitative guidance about, the behavior (e.g., direction and rate of growth of the fire perimeter) of wildland fires span a wide range of spatial scales, complexities, and types of applications. The categories of operational and research coupled-modeling systems are summarized as follows.

- Standard mesoscale NWP models are used to predict wind speed and direction, temperature, relative humidity, and precipitation, all quantities that strongly impact the evolution of existing or potential fires. Accurate forecasts of these variables are critical for use by wildfire managers who must (1) define the strategy for fighting an existing fire, and deploy the firefighters in the most safe and effective way or (2) decide whether to proceed with an intentional controlled burn of dead fuelwood. Such models generally have horizontal resolutions on the mesogamma or mesobeta scales. These are Type-1 coupled systems.
- High-resolution NWP models, or even-higher resolution computational fluid-dynamics (CFD) models (see Chapter 15), provide meteorological input to a fire-growth model, but there are no feedbacks from the fire to the atmosphere – i.e., fire impacts on humidity, temperature, and winds are not represented (Fujioka 2002). These are Type-3 coupled systems.
- The NWP or CFD models interact with a fire model, such that the fire feeds back to the atmospheric state (Coen 2005). These are Type-4 or -5 coupled systems.

14.9 The energy industry

There are a number of sectors of the energy industry that use special models that are driven by atmospheric predictions. For example, hydropower-generation facilities use decision models to determine how much water to release in anticipation of a heavy rainfall event over their supply watersheds (Section 14.4). And, energy companies that have nuclear facilities use air-quality and plume models to assess the potential impact of accidental releases from their facilities on public health (Section 14.5). Thus, the following sections only illustrate a few examples of the use of coupled models by this large industrial sector.

14.9.1 Electricity-demand models

Because electric-power providers benefit from being able to anticipate the demand, they use models to estimate this quantity from the many governing meteorological and nonmeteorological factors. Meteorological variables that are relevant are cloud cover, wind speed, temperature, and humidity. Taylor and Buizza (2003) summarize the use of atmospheric ensemble models for providing 10-day lead time probabilistic demand forecasts. Electricity-demand models are also used with input from climate projections to provide insight into long-term trends in requirements (e.g., Miller *et al.* 2008). These would typically be Type-2 or -3 coupled systems.

14.9.2 Wind-power prediction

Because available wind power is a function of the wind speed at 80–100 m AGL at the farms where the turbines are located, estimates of future power require wind-speed forecasts for these heights. The forecast wind speeds are translated to power production using an algorithm that is based on the number of turbines operating, the mix of turbine types, the efficiency of each turbine, etc. These also would typically be Type-2 or -3 coupled systems.

Forecasts of wind-power production are required in order to plan how to balance the load among the various available sources, such as gas, coal, nuclear, and wind. Especially problematic for energy companies are wind "ramp events" that are not correctly forecast. In these cases, the speed increases or decreases precipitously because of a frontal passage, the variation in the height of the shear zone below a low-level jet, orographically forced lee waves, or the passage of a convective outflow boundary. All of these can be challenging for a model to predict well.

As wind power becomes a greater percentage of the total power supply, regionally at least, coupled-model forecasts of power from this source must become increasingly accurate in order to avoid (1) brownouts if the wind speed decreases unexpectedly and (2) wasting fossil fuels and releasing greenhouse gases unnecessarily if the wind speed increases unexpectedly. This will be especially challenging because of the mesoscale character of many of the above processes, and because advantageous locations for wind farms are in complex terrain and in complex littoral zones.

