RESEARCH & DEVELOPMENT

Improved Climatic Data for Mechanistic-Empirical Pavement Design

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16. Abstract

In an effort to improve pavement design for North Carolina roads, NCDOT has adopted the AASHTOWare Pavement ME Design software. A critical component of the software is the Enhanced Integrated Climatic Model (EICM), which accounts for environmental effects. The EICM requires hourly historical climate records for the entire expected lifespan of the road, yet NCDOT presently has access only to small 5-year samples of climatological data from select locations. These short records must be repeated to fill in data for long analysis periods. Studies have shown that repeating small samples of climatic data may adversely affect pavement performance predictions. This report describes the development of long-term, high-quality, historical climate data (HCD) files for use by the EICM at multiple locations across North Carolina. Ordinary kriging and other spatial and short-term temporal interpolation techniques address the significant gaps in data coverage present in the observational record so that the new HCD files consist of continuous hourly data that span a period of 35 years. Sensitivity tests assess the impact of the improved HCD files on pavement performance predictions and reveal statistically significant differences in concrete pavement performance measures between Pavement ME Design simulations with and without the new HCD files. The new climate data more subtly influence pavement performance predictions for flexible pavement designs. Nevertheless, the poor quality of the original climate data samples warrants a recommendation that NCDOT use the improved climate files in the development of future pavement designs to boost confidence in pavement performance predictions.

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List of Abbreviations

ABC	Aggregate base course
AC	Asphalt concrete
ASOS	Automated Surface Observing System
AWOS	Automated Weather Observing System
CLCV	Cloud cover
CoCoRaHS	Community Collaborative Rain, Hail, and Snow volunteer observer program
COOP	Cooperative Observer Program
CRCP	Continuously reinforced concrete pavement
CTABC	Cement-treated aggregate base course
DEWP	2-m dewpoint temperature
EDAS	Eta Data Assimilation System
EICM	Enhanced Integrated Climatic Model
EOF	Empirical orthogonal function
FDA	Full depth asphalt
GHCN-Daily	Global Historical Climatology Network-Daily
HCD	Historical climate data
HRLDAS	High-resolution land data assimilation system
IRI	International Roughness Index
ISD	Integrated Surface Data
JPCP	Jointed plain concrete pavement
LST	Local standard time
MAE	Mean absolute error

MEPDG	Mechanistic-Empirical Pavement Design Guide
METAR	Aviation routine weather report
NARR	North American Regional Reanalysis
NC	North Carolina
NCAR	NOAA/National Center for Atmospheric Research
NCDC	NOAA/National Climatic Data Center (now NCEI)
NCDOT	North Carolina Department of Transportation
NCEI	NOAA/National Centers for Environmental Information (formerly NCDC)
NCEP	NOAA/National Centers for Environmental Prediction
NCHRP	National Cooperative Highway Research Program
NIMA	National Imagery and Mapping Agency
NOAA	National Oceanic and Atmospheric Administration
NWS	NOAA/National Weather Service
PCC	Portland Cement Concrete
POR	Period of record
PREC	Precipitation
PSUN	Percentage of possible sunshine
RELH	Relative humidity
TAIR	2-m air temperature
USAF	United States Air Force
USCRN	United States Climate Reference Network
UTC	Coordinated Universal Time
WBAN	Weather Bureau Army Navy
WGS 84	World Geodetic System 1984
WMO	World Meteorological Organization
WSPD	10-m wind speed

ABSTRACT

In an effort to improve pavement design for North Carolina roads, NCDOT has adopted the AASHTOWare Pavement ME Design software. A critical component of the software is the Enhanced Integrated Climatic Model (EICM), which accounts for environmental effects. The EICM requires hourly historical climate records for the entire expected lifespan of the road, yet NCDOT presently has access only to small 5-year samples of climatological data from select locations. These short records must be repeated to fill in data for long analysis periods. Studies have shown that repeating small samples of climatic data may adversely affect pavement performance predictions. This report describes the development of long-term, high-quality, historical climate data (HCD) files for use by the EICM at multiple locations across North Carolina. Ordinary kriging and other spatial and short-term temporal interpolation techniques address the significant gaps in data coverage present in the observational record so that the new HCD files consist of continuous hourly data that span a period of 35 years. Sensitivity tests assess the impact of the improved HCD files on pavement performance predictions and reveal statistically significant differences in concrete pavement performance measures between Pavement ME Design simulations with and without the new HCD files. The new climate data more subtly influence pavement performance predictions for flexible pavement designs. Nevertheless, the poor quality of the original climate data samples warrants a recommendation that NCDOT use the improved climate files in the development of future pavement designs to boost confidence in pavement performance predictions.

1. Introduction

In an effort to improve pavement design for North Carolina roads, NCDOT has adopted the AASHTOWare Pavement ME Design software (also known as DARWin-ME), which incorporates the guidelines set forth in the NCHRP (2004) Mechanistic-Empirical Pavement Design Guide (MEPDG). Kim and Muthadi (2007) describe the implementation of the MEPDG in North Carolina. The software predicts stresses for both flexible and rigid pavements over the expected lifespan of the roadway by accounting for design properties, traffic volume and volume growth rates, expected vehicle distributions, and environmental influences. The MEPDG software accounts for environmental effects through the incorporation of the Enhanced Integrated Climatic Model (EICM), a one-dimensional coupled heat and moisture flux parameterization that simulates temperature and moisture gradients within the pavement structure and returns this information to the materials characterization, structural response, and performance prediction modules of the MEPDG software (Larson and Dempsey 1997; NCHRP 2004; Zapata and Houston 2008).

To predict temperature and moisture profiles for all depths, the EICM requires hourly data derived from historical observations in order to characterize the environmental conditions appropriately. Required variables include air temperature, precipitation accumulation, wind speed, percentage of possible sunshine, and relative humidity observations throughout the expected lifetime of the pavement. Additional data required by the model include latitude, longitude, elevation, and seasonal groundwater table depths (for use as a lower boundary condition) for each station. NCHRP (2004) and Johanneck et al. (2010) detail the use of each of these variables within the components of the EICM.

The EICM input variables vary in their degree of importance to the model. Air temperature is the most important element because it directly influences the temperature of the pavement through the surface energy balance. The air temperature also determines frozen and thawing periods and the number of freeze-thaw cycles (NCHRP 2004). Additionally, the percentage of sunshine is critically important because it impacts the thermal gradients generated within the pavement through calculations of the surface energy balance at all times throughout a calendar day. The percentage of sunshine is defined by the model developers as the inverse of cloudiness, where 100% corresponds with clear skies and 0% corresponds with overcast sky conditions. Together, the air temperature and the percentage of sunshine are the two most important input parameters. Wind speed is less influential, but this parameter impacts the convective heating or cooling at the surface of the pavement. The model uses precipitation both on a monthly basis and in the calculation of the number of wet days. Therefore, daily precipitation totals supply sufficient information to the model. The model uses mean monthly relative humidity to estimate moisture warping of PCC slabs and to model moisture gradients through JPCP and CRCP slabs. However, hourly relative humidities impact drying shrinkage of JPCP and CRCP slabs and influence crack spacing (NCHRP 2004). Lastly, groundwater table depth plays a significant role in the moisture content of the pavement and foundation materials. Kim and Muthadi (2007) report that while groundwater table depths do not influence rigid pavement distresses, these values significantly impact flexible pavement distresses. The EICM will accept either seasonal average groundwater table depths or an annual average depth (NCHRP 2004).

