Chapter 23

100 Years of Progress in Applied Meteorology. Part II: Applications that Address Growing Populations

SUE ELLEN HAUPT,^a STEVEN HANNA,^b MARK ASKELSON,^c MARSHALL SHEPHERD,^d
MARIANA A. FRAGOMENI,^d NEIL DEBBAGE,^{e,d} AND BRADFORD JOHNSON^d

^a *National Center for Atmospheric Research, Boulder, Colorado*

^b *Hanna Consultants, Kennebunkport, Maine*

^c *University of North Dakota, Grand Forks, North Dakota*

^d *University of Georgia, Athens, Georgia*

^e *The University of Texas at San Antonio, San Antonio, Texas*

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ABSTRACT

The human population on Earth has increased by a factor of 4.6 in the last 100 years and has become more centered in urban environments. This expansion and migration pattern has resulted in stresses on the environment. Meteorological applications have helped to understand and mitigate those stresses. This chapter describes several applications that enable the population to interact with the environment in more sustainable ways. The first topic treated is urbanization itself and the types of stresses exerted by population growth and its attendant growth in urban landscapes—buildings and pavement—and how they modify airflow and create a local climate. We describe environmental impacts of these changes and implications for the future. The growing population uses increasing amounts of energy. Traditional sources of energy have taxed the environment, but the increase in renewable energy has used the atmosphere and hydrosphere as its fuel. Utilizing these variable renewable resources requires meteorological information to operate electric systems efficiently and economically while providing reliable power and minimizing environmental impacts. The growing human population also pollutes the environment. Thus, understanding and modeling the transport and dispersion of atmospheric contaminants are important steps toward regulating the pollution and mitigating impacts. This chapter describes how weather information can help to make surface transportation more safe and efficient. It is explained how these applications naturally require transdisciplinary collaboration to address these challenges caused by the expanding population.

1. Introduction

Many of the advances in science in the past 100 years were spurred by an inherent human need to better understand the world in which we live. To that end, we have developed mental models, translated them into mathematical models, and, in the past century, built numerical models that can be implemented on modern computers. Correspondingly, the science of meteorology has advanced. Our ability to model the weather, environment, and climate has grown immensely, as documented in the chapters of this monograph.

Over the same century, human population has grown. The world population was 1.65 billion in 1900 and had grown to 7.7 billion by the end of 2017 ([Worldometers 2018](#)), seeing the highest growth rates between 1955 and 1975, with annual growth of those years at about 2% ([United Nations 2018](#)). Providing for billions of people requires clever innovations to continue to supply sufficient food, energy, water, housing, health care, and so on. It is inevitable that meeting these basic needs for these billions of interacting humans adds stress on the environment, as documented in this chapter. Applied research enables us to determine how to use our resources wisely to solve the challenges of humankind while preserving those natural resources to continue to provide for future generations. As W. Hooke posits in

Corresponding author: Dr. Sue Ellen Haupt, haupt@ucar.edu

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FIG. 23-1. Depiction of a weather information value chain to demonstrate a path that can be used to foster communication between researchers and end users to generate a value for the end user (after Lazo 2017).

Living on the Real World: How Thinking and Acting Like Meteorologists Will Help Save the Planet (Hooke 2014), to provide the type of lifestyle that society wants, we must go beyond physical science and engineering and venture into understanding the social and spiritual issues in order to solve the problems. We must balance self-interest with the common good. He also points out that we all live in a common reality of continual change in the environment, and it is critical to anticipate and build resilience to those changes. He identifies the approach of meteorologists as an example of a way to tackle a complex problem with interacting parts. Meteorologists take a systems approach to understanding and modeling the individual subsystems of the environment, then integrate those subsystems and use that knowledge to predict the future, even though the interactions are nonlinear and complex. Small advances in our understanding of the subsystems can have profound implications to the modeled integrated system. He encourages applying that approach on a larger scale to solve society's most difficult problems, particularly those due to interactions with the environment. For instance, what are the impacts of urbanization? How do we supply sufficient food and energy to these growing numbers of humans? How do we transport these people from place to place? How do we deal with increasing pollution? More of these people have been gravitating to urban areas, which concentrates the impact on the environment.

The impact can be discerned from the statistics. In 1900, just 16.4% of the world population lived in urban areas. That percentage had grown to 54.4% by 2016 (Ritchie and Roser 2018). The more developed countries urbanized at a faster rate over that time period (United States from 40.0% to 81.9% and Japan from 12% to 91.5%, as compared with India from 10% to 33.2%; Ritchie and Roser 2018). In 1920, the world consumed approximately 18 000 TW h of energy. That number grew to about 150 000 TW h by 2015 (Ritchie and Roser 2018). The mix of fuels changed over that time period too, from roughly a balance between biofuels and coal to more recently include oil, natural gas, hydropower, nuclear, and now wind and solar renewable energy (Ritchie and Roser 2018). Although the

deployment of energy typically corresponds to the development in a region, its air pollution is shared around the world via long-range transport, although the impact is worse near the source. Additionally, as commercialization grew, so did its impact on air quality. In the mid-1900s, pollution in cities caused major health issues, with stories of devastating results, such as the famous four-day London fog that is credited with 4000 deaths (Morrison 2016). As discussed in section 4, environmental regulation has made positive changes, decreasing concentrations of pollutants and largely eliminating harmful concentrations of some of the most toxic elements, such as lead. This regulation led to the need for transport and dispersion modeling as detailed below. With regard to transportation, in 1900 people moved around largely via horse and some railroad use. Today there are roughly 1.2 billion vehicles in use (Voelcker 2014). Because the atmosphere is shared, these changes in meeting the needs of the growing population speak to the importance of leveraging meteorology to understand and mitigate the problems.

To best address these issues requires transdisciplinary research. It is critical that to solve a problem one must first fully understand it from the point of view of the stakeholder; the first stage is thus to listen to the end users of the solution technology and strive to comprehend what they need. To that end, social scientists find that working with an information value chain approach has proven useful (Lazo 2017; Lazo et al. 2017; Haupt et al. 2018). Figure 23-1 depicts a basic information value chain. One begins with the end in mind, by visualizing the societal or economic value that one wishes to generate at the end of the process. On the other side of the chain are the environmental conditions or meteorological phenomena that impact the process. Basic physical science methods are needed to observe and model those phenomena. The modeled or predicted information must be translated into the variables or language that the end user will understand and apply to make a decision. The form of that decision must be cast in a way that can best provide the desired value. Simply progressing along that chain is not sufficient: one must also consider how to quantify the value and whether the

original goals have been met. This process is iterative and requires implementation through engagement of a host of stakeholders, including the physical scientists, social scientists, and end users. Many examples exist of success in applying this value chain approach in the hydrometeorological community, particularly through workshops held in developing countries that have built capacity (WMO 2015).

This series of three chapters on 100 years of progress in applied meteorology documents the story of some of the problems and solutions in progress. Part I addresses some of the most basic advances in modifying the weather and in providing the necessary meteorological information for aviation and defense (Haupt et al. 2019a). This Part II discusses those topics that result from and deal with the stresses of the increasing population—applications in urban meteorology, energy, air pollution management, and surface transportation. Part III continues along this line by discussing meteorological applications in agriculture and food security and then treating those topics that have emerged more recently, including space weather, use of meteorology in managing wildland fires, and applications of artificial intelligence (Haupt et al. 2019b). The examples in this chapter and its partners describe steps toward communicating and collaborating to provide scientific solutions to society's problems.

Section 2 of this chapter describes how increasing urbanization interacts with and modifies the weather and climate. Section 3 conveys how energy enables and maintains our lifestyle in both urban and rural areas, yet both leverages and impacts the environment. Many of its traditional fossil sources contribute to pollution and environmental degradation, while renewable energy uses the environmental variables themselves as the fuel. Both types require applications of meteorology to operate effectively. Air pollution is treated in section 4, which describes the history of model development, the various categories of models, their use in the modern regulatory environment, and methods of verification. Section 5 addresses the impact of weather events on the safety and efficiency of surface transportation and how meteorological information can be used to warn of impending severe weather, mitigate traffic issues, etc. Each of these sections reviews some of the history, describes the current state of practice, then postulates how meteorological information may be used even further in the future. Section 6 offers a summary, concluding remarks, and discussion of the prospects for future applications to aid the growing and urbanizing population.

2. Urban meteorology and climate

a. Introduction to urban meteorology and climate

In his landmark synopsis, Changnon (2005) laid out the definition, evolution, and implications of applied

climatology. The interactions involving urbanization, weather, and climate characterize the interdisciplinarity at the core of applied climatology. Urbanization represents the transformation of natural landscapes and escalation of human activities in cities. The urbanized environment is characterized by reduced vegetation, increased heat-retaining materials, modified water cycle circuits, and more pollutants. An important event occurred at the turn of this century: for the first time in history, more people (54%) live in cities than rural areas (United Nations 2014). Current projections suggest that the notion of an “urbanized century” will become the norm as 60%–80% of the world population will live in urban settlements by the year 2100 (United Nations 2014; Mitra and Shepherd 2016).

Such unprecedented urban growth (Hodson 2016) carries profound implications for Earth's weather and climate processes. Cities are built environments of impervious surfaces, buildings, energy generation, pollution, and anthropogenic emissions. The modified landscape, water cycle, atmospheric composition, and biogeochemical processes interact with weather and climate processes at various scales. Urban climatology has become an enduring subdiscipline of applied climatology that aims to better understand these complex multiscale interactions.

Seto and Shepherd (2009) and Voogt (2017) have highlighted the multiple pathways through which urbanization interacts with the climate system (Table 23-1). Such interactions are relevant at the local to regional scale, but increasingly, the influence of urban processes is relevant at larger scales. For example, Shepherd (2013) discussed the concept of urban climate archipelagos (UCAs), defined as “chain[s] of distinct urban entities with discernible aggregate impacts on at least one segment of the climate system.” The satellite image of Fig. 23-2 shows a large storm superimposed on city lights, directly picturing the interaction of the built environment with the natural one. UCAs in the United States are apparent in the Northeast (from Washington, D.C., to Boston, Massachusetts), the Interstate Highway 35 (I-35) Texas corridor, and the Florida peninsula. Johnson and Shepherd (2018) have revealed how the distribution of frozen precipitation in the Northeastern corridor is affected by the urban heat islands within this particular UCA. Shepherd (2013) pointed out that such systems of urbanization can modify precipitation, land surface hydrological processes, air quality, and wind flow at scales larger than the sum of each individual city. Recent modeling simulations provide additional support for the UCA theoretical framework (e.g., Bounoua et al. 2015). Aspects of the broader climate system can also scale down and impact individual cities. Argüeso et al. (2014) examined midcentury relative to current

TABLE 23-1. Current opinion in environmental sustainability, showing various pathways for urbanization to impact the climate system (from [Seto and Shepherd 2009](#)).

	Urban land cover	Urban aerosols	Anthropogenic greenhouse gas emissions
Urban heat island and mean surface temperature record	Surface energy budget	Insolation; direct aerosol effect	Radiative warming and Feedbacks
Wind flow and turbulence	Surface energy budget; urban morphological parameters; mechanical turbulence; bifurcated flow	Direct and indirect aerosol effects and related dynamic/thermodynamic response	Radiative warming and feedbacks
Clouds and precipitation	Surface energy budget; UHI destabilization; UHI mesocirculations; UHI-induced convergence zones	Aerosol indirect effects on cloud-precipitation microphysics; insolation effects	Radiative warming and feedbacks
Land surface hydrology	Surface runoff; reduced infiltration; less evapotranspiration	Aerosol indirect effects on cloud-microphysical and precipitation processes	Radiative warming and feedbacks
Carbon cycle	Replacement of high-NPP land with impervious surface	Black carbon aerosols	Radiative warming and feedbacks; fluxes of carbon dioxide
Nitrogen cycle	Combustion, fertilization, sewage release, and runoff	Acid rain; nitrates	Radiative warming and feedback; NO _x emissions

century simulations at high resolution (1 km). They found that the growth of Sydney, Australia, and global warming were evident, although the relative contribution of each was not calculated. [Stone et al. \(2010\)](#) revealed that urban spaces are particularly vulnerable to climate change because of the combined influence of greenhouse gas warming and the urban heat island (UHI) effect ([Fig. 23-3](#)). However, [Georgescu et al. \(2014\)](#) found that adaptation strategies can reduce warming in UCA-type urban environments within the context of a warming climate system.