14.9.3 Wind-power resource assessment

Wind-power resource assessment, or prospecting, involves the generation of short- to long-term reanalyses (see Section 16.2) of the near-surface climate. The resulting statistics of the windfield and air-density field, when used as input to power-production algorithms or models, enable wind-farm developers to determine where installation of turbines would be economically successful. Current climatological maps that have been produced show the most favorable regions to be over water in littoral zones, over some elevated terrain, and where low-level jets prevail. Because low-level wind-speeds vary greatly in space because of landscape forcing, especially high-resolution regional reanalyses are desirable, but it is very computationally demanding to produce them for long periods. Note that the PDF of the wind speed is needed for such wind-farm-siting decisions because it is important for the winds to not be excessively intermittent. Figure 14.8 shows an example of a wind-speed climatology for North America based on an MM5, 40-km grid increment, global reanalysis. This map defines the 120-m AGL wind speed at 0600 UTC for July 1997, and is especially relevant to wind-resource assessment because it shows the importance of the warm-season, nocturnal, low-level jet in the Southern Plains. See Landberg *et al.* (2003) and Petersen *et al.* (1998a,b) for an overview of wind-resource estimation, and Section 16.3 for a discussion of dynamical and statistical methods for downscaling coarse-resolution analyses to represent finer scales.

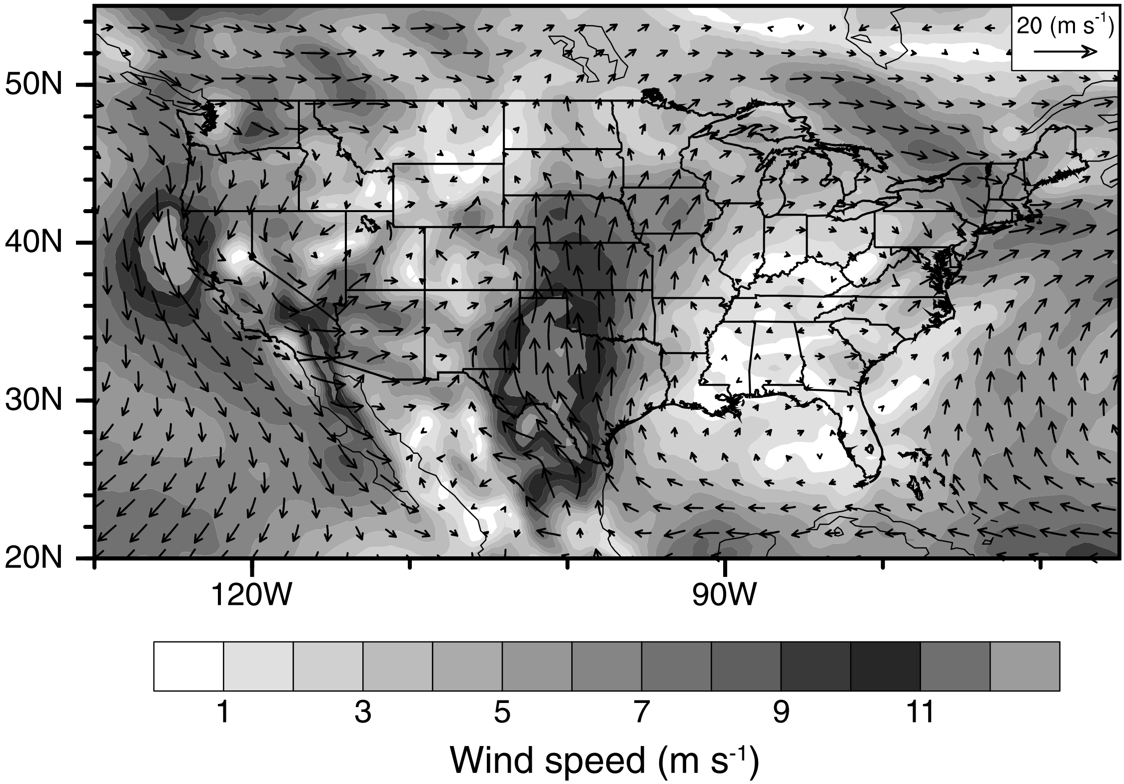

Fig. 14.8 The 120-m AGL wind-speed climatology of the US for 0600 UTC for July 1997, based on a 40-km grid increment, 21-year, MM5 global reanalysis. Every sixth wind vector is shown. This month and time are especially relevant to wind-resource assessment because they show the importance of the warm-season, nocturnal, low-level jet in the Southern Plains. Provided by Daran Rife, NCAR.