The construction of high-quality, long-term hourly climate records remains challenging. The required climate data files provided for use with the MEPDG software therefore generally represent only small samples of climatological data from select locations, though the period of record for each station varies considerably. Among the historical climate data (HCD) files provided for use with the MEPDG software, the shortest continuous period of record (POR) among the available climate data locations is 1 year and 8 months at Gillam, Manitoba, Canada (station 15903), while the longest POR is an impressive 55 years and 10 months at Pueblo, Colorado (station 93058). The median POR among all 1083 locations is only 9 years and 2 months. In North Carolina, the shortest POR is 5 years and 5 months and the longest is 9 years and 8 months, with a median POR among all 20 available stations of 7 years and 8 months. If the expected design life of the pavement exceeds the length of the climate record, the MEPDG software repeats these short records back-to-back to fill in data for long periods of pavement design prediction (Johanneck et al. 2010). This approach either misses or oversamples extreme events with long return periods and fails to capture an accurate representation of the interannual variability present in realistic climatic conditions at one location over several decades. Such short sample periods, for example, may miss a year where drought conditions prevail or a year with prolific rainfall or unusually warm or cold seasons that are well within the normal range of variability. Alternatively, the repetition of extreme events within a small sample period will undermine the representativeness of the resulting meteorological time series.

A discussion of climate normals—averaging periods widely used to characterize the most likely conditions experienced at a given location—may help to put these short records in context. Climatologists traditionally calculate normals over a 30-year period (e.g., Arguez et al. 2012), but this recommendation derives from the fact that 30 years corresponds with the length of records available at a large number of stations when climatologists first devised the concept of climate normals in the early twentieth century (WMO 2007, 2011). Nevertheless, this remains widely accepted as a suitable averaging period (WMO 2007). When intended for use as a predictor for future weather, studies have shown that a shorter period of 10–15 years is a suitable analysis period for assessing the likely long-term extremes in temperature. However, a short record of even this length could provide unrepresentative results within individual months (WMO 2007). Additionally, the WMO (2007) recommends a minimum of 30 years of data to determine the statistical distribution of precipitation at a given location. Though the WMO (2007) recommendations derive from daily data, capturing representative extremes from hourly data would naturally require a similar POR. Repeated short historical data records within the MEPDG software, therefore, will likely fail to capture representative climate conditions at a given location. Notably, hourly climate normals derived from 30-year averages do exist for six stations in North Carolina (Applequist et al. 2012) and the temptation may exist to substitute hourly normals within gaps in the observational record. While useful for characterizing the most likely diurnal cycle at a given location, these hourly normals by their nature do not include extremes. The hourly climate data files ingested by the EICM must include observed extreme values because it is these extremes that often result in pavement failure.

Studies have shown that missing or incomplete climatic data can cause unreliable MEPDG predictions (e.g, Johanneck et al. 2010; Heitzman et al. 2011). Heitzman et al. (2011) studied the sensitivity of the climate input files in the MEPDG and found that repeating limited climatic data to predict pavement stress over 20 to 40 years may result in significantly higher predicted pavement stress. They concluded that the effort required to produce climate input files for the EICM will produce a measurable, long-term benefit. Breakah et al. (2011) found that differences in historical data files developed from data from the Iowa Environmental Mesonet and those provided for use in the MEPDG software resulted in significant differences in pavement performance predictions, as did Saha et al. (2014), who studied the impact of variations in data quality and record length for stations in Canada. Johanneck et al. (2010) provide some evidence that suggests that problems exist with the historical data files supplied by the MEPDG and recommend rigorous quality control to correct these problems. They also suggest lengthening the POR for each station to capture interannual variability more reliably. Similarly, Johanneck and Khazanovich (2010) recommend removing incomplete and questionable data files to avoid adverse effects on pavement performance prediction.

For small periods of missing data (e.g., less than 12 hours for temperature data or perhaps a few days for cloud cover), the Pavement ME Design developers have linearly interpolated missing observations as necessary across multiple hours or days to create a complete time series in the HCD files. For example, the developers fill in short temperature gaps by interpolating between the closest daily maximum and minimum temperatures. However, this method fails to capture catastrophic cracking events such as those that would occur under stresses induced by large thermal gradients within the pavement. While this method would still capture extreme loading events such as hot spring days where the subsurface remains frozen, it would not address fast temperature changes, such as a strong cold front that drops the temperature by several tens of degrees Fahrenheit. Indeed, studies have shown that the inclusion of incomplete data may decrease the quality of pavement performance predictions (e.g., Johanneck et al. 2010). Some HCD files still contain large gaps of a month or more. The EICM can fill in data gaps or even create a virtual weather station by interpolating data from up to six nearby existing stations (Johanneck et al. 2010). This method utilizes a simple weighting algorithm that averages the influence of the nearby stations according to the inverse of the square of the distance to each station. Spatial interpolations for temperature involve an additional correction for elevation differences using the standard tropospheric lapse rate (i.e., a change of ± 6.5°C per kilometer of ascent or descent).

North Carolina is not the first state to attempt to produce long-term HCD files for use with the MEPDG software. Heitzman et al. (2011) extended the POR for HCD files in Mississippi to 40 years for locations along a dense spatial grid. They accomplished this via a natural neighbor interpolation method using available hourly and daily observations. However, the spatially-coarse nature of the hourly observations forced the authors to downscale the daily high and low temperature observations to reconstruct an hourly time series for temperature. Additionally, Heitzman et al. (2011) linearly interpolated between valid values in the temporal domain to fill in short-term gaps caused by a lack of spatiotemporal coverage across the state. The authors also accounted for future climate variations by using a regional climate model to adjust the historical data for use in future pavement performance predictions. Other states (e.g., Tennessee) are currently exploring options for extending and improving the Pavement ME Design HCD files.

Given the requirements of the EICM and the failure of short-term climate records to capture an accurate representation of the interannual variability present in realistic climatic conditions, it remains critical for NCDOT to obtain long-term, continuous, quality-controlled, hourly data for multiple locations across North Carolina. The following sections summarize the steps taken to achieve this goal to produce long-term climate input data files for the MEPDG software spanning 35 years for each location. This effort requires the development of a robust gap-filling procedure to fill in missing hourly observations, sometimes over long time periods, in order to generate high-quality, continuous historical climate records. A sensitivity analysis in section 6 assesses the impact of the improved climate data files on pavement performance predictions for several North Carolina pavement design projects.

2. Data Sources

The meteorological data used in the construction of long-term continuous hourly data files derive from the Integrated Surface Data database, North American Regional Reanalysis, and the Global Historical Climatology Network (GHCN)-Daily climate summaries. The geographical region from which these data are drawn includes all of North Carolina and parts of South Carolina, Georgia, Tennessee, and Virginia bounded by 33.0–37.5°N latitude and 67.0–85.5°W longitude. All data span the period 1 January 1979 through 31 December 2013.