Early-nineteenth-century weather observation networks were critical in revealing that the weather and climate of

urban areas differed from rural ones ([Howard 1833](#)). As the twentieth century advanced, critical knowledge and confirmation of urban climate processes emerged. The defining text of that time was H. Landsberg's classic "The climate of towns" ([Landsberg 1956](#)). The American Meteorological Society (AMS) honored Dr. Landsberg, an influential scholar in urban climatology, with an annual award given to a scholar studying urban climatology. By the turn of the century, [Dabberdt et al. \(2000\)](#) called for substantial national and international focus on the urban environment. This report stimulated vigorous research to better understand weather and climate processes in the urban environment and how to forecast them.

FIG. 23-2. A large storm and major cities in the eastern United States (Source: NOAA/NASA).

FIG. 23-3. The combined impact of urbanization and climate change on heating (Stone 2012; copyright B. Stone Jr., reproduced with permission of the licensor through PLSclear).

By 2007, the Intergovernmental Panel on Climate Change (Trenberth et al. 2007) and other climate assessment reports were discussing the role of urbanization on climate. This additional attention was partly due to the complex two-way interactions between urban environments and global climate change. On one hand, urban areas are a major source of anthropogenic carbon dioxide emissions that are a primary driver of climate change. Some estimates suggest that cities are responsible for more than 90% of anthropogenic carbon emissions (Svirejeva-Hopkins et al. 2004). The land use/land cover change associated with urbanization also negatively impacts carbon sinks (Hutyra et al. 2014). While being a major driver of global climate change, urban environments are simultaneously vulnerable to many of the ramifications associated with a shifting climate, such as more frequent heat waves, more intense precipitation events, and sea level rise (Hunt and Watkiss 2011). These important interactions between cities and broader global climate change have prompted the creation of additional climate policies at the regional and local scales.

b. A snapshot of urban climate milestones

Horton (1921) first provided evidence that cities tended to be warmer than their surrounding rural areas. This so-called urban heat island is arguably the most thoroughly investigated aspect of urban climatology (Oke 1987; Arnfield 2003). Over time, primary causes of

the UHI have been linked to changes in the surface energy budget due to less reflective and more heat-absorbing surfaces, reduced evapotranspiration resulting from a lack of vegetation, complex radiative trapping in urban canyons, and anthropogenic waste heat (Grimmond et al. 2010). While often described as “the heat island,” there are actually three manifestations: the skin or surface UHI, the canopy layer (above the ground) UHI, and the boundary layer UHI. Over the years, it became clear to researchers that these heat islands are different. For example, the surface heat island magnitude peaks during the afternoon hours, whereas the canopy layer heat island peaks at night or during early morning hours. As research evolved, it became apparent that some cities may also exhibit a deficit in moisture referred to as the urban dry island (Hage 1975; Wang and Gong 2010).

While most UHI studies have relied on point-to-point comparisons (Yow 2007) of air temperatures to evaluate the canopy layer UHI or remote sensing to measure the skin temperature UHI (Voogt and Oke 2003), Stewart and Oke (2012) introduced the concept of local climate zones to counter problems associated with point-by-point comparisons. Debbage and Shepherd (2015) proposed a method for examining the UHI using more spatially representative measurements of urban and rural temperatures. That same study helped to clarify one of the prevailing arguments in urban climate. Many papers have argued that the UHI is strongly associated with dense cities (Oke 1987; Coutts et al. 2007). However, Stone et al.

(2010) posited that more sprawling cities may enhance UHI intensity. Debbage and Shepherd (2015) found that the contiguity of urban surfaces, irrespective of density, largely explains UHI magnitudes.

Decades of field studies (Grimmond 2006; Huang et al. 2017), modeling studies (Kanda 2006), and sophisticated observation techniques (Grimmond 2006; Shepherd 2013) have advanced knowledge, and the discipline is now entering an era in which urban energy and radiative attributes are becoming represented in weather and climate models (Wan et al. 2015; Garuma 2017). Although climate-cognizant urban design likely dates back to the origins of cities themselves (Morris 1994), the science has advanced to a point where stakeholders and practitioners more explicitly design cities, neighborhoods, and buildings with UHI mitigation strategies in mind, such as employing greening, intentionally modifying albedo, enhancing natural ventilation, implementing bioclimatic and sustainable design concepts, considering alternate construction materials, and planning for land use (Lowry and Lowry 1988; Eliasson 2000; Gaffin et al. 2012; Stone et al. 2012; Olgyay et al. 2015; Hunt et al. 2017).

Urban pollution and air quality are well-known urban climate phenomena, and methods of modeling them are discussed in section 4. Anthropogenic activities associated with energy production (section 3), transportation (section 5), and other industrial processes are often associated with primary (aerosols and particulate matter) and secondary (photochemical smog) pollution. While ground-based monitoring of aerosols and pollution has made progress, in part because of the air quality standards mandated by the Clean Air Acts and Amendments legislation of the 1970s and 1990s, respectively (Popp 2003), satellite-based methods (Akimoto 2003) continue to emerge as viable platforms for observing the four-dimensional evolution of aerosols. Aerosols have a “direct effect” on solar and terrestrial radiation through scattering and absorption. Studies continue to investigate the “indirect effects” that aerosols can have on the evolution of cloud and precipitation processes (Jin et al. 2005; Jin and Shepherd 2008). It has become increasingly clear to researchers that aerosols must be adequately resolved in the current and future generation of weather and climate models for improved precipitation forecasts, climate sensitivity analyses, and feedback processes, as well as forecasting surface irradiance for solar power networks as discussed in section 3.

Impervious surfaces and structures of the urban landscapes modify atmospheric stability, airflows, and circulation patterns (Klein and Clark 2007). Horton (1921) noticed that storms seem to develop over large cities. Other European scholars including Kratzer (1937,

1956) supported Horton’s observations, and Landsberg (1956) further affirmed the hypothesis. A landmark set of experiments, including the Metropolitan Meteorological Experiment (METROMEX; Braham 1981; Changnon 1981), executed in the 1970s confirmed that cities modify the spatiotemporal distribution of rainfall. However, Lowry (1998) challenged some of the underlying findings and experimental designs.

In response to Lowry’s criticisms, Shepherd et al. (2002) reinvigorated research (Souch and Grimmond 2006) by employing satellite and other remote sensing approaches on what Shepherd (2013) ultimately called the “urban rainfall effect.” In reality, Bornstein and Lin (2000) and their work associated with the National Aeronautics and Space Administration (NASA)’s “Project ATLANTA” were critical to Shepherd’s work. While the methods of Shepherd et al. (2002) were limited and problematic, a new generation of studies emerged. In fact, it is fairly conclusive that the question “Does the urban environment affect precipitation processes?” has been answered. Urban environments do indeed impact precipitation and storm processes (Haberlie et al. 2015; Ashley et al. 2012; Mitra and Shepherd 2016). Urban effects on precipitation are a complex web of mechanisms, including destabilization of the urban boundary layer (Kusaka and Kimura 2004; Baik et al. 2007), building-induced convergence from mechanical turbulence (Fujibe 2003), urban–rural thermally direct circulations (Ohashi and Kida 2002), and aerosol–microphysical interactions (Jin and Shepherd 2008). In the 2000s, researchers extended this line of research to expose relationships between the urban environment and lightning (Orville et al. 2001; Stallins and Rose 2008).

Current research is now attempting to establish which physical processes are most dominant and how they can be represented in weather and climate models. Many research questions remain in diverse areas. These include understanding whether aerosols have net additive or subtractive effects on precipitation (Rosenfeld et al. 2008), if the distribution of frozen precipitation is a function of cities (Johnson and Shepherd 2018), and the degree to which severe weather systems associated with large-scale forcing can be modified by the urban environment (Debbage and Shepherd 2019). In response to the UCA approach, research is also evolving from a city-centric perspective into questions tailored at discerning the regional impacts of urbanization.

A relatively recent (perhaps past several decades) thrust of urban hydroclimate research has focused on the hydrologic response in cities and addressed issues such as flash flooding and surface runoff variability (Bhaduri et al. 2001; Reynolds et al. 2008). Urban impervious surfaces modify the water cycle through

reduced infiltration and increased surface runoff (Leopold 1968; Sauer et al. 1983; Debbage and Shepherd 2018). As with many urban climate phenomena, there is strong interest in understanding the two-way paths of these processes. A warming climate system is associated with increased rainfall rates in the top 1% of storms as based on intensity (Yang et al. 2013). Researchers are now focused on downscaling the climate change effects on precipitation to the localized hydrologic responses in cities. The complexity of urban land surfaces must be resolved in future hydrologic or coupled atmosphere–land surface modeling systems to fully and accurately evaluate the implications of these precipitation trends for cities.

Biogeochemical cycles are also sensitive to the two-way interactions. For example, how does excessive carbon (so-called carbon domes; Idso et al. 2001; Jacobson 2010) in cities scale up to the regional and global scale and how will heat waves or mortality issues be amplified because of climate warming superimposed on urban heat islands? The impact of urbanization on one of the important currencies of carbon, net primary productivity (NPP), has significant consequences on vital life-sustaining activities such as food production and carbon balance (Imhoff et al. 2004). Researchers are vigorously trying to quantify such processes, as urbanization tends to thrive on the most fertile lands and has a disproportionately larger net negative impact on continental- to regional-scale NPP (Imhoff et al. 2004).

The nitrogen cycle has also been modified or disrupted by urban-related activities such as fertilization, sewage release, and combustion (Seto and Shepherd 2009). Nitrous oxide is a greenhouse gas that can deplete the ozone layer, contribute to the formation of photochemical smog, and acidify precipitation.

c. A look to the future

Urban footprints will continue to expand and weather and climate models must be able to represent the full suite of urban-related processes on the land surface and in the air. To achieve that goal, urban morphology, atmospheric composition, land cover/land use, modified hydrology, and associated multipath feedbacks must be appropriately resolved and represented at urban scales from localized and regional perspectives (Grimm et al. 2008). The National Research Council Committee on Urban Meteorology (National Research Council 2012) provides valuable guidance on how urban weather and climate research must evolve to provide critical societal applications in planning, transportation, flood management, energy production, public health, and so forth (Sailor et al. 2016). As Mills et al. (2010) and Georgescu et al. (2013) warn, such activities will continue to be vital

as megacities proliferate. KC et al. (2015), for example, found that much of the climate vulnerability faced by human beings is clustered in urban spaces because of increased exposure to heatwaves and flooding. Landsberg (1970) had the foresight to recognize that urbanization can actually be visualized as a prototype for understanding human impacts on weather and climate. Today, the complex interconnectivity of these various urban processes still offers more questions relevant to both society and the scientific community.

3. Energy applications

a. Introduction to meteorology in the energy industry

The activities of the world's human population, both urban and rural, are powered by the energy industry. Gone are the days when each building's fireplace warmed the family during the cold periods of the year. Populations and industry grew and developed with an energy industry that provides power on demand for a wide range of users. No longer do we rely on domesticated animals to get from place to place. The gasoline, diesel, or electricity that powers vehicles enables transportation to drive the growth of business, industry, and government. As stated in the preface to the International Renewable Energy (IRENA) Sustainable Energy for All report (SEforALL 2014, p. 4):

Energy is the golden thread that connects economic growth, increased social equity and an environment that allows the world to thrive. Energy enables and empowers. Touching on so many aspects of life, from job creation to economic development, from security concerns to the empowerment of women, energy lies at the heart of all countries' core interests.

The energy industry relies on meteorological information. Increasingly, electricity is produced by renewable energy, derived from the atmosphere, which varies in time and place. Even traditional fossil fuel energy critically depends on the weather and climate. Cooling for fossil and nuclear plants requires a fluid with a sufficient temperature difference from the effluent. Energy facilities are subject to damage from extreme weather events. Weather impacts transport of fossil fuels, with extreme weather particularly impacting coal, oil, and gas transport. On the demand side, the electricity load depends on meteorological variables such as temperature, wind, and humidity as well as human behavior. The efficiency of transmission and distribution lines are a function of temperature, wind, icing, and snow. Maintenance planning relies on knowledge of weather in the coming weeks to months. Preparation for the next season is very weather dependent. Long-term

FIG. 23-4. Impact of weather and climate events on energy systems [after Dubus et al. 2018a; CC BY 4.0 (<https://creativecommons.org/licenses/by/4.0/>)]. Photograph credits: Copyright University Corporation for Atmospheric Research from (left to right and then top to bottom) R. Bumpas, S.E. Haupt, C. Calvin, NWS/NCEP/Climate Prediction Center, S.E. Haupt, J. Weber, C. Calvin, and the Research Applications Laboratory; most are licensed under CC BY-NC 4.0 via OpenSky.

planning for the next series of power plants relies on climate information. Thus, a host of important applications have developed in the atmospheric and hydrological sciences around providing information to the energy industry. Figure 23-4 summarizes the different time scales of weather phenomena and provides examples of how energy decisions rely on weather and climate information.