14.10 Agriculture

There are many agricultural applications of atmospheric models.

- *Planting and harvesting* – This often requires dry conditions, and necessary planning is based on weather predictions of at least 12–72 h lead time. The use of appropriate soil models coupled with atmospheric-prediction models can allow the diagnosis of soil trafficability by farm machinery.
- *Application of pesticides* – Integrated pest-management systems require that chemicals be applied a specific number of hours before rainfall, and at appropriate temperatures and relative humidities. Low-wind conditions also allow for more-accurate application.
- *Application of herbicides* – Herbicides must not be allowed to drift with the wind into areas where unintended damage to vegetation will take place.
- *Application of fertilizers* – Chemical or natural fertilizers should not be applied too soon before rainfall because the fertilizer will run off into waterways, not serving its intended purpose and contaminating waterways with nitrogen and other chemicals.
- *Insect movement* – Insects that can damage crops are carried by winds from their breeding grounds to agricultural areas, and predictions of weather patterns can allow for assessment of this risk.
- *Crop selection* – For agricultural areas in which irrigation water is not available, crops can be selected for planting that will be appropriate for the weather conditions that are expected during the growing season. For example, if dry conditions are forecast to accompany the onset of a particular phase of the ENSO cycle, crops can be selected accordingly.
- *Development and spread of plant and animal disease* – This is discussed in Section 14.3.2.
- *Crop yield estimation* – This is an especially important agricultural application of ensemble NWP systems (Cantelaube and Terres 2005, Challinor *et al*. 2005, Marletto *et al.* 2005).

Two well-established crop-yield modeling systems are summarized in Mera *et al.* (2006), who studied the impact of climate-related changes in radiation, temperature, and precipitation on crops, specifically soybeans and corn. The two models are CROPGRO (soybean) and CERES-Maize (corn), which are part of a Decision Support System for Agrotechnology Transfer (DSSAT). Both are predictive, deterministic models that simulate physical, chemical, and biological processes in the plant as a function of weather, soil, and crop-management conditions.

14.11 Military applications

Many military requirements for coupled models are very similar to those discussed above, for example related to forecasting quantities that are important for aviation safety and efficiency, and calculating the transport and diffusion of hazardous material in the atmosphere. There are, however, additional types of coupled models that specifically address the needs of military activities. A few are noted below.

- *Soil trafficability* – Heavy vehicles have difficulty operating on soils that are wet or too loose. Special types of land-surface models, called soil-trafficability models, employ analyses and forecasts of meteorological variables that affect substrate wetness (precipitation, temperature, wind speed, and humidity), and are used to estimate the ability of the substrate to support different vehicle types.
- *Guided and unguided missile trajectories* – Winds, turbulence, and air density affect the trajectory of missiles. The aerodynamic impact of observed and modeled meteorological conditions on the trajectories is calculated using a trajectory model.
- *Electro-optical visibility* – Weapons targeting systems are sometimes optical, so atmospheric turbulence and aerosol influences on feature detection by existing and proposed systems are anticipated using a model that employs atmospheric-model input.

See Sharman *et al.* (2008) for additional discussion of some of these applications.

SUGGESTED GENERAL REFERENCES FOR FURTHER READING

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PROBLEMS AND EXERCISES

1. Predictability of atmospheric processes is an important topic in NWP. Speculate on the likelihood that the coupling between an atmospheric model and a secondary model will be such that there is a nonlinear sensitivity of the error in the solution of the secondary model to the error in the solution of the atmospheric model. Provide an example of a type of coupled-model application that might have a high degree of sensitivity to the accuracy of the atmospheric forecast.
2. Perform a literature search to determine the ways in which atmospheric information (observations, analyses, forecasts) is used in disease surveillance, early-warning, and response systems, and summarize them.
3. The use of coupled atmospheric models and decision models by many businesses and industries is not discussed in this chapter. Speculate on such applications of coupled modeling systems.