2.1 Integrated Surface Data

The primary source for producing a long-term meteorological time series at any location is of course the hourly observations themselves. The Integrated Surface Data (ISD) database (digital data set DSI-3505; also called Integrated Surface Hourly) from the NOAA/National Climatic Data Center[1] (NCDC) contains hourly surface data for over 20,000 locations across the world (Del Greco et al. 2006; Smith et al. 2011). This dataset represents a merged repository of both manual and automated surface data from a multitude of original data sources, including data from the Automated Surface Observing System (ASOS), the Automated Weather Observing System (AWOS), surface synoptic observations, aviation routine weather report (METAR) observations, and various others (Smith et al. 2011). Of

[1]The National Climatic Data Center recently merged with NOAA's National Geophysical Data Center and the National Oceanographic Data Center, which includes the National Coastal Data Development Center, to become the National Centers for Environmental Information (NCEI). For the purpose of the present discussion, the name will remain the National Climatic Data Center (NCDC).

the nearly 1000 data columns in each ISD data record (most of which represent missing data), only a handful provide important information for the present work. These include observations of hourly 2-m air temperature, liquid precipitation, and 10-m wind speed that, after adjustments for units and observation times, feed directly into new HCD files. The hourly 2-m dewpoint temperature, when combined with the air temperature observations, allows computation of the relative humidity. Hourly observations of the fraction of the total celestial dome covered by clouds or other phenomena allow calculation of the percentage of sunshine for use by the EICM. Details on these calculations appear in section 3.

Traditionally, hourly observations occur 6–7 minutes before the top of the hour, particularly for automated reports, but regular observations and special reports may take place at any time, depending on the station. Since the ISD data contain original observations, it becomes necessary to standardize these observation times to a particular hour in order to compare the data both spatially and temporally in a meaningful way. Therefore, a script rounds any observation that occurs at or later than 48 minutes after the hour forward to the nearest hour and any observation that occurs at or earlier than 12 minutes after the hour backward to the nearest hour. The same script ignores any non-standard observation that occurs between 13 and 47 minutes after the hour. If multiple reports occur in the same hour for the same station (e.g., a METAR report and a synoptic report), the script always gives preference to the latest METAR report for that hour.

An observing station may have either a United States Air Force (USAF) or Weather Bureau Army Navy (WBAN) number assigned to it, or both. Unfortunately, these numbers can change over decades, causing discontinuities in the period of record for a given station and making it difficult to create a long time series based solely on the station identification number. For this reason, a script determines which USAF/WBAN combinations are assigned to the same geographic location and combines the data to create a single period of record. The script looks for shared station numbers, a shared station name and state, or similar geographic coordinates. The maximum possible cutoff distance for pairing similar

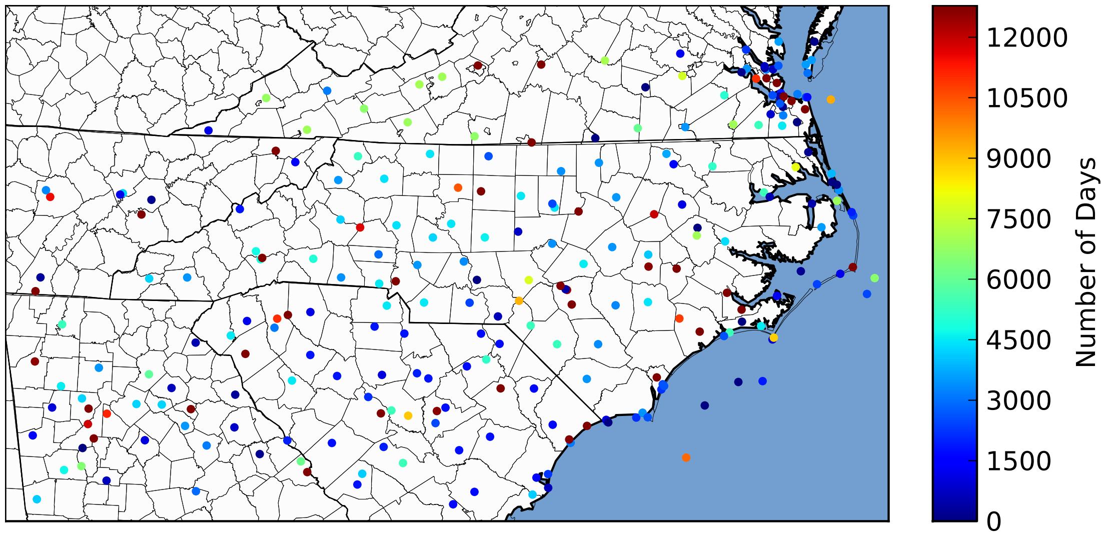

FIG. 2.1: Integrated Surface Data (ISD) database sites in North Carolina and adjacent states providing hourly historical data between 1979 and 2013. Colors indicate the number of days with at least one observation for each site during this period. Sites far from North Carolina have been removed.

sites is just over 1.43 km (±0.01 degrees latitude and/or longitude). Figure 2.1 shows the location of all 243 unique ISD stations in the study domain (107 are in North Carolina), along with a representation of the length of the period of record between 1979 and 2013 at each site.

2.1.1 Data quality

NCDC applies quality control procedures to the ISD data (Lott 2004; Smith et al. 2011). Unfortunately, problems remain in the database. The station metadata file provided with the ISD data contains some questionable locations and station elevations. For example, the list may indicate a reasonable name and state paired with geographic coordinates in a different state or two station names and geographic coordinates may match, but the station elevations differ slightly. For minor discrepancies, the best guess for the station location simply replaces the original station metadata here. For major discrepancies, the station is thrown out altogether. Additionally, data for some stations may include only sporadic observations that contradict the data from a more reliable colocated site. Again, such stations were removed from the database. In some cases, the best approach for collecting a complete set of observations at a given hour requires combining valid but irregular data from one type of observation (e.g., a synoptic report) with a partial report (e.g., a METAR report with missing data) to create a full data record.

The ISD data contain data quality flags that indicate whether or not the observation passed quality control checks or if the observation is suspect or erroneous. Despite these quality control procedures, there exist some observations that have passed NCDC's quality control, yet obviously remain incorrect. For example, there are instances where a temperature or dewpoint sensor produces wild data and then recovers after several hours; where the sensor may slowly die before NCDC's quality control algorithm flags the data as suspect, erroneous, or missing; where the value suddenly drops to zero before recovering; or where the value suddenly exceeds a state extreme for maximum or minimum temperature or precipitation. Examples include an observation of 141.8°F (61.0°C) at Boone, NC on 20 September 2009 and an observation of (coincidentally) −77.8°F (−61.0°C) at Fayetteville, NC on 6 March 2004. Overall, these issues account for a very small fraction of the tens of millions of observations analyzed here, but it would be unacceptable for these problems to filter into the final HCD files for use with the MEPDG software.

2.1.2 Initial quality assurance

To address some of these quality concerns, an initial pass through the data compares each temperature and precipitation value with the monthly extreme value obtained from all cooperative observing sites in each station's respective state. If an otherwise valid temperature observation exceeds these bounds by a very generous 18°F (10°C), a script removes it, along with all observations in the previous 12 hours and the following 48 hours. The script also removes extreme short-term spikes in the temperature and dewpoint data. More rigorous quality control procedures (see section 4) later handle additional spikes and other values that exceed the state extreme maximum or minimum temperature, but remain within the ±18°F (±10°C) threshold. Further, a script marks as missing all original temperature, dewpoint, wind speed, precipitation, and cloud cover values flagged as suspect or erroneous via NCDC quality-control algorithms.

The ISD data often contain short-term gaps that occur for a variety of reasons. A script addresses these missing data by performing a simple linear interpolation temporally between valid values across short gaps of 1–2 hours to replace up to two consecutive missing observations, akin to the procedure implemented by Heitzman et al. (2011) for filling short-term gaps in their analysis. This short-term gap-filling procedure produces entirely appropriate estimates for all variables and saves computation time compared with more complex spatial or temporal interpolation procedures. Indeed, any spatial interpolation method is unlikely to produce a more useful estimate on such a short time scale.