Energy meteorology has developed as a field relatively recently, although many energy companies have long used weather and climate data. Hydropower has been a long-standing source of renewable power. The run-of-river hydropower is often thought of as a consistent source of inexpensive base power that varies slowly. Release from dams can be timed to meet the needs of peak loads, subject to constraints of other uses of the water (Miller et al. 2016). Issues related to hydrology and its use in the power grid are treated more fully in a companion chapter in this monograph (Peters-Lidard et al. 2019).

In the 1980s when companies began to trade in energy markets, both between neighboring companies and when longer-term trades in energy futures began, utilities and the trading companies began hiring in-house meteorologists to provide customized information or consultants to provide that service. As the Clean Air Act regulations began to be applied in the 1970s and 1980s, meteorologists were needed to model and track

compliance, as discussed in the following section. When just a few wind turbines dotted the landscape, integrating them into regular grid operation was not a problem and meteorological information was not employed. In the last decade, however, wind capacity grew by a factor of 4.6 in the United States (Weissman et al. 2018). Solar capacity grew even more between 2008 and 2018, by a factor of 39, with a capacity to power 10 million U.S. homes (Weissman et al. 2018). With this growth in renewable energy came the need for customized meteorological decision support information. The need for this information became even more obvious as large amounts of wind and solar power could become available very quickly with a change in the weather pattern and then disappear just as rapidly. These needs and how they are met have been documented in books by the World Energy and Meteorology Council (Troccoli et al. 2014; Troccoli 2018).

As the utility with the highest percentage of wind capacity in the United States for the past decade, Xcel Energy became the first major utility in the United States to have sufficient capacity in wind energy to recognize the need for targeted meteorological forecasts. It experienced some periods with rapid wind ramps, both up and down, that challenged its ability to integrate the wind into the grid efficiently. Thus, it commissioned the National Center for Atmospheric Research (NCAR) in collaboration with the National

Renewable Energy Laboratory (NREL) in 2008 to perform customized research on their needs, which resulted in a decision support tool for integrating wind energy (Xcel Energy 2018; Mahoney et al. 2012; Parks et al. 2011). Similar studies progressed in Europe, producing recommendations for best practices (Giebel and Kariniotakis 2007). Various commercial interests began providing specialized forecasts to meet the needs of the energy sector. Several international conferences ensued that brought together the wind and meteorology communities, including ones hosted by the AMS (the “Conference on Weather, Climate, and the New Energy Economy,” begun in 2009), European Meteorological Society (also begun in 2009), International Conference on Energy and Meteorology (first hosted in Australia in 2011), American Geophysical Union, and European Geophysical Union. Many of these societies host committees to foster a collaboration between the energy and meteorology disciplines.

b. Load forecasting

Forecasting the electric load in real time is critical to utilities and transmission system operators (TSOs) for balancing the electric grid. The grid must be balanced at several time scales: 1) long term for planning beyond a year for fuel supplies, 2) medium term on time ranges of a week to a year for maintenance and fuel transport, and 3) short term on time scales of 15 min to a week for day-to-day operations (Feinberg and Genethlion 2005; Hong 2014). To maintain the most efficient and economic operation of the grid requires accurate load predictions, allowing utilities to avoid spot market power purchases or unnecessary use of expensive spinning reserves.

Electric load depends on customers’ daily and weekly usage patterns, which in turn changes with the varying weather. Some of these usage patterns are industrial, while others are driven by residential and commercial use. The balance between these sectors depends on the climate and land usage of the region. The U.S. Energy Information Agency (EIA 2018) reports that in 2016 40% of U.S. electricity usage went to residential and commercial users, which is largely spent in heating and lighting buildings. Figure 23-5 shows typical curves of electric and gas load versus temperature for portions of the state of Colorado. The highest electric loads occur for the highest temperatures, when air conditioning is needed to make buildings habitable. The lowest temperatures are also correlated with high loads, only partially for heating since much of the heating in Colorado is not electrical, but likely more due to the increased need for lighting during the darker winter period. The gas load curve shows a fairly linear correlation with

FIG. 23-5. Plots of percentage of maximum load vs temperature for example regions in Colorado for (top) electric load and (bottom) gas load.

temperatures below about 10°C, indicating that more gas is used for heating during the coldest periods. Not only is the temperature itself important, but so is the variability in temperature, as the thermal mass of the building determines a time lag in heating or cooling to the desired temperature.

Predicting electrical load requires high-quality meteorological data, both current and historical, of variables including temperature, solar insolation, humidity, precipitation, and wind speed (Feinberg and Genethlion 2005; Haupt et al. 2017a). The weather data are correlated with historical usage patterns and used to train prediction algorithms. One well-used method to predict electrical load is to search for similar days in the past (analog) and to summarize the corresponding observed daily load curves for use as a prediction. Other methods include statistical or artificial intelligence learning methods, such as regression models, time series methods (Almeshaie and Soltan 2011), artificial neural networks

(Park et al. 1991; Lee et al. 1992), and support vector machines (Hong 2009). Some advanced approaches incorporate multiple artificial intelligence methods (Wang et al. 2012). Note that due to nonstationarity of the human population, one must be careful to recognize any trends due to changing demographics.

A relatively new challenge is correctly incorporating the impact of distributed renewable energy on the load. In particular, much of the rooftop solar is “behind the meter” so that increases in solar power production cannot be readily distinguished from decreases in electricity usage. Two different approaches have developed to deal with this issue, “bottom up” and “top down” approaches (Tuohy et al. 2015). In the bottom-up approach, a full inventory of the details of each system is used to compute the production for each solar installation (Hoff 2016). Often, this level of data is not available, which necessitates a top-down approach. This method predicts solar irradiance at points where observations are available, then uses the percentage of capacity available to multiply with the total installed capacity of the nearby region. Despite the mostly ad hoc nature of this approach, it can be surprisingly accurate within a few percent out to 2 days (Lorenz et al. 2014; Haupt et al. 2017a).

Note that some physical modeling involving numerical weather prediction (NWP) models such as the Weather Research and Forecasting (WRF) Model is being explored to examine the interaction of anthropogenic systems, such as air conditioning, with temperatures for urban environments (Salamanca et al. 2014). Approaches such as this one could augment the current methods in the future.

c. Weather support for longer-term planning for units, fuel, and maintenance

The energy industry requires predictions for weather events that could cause outages to their generating units or transmission and distribution system. They often correlate storm predictions with historical patterns of outages to prepare for mitigating such events (Dubus et al. 2018a). Prediction of fair weather can help them to plan and schedule routine maintenance in order to provide a higher level of resilience to severe weather events. Longer-term prediction of storm events can aid in planning for the manpower and material costs of mitigating the effects of such storms.

The energy industry has long relied upon meteorological information for its long-term planning. During winter, it must plan how much fossil fuel to have on hand to deal with prolonged cold spells. In the summer, the reverse is true—during heat waves, the use of electricity for cooling increases. Fossil fuels require time to transport.

The well-known “polar vortex” of January 2014 caused prolonged periods of anomalously low temperatures in the United States that led to record high fuel demand, resulting in fuel shortages, particularly of natural gas, as well as temperature-related problems with generators, causing major load interruptions (NERC 2014). Part of the problem was that the temperatures were so low that coal piles froze and those plants were unable to operate, accounting for 26% of the plant outages (NERC 2014). To anticipate the fuel requirements, the energy industry requires accurate subseasonal to seasonal probabilistic forecasts (Dutton et al. 2018). Although public weather services and commercial interests make such forecasts, the research to improve accuracy is ongoing (Troccoli et al. 2018).

Utilities also require information on how changes in climate may impact their operations, so that they can better plan for future operations and configurations of energy sources. For instance, it may not be prudent to site a plant near the coast in a region where sea level is expected to rise. The impact of rising temperatures may mean that cooling water required for operating fossil or nuclear plants may become too warm to effectively cool, changing their efficiency (Dubus et al. 2018a), or the discharge water may become too warm to discharge into water bodies without a negative environmental impact. Regional and local changes in rainfall and snowpack may alter planning for the siting of future hydropower plants (HydroQuebec 2018). In addition, the energy community is focusing on building resilience to the possibility of more frequent and more severe extreme events and other changes likely resulting from changing climate. Such actions could include optimizing the cost of emergency operations, incorporating more distributed generation, taking actions to decrease the durations of outages, and improving communications with customers during storms that could lead to outages (Dubus et al. 2018a). All of these potential impacts signal that the meteorological information can provide value for the energy community (Dubus et al. 2018b).

d. Using meteorological information for renewable energy

The need for integrating meteorological information into the energy system is intensifying as wind and solar become the fuel for the energy system. The environmental energy is converted into electric energy—the kinetic energy of atmospheric motion and the solar insolation become the source of energy for conversion into electricity through turning turbines or transformed via solar panels. Growth in the deployment of wind and solar has accelerated over the past decade with new installation of renewables at 161 GW (REN21 2018)

worldwide, accounting for 62% of net capacity additions in 2016 (REN21 2018). This brings the total amount of hydropower plus wind plus solar capacity to 2017 GW (REN21 2018), which represents roughly 27% of total global electricity capacity.

Hydropower has been a long-standing part of the energy system, making up 16% of the world's electricity with 1200 GW of installed capacity (IEA 2018). That installation has slowed, however. Hydropower was generally considered to be part of a reliable baseload that changed very slowly. Although hydrological forecasting has been employed, it was more for seasonal planning purposes.

In comparison, by the end of 2016, total wind power capacity was 487 GW and solar power capacity was 308 GW, with new installation of the two at 129 GW (REN21 2018). Wind and solar are growing at 2 times the rate of the growth in energy demand (REN21 2018). The reasons for the rapid growth in these variable renewables are many, previously being spurred by policy in many countries to secure local energy sources and decrease emissions of carbon dioxide (CO₂) and other pollutants (IEA 2017). More recently, the costs of the technology associated with renewable energy have decreased to where these sources are extremely cost competitive. For the fifth consecutive year, the world invested 2 times the amount in renewable sources as compared with fossil fuel plants (REN21 2018). Much of this growth in renewable generation is in Asia. The International Energy Agency (IEA 2017) estimates that China will have more than one-third of onshore wind and solar photovoltaic (PV) capacity by 2021. The PV capacity in India is expected to grow by a factor of 8 in the same time period (IEA 2017). In 2017, India installed 4.1 GW of wind capacity as part of fulfilling a goal to double their wind capacity over a 5-yr period (McCracken 2018), so that a total wind capacity is 34.3 GW, which is about 10% of total installed power capacity (India Ministry of Power 2018). The United States installed 7 GW of wind in 2017, which is 41% of all new installations, bringing the total wind capacity to 90 GW (AWEA 2018). Solar installation has grown at an annual rate of 68% in the past decade in the United States, reaching an installed capacity of 44.7 GW (3% of total) by the end of 2016 (SEIA 2017). Much of that solar installation (72% in 2016) is at the utility scale (SEIA 2017).

This increase in capacity of these variable renewable energy sources implies a burgeoning need to forecast the resource on several scales. Forecasting the wind or solar resource on relatively short time scales allows more efficient and economical integration of the power in the electric grid. For planning where to site wind and solar

resources, an assessment of the available power must be accomplished. Once built, the operation and maintenance of the plants rely on subseasonal to seasonal forecasts. Forecasts on scales of 5 min to several days are required for economic and efficient integration of the variable renewables in the grid (Curtright and Apt 2008; Ela et al. 2013; Dubus 2014; Dubus et al. 2018b).

1) RESOURCE ASSESSMENT

When planning development of a site for renewable power, the first consideration is the long-term expected production of the facility. These include assessments of seasonal wind or irradiance patterns and their interannual variability. Such an analysis requires a comprehensive historical dataset (Lopez et al. 2012; Clifton et al. 2017). Because the infrastructure is expected to last decades, one should also consider any changes expected in the power potential, including that due to projected changing climate conditions.

Quantifying the changes expected under projected future climate conditions is primarily based on data dynamically downscaled from global climate models by using regional climate models. Such studies have been accomplished over northern Europe by Pryor et al. (2005, 2012a), Hueging et al. (2013), and Nolan et al. (2014). Expected changes in wind speed over North America have also been quantified (Pryor and Barthelmie 2011; Pryor et al. 2012b,c; Haupt et al. 2016), including estimating variability in the wind and solar resource and its potential changes under future climate conditions.

2) FORECASTING

Short-range forecasting has developed rapidly over the past decade, from using standard output from forecasting center models to highly specialized systems with components targeting best-practice methods at each time scale of interest (Ahlstrom et al. 2013; Kleissl 2013; Haupt et al. 2014; Orwig et al. 2014; Mahoney et al. 2012; Tuohy et al. 2015; Haupt and Mahoney 2015). Figure 23-6 depicts the types of models that might be used in a forecasting system that spans time scales from a few minutes through several weeks or more.

For time periods less than about 3–6 h, forecasting methods rely on measurements, either in situ or remotely sensed, plus often some type of statistical learning method. For wind prediction, upstream observations as well as radar data can be leveraged to provide forecasts (Mahoney et al. 2012; Wilczak et al. 2015; Haupt et al. 2014; Cheng et al. 2017). For solar energy, instruments such as sky cameras (Chow et al. 2011; Marquez and Coimbra 2013; Huang et al. 2013, Quesada-Ruiz et al. 2014; Nguyen and Kleissl 2014; Chu et al. 2015; Peng et al. 2015) as well as pyranometer

FIG. 23-6. Scales and methods for forecasting for renewable energy.

observations can be combined with other meteorological information to provide relatively accurate forecasts. Methods used for these techniques include Markov process models (Morf 2014), autoregressive models (Hassanzadeh et al. 2010; Yang et al. 2012; Reikard et al. 2017), artificial neural networks (Mellit 2008; Wang et al. 2012), gradient-boosted regression trees (Gagne et al. 2017), or support vector machines (Sharma et al. 2011; Bouzerdoum et al. 2013). Some studies have seen enhanced success by employing regime-specific models (Zagouras et al. 2013; Mellit et al. 2014; McCandless et al. 2016a). Satellite methods have also shown success for short time periods (Miller et al. 2013, 2018), but for longer lead times, cloud formation and dissipation become important, which requires implementing physical models (Haupt et al. 2017b, 2019d). In some cases, satellite data have been added to the regime-dependent machine-learning methods (McCandless et al. 2016b). Variability of the renewable resource can also be forecast with machine learning (McCandless et al. 2015).

NWP is an important tool beyond the first 2 h. It includes information on the current global patterns and integrates forward to predict the changes (Perez et al. 2013; Wilczak et al. 2015). Studies have shown that assimilating data from the wind farms themselves can greatly improve the value of the forecast for the wind farm. (Mahoney et al. 2012; Wilczak et al. 2015; Cheng et al. 2017). Models have also been modified specifically to improve prediction of the specific variables of most importance to energy, such as wind (Wilczak et al. 2015), solar (Jimenez et al. 2016a,b), and hydropower (Gochis et al. 2015).

To be of utility for the end user, the various forecasts must be blended. Skill can be gained by additional post-processing at this phase to train the models to better match the local observations using statistical or artificial intelligence techniques. Practitioners often blend multiple models using statistical learning or artificial intelligence techniques and produce better forecasts than possible with any single model. Methods such as autoregressive models, artificial neural networks, support vector machines, and blended methods have shown success at providing non-linear corrections to models (Myers et al. 2011; Giebel and Kariniotakis 2007; Pelland et al. 2013). Such techniques can improve upon a forecast by 10%–15% over the best model forecast (Myers et al. 2011; Mahoney et al. 2012; Haupt et al. 2014). The various methods must then be seamlessly blended to provide a consistent forecast to the end user. Bringing all of these systems together constitutes a “Big Data” application (Haupt and Kosovic 2017).

The targeted forecasting enables the utility to run its operations more efficiently and economically. For instance, Xcel Energy (2018) is able to optimize its processes by

- 1) accommodating the lower cost wind generation by cycling less efficient coal and natural gas plants offline, reducing fuel costs and emissions,
- 2) letting wind farms operate at peak levels through use of set-point controls in combination with automatic generation controls on thermal units, reducing fossil fuel production,
- 3) carrying only a 30-min flexibility reserve that maintains reliability while significantly reducing the costs

associated with reserve power—this is in contrast to the prior method of carrying sufficient backup power to meet all of the wind power available, and

- 4) investing in more flexible natural gas generation that can ramp up and down more efficiently to operate in concert with variable wind generation.

[Xcel Energy \(2018\)](#) estimates that it has saved \$66.7 million for their ratepayers through 2016 by having a specialized wind power forecasting system in addition to avoiding emission of substantial amounts of CO₂ and other pollutants.

3) UNCERTAINTY QUANTIFICATION

Because these renewable resources are inherently variable, it becomes essential to develop a capability to forecast the resource, its variability on several scales, and the uncertainty. Utilities and TSOs have begun requesting probabilistic information to plan for renewable operations, resolve transmission bottlenecks, and create strategies for operating reserves ([Dobschinski et al. 2017](#); [Bessa et al. 2017](#)). The best-known method to quantify uncertainty in meteorological forecasts is to run multiple realizations of the forecasts with perturbations to the initial conditions, boundary conditions, physics parameterizations, or other model parameters. These ensemble forecasts are routinely produced at the major forecasting offices as well as by some firms supplying specialized forecasts to the end users. Various post-processing methods can sharpen the probability density function, remove bias, and calibrate the spread, or reliability, of the forecast.

An alternate method for quantifying uncertainty while simultaneously removing bias from the deterministic forecast is the analog ensemble (AnEn) technique. The AnEn uses historical and real-time forecast output from a single, often higher-resolution simulation. One identifies the set of most similar, or analogous, historical forecasts to the one currently made. Because one can associate observations with the historical forecasts, those observations compose a probability density function (pdf) for the current forecast, which becomes the analog ensemble. The mean of that ensemble is a correction to the deterministic forecast and the spread quantifies the uncertainty. This method has been applied for wind and solar power ([Delle Monache et al. 2013](#); [Haupt and Delle Monache 2014](#); [Alessandrini et al. 2015](#)).

4) PLANT MANAGEMENT

As more wind and solar plants are coming online, the developers/owners are becoming more interested in optimizing plant management through more detailed knowledge of the meteorological conditions. This is

particularly true for wind plants, where the front row of turbines may produce the power expected for a given inflow wind speed, but the downwind turbines' output is reduced due to by the interference of the wakes from the upstream turbines and momentum fluxes generated by the turbines themselves. Both numerical and field experiments are being accomplished to study whether controlling the pitch of the upstream turbines to alter the direction of their wake out of the direct path of those downstream will allow them to harvest more energy. This approach is expected to allow higher production of energy over the entire plant. One must understand and be able to model these complex flow interactions to enable such controlling techniques. These types of analyses require being able to couple the NWP models that represent the large-scale forcing with very-fine-resolution large-eddy simulation (LES) and computational fluid dynamics (CFD) models, which allow simulating details of the flow in the wind plants.

To that end, various research organizations are studying the necessary coupling to do these kinds of analyses. The U.S. Department of Energy (DOE) is running an Atmosphere to Electrons (A2e) program to advance all levels of this type of modeling ([DOE 2018](#)). The Mesoscale to Microscale Coupling (MMC) team is studying the coupling of these levels of models, including during nonstationary conditions and in complex terrain ([Haupt et al. 2015, 2017c,d, 2019c,d](#); [Muñoz-Esparza et al. 2017](#); [Mirocha et al. 2018](#)). Another A2e team is studying the impact of wakes on the downstream turbines through use of both models and field experiments. The controls team is studying the impact of controlling turbines on the production of the downstream turbines ([Fleming et al. 2014, 2015](#)). This work is being widely documented and is expected to enable the industry to better plan future deployment and operation strategies to optimize power production from wind plants.

e. A look to the future

As the energy industry makes the transition to using more renewables, electrical energy is increasingly being obtained from the kinetic energy of the wind, the potential and kinetic energy of water reservoirs and streams, and solar radiation. Thus, detailed knowledge of how to best utilize the information from the meteorological community is becoming ever more important. Not only is the meteorological community providing probabilistic information, but the energy operators are considering stochastic unit commitment. As these efforts advance in parallel, we come closer to being able to integrate real-time observations, use model output and machine-learning methods to predict probabilistic estimates of the most likely output, and use it to balance

load and automatically optimize the balance between load and production to optimize the economic dispatch of the units.

Another important aspect of future energy use will be impacts from a changing climate. Climate change is projected to impact various aspects of the energy system, including electricity demand, hydropower generation, generation from wind and solar, transmission, and cooling of traditional plants (Craig et al. 2018). The growth of renewables itself helps to mitigate the changing climate and provides hope for limiting potential changes.

In the past decade, a dialog has begun between the energy community and the meteorological community that is already culminating in a close collaboration (Dubus et al. 2018a,b; Troccoli et al. 2013, 2018). This collaboration is essential to optimize the energy systems of the future.

4. Applications of air pollution meteorology

a. Introduction to applications of air pollution meteorology

The scope of this section could be broad, since topics such as atmospheric chemistry, aerosol formation, wet and dry deposition, and source term estimation fall under the general subject area of air pollution meteorology applications, in addition to the more traditional topic concerning operational air pollution transport and dispersion models. Also, there are growing numbers of comprehensive health and environmental modeling systems, in which the meteorological model and the transport and dispersion model are just part of the total system. The climate modeling systems are a good example. Our main focus here is on the more traditional definition, as described in basic texts on boundary layers and transport and dispersion (e.g., Pasquill 1974; Gifford 1975; Arya 1999; Stull 2000) as well as other chapters in this monograph. This section is complementary with the section entitled “Air pollution meteorology” written by J. Weil for chapter 9 of this monograph (LeMone et al. 2019). That section covers the theory and the derivations of models, whereas this section focuses on applications.

b. History

As with most scientific fields, applied research in air pollution meteorology (field experiments, data analysis, and model development) addresses issues that are of interest to funding organizations. Interests of funding agencies shift from decade to decade and country to country. This section focuses on U.S. applications, although many topics have broad interest across the globe.

In the 1910s–50s, the use of chemical weapons in World Wars I and II generated the need to be able to model the transport and dispersion and downwind patterns (out to a few kilometers) of concentrations in the chemical clouds. In those “precomputer” days, clever analytical and empirical basic physics models were developed (e.g., Taylor 1921; Richardson 1926; Calder 1961; Pasquill 1961; Gifford 1961). The models were developed and evaluated using data from field experiments such as those at Porton, United Kingdom (Pasquill 1956), and Project Prairie Grass in Nebraska (Barad 1958a,b). Gaussian plume models and analytical “K theory” models became widely used.

In the 1950s–70s, concerns arose about possible radiological releases from weapons and industrial facilities. Although many potential releases were from ground level and could be studied using models developed earlier, the threat of long-range missiles led to many studies of dispersion in the stratosphere and development of long-range transport models (Machta et al. 1957; Randerson 1972). The new field of NWP modeling [see the monograph chapter by Benjamin et al. (2019)] allowed regional and global wind patterns to be simulated. This period also saw studies of short-range effects from stack plumes and vents, particle formation, interactions with rain and snow, and deposition (wet and dry). Increased frequency of major air pollution episodes across the world was raising public concerns that later led to regulation of industrial air pollution sources.

In the 1970s–80s, the Clean Air Act in the United States and similar regulations elsewhere led to U.S. Environmental Protection Agency (EPA) and other countries’ studies of short-range dispersion from industrial stacks and the development of Gaussian plume dispersion models accounting for plume rise. The EPA’s *Workbook of Atmospheric Dispersion Estimates* (Turner 1967) formed the basis for regulatory models for industrial stacks. Van Ulden (1978) suggested a similarity model for near-ground sources. Figure 23-7 contains three examples of plumes from industrial stacks. All are buoyant plumes that rise up through the boundary layer until they reach an equilibrium level. Sometimes cooling tower plumes, such as the example in the top panel of Fig. 23-7, form a visible water aerosol. That photograph was taken when winds were very light and the plume rose vertically several hundred meters. The plumes in the middle panel of Fig. 23-7 have typical “bent over” shapes characteristic of windy, neutral conditions. The bottom panel of Fig. 23-7 illustrates buoyant plumes that rise until they encounter stable layers in the boundary layer and then spread out laterally with little vertical dispersion after they reach their final rise.

FIG. 23-7. (top) A buoyant plume is visible from a group of cooling towers at an industrial plant on the Ohio River at midday with very light winds and a deep boundary layer. The temperature is about 30°F (−1.1°C). The visible plume consists of a mixture of warm air and water vapor and condensed water drops. (photograph credit: S. Hanna). (middle) Plumes are seen from three industrial stacks in steady wind conditions with moderate to high wind speeds. The boundary layer is likely well mixed and adiabatic (neutral stability). (bottom) A power plant tall stack plume (upper orange plume) is seen, as well as the plume from a shorter industrial stack (smaller, lower white plume) on a stable morning with a deep inversion. Both plumes are seen to stabilize (flatten out with reduced vertical turbulence) after they reach their level of final buoyant plume rise.