2.2 GHCN-Daily

Daily records of maximum and minimum temperatures across the study region serve as a check against poor-quality hourly observations or gap-filled temperature values. Total daily precipitation records also assist in the construction of hourly precipitation estimates. The Global Historical Climatology Network (GHCN)-Daily dataset (Menne et al. 2012a) provides daily observations at over 80,000 stations in 180 countries and territories. A total of 2905 unique stations in North Carolina, South Carolina, Tennessee, Georgia, and Virginia (Fig. 2.2) provide valid data during the 1979–2013 period, with ample spatial coverage across the region (many of the more than 4000 stations are colocated). Since NCDC continually updates the dataset with new data and modifications from quality assurance algorithms, various versions of the dataset may contain a differing number of stations and different values, depending on the download date from NCDC (see Menne et al. 2012b).

GHCN-Daily data sources for the study region during the period under consideration include daily summaries from the NOAA/National Weather Service (NWS) Cooperative

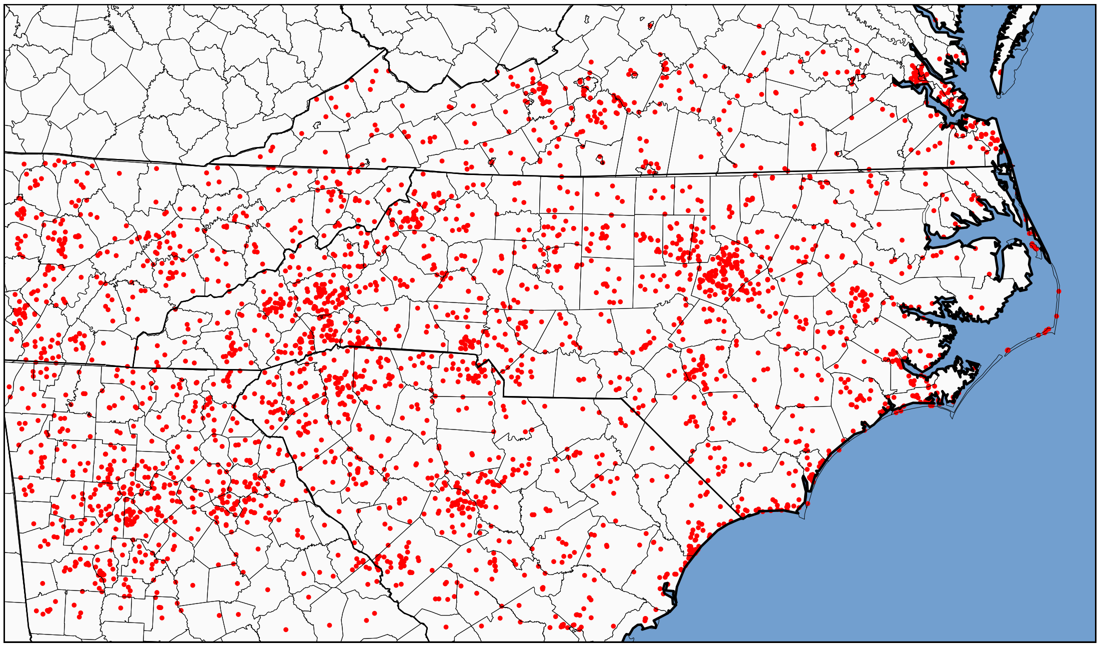

FIG. 2.2: Global Historical Climatology Network-Daily (GHCN-Daily) sites in North Carolina and adjacent states that provide daily observations of temperature and precipitation. A total of 2905 unique stations in the region shown here covering North Carolina and parts of South Carolina, Tennessee, Georgia, and Virginia provide valid data during the 1979–2013 period.

Observer Program (COOP), first-order stations, ASOS stations, surface METAR observations at major airports, the U.S. Climate Reference Network (USCRN), and the Community Collaborative Rain, Hail, and Snow (CoCoRaHS) volunteer observer program. The observation time of the GHCN-Daily temperature and precipitation measurements is an important consideration when reconstructing hourly precipitation values or for determining the maximum or minimum temperature on a given day, but observation times vary depending on the data source. A script removes some of the GHCN-Daily sites from consideration primarily because many COOP reports do not include the observation time, which varies by station. The script also assigns observation times to other stations that do not report them based on the data source. For example, most summary of the day products cover the period midnight to midnight local standard time (LST; NCDC 2005a,b), as do USCRN daily precipitation totals (NWS 2009). CoCoRaHS precipitation observations do not contain observation times, but the script assigns a time of 0700 local time since observers are encouraged to take their measurements at this time (Menne et al. 2012a). The script also adjusts observation times to account for daylight saving time when appropriate.

NCDC regularly performs automated quality assurance routines on the GHCN-Daily dataset with occasional manual evaluation of the data (Menne et al. 2012a). For the daily temperatures, however, the maximum temperature in the GHCN-Daily data is sometimes lower than the minimum temperature. While this could conceivably result from an observer who records a morning minimum temperature as having occurred on the current day and the morning maximum temperature as having occurred on the previous day, contrary to standard practice (Menne et al. 2012a), it is somewhat obvious through inspection of the data that the temperature values are reversed in the majority of the 1912 instances where this occurred in the entire study region for the whole period of record. For this reason, a script simply switches them back to more appropriate values for use in the present work. Similarly, there are instances where the maximum temperature on a given day is less than the minimum temperature on the previous day and vice versa. A final quality assurance check handles these cases (see section 4). Additionally, 2966 values exceed the observed state extremes for a given month by a small buffer of ±1.08°F (±0.60°C), though the measurements often exceed this buffer by a wide margin in a majority of these instances. In cases such as these, a script marks as missing both the maximum and minimum temperature measurement for that day.

A handful of precipitation observations in the GHCN-Daily data appear questionable as well. In some instances, the record indicates a trace of precipitation, but the actual precipitation amount is non-zero. More importantly, the data also contain suspicious short-term extreme rainfall events that exceed the state extreme daily precipitation total for a given month, yet NCDC has not flagged these as having failed their quality assurance procedures. To avoid incorporating these values into new HCD files, a script marks as missing such clearly incorrect values in the present work.

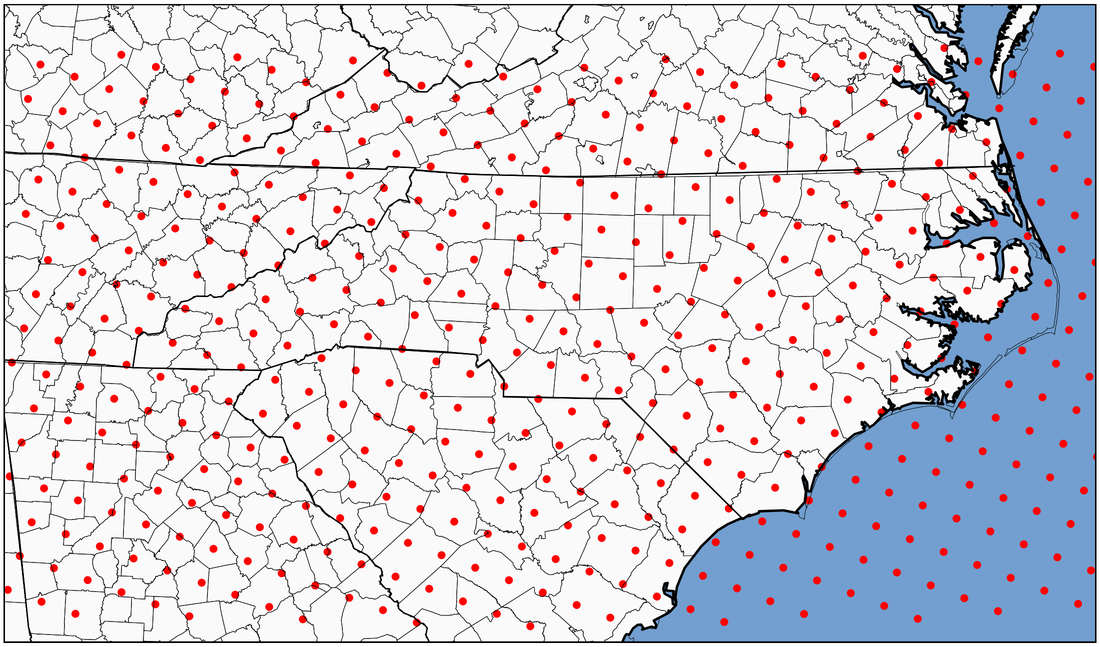

FIG. 2.3: North American Regional Reanalysis (NARR) grid points over North Carolina and adjacent states. Surface data are available continuously from 1979 through 2013 in 3-hour increments.

2.3 North American Regional Reanalysis

The National Centers for Environmental Prediction (NCEP) North American Regional Reanalysis (NARR) is a long-term, dynamically consistent, high-resolution climate dataset with 32-km spatial resolution and surface variables available every three hours since 0000 UTC 1 January 1979 (Mesinger et al. 2006). Based on a previously operational version of the NCEP Eta Model (Black 1988) used by weather forecasters across the country, the NARR provides a best guess at the four-dimensional state of the atmosphere. The NARR produces a good representation of extreme events such as floods and droughts, successfully captures broad precipitation patterns, and produces reasonable 2-m temperatures and 10-m wind vectors when compared with observations (Mesinger et al. 2006). Figure 2.3 shows the location of all NARR grid points bounded by the study domain boundaries between 33.0–37.5°N latitude and 67.0–85.5°W longitude.

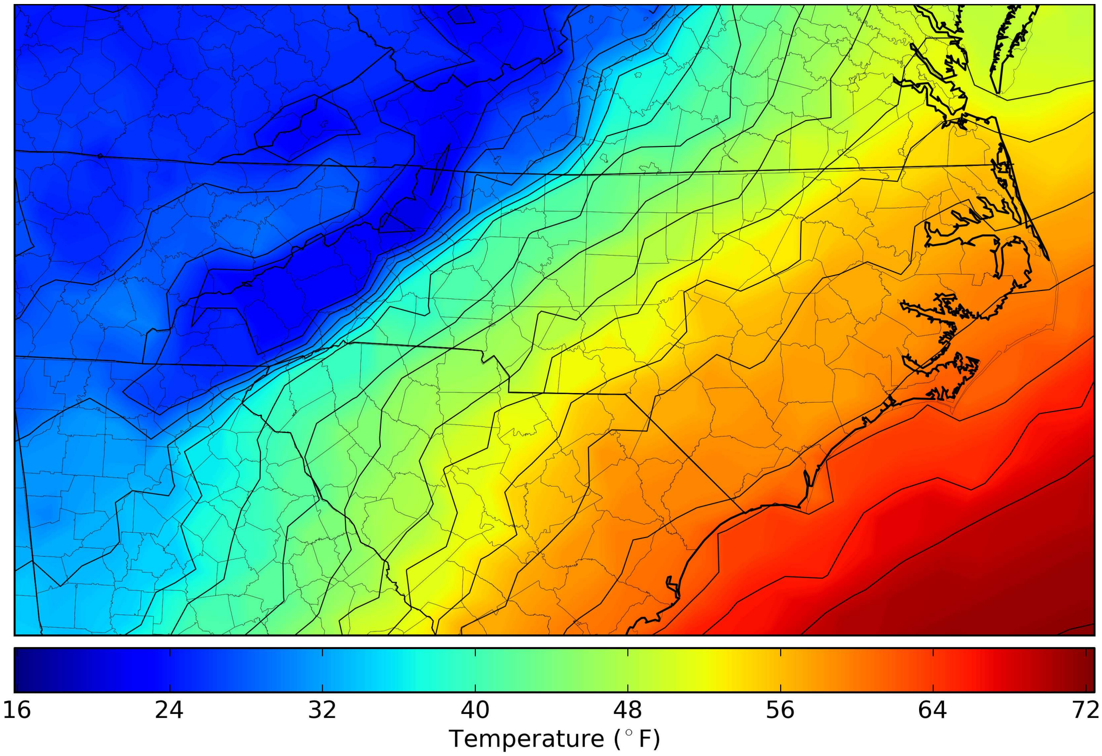

FIG. 2.4: NARR 2-m air temperature at 1500 UTC 30 January 2008 during the passage of a strong cold front. Black contours every 3°F highlight the influence of both terrain and the cold front on surface air temperatures.

The data fields extracted from the NARR output include 2-m air temperature, 2-m dew-point temperature, 3-hr accumulated liquid precipitation, total cloud cover, 10-m wind vectors, and the air temperature and geopotential height at the first hybrid model level (typically several tens of meters above the surface) and the 850-mb level. Figure 2.4 illustrates the NARR 2-m temperature field over North Carolina during the passage of a strong cold front. The model successfully captures the strong gradients and the spatial variability of the air temperature. This figure also implies that a simple distance-weighted average between three adjacent, but widely-spaced, observing stations at different elevations or on either side of the front would have the potential to produce poor estimates of the temperature at a fourth location. The fine resolution of the NARR output fields therefore produces superior estimates for highly-variable meteorological fields compared with simple spatial interpolations using measurements solely from widely-spaced observing locations.

Estimates of variables derived from the NARR data require disaggregation to hourly values from the original 3-hourly output. Three options for the temporal interpolation procedure include a local harmonic analysis, cubic spline interpolation, and a simple linear interpolation. Letting a local harmonic analysis create a perfect harmonic fit to seven consecutive NARR data points, the interpolated values for the two hours immediately preceding the middle NARR data point then fall on the resulting harmonic curve. Though the local harmonic fit perfectly reproduces the 3-hourly data points, the disaggregated values often contain spurious deviations from these fixed values in order to achieve the fit. A cubic spline interpolation mitigates the spurious deviations, as does a simple linear interpolation. The linear temporal interpolation method simply fits a straight line between adjacent NARR data points to create an estimate of hourly data between those points and follows the approach of Chen et al. (2007), who use a linear interpolation of the three-hourly analyses from the NCEP Eta Data Assimilation System (EDAS) regional coupled forecast model (Rogers et al. 1995) to produce hourly values for the National Center for Atmospheric Research (NCAR) high-resolution land data assimilation system (HRLDAS), and Fan et al. (2006), who linearly interpolate 6-hourly NCEP–NCAR Global Reanalysis (Kalnay et al. 1996; Kistler et al. 2001) data to hourly values.