Computers began to be used for model applications in the 1970s. However, the operational dispersion models were not yet linked with mesoscale or regional NWP models. Late in the 1980s and into the 1990s, acid-rain concerns led to funding of extensive studies of regional air pollution problems involving chemical reactions and deposition. Early EPA and DOE regional 3D time-dependent Eulerian models were developed and applied.

The 1990s began to see formal links between NWP and regional air pollution models, although they were mainly used for research, historical analysis, or planning. In the 1990s, the widely used Gaussian dispersion models for industrial sources began to be improved to accommodate enhanced knowledge of boundary layer processes [such as incorporation of the [Monin and Obukhov \(1953\)](#) length scale L and the convective velocity scale w^*]. Another category of new models, called Lagrangian puff and particle models, became widely used in the 1990s. They use diagnostic mass-consistent wind models to account for time and space variations in winds on scales up to 100–200 km.

In the 2000s through the present, there have been improvements of knowledge and models of air pollution meteorology at all scales. There is now widespread linking of the transport and dispersion models with several options for meteorological inputs, including NWP model outputs. The NWP links are used for real-time air pollution forecast models in several agencies. Computer advances allow 3D Eulerian models with reasonable grid sizes to be used operationally [e.g., 10 km or less per grid cell for the EPA's Community Multiscale Air Quality (CMAQ) modeling system and a gridcell size of 1 m or less for small-scale CFD models]. Major improvements have been made to chemical mechanisms, including gas-to-particle conversions ([Seinfeld and Pandis 2016](#)). There is renewed focus on urban meteorology and dispersion, as mentioned in [section 2](#). Improvements have been made to short-range models such as the AMS–EPA Regulatory Model (AERMOD; [EPA 2004](#); [Cimorelli et al. 2005](#); [Perry et al. 2005](#)) to account for L , friction velocity u^* , convective velocity scale w^* , and other advanced aspects of boundary layer knowledge. At this time, EPA requires use of AERMOD for applications that calculate dispersion from industrial stacks and other sources in the near field. Improvements have been made to models of toxic chemical releases (accidental and intentional). Also, there has been a shift to using inverse transport and dispersion models to estimate source emissions magnitudes and locations ([Hanna and Young 2017](#); [Bieringer et al. 2017](#)). There are extensive ongoing studies of the effects of climate change on air pollution and vice versa.

FIG. 23-8. Condensation plumes from 76- and 152-m stacks on the coast in Salem, Massachusetts, show complex thermal structure and large wind shear in the lower atmosphere on a very cold February morning in the 1970s. Steaming fog is seen in the foreground over Beverly-Salem Harbor. (Photograph by R. Turcotte of the *Beverly Times*; credit to B. Egan.)

c. Major science issues relating air pollution to meteorological conditions in operational applications

1) SHORT- AND MEDIUM-RANGE DISPERSION

What boundary layer meteorological factors lead to reduced dilution and dispersion, and therefore, to increased concentrations (at the center of the pollutant cloud)? Pasquill (1974) provides one of the best overviews of the topic. Low wind speed u (which can happen anytime, day or night) and low standard deviations of turbulent velocity fluctuations σ_u , σ_v , and σ_w (which most often tend to happen at night) contribute to increases in pollutant concentrations. Vertical stability (as expressed by Pasquill class, L , or Richardson number Ri) strongly influences turbulent velocities, mixing depth, and wind speed profiles. The effects of vertical stability and winds are seen in Fig. 23-7.

Wind direction obviously has a major effect on the location of the major impacts. Knowledge of mesoscale wind variability within the geographic domain of interest is useful. Seldom are local wind observations available, and NWP model predictions may have large biases. For example, Fig. 23-8 shows two plumes released from different elevations in a coastal zone during an early morning stable period with a 180° wind direction shear between heights of about 100 and 300 m. This wind shear would not be known without a local observation of wind profiles (perhaps by a remote system).

Stability *within* the pollutant cloud can have a large influence on ground-level pollution concentrations, which are reduced if the plume is buoyant (i.e., its density is less than that of the ambient atmosphere) and initially rises. However, if the plume is denser than the ambient atmosphere, it may sink to the ground and have minimal vertical dispersion, thus increasing concentrations and increasing the spatial extent of the impact.

Land use (parameterized by surface roughness length, albedo, soil moisture, etc.) has a major influence on all boundary layer variables. The rougher the surface, the less the wind speed and the greater the turbulence intensity. Albedo and soil moisture influence the magnitude of the sensible heat flux, which affects the stability.

Small mixing depth (z_i) will limit vertical mixing. However, in practice z_i can be indeterminate when the vertical profiles of temperature and other variables have no obvious discontinuities between the ground and heights of 1000–2000 m. Also, very low z_i (<10 m) that may occur during very stable, low-wind, conditions can impose a shallow lid to a pollutant cloud such that concentration is inversely proportional to z_i . Thus, it is crucial that z_i be well known during such conditions. Also, terrain, vegetation, or anthropogenic obstacles can constrain the pollutant cloud, force the direction of mean flow, increase turbulence, and force upslope and downslope flows.

“Weather” such as rain or snow can remove air pollution, either by physically capturing a particle or by reactions between the gaseous pollutant and the raindrop or snowflake. Rain or snow can worsen the air pollution impact for some pollutants where deposition is the dominant effect (e.g., the Fukushima, Japan, reactor accident, in which the major health and environmental effects occurred during a brief period of rain northwest of the plant). However, if ambient air concentrations are most important, then rain or snow can remove pollutants from the air and mitigate inhalation effects

2) MESOSCALE, REGIONAL, AND GLOBAL POLLUTION

At these larger scales, meteorological conditions always vary in time and space over the geographic domain and time periods of interest, and these variations must be accounted for using a combination of observations and NWP model simulations. Worst-case conditions from the point of view of regional air pollution often involve high pressure systems with low mixing depths, light winds (small pressure gradients), stable nighttime conditions, and no precipitation. Often multiple primary pollutant sources spread across the regional domain (e.g., traffic emissions of nitrogen oxides, or NO_x). Secondary pollutants can be formed by chemical reactions, thus requiring that a model have a comprehensive chemical mechanism. Because the residence times and distances are large, chemical reactions and deposition (wet and dry) can be important. Many pollutants will be removed (deposited to the surface) from the domain during a widespread heavy rain event. For pollutants where wet deposition is a primary cause of health and environmental effects, the timing and location of

precipitation is important (e.g., Fukushima, Chernobyl in the Ukraine, and acid-rain scenarios).

Most pollutants have significant background concentrations [e.g., ozone, atmospheric particulate matter (PM) with diameter less than $2.5\ \mu\text{m}$ (PM_{2.5})], partially caused by biogenic processes and partially by anthropogenic processes, and their time and space variations are not well known. Sometimes the natural sources can, by themselves, cause exceedances of pollution concentration regulatory standards (e.g., sulfur dioxide and PM around volcanoes, forest fires, and dust storms).

Because of the need to know the fluxes of CO₂ and other greenhouse gases to and from the surface (land and water) around the globe, great advances have been made over the past 20 years in improving the accuracy of surface turbulent flux observations and operational models over all types of land use and scales (see Seinfeld and Pandis 2016). This knowledge has been transferred to other chemicals.

d. Applied (operational) air pollution transport and dispersion models

This section describes some applied (operational) transport and dispersion (“T&D”) models, lumped into five major categories. Each of the T&D models has specific meteorological input requirements or options, such as one or more NWP model options (e.g., WRF), and/or a diagnostic wind model [e.g., California Meteorological Model (CALMET), Quick Urban and Industrial Complex (QUIC), or Micro-Swift-Spray (MSS)], and/or a single meteorological observation site (perhaps also using a nearby radiosonde profile).

1) CATEGORY 1: GAUSSIAN PLUME OR PUFF MODELS

This category of T&D model includes the early (1960s) Gaussian plume and puff models suggested by Pasquill (1961) and Gifford (1961), the EPA workhorse model Industrial Source Complex (ISC) from the 1990s (EPA 1995), and several current operational models for calculating air pollution concentrations within a few tens of kilometers of industrial stacks [e.g., AERMOD in the United States (see Cimorelli et al. 2005) or the Atmospheric Dispersion Modeling System (ADMS; Carruthers et al. 1994) in Europe]. These are also commonly called “straight line” models because they assume that the given winds and stability persist over the duration of the plume trajectory (assumed to be 1 h for EPA applications). In reality, because of shifts in winds and stability, the plume direction, dilution, and dispersion rate can vary. Thus, for sufficiently long travel times and distances, it becomes more and more necessary to use a Lagrangian or Eulerian model that can account for wind variability.

Because these models are intended for application to industrial stacks, they include plume rise algorithms to account for enhanced plume buoyancy and momentum, as well as downwash algorithms to account for possible influences of wakes behind nearby buildings (see Hanna et al. 1982). Some of the state-of-the-art Gaussian models (e.g., AERMOD and ADMS) have been upgraded to include state-of-the-art boundary layer and dispersion parameterizations and to accept NWP model outputs as inputs.

2) CATEGORY 2: SIMILARITY AND SLAB MODELS

For dispersion close to the ground ($z < 10\text{--}20\text{ m}$) and when the release is close to ground level, the Gaussian formulation does not work as well as similarity formulas. Thus, operational models such as the EPA’s “RLine” model, applied to traffic sources and distances close to the road, employ the van Ulden (1978) similarity formulation. RLine is also being applied to harbors and airports. Slab models [e.g., Aerial Locations of Hazardous Atmospheres (ALOHA); EPA 2007] are generally applied to dense gases, which initially form a shallow and broad cloud whose concentration is assumed to be constant across the rectangular-shaped core or “slab.” Dispersion subsequently occurs due to entrainment of ambient air into the slab. The entrainment formula can also be considered a similarity formula since it is an empirical function of u^* and cloud Richardson number Ri_{cloud} .

3) CATEGORY 3: LAGRANGIAN PUFF AND LAGRANGIAN PARTICLE MODELS

As mentioned in the paragraphs under Category 1 (Gaussian plume models), the Lagrangian models can account for time and space variability in boundary layer meteorological inputs, usually over domains ranging from 1 km to a few hundred kilometers. This requires a link with either a mass-consistent diagnostic model or an NWP meteorological model. The California Puff (CALPUFF) model (Scire et al. 2000) is linked with the CALMET mass-consistent wind model, which requires inputs from a mesoscale network of surface wind sensors plus at least one nearby National Weather Service (NWS) or World Meteorological Organization (WMO) radiosonde station. The wind inputs and terrain files are input to an iterative procedure that produces a wind field that is close to mass consistent. The Second-Order Closure Integrated Puff (SCIPUFF) model (Sykes et al. 2007) uses the Stationary Wind Flow and Turbulence (SWIFT) diagnostic wind model. A higher-resolution version of SWIFT that also can accommodate 3D building geometry is part of the MSS modeling system, which includes a Lagrangian particle model (Tinarelli

et al. 2007). The QUIC model, specifically designed for urban areas, links a similar diagnostic wind model that accounts for building geometry with a Lagrangian particle model (Williams et al. 2004; Nelson and Brown 2013). The diagnostic wind models produce a gridded 3D mass-consistent wind field as well as mixing depths that vary in time (piecewise; i.e., the solution represents an average over the observed wind averaging time, which is usually 1 h for routine observations).

All of the abovementioned Lagrangian puff or particle models also have the option to use NWP model outputs as inputs to their dispersion model. The mass-consistent diagnostic wind models run much faster than NWP models but do not represent a full solution to the equations of motion and other governing equations. Thus, as computers have improved, there has been a shift toward use of NWP models to provide meteorological inputs to operational air pollution models. Most of the NWP models use data assimilation to allow the model to better match the observations (see Benjamin et al. 2019). However, data assimilation weakly nudges the solution toward the observation. Also, most operational NWP models often do not have the fine grid resolution ($\ll 10$ km) necessary for resolving air pollution gradients on the local scale, such as the plume from a power plant stack at distances less than 1–2 km from the stack.

The Lagrangian puff or particle model transports and disperses the puffs or particles using the meteorological fields. Lagrangian models need the three components of the turbulent velocity as well as a Lagrangian time scale. These are usually parameterized internally by the T&D model meteorological preprocessor. This category of T&D model can often handle chemical reactions and buoyant or dense clouds.

There are currently discussions in environmental regulatory agencies about whether the straight line Gaussian T&D models should all be replaced by Lagrangian puff or particle models in operational applications. However, there are practical problems when an environmental agency switches T&D models, because many industrial sources have been permitted using predictions by a specific model (such as AERMOD).

4) CATEGORY 4: HYBRID MODELS

Some models are called hybrid models because they combine characteristics from two or more categories. An example is the National Oceanic and Atmospheric Administration (NOAA) Hybrid-Split (HYSPLIT) plume modeling system, which is available online (Stein et al. 2015). It uses an operational NWP model (currently the WRF Model) for meteorological inputs. Its T&D model is a hybrid in the sense that it combines Lagrangian puffs with Gaussian distributions for horizontal dispersion and

FIG. 23-9. NCEP forecast product containing CMAQ-predicted maximum daily ozone for 17 May 2017 for the northeastern United States. This was a day with 100°F (37.8°C) afternoon temperatures in the New York City–Boston corridor. All ozone concentrations have units of parts per billion. Forecast ozone concentrations are indicated by solid colors bounded by solid contour lines. The observations, indicated as small circles with concentrations that follow the same color scheme as the forecast concentrations, were added by NWS to the figure after the observations became available. Surface wind vectors are also shown. The model is described by P. Lee et al. (2017). This figure is from NOAA/NCEP (<http://www.emc.ncep.noaa.gov/mmb/aq/cmaq/web/html/max.html>).

K theory for vertical dispersion. One of the more widely used HYSPLIT options is the trajectory calculation, often used to calculate “back trajectories” to identify the source region of the observed pollution. HYSPLIT is frequently used to predict mesoscale, regional, and global transport and spread of pollution clouds from forest fires and volcanoes.

5) CATEGORY 5: EULERIAN GRID MODELS

An Eulerian grid model solves the basic equations (e.g., Navier–Stokes and mass conservation) in time on a 3D grid. The total domain size can extend from 10 m (in a CFD study of the initial plume from an industrial source) to 10 000 km (global chemistry model). At the present time, computer speed and storage are sufficient to allow the meteorological variables to be solved on the same grid by a linked NWP model or CFD model (often with feedback). For example, the EPA’s CMAQ modeling system is linked with the WRF NWP model (Astitha et al. 2017). CMAQ and other regional air pollution models are also linked with emissions models and include detailed chemical mechanisms. Figure 23-9 displays an example of an operational National Centers for Environmental Prediction (NCEP) forecast (using CMAQ) of maximum 1-h averaged ozone concentration in the northeastern United States for 17 May 2017. Ozone concentrations are relatively high in the urban corridor that runs from the city of New York, New York,

to Boston because of very hot weather on that day. The forecast concentrations are shown as solid colors with contour lines between them. The observed concentrations (added by NOAA later) are shown as solid-colored circles. This air pollution event is an example of the UCA discussed in [section 2](#). Several countries have joined in an exercise in which many regional air quality–NWP modeling systems are used as components of an ensemble regional modeling approach (e.g., [Rao et al. 2011](#)).

Several types of CFD models are used for atmospheric T&D calculations. The direct numerical simulation (DNS) model does not use a subgrid turbulence model, since its grid size is so small that turbulence can be directly simulated. However, DNS models are currently only used for fundamental research purposes, since their computational times are long. The most widely used CFD models include subgrid turbulence models and are generally classed as either LES or Reynolds-averaged Navier–Stokes (RANS). These CFD models are seeing increased operational use. LES models require much more storage space and time because they produce time-variable 3D fields. In contrast, RANS CFD models by definition produce time-averaged output fields. However, many RANS models are run in unsteady mode, producing time-varying output much like the LES models and requiring the same amount of storage.

All NWP models used to forecast the weather on a daily basis predict finescale time variations. Operational linked NWP and air pollution T&D models make use of the routine daily NWP model runs made by weather services. However, in most cases, air pollution cannot affect the NWP runs (e.g., by having pollution clouds block some of the sunlight and therefore alter the surface energy balance).

Because regional models like CMAQ predict gridcell-averaged variables, they cannot resolve finescale plume structure at scales less than the grid size. There is, however, often interest in predicting local concentrations from large point sources such as power plants. Consequently, several regional models can accommodate a “plume in grid” module, which calculates concentrations for the largest emitters using a Gaussian plume or puff model until the plume size exceeds the grid size, after which the plume is “absorbed” into the Eulerian grid cell.

As computer storage and speed increase, the regional modelers keep reducing the model grid size (now with a minimum of about 0.5 km in research studies for a domain size of about 500 km). The models are often run in “nested” mode, with larger domains having larger grid sizes, and providing boundary and initial conditions to an inner nested grid. There are often four or more nests, although there is seldom feedback to the larger grid.

Because the EPA air quality permitting rules require 5 years of hourly averaged model runs, it is currently impractical to run a model like CMAQ (with plume-in-grid module) for each industrial stack. Therefore, the enhanced Gaussian model AERMOD is used for the permitting applications.

e. Model evaluation

It is essential that an applied air pollution T&D model demonstrate reasonable agreement with available field and laboratory observations. Because many parameterizations in the models already use field observations (e.g., the Pasquill–Gifford–Turner sigma curves; [Pasquill 1961](#); [Gifford 1961](#); [Turner 1967](#)), it is often difficult to find new independent field data to evaluate the models. In the case of linked model systems (e.g., emissions, NWP, regional air pollution), the components should be separately evaluated, since compensating errors could occur.

Because of random turbulence (natural variability) in the atmosphere, it is not possible for any model to be “perfect.” [Seaman \(2000\)](#) discussed the accuracy of NWP models used for providing inputs to regional air quality models. Inputs of most interest are boundary layer variables such as wind speed and direction, mixing depth, and inversion strength. As [Seaman \(2000\)](#) mentions, and several other more recent studies have shown, the best NWP models have about a 1 ms^{-1} root-mean-square error for the boundary layer near-surface wind speed. Mixing depth may be well known for high pressure areas with strong capping inversions but may be indeterminate when there is a deep layer with no obvious separations between vertical layers.

The maximum relative variability in observed and predicted air pollution concentrations across a geographic domain or over a certain time period depends on the “background,” which can be composed of both biogenic and anthropogenic pollutants. The background can be the result of transport from distant source areas, and can vary from day to day. Thus, for pollutants such as particulate matter and ozone, the observed concentration can include a significant fraction of so-called background, and consequently, the observed concentrations may vary only over one or two orders of magnitude. Contrast this with the percentage variability in a field experiment involving tracer gases such as SF_6 or perfluorocarbons, where the background is usually insignificant. There the observed concentrations can vary over many orders of magnitude. The most widely used rule of thumb on air quality model performance is [Pasquill’s \(1974\)](#) conclusion that T&D model accuracy, for observations and predictions paired in time and space, is “within a factor of two.” Accuracy improves as averaging time increases, for relaxation of the pairing

constraints (e.g., by comparing maximum concentrations observed or predicted anywhere on an arc) and for integrated outputs such as line averages.

Field experiments used for operational air pollution model evaluation have been archived in several studies. For example, the Modelers' Data Archive has been set up by S. Hanna and his collaborator J. Chang and consists of several stack plume and surface point source studies employing both pollutants and tracers, mesoscale tracer studies, regional tracer studies, and specialized studies such as within urban areas and for dense gas releases (Chang and Hanna 2004; Hanna and Chang 2012). Many of these datasets are also on the Model Validation Kit Internet site of the European Union project titled "Harmonization of Air Quality Models Used for Regulatory Purposes" (<http://www.harmo.org/kit.php>). Perhaps the most widely used of these tracer studies are at the opposite ends of the distance spectrum—at short distances, the Prairie Grass dataset (see Barad 1958a,b), and at long distances the European Tracer Experiment (ETEX) dataset (see Nodop et al. 1998). The EPA archives a subset of 17 field experiments that emphasize point sources and observations in the near-field to evaluate AERMOD (see Perry et al. 2005).

Specialty field experiments have been carried out on many topics; for example, continuous point sources in complex terrain, various types of sources in urban areas, and releases of toxic chemicals that exhibit dense gas behavior. The EPA carried out a multiyear program on Complex Terrain Model Development (CTDM; Strimaitis et al. 1987), which involved both field and wind-tunnel experiments and model development. The results of these efforts became the basis for the many operational-model (e.g., AERMOD) algorithms for accounting for plume transport and dispersion around various shapes of hills. A series of urban field studies in which the air pollution source was at street level in city centers took place in the 2000s (see Allwine et al. 2002, 2004; Allwine and Flaherty 2007). These led to improved urban T&D algorithms within models such as SCIPUFF, ADMS, and QUIC. Hanna and Chang (2012) used several of the urban field studies in their development of urban T&D model acceptance criteria. T&D of dense gases have been the subject of many field experiments and model evaluation development and evaluation exercises over the past 30–40 years (since the 1984 methylisocyanate chemical accident in Bhopal, India, in which thousands of persons were casualties). An example of a collaborative field study between industry and government agencies is the Kit Fox CO₂ field experiment at the Nevada Test Site, where the results were used to improve and evaluate the "HGSYSTEM" T&D model (see Hanna and Chang 2001).

For operational regional air quality evaluations, for which there are extensive emissions over a broad region and all models are Eulerian grid models, the international Air Quality Model Evaluation International Initiative (AQMEII; see Rao et al. 2011) has emphasized verification of processes (e.g., chemical mechanisms and physical phenomena) and de-emphasized the statistical performance measures that are commonly used for small-scale and/or point sources. Appel et al. (2017) provide results of evaluations of CMAQ. One issue at regional scales is that the model predictions are for grid cells but the observations are at fixed sampling points. The evaluations leverage detailed data from multiweek regional field experiment programs involving aircraft, remote sounders, and fixed samplers.

f. A look to the future

Many air pollution model evaluation concerns are shifting to better defining endpoints (specific outputs to be evaluated) and including health and environmental endpoints (e.g., numbers of excess cancers in the state population over a year, or fraction of trees killed by anthropogenic chemicals during a railcar accident). There is an attempt to better match T&D field experiments to the needs of decision-makers. In addition, there is a hope that we can better communicate uncertainties and probabilities to the decision-makers. For example, although the T&D model and the health and exposure model may predict 58 excess cancers due to emissions of a certain chemical in Massachusetts over the year 2018, the 95% confidence range may be from 20 to 200.

5. Applications in surface transportation

a. Introduction to surface transportation meteorology

As the human population grows, there is an increasing need and desire to move from place to place. Thus, the number of vehicles on the road has increased, leading to congestion and increasing challenges to safety, especially related to adverse weather conditions. This section describes the issues associated with surface transportation and how meteorology helps to address them. Surface transportation weather is concerned with the impacts of weather upon surface transportation and utilization of weather information to mitigate negative surface transportation impacts.

Surface transportation includes many modes, which can be categorized according to the medium upon which the transportation is conducted. The four predominant media are road, rail, water, and footway/pathway. One could also include trail for pursuits such as

TABLE 23-2. Surface transportation media and modes.

Medium	Mode
Road	Truck
	Bus
	Automobile
	Motorcycle
	Bicycle
Rail	Animal (e.g., horse-drawn cart)
	Train
	Light rail
Water	Ship
	Boat (commercial)
	Boat (recreational)
Footway/pathway	Pedestrian
Trail	ATV
	Snowmobile
	Biking
	Skiing

all-terrain-vehicle (ATV)-based recreation, snowmobiling, and horseback riding. For the purposes of this monograph, the primary focus is roadway-based modes, with consideration given to rail-based transportation. A nonexhaustive list of surface transportation media and corresponding transportation modes is provided in [Table 23-2](#).

b. Weather impacts on surface transportation

1) IMPACTS ON SAFETY

The U.S. Department of Transportation (DOT) Federal Highway Administration Road Weather Management Program ([USDOT FHWA Road Weather Management Program 2017a](#)) provides results from an analysis performed by Booz Allen Hamilton that used 2005–14 National Highway Traffic Safety Administration vehicle crash data. This analysis includes statistics for weather-related crashes, which are defined as crashes that occur in the presence of adverse weather and/or slick pavement conditions. [Table 23-3](#) summarizes these results. As is apparent in this table, weather-related crashes account for 22% of all crashes ($1\,258\,978\text{ yr}^{-1}$), 19% of all crash injuries ($445\,303\text{ yr}^{-1}$), and 16% of all crash fatalities (5897 yr^{-1}). The order of impact for road weather conditions is wet pavement, rain, snow/sleet, icy pavement, snow/slushy pavement, and fog. As indicated by the [Office of the Federal Coordinator for Meteorological Services and Supporting Research \(2002\)](#), this corresponds to ~\$42 billion in economic costs each year.

[Rossetti \(2007\)](#) analyzed 1995–2005 Federal Railroad Administration Railroad Accident and Incident

TABLE 23-3. Annual-average crash, injury, and fatality statistics associated with weather-related crashes that occurred from 2005 to 2014. The “weather related” percentages (last row) are not normalized by total number of weather-related outcomes. The “No.” and “10-yr percentage of all weather-related outcomes” columns are not normalized and have overlap between conditions (e.g., wet pavement and rain) that result in the total numbers in the last row not corresponding to a summation of the numbers associated with the individual conditions and the percentages adding up to >100%. The “10-yr percentage of all outcomes” column (except for the last row) is normalized by total number of weather-related crashes such that those percentages sum to 100%. This table is adapted from [USDOT FHWA Road Weather Management Program \(2017a\)](#).