Hourly observations from the Asheville Regional Airport (station 03812) provide a way to test these three potential interpolation schemes by comparing actual measurements with interpolated values between every third hour from 0000 UTC 1 January 1985 to 0000 UTC 1 January 1986. Remarkably, there were no missing observations for the entire year, leaving 5842 estimate–observation pairs. Table 2.1 lists scalar accuracy measures for the interpolated temperature, dewpoint, and wind speed (cloud cover and precipitation are handled differently; see section 3) compared with the observed values at each hour, *excluding* the exact matches at each three-hour interval. For physical reasons, the interpolation procedure prevents the dewpoint from exceeding the temperature. Though the cubic spline interpolation performs best for temperature estimates, the linear interpolation produces the

TABLE 2.1: Scalar accuracy measures for temporally-interpolated temperature, dewpoint, and wind speed measurements using every third hour of observations at the Asheville Regional Airport from 0000 UTC 1 January 1985 to 0000 UTC 1 January 1986. Interpolation methods include local harmonic analysis (Harmonics), cubic spline interpolation (Spline), and a simple linear interpolation (Linear). Bold values indicate the best-performing method.

Mean error (bias)			
	Harmonics	Spline	Linear
Air temperature (K)	**0.0098**	0.0115	0.0116
Dewpoint (K)	−0.0278	−0.0143	−**0.0062**
Wind speed (m s^{-1})	−**0.0469**	−0.0470	−**0.0469**

Mean absolute error			
	Harmonics	Spline	Linear
Air temperature (K)	0.6540	**0.5454**	0.5953
Dewpoint (K)	0.6224	0.5267	**0.5106**
Wind speed (m s^{-1})	1.1030	1.0284	**0.9682**

Root-mean squared error			
	Harmonics	Spline	Linear
Air temperature (K)	0.8892	**0.7773**	0.8445
Dewpoint (K)	0.8805	0.7718	**0.7617**
Wind speed (m s^{-1})	1.4321	1.3424	**1.2705**

best overall set of accuracy measures for all three variables. These results and the work of others, therefore, support the use of a linear temporal interpolation to disaggregate the three-hourly NARR data to hourly values.

Since the NARR provides precipitation accumulation as a three-hourly total, disaggregation to hourly accumulations requires a different procedure. Any three-hour total less than 0.015 mm is left as is for that hour and the previous 2 hours remain zero. Otherwise, the three-hour total is spread evenly over the preceding three hours.

2.4 Groundwater

Recall that the EICM accepts hourly groundwater table depths, but the model uses only quarterly groundwater table data in the simulation. Ideally, groundwater table depths would be found through profile characterization borings prior to design (NCHRP 2004), but historical groundwater levels would provide a satisfactory substitution. The North Carolina

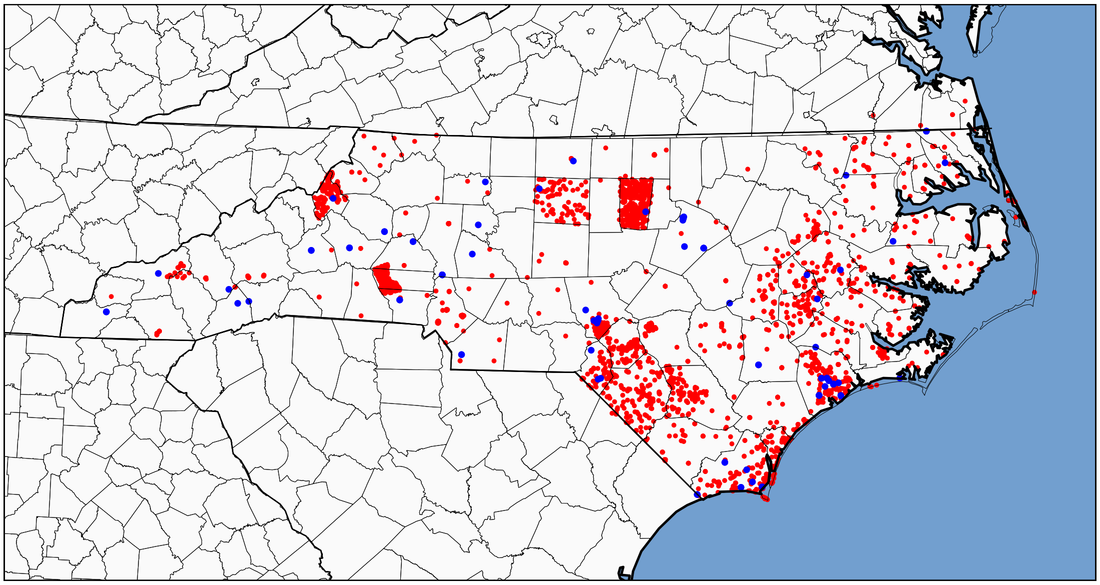

FIG. 2.5: Location of groundwater wells providing irregular field measurements (red; 3542 stations) and daily observations (blue; 92 stations) of groundwater depth in North Carolina between 1979 and 2013. Many sites are colocated.

Water Science Center, a division of the U.S. Geological Survey, provides these historical groundwater levels. Daily data are available from 92 sites across North Carolina for long periods of record, over half of which exceed a decade. Irregular field measurements are available for 3542 sites in North Carolina. Three-month seasonal averages derived from these data for each year could provide sufficient input to the EICM. Despite this wealth of observations, the extreme clustering of the groundwater wells leaves a rather sparse spatial coverage in the historical data (Fig. 2.5). Actual groundwater levels at any single location respond to a variety of factors that depend on the specific features of that location (e.g., wells, rock or sediment types, topography, and discharge features such as springs, streams or rivers). Spatial interpolation beyond a particular measurement site would require hundreds of measurements and groundwater flow modeling (J. Wilcox, personal communication). Given the significant spatial dependence of groundwater depths and the inability to interpolate groundwater depths spatially, the author recommends using the default values in Pavement ME Design simulations in the absence of more complete groundwater data.

3. Gap Filling

The construction of a continuous time series of hourly meteorological data for several decades is a challenging prospect. No observing location boasts an unbroken set of hourly observations for this length of time. As such, a robust gap-filling technique must achieve reliable estimates of meteorological values for both short and long temporal gaps in the observed data. Given daily maximum and minimum temperatures, Schaub (1991) proposes a hyperbolic tangent curve-fitting procedure to disaggregate daily data to hourly temperatures. In other circumstances this could prove useful, but the availability of NARR data precludes the need to guess at the evolution of the diurnal cycle. Variables other than temperature have no well-defined short-term temporal cycle that would lend itself to disaggregation from daily data. Spatial interpolation of existing meteorological data to fill in temporal gaps at a given location using simple inverse-distance weighting algorithms, as presently implemented in the EICM to build virtual stations, can introduce large errors in regions of varying topography, as in the mountains of Western North Carolina, and along coasts where large discontinuities in meteorological surface variables may exist. Other simplistic point estimation methods such as polygonal estimates or triangulation use only a few sample points and thus ignore nearby information. More suitable options could include a natural neighbor interpolation (Liang and Hale 2010) as in Heitzman et al. (2011), trend surface analysis and spline models (e.g., Jarvis and Stuart 2001), or more complex empirical orthogonal function (EOF) analyses (e.g., Beckers and Rixen 2003), maximum likelihood estimates for incomplete data (e.g., Schneider 2001), and artificial neural networks (e.g., Kashani and Dinpashoh 2012). Many other spatial interpolation methods exist (see Li and Heap 2008). However, a promising and popular geostatistical interpolation technique is ordinary kriging, a statistical interpolation method that predicts a value at a given location based on weighted linear combinations of the surrounding measurements. Many authors in the geosciences have relied on kriging as a spatial interpolation technique (e.g., Ashley et al. 2003; Goovaerts 2000; Holdaway 1996; Hunter and Meentemeyer 2005; Li et al. 2005; Ray et al. 2003; Schuurmans et al. 2007), while others have shown that kriging generally outperforms other spatial interpolation methods (e.g., Dodd et al. 2015; Jarvis and Stuart 2001; Stahl et al. 2006).