Road weather conditions	Outcome	No.	10-yr percentage of all outcomes	10-yr percentage of all weather-related outcomes
Wet pavement	Crashes	907 831	16%	73%
	Injuries	352 221	15%	80%
	Fatalities	4488	13%	77%
Rain	Crashes	573 784	10%	46%
	Injuries	228 196	10%	52%
	Fatalities	2732	8%	47%
Snow/sleet	Crashes	210 341	4%	17%
	Injuries	55 942	3%	13%
	Fatalities	739	2%	13%
Icy pavement	Crashes	151 944	3%	13%
	Injuries	38 770	2%	9%
	Fatalities	559	2%	10%
Snow/slushy pavement	Crashes	174 446	4%	14%
	Injuries	41 597	2%	10%
	Fatalities	538	2%	10%
Fog	Crashes	28 533	1%	3%
	Injuries	10 448	1%	3%
	Fatalities	495	2%	9%
Weather-related	Crashes	1 258 978	22%	
	Injuries	445 303	19%	
	Fatalities	5897	16%	

TABLE 23-4. Reduction of freeway speeds and capacities as a result of precipitation. Precipitation rates for snow are liquid-equivalent rates. Capacity is the maximum number of vehicles that can pass a point during a specified time period. This table is adapted from [Federal Highway Administration \(2006\)](#).

Weather condition	Free-flow speed (%)	Speed at capacity (%)	Capacity (%)
Light rain ($<0.01 \text{ cm h}^{-1}$)	2–3.6	8–10	10–11
Rain ($\sim 1.6 \text{ cm h}^{-1}$)	6–9	8–14	10–11
Light snow ($<0.01 \text{ cm h}^{-1}$)	5–16	5–16	12–20
Snow ($\sim 0.3 \text{ cm h}^{-1}$)	5–19	5–19	

Reporting System (RAIRS) data to determine weather impacts on railroad accidents and incidents. Over the 11-yr period, weather contributed to 861 accidents and incidents that involved 10 fatalities, 1242 injuries, and \$182,849,035 in damages (in 2007 dollars). Weather phenomena having the greatest impact, in order according to number of accidents and incidents (in parentheses), are temperature extremes (225), liquid precipitation (current and antecedent; 199), wind (180), frozen precipitation (current and antecedent; 160), slides (snow, mud, or rock; 43), fog (22), frozen load (load imbalances owing to freezing in cold weather conditions; 10), and lightning (4). Thus, it is apparent that weather impacts on rail, although much less than those on roads, are still considerable.

For water, the U.S. Coast Guard compiles reports for recreational boating. In 2016, 214 accidents, 41 fatalities, and 103 injuries were attributable to weather ([U.S. Coast Guard 2017](#)). Statistics for commercial operations are more difficult to aggregate. However, for commercial fishing, [Centers for Disease Control and Prevention \(2010\)](#) indicates that severe weather conditions contributed to ~ 90 fatal vessel disasters (61% of 148 total vessel disasters) from 2000 to 2009, which, with linear scaling, corresponds to ~ 159 fatalities (61% of 261 fatalities associated with 148 vessel disasters). Thus, for commercial fishing weather contributes to ~ 1 vessel disaster and ~ 16 fatalities each year. Statistics for other commercial interests are harder to aggregate, but individual reports of ship/boat losses, damage, and related fatalities associated with weather events are readily identified (e.g., [McCall 2017](#)).

Weather impacts on footway/pathway and trail-based surface transportation have received much less attention than for other modes of surface transportation. This is starting to change, however, as studies such as that conducted by [Gevitz et al. \(2017\)](#) highlight the significant number of injuries (estimated to be 56%–74% of winter-storm related injuries), economic impacts, and increased burden on hospital emergency department resources resulting from slippery sidewalks and walkways. Despite this, understanding and mitigation of such impacts is still limited and, thus, transportation modes

involving footway/pathway and trail will receive little attention henceforth.

2) IMPACTS ON MOBILITY/EFFICIENCY

[Federal Highway Administration \(2006\)](#) provides typical results for weather impacts on freeway mobility/efficiency. [Table 23-4](#) indicates that nonextreme precipitation can have significant effects on freeway speeds and capacities. Complete closure of road systems, causing zero mobility, can result from heavy precipitation that damages roadways and heavy snow and/or blowing snow that deteriorate safety to the point that road closures are enacted. Such closures can even occur with excessive ice build-up on the road, which occurred on a stretch of I-78 in Pennsylvania and snarled traffic for hours ([Hall 2019](#)).

For rail, [Hay \(1957\)](#) documents the magnitude of weather delays for operations for different carriers. At that time and for the Milwaukee Road main line for the months of January and March 1952, weather delays in given months ranged from 12.6% to 30.6% of all delays. In addition, for that line 15 transports were cancelled in January 1952 and 17 were cancelled in March 1952. While railroad operations have evolved significantly since the 1950s, [Rossetti \(2007\)](#) indicates that currently weather impacts on railroads result in rerouting, slowing, delaying, and stopping departures. [Changnon \(2006\)](#) provides some economic impacts associated with significant events. In 2005 dollars, the record 1993 flood across the central United States resulted in \$480 million in impact to railroad companies. This cost is not all associated with diminished mobility, as it includes facility costs, damages, and revenue losses.

Data for impacts on maritime ship transport are more difficult to obtain. [Henningsen \(2000\)](#) estimates that effective weather routing could reduce fuel consumption by 2%–4%. While this is not a direct estimate of weather impacts on shipping mobility, it does indicate that utilization of weather information can have a measureable and beneficial impact on shipping.

3) IMPACTS ON PRODUCTIVITY

Productivity is a means for summarizing all weather impacts. While the focus here is negative impact, note

TABLE 23-6. Weather phenomena and corresponding rail impacts. This table is adapted from [Changnon \(2006\)](#), with input from [Rossetti \(2007\)](#).

Weather phenomena	Railway impact	Operational impact
Precipitation (rain, freezing rain, sleet, hail, snow)	Reduced visibility Reduced rail friction Precipitation accumulation	Communication disruption Slowed trains Halted trains (blocked rail lines) Accidents (derailment, collision, etc.) Halted trains (washout and blockage)
Flooding	Roadbed washout Landslides	
Frost	Reduced rail friction Track heaving	Slowed trains Halted trains Accidents
Fog	Reduced visibility	Slowed trains Accidents
Wind	Reduced visibility Reduced stability (crosswinds) Railway blockage (downed trees, etc.)	Communication disruption Slowed trains Halted trains (blocked rail lines) Accidents
Extreme temperatures	Thermal expansion/contraction (sun kinks; brittle track—separated and broken rail; warp and misalignment) Load imbalances	Equipment failures Accidents (derailments)
Lightning	Damage to trains and supporting infrastructure	Damage Accidents

to be a surface transportation application, surface transportation weather is commonly regarded to involve utilization of specialized equipment, observations, and forecasts to enable surface transportation. This is generally accomplished in three ways: communication systems, enhanced maintenance of the transportation medium, and enhanced monitoring.

1) COMMUNICATION SYSTEMS

The communications step is one component of an intelligent transportation system (ITS), which is defined by [Chowdhury and Sadek \(2003\)](#) to be “a variety of tools, such as traffic engineering concepts, software, hardware, and communications technologies, that can be applied in an integrated fashion to the transportation system to improve its efficiency and safety.” As such, communication systems, enhanced maintenance, and enhanced monitoring are all components of ITSs.

For road, weather information is communicated by several means that are directed at surface transportation users. One is traffic advisory/dynamic message signs, such as the one shown in [Fig. 23-11](#). Another means for delivering weather information to travelers is via cellular telephone. Currently, 511 is one means by which information is provided to the traveler ([USDOT FHWA Road Weather Management Program 2017b](#)). As of 2016, 511 was deployed across 35 states, was partially deployed across 3 states, and was being explored in 11 states as part of the 511 Planning Assistance Program. The 511 number was designated on 21 July 2000 by the

Federal Communications Commission, with its deployment significantly enabled by the 511 Deployment Coalition ([USDOT FHWA Road Weather Management Program 2017b](#)).¹ A major foundational step in developing this capability was the Advanced Transportation Weather Information System, which utilized the #SAFE (#7233) number for dissemination of road weather information ([Owens 2000](#)).

Internet-based delivery of road weather information to travelers has become common. Such information is often provided to travelers using statewide road condition websites. [Figure 23-12](#) provides an example of such a site. Such information can be delivered through any connected client, including computers, kiosks, smart telephones (including use of “apps”), and connected vehicles ([Hill 2013](#)).

For rail and water, information enabling these modes of transportation is communicated via Internet-based delivery (e.g., [Sznajder and Block 2003](#)). Information for boaters is also commonly delivered via traditional means (e.g., radio, including NOAA weather radio).

¹The 511 Deployment Coalition was established in 2001 by several organizations, including the American Association of State Highway and Transportation Officials (AASHTO), the American Public Transportation Association (APTA), the Intelligent Transportation Society of America (ITS America), and the U.S. Department of Transportation ([USDOT FHWA Road Weather Management Program 2017b](#); [Khattak et al. 2008](#)).

TABLE 23-7. Weather phenomena and corresponding water impacts.

Weather phenomena	Boat/shipping impact	Operational impact
Precipitation (rain, freezing rain, sleet, hail, or snow)	Reduced visibility	Increased journey time
	Reduced deck friction	Accidents (boat/ship damage, boat/ship loss, fatalities, and injuries)
Frost	Reduced deck friction	Accidents
Fog	Reduced visibility	Increased journey time
		Accidents
Wind	Reduced visibility	Increased journey time
	Agitated water surface	Decreased fuel efficiency
	Reduced stability	Loss of cargo
		Accidents
Extreme temperatures	Reduced water levels	Reduced cargo capacity
	Shipping-route freeze-up	Halted shipments
	Reduced deck friction (ice accumulation)	Increased journey time (reduce ice accumulation)
	Reduced stability (ice accumulation)	Crew stress
Lightning	Boat and equipment damage	Damage
		Accidents (including lightning strikes of crew)

2) ENHANCED MAINTENANCE

Enhanced maintenance can significantly enhance surface transportation safety and mobility. One of the most advanced means by which weather information has

been utilized to enhance road maintenance is through a Maintenance Decision Support System (MDSS). While numerous versions of these have been produced, versions developed via public entities are the focus here. A road weather MDSS is a tool designed to support the

FIG. 23-10. Examples of weather impacts on surface transportation: (top left) heavy snow decreasing visibility along I-29 (photograph credit: M. Askelson, taken from the Surface Transportation Weather Research Center Road Weather Field Research Facility), (top right) railroad track sun kink (<https://www.iowadot.gov/sunkink.aspx>; copyright Iowa Dept. of Transportation, used with permission), and (bottom left) heavy ice coating on the NOAA ship *Miller Freeman* [credit: NOAA Marine and Aviation Operations Pacific Marine Center (<https://flic.kr/p/8EQArU>)].

FIG. 23-11. Traffic advisory/dynamic message sign providing route weather information (from <http://www.dot.state.wy.us/news/wydots-dynamic-message-and-variable-speed-limit-signs-help-motorists-s>; credit: Wyoming Dept. of Transportation).

winter maintenance decision process by providing objective guidance regarding how to treat roadways prior to, during, and after winter weather events. Guidance is based upon weather and road condition analyses and forecasts, along with best practices for winter maintenance operations. Petty and Mahoney (2008) describe the functional prototype MDSS, which is illustrated in Fig. 23-13. Another prominent MDSS is the Pooled Fund Study (PFS) MDSS (Hart et al. 2008), which is

illustrated in Fig. 23-14. Lawrence et al. (2015) estimate that implementation of an MDSS, using New Hampshire, Minnesota, and Colorado as evaluation states, resulted in annual benefits that outweighed costs in a range from \$488,000 to \$2.68 million. Thus, the benefits of enhanced maintenance can be very significant.

As indicated earlier, decision support systems for railroads have been developed (e.g., Sznajder and Block 2003). These can be used to identify hazards and enable maintenance of railways. Decision support systems have also been explored for water (e.g., H. Lee et al. 2017), although these would not generally be directed at maintenance of the transportation medium.

3) ENHANCED MONITORING

Enhanced monitoring includes utilization of additional (beyond those deployed by NOAA, etc.) observational systems, use of advanced techniques for diagnosing relevant surface transportation weather variables, and utilization of observational data to enhance weather prediction, which then benefits surface transportation weather. A high-level summary is provided here because capture of all efforts in this area is impractical.

The most impactful additional observational system is the Environmental Surface Station (ESS), a collection of which, combined with a communication system for

FIG. 23-12. Example of an Internet-based road-weather traveler information map for the state of North Dakota (<http://www.dot.nd.gov/travel-info-v2/>; source: North Dakota Dept. of Transportation). The layout includes a road-condition-based color-coded roadway map and text boxes along the left side that provide a map legend and the ability to toggle display layers (weather radar, work zones, etc.).

FIG. 23-13. Example (from Petty and Mahoney 2008) from the district view of the functional prototype MDSS. The layout includes a roadway map with maintenance-vehicle locations and overlaid radar, roadway-centric alerts (upper-left corner), a map-customization area (middle left), a timeline of treatments (below the map), and a time/input (observations, forecast, or observations and forecast) selector (bottom).

data transfer and a central system for collecting ESS data, composes a Road Weather Information System (RWIS). An ESS is a roadway location with one or more fixed sensors measuring atmospheric, pavement, and/or water-level conditions. Currently, over 2400 ESS sites are owned by state transportation agencies (USDOT FHWA Road Weather Management Program 2017c).

Use of ESSs began in the 1970s and early 1980s when Surface Systems, Inc. (SSI), developed a monitoring system for airport runways and ramps and then transitioned that technology to the highway environment. This was followed by testing by a few state departments of transportation in the 1980s. These tests indicated that decision-makers could make their operations more efficient and effective by incorporating weather and pavement condition information. Following this, the Strategic Highway Research Program-207 (SHRP-207) effort was conducted, which further illustrated the value

of RWIS (Boselly et al. 1993; Boselly 2001). From this, modern RWIS instantiations grew. Modern ESSs include a variety of sensors for observing atmospheric, road, and water-level conditions, including “webcams” that provide transportation personnel visual context of current road weather conditions.

Railroads also utilize sensor stations to enable operations. Union Pacific, for example, maintains a network of stations along its rail corridors in the West. These are part of the MesoWest mesonet, which also feeds the Meteorological Assimilation Data Ingest System (MADIS; Rossetti 2007).

A transformative monitoring capability that is currently being developed is provided through connected vehicles. With this, numerous surface transportation variables can be obtained by deploying on a variety of vehicle types. One type of vehicle onto which sensors have been deployed is maintenance trucks. This

FIG. 23-14. Example web-interface PFS MDSS image. The layout includes a roadway map that shows roadway condition (dry, slushy, etc.), maintenance-vehicle location and condition (stopped, reporting, etc.), radar (middle), a customization menu (left), a time slider (lower-left corner), alerts and maintenance recommendations (right), and current weather and additional menu options (lower right) (this image is provided through the courtesy of B. Hershey).

approach is being developed through the Concept Highway Maintenance Vehicle research project ([Center for Transportation Research and Education 2007](#)), in which both road state (e.g., pavement freeze point and friction) and weather conditions are observed ([Andrle et al. 2002](#)).

Connected vehicles also enable utilization of sensors that are already present on vehicles (e.g., temperature and pressure) and of vehicle state (windshield wiper state, vehicle stability control status, antilock braking system status, etc.; e.g., [Stern et al. 2007](#); [Drobot et al. 2010a,b](#); [Mahoney et al. 2010](#); [Mahoney and O'Sullivan 2013](#)). The concept leverages the vast amount of data available from vehicles to improve understanding of the road weather environment, which can result in providing more accurate information to travelers and better maintenance. [Figure 23-15](#) provides a schematic for how such data could be used to alert motorists. As with any technological advancement, barriers to adoption are present. These include technological barriers (communications infrastructure and standards; data management; sensor bias, maintenance, and quality control; atmospheric state estimation from vehicle state; etc.), fiscal barriers (cost of sensors, supporting equipment, business case for automotive companies, etc.), and institutional barriers (privacy, cybersecurity, etc.). However, connected vehicles have the potential to be

transformative by significantly enhancing traveler safety and improving weather analysis and prediction through providing surface data in both traditionally well-sampled (urban) and poorly sampled (rural) areas.

The Clarus initiative, a joint effort of the U.S. DOT ITS Joint Program Office and the FHWA Road Weather Management Program, was a major advancement for road weather. It was established to provide an integrated surface transportation weather observation data management system that enabled DOTs to take full advantage of their RWIS. Clarus had three phases: development of concepts of operation for use of ESS data, connection enablement, and implementation and evaluation of concepts of operation ([USDOT FHWA Road Weather Management Program 2017d](#)). Reports for the evaluation of concepts of operation and development of quality checking algorithms are provided by [Haas and Bedsole \(2011\)](#) and [Limber et al. \(2010\)](#), respectively. Clarus advanced the use of RWIS data in weather analysis and forecasting (e.g., the Local Analysis and Prediction System and the WRF Model), transformed RWIS data collection and quality checking procedures (Clarus data are being transitioned into MADIS), and provided a possible framework for utilization of connected-vehicle data.

Techniques for diagnosing relevant surface transportation variables have been pursued by numerous investigators. These include efforts to enhance utilization of

FIG. 23-15. Schematic (from Hill 2013) of how connected-vehicle data could be utilized to provide motorist advisories and warnings. VDT denotes vehicle data translator.

load restrictions (e.g., Tighe et al. 2007; Hart et al. 2012), to estimate blowing snow (e.g., Osborne 2006), to estimate precipitation occurrence and accumulation along roadways (e.g., Askelson et al. 2013), to estimate freezing drizzle (Osborne 2012), to forecast frost occurrence on bridges (Takle and Greenfield 2005), and other efforts to enable surface transportation (an exhaustive list is beyond the scope of this examination). Government, industry, and academia have worked together to advance surface transportation safety and efficiency.

e. Brief history

Table 23-8 provides a timeline of events for road weather, delineating the associated concerted effort and significant number of relevant milestones. While this timeline undoubtedly leaves out milestones that some view as important, it attempts to capture major steps associated with road weather.

f. A look to the future

Current developments provide guidance regarding relatively near-term (5–25 years) trends. The rapid advancement of technology—principally in the areas of computing, communications, and automation—is setting the stage for realization of transportation systems that benefit from both increased safety and mobility.

Connected surface transportation participants (vehicles, pedestrians, bicyclists, etc.), when paired with software and communications systems, can receive warnings regarding surface transportation weather hazards and impacts (e.g., traffic delays and accidents). Such information can be used to alter traveler behavior, such as slowing traffic owing to the presence of the hazard, re-routing, etc. It can also be used to avoid accidents by tracking travelers' routes and identifying potential conflicts (e.g., ITS International 2017).

Of great interest is how automation will further enhance safety. With connected vehicles, for example, automated systems could be used to mitigate a crash (automatically apply brakes) if the driver is not responding appropriately. This, of course, raises the challenging question of when should automation take over versus when should systems be used to simply alert travelers to issues. Moreover, privacy is an important consideration in this context. Who owns the data? Can a driver opt out or, at the very least, request that they be anonymous? Mitigating weather impacts on surface transportation using emerging technologies will require solving both technical and policy challenges.

The overall transportation system is evolving. Companies are exploring the utilization of hybrid transportation (e.g., flying cars). Unmanned aircraft will be operated over surface transportation systems, thus

TABLE 23-8. A timeline of major road weather events.

Milestone	Date(s)	Notes
SSI monitoring system	Late 1970s–early 1980s	Developed for airport runways and ramps and tested in highway environment
State DOTs testing pavement sensors; Parallel efforts in Europe (COST: Cooperation in Science and Technology)	Mid-1980s	
Strategic Highway Research Program (SHRP)	1987	Five-year program for improving safety, performance, and durability of U.S. highways
SHRP-207 and SHRP-208	Late 1980s–early 1990s	SHRP-207: RWIS for maintenance SHRP-208: Proactive use of chemicals
AASHTO Snow and Ice Pooled Fund Cooperative Program (SICOP)	1993	Mission to experiment with snow and ice technology and systems (https://sicop.transportation.org/)
Aurora Program	1996	International partnership of public road agencies working together to perform joint road weather research (http://www.aurora-program.org/)
Road Weather Management Program	1999	Seeks to better understand safety and mobility impacts of weather on roadways and promote strategies and tools to mitigate those impacts (https://ops.fhwa.dot.gov/weather/index.asp)
Weather information for surface transportation (WIST)	1998	Report published in 2002
Functional prototype MDSS	1999	Open source; development ended ~2014
511 number commissioned	2000	
511 deployment coalition	2001	
		Help state and city planners develop, launch, publicize, maintain, evaluate, and improve their 511 systems (http://deploy511.org/)
Pooled-fund study MDSS	2002	Ended 2017
Vehicle Infrastructure Integration (VII) Program	2003	http://www.vehicle-infrastructure.org/index.htm
Surface Transportation Weather Research Center (University of North Dakota Regional Weather Information Center)	2004	http://www.rwic.und.edu/
Clarus	2004	https://www.its.dot.gov/research_archives/clarus/index.htm
SAFETEA-LU (Safe, Accountable, Flexible, Efficient Transportation Equity Act: A legacy for users)	2005	Road Weather Research and Development Program established within USDOT; enabled by the AMS Policy Program Weather and Highways symposia (2003–04) and National Research Council (2004)
ESS siting guidelines	2005; 2008	Manfredi et al. (2005, 2008)
Transportation Research Board Surface Transportation Weather Committee (AH010)		http://www.trb.org/AH010/AH010.aspx
Connected-vehicle Pikalert System	2016	https://ral.ucar.edu/solutions/products/pikalert

offering additional opportunities for enhancing analyses and forecasts of weather hazards for surface transportation and mitigating impacts. Vehicle usage, as opposed to vehicle ownership, is becoming more popular with the growth of “transport as a service” (TaaS),

which could trigger significant changes in the transportation infrastructures of cities (e.g., [Lampinen 2018](#)). These changes come at a time in which increasing population and urbanization are putting significant pressure on transportation systems. Thus, technological

advancements are about to significantly enhance mitigation of weather impacts on surface transportation, with the greatest benefits likely realized where they are most desperately needed: urban areas.

6. Summary and concluding thoughts

This chapter on applications of meteorology to meet the needs of growing populations has treated four distinct but interrelated topics relevant to meeting the needs of current and future populations. The world is becoming more urbanized, and [section 2](#) discussed the many impacts of that urbanization. Careful scientific thought has identified the urban heat island effect and ways to mitigate its related consequences, including urban planning to assure sustainable designs, enhancing natural ventilation, modifying albedo, planning for land use, and more.

[Section 3](#) documented how the world's population requires energy for its technological advances, but traditional energy sources exert a pressure on the environment in terms of emissions of contaminants and heat when burning fossil fuels. The newer energy sources, however, instead use the meteorological variables as their fuel. The ongoing transformation of this energy mix relies on specialized knowledge of the atmospheric environment, and a dialog has ensued between the meteorological and energy communities to meet that need.

Meeting the energy, transportation, and industrial needs of the global population fouls the air with pollutants. The effort to control and mitigate those contaminants requires knowledge and modeling capabilities of their transport, dispersion, and deposition. [Section 4](#) described the development and current state of those models.

The human population largely relies on surface transportation to move itself and its cargo from place to place. This produces challenges for safety and efficiency due to weather phenomena. [Section 5](#) discussed the needs and fulfillment of the surface transportation sector for meteorological information. This sector increases in importance with additional urbanization and also contributes to the air pollution discussed in the prior sections. Connected vehicles provide a promise for more real-time weather information to improve safety and efficiency for surface transportation.

All of these interrelated applications demonstrate using the systems approach to identify and describe portions of the problem, formulate models that integrate multiple systems, and apply those models in sensible ways to provide information to end users to mitigate the stresses imposed on the environment. For the urbanization problem, understanding the interactions between human and environmental systems is a first step toward

mitigating environmental impacts while making the best use of natural resources. In energy applications, knowledge and modeling of the atmosphere is in the midst of enabling transformation from a fossil fuel-based energy system to one based on renewable energy. The developments in air pollution meteorology have allowed the pollution control agencies to set and monitor emissions, helping to ameliorate the problem. Advances in applications targeted at surface transportation foster safer, more robust roadway, rail, and waterway systems, ready for the autonomous vehicles of the future.

[Hooke \(2014\)](#) was right when he talked about the approaches of the meteorological community providing an example of how to solve the world's problems. Meteorologists are primed to play an important role in this conversation through using a systems approach to integrate multiple types of models and by working together with specialists in the broader network. The hope is that addressing this issue can lead to sustained development while avoiding depletion of Earth's resources or greater pollution of the environment.

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