As with other interpolation methods, ordinary kriging is both linear and unbiased, in that the mean error is zero, but unlike other methods, ordinary kriging additionally attempts to minimize the variance of the errors (Isaaks and Srivastava 1989). One of the unique properties of kriging is that it assigns less weight, or even a negative weight, to certain sample values if another sample falls between it and the estimated point. This property allows kriging to yield estimates larger than the largest sample value or smaller than the smallest sample value (Isaaks and Srivastava 1989), a property especially suited to meteorological data since widely-spaced sample locations likely cannot capture the entire range of variability in the real atmosphere. As implemented here, ordinary kriging estimates fill temporal gaps only in temperature, dewpoint temperature, and wind speed records. For reasons discussed fully in sections 3.5 and 3.6, estimates for both precipitation and cloud cover derive from alternative approaches.

3.1 Ordinary kriging

The first step in point estimation via kriging involves building a sample variogram, which describes how the spatial continuity of a data field changes with distance (Isaaks and Srivastava 1989). The classical variogram estimator (Matheron 1963) is defined as half the average squared difference between all possible paired data values within specified ranges of distances separating each pair. That is, the variogram function is half the variance (i.e., the semivariance) between pairs of data points separated by specific distance ranges. A variogram (or semivariogram) displays a plot of the variogram function $\gamma(h)$ against the range of distances h, or lag, used to determine each value in the function. The variogram begins at relatively low values for small h, often leaving a discontinuity at the origin called the nugget effect, and increases before leveling off at a nearly-constant maximum value, called the sill, for large distances. The lag at which the variogram reaches the sill, called the range, represents the distance at which the spatial autocorrelation between data pairs becomes negligible. The kriging system employed here implements a robust variogram estimator (Cressie 1985), given by

$$\gamma_r(h) = \frac{\left(\frac{1}{N_h}\sum_{i=1}^{N_h}|x_{i+h} - x_i|^{\frac{1}{2}}\right)^4}{2\left(0.457 + \frac{0.494}{N_h}\right)}, \tag{3.1}$$

where x denotes a data value, N_h is the number of data pairs at lag h, and the data value at location $i+h$ is separated in space by a distance of approximately h from the data value at location i. Robust variogram estimator values at all lags differ slightly from the classical variogram estimator, but the former estimator remains robust to contamination by outliers.

Assuming a spherical Earth with a constant radius would introduce large errors in distance calculations over the large domain of the study region. To avoid such errors, the World Geodetic System 1984 (WGS 84) Ellipsoid (NIMA 2000) provides the geographic datum upon which to calculate distances between meteorological stations given the geographic coordinates of each location. The most accurate inverse geodetic formulae presented in Sodano (1965) yield the distances between data points. As implemented here, the lag separation distance for the sample variogram spans 35 km and coincides approximately with the grid spacing for the NARR data.

There must exist one unique solution to the ordinary kriging equations that provide a

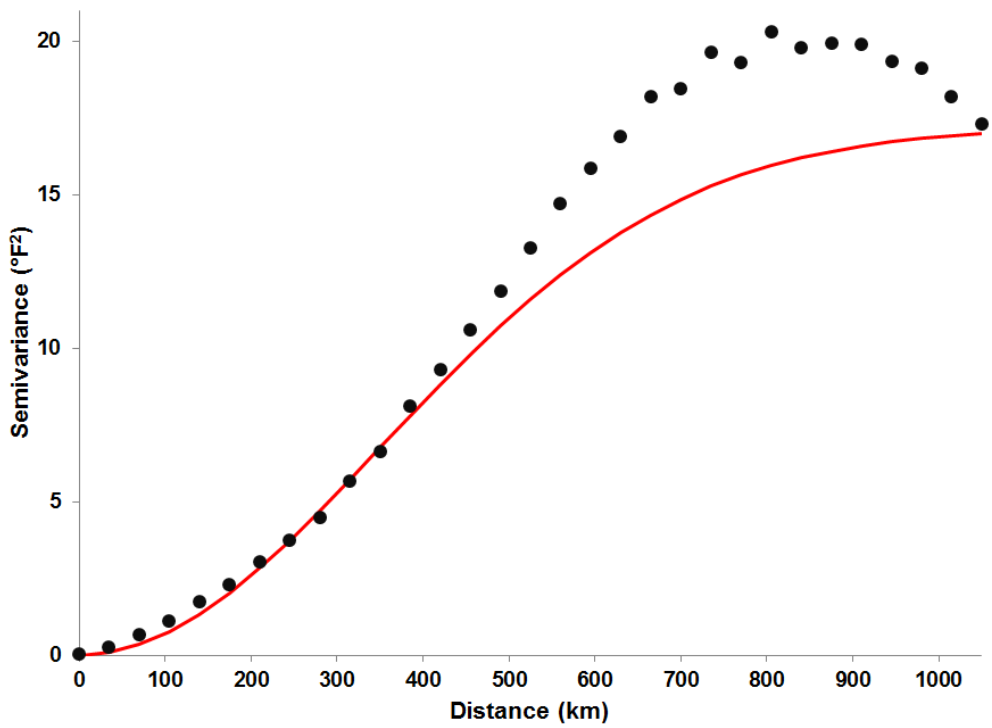

FIG. 3.1: Variogram (dots) for lapse-rate corrected 2-m air temperature (see section 3.2) across the study region based on NARR model output at 1900 UTC 28 April 2011. An automated scheme produces the weighted least squares fit (red) with $c_0 \approx 0.0°\mathrm{F}^2$, $c_1 = 17.16°\mathrm{F}^2$, and $a = 857.46$ km. The weighted least squares fit gives more weight to the values near the origin that are actually used in the kriging estimate.

point estimate within a field of meteorological values. This can only happen when the kriging matrices satisfy a mathematical condition termed positive definiteness (Isaaks and Srivastava 1989). Though the sample variogram provides a summary of the spatial continuity within a field of data points, the kriging system requires knowledge of the variance over a continuous function. This necessitates the use of a continuous variogram model and, because of the positive definiteness requirement, limits that model to only a few possible functions that obey certain constraints (Marchant and Lark 2004).

Of the limited choices for positive definite variogram models, the Gaussian model is best suited for continuous fields such as meteorological data. Tests show that the variograms for the meteorological data in North Carolina display a very clear parabolic behavior near the origin and display an inflection point before arriving at the sill (e.g., Fig. 3.1).

The Gaussian model is the only variogram model that displays these characteristics. The theoretical variogram associated with the Gaussian model is given by

$$\widetilde{\gamma}(h) = c_0 + c_1 \left(1 - \exp\left[\frac{-3h^2}{a^2} \right] \right), \tag{3.2}$$

where $\widetilde{\gamma}(h) = 0$ if $h = 0$, c_0 is the nugget effect, c_1 is the scale, $c_0 + c_1$ is the sill, and a is the practical range, arbitrarily defined as the distance at which the variogram reaches 95% of the value at the sill (Isaaks and Srivastava 1989). So the kriging system requires knowledge of the nugget effect, sill, and range for the variogram model that best fits the experimental variogram. When determining a kriging estimate for up to a handful of data fields, hand selection of these three parameters is a viable option. However, for the hundreds of thousands of variogram models required to estimate values over decades of hourly data gaps, hand selection seems a bit impractical.

A few objective techniques can accomplish a best fit by minimizing error measures between the experimental variogram values and the theoretical variogram model. The minimization scheme selected here is the method of weighted least squares (Cressie 1985). In contrast to the simpler least squares method, a weighted least squares fit gives more weight to the values near the origin so that they contribute more strongly to the final estimate of a sample point via kriging. This produces a reliable fit and the method performs well compared with more computationally-demanding procedures (Zimmerman and Zimmerman 1991). The weighted least squares method seeks to minimize the function

$$\sum_{j=1}^{k} N_{h(j)} \left[\frac{\gamma_r(h_j)}{\widetilde{\gamma}(h_j)} - 1 \right]^2 \tag{3.3}$$

with respect to c_0, c_1, and a (Brunell 1992; Cressie 1985). The Nelder-Mead simplex algorithm (Nelder and Mead 1965; Wright 1996) accomplishes the minimization given default values for the initial nugget effect, scale, and range as suggested by Jian et al. (1996). Though the Nelder-Mead simplex algorithm is relatively fast, it may fail to converge. If this happens, the procedure attempts to use a modified Powell's method (Powell 1964; Press et al. 2007) to find the three parameters that minimize the function in equation 3.3. Here, a script forces $c_0 \geq 0$, $c_1 > 0$, and $0 < a \leq h_{\max}$ within the minimization scheme, where $h_{\max}$ is half the distance to the farthest data point.

With the theoretical variogram parameters in hand, the kriging system proceeds in a relatively straightforward fashion. The covariance function is given by

$$\widetilde{C}(\mathbf{d}) = \begin{cases} c_o + c_1, & \text{if } \mathbf{d} = 0 \\ c_1 \exp\left(\frac{-3h^2}{a^2}\right), & \text{if } \mathbf{d} > 0 \end{cases}, \tag{3.4}$$

where $\mathbf{d}$ is the $n \times n$ matrix of distances between all possible paired data points within a small search window and n is the number of data pairs. The $(n+1) \times (n+1)$ matrix $\mathbf{C}$ is then the values of $\widetilde{C}(\mathbf{d})$, where the diagonal values equal c_0, padded with ones on the bottom and right sides and a zero in the bottom right corner such that

$$\mathbf{C} = \begin{bmatrix} \widetilde{C}_{11} & \cdots & \widetilde{C}_{1n} & 1 \\ \vdots & \ddots & \vdots & \vdots \\ \widetilde{C}_{n1} & \cdots & \widetilde{C}_{nn} & 1 \\ 1 & \cdots & 1 & 0 \end{bmatrix}. \tag{3.5}$$

The $(n+1) \times 1$ matrix $\mathbf{D}$ is the set of covariance functions for the distances between the desired location of the kriging estimate and all other data points, padded by a one at the end of the column, such that

$$\mathbf{D} = \begin{bmatrix} \widetilde{C}_{10} \\ \vdots \\ \widetilde{C}_{n0} \\ 1 \end{bmatrix}. \tag{3.6}$$

The set of weights that minimizes the error variance under the constraint that the weights sum to unity in order to satisfy the unbiasedness condition becomes the $(n+1)\times 1$ matrix

$$\mathbf{w} = \begin{bmatrix} \widetilde{w}_1 \\ \vdots \\ \widetilde{w}_n \\ \mu \end{bmatrix}, \tag{3.7}$$

where μ is a Lagrange multiplier required to find a solution for the system of equations. Solving for the weights,

$$\mathbf{w} = \mathbf{C}^{-1} \cdot \mathbf{D}. \tag{3.8}$$

By multiplying this set of weights by the matrix of values at the corresponding data points $\mathbf{x}$, the kriging system arrives at an estimate of the data value at the desired location:

$$x_0 = \sum_{i=1}^{n} w_i x_i. \tag{3.9}$$

Preliminary tests show that the ordinary kriging estimates consistently perform poorly (i.e., they produce improbable meteorological values) in some parts of North Carolina, particularly in the Piedmont in the vicinity of several closely-spaced observing locations, but produce very reasonable estimates in other parts of the state, such as Asheville, far away from other ISD stations. The problem likely involves the introduction of strong gradients within the NARR gridded field with the inclusion of the actual observations. If a temperature observation differs from the nearest NARR grid point value by a few degrees Celsius, for example, then the strong local gradient will artificially inflate the variance near the origin of the variogram and lead to inappropriate kriging parameters, which would introduce the potential for large deviations from the mean of the entire field in the final point estimate. However, the ordinary kriging algorithm works exceptionally well for isolated stations such as Asheville when compared with actual observations.

To address this problem, all kriging estimates that fill in missing temperature, dewpoint, and wind speed observations neglect ISD observations and instead rely solely on the gridded NARR data field. This decision greatly improves the temporal continuity of the independent hourly kriging estimates. The choice to abandon actual observations in favor of a model data field does not abandon truly independent data because the data assimilation scheme utilized by the NARR incorporates all available surface wind and moisture observations over land. The wind and dewpoint fields should therefore match observations fairly well. On the other hand, the NARR data assimilation scheme does not incorporate 2-m temperature observations due to the detrimental effect on the modeled vertical structure of the atmosphere (Mesinger et al. 2006). For this reason, the NARR output fields will not exactly match the observed 2-m surface temperatures, yet those fields remain temporally and spatially consistent both horizontally and vertically. The overspecification of the surface variables through the inclusion of ISD observations would therefore result in sharp gradients that would lead to erroneous kriging estimates.

The ordinary kriging algorithm remains completely automated because hand-checking individual kriging parameters and estimates would prove impossible. Despite the overall success of the ordinary kriging estimates compared with observations, some of the independent hourly estimates can produce outliers. During post-processing, a quality-assurance algorithm removes such outliers and replaces them with revised estimates (see section 4). Of course, actual quality-controlled observations always appear in the final HCD files at the target locations when available.

3.2 Temperature and dewpoint temperature

Elevation strongly influences temperature, making it imperative to account for elevation differences in any spatial interpolation approach to fill gaps in missing temperature data. Preliminary tests indicate that ignoring environmental lapse rates in kriging estimates produces unsatisfactory results, particularly at stations in Western North Carolina within relatively complex topography. Both Li et al. (2005) and Stahl et al. (2006) combine ordinary kriging with adjustments to the temperature based on the local lapse rate in mountainous terrain and find dramatic improvements in the performance of the combined approach when estimating temperatures.

Recall that the EICM uses the standard tropospheric lapse rate when constructing virtual stations, yet the actual change of temperature with height can vary considerably depending on ambient atmospheric conditions. The present approach therefore accounts for the local lapse rate of temperature defined at each NARR grid point in order to bring the entire gridded temperature field to a common elevation at mean sea level. The ordinary kriging procedure estimates the temperature at a given location at this common elevation and then the estimated temperature receives an adjustment that brings it back to the actual elevation of that location based on the lapse rate at the NARR grid point nearest to that location. This approach generally produces a larger diurnal spread in temperatures that more closely replicates observations when compared with results obtained by ignoring lapse rates in the spatial interpolation.

The lapse-rate correction uses a local lapse rate defined as

$$\Gamma_{\mathrm{local}} = -\frac{T_{850} - T_{\mathrm{hybrid}}}{Z_{850} - Z_{\mathrm{hybrid}}}, \tag{3.10}$$

where T_{850} and Z_{850} are the temperature and geopotential height at 850 mb, respectively, and T_{hybrid} and Z_{hybrid} are the temperature and geopotential height at the first hybrid model level, respectively. The choice to use the first hybrid model level at several tens of meters above the surface rather than the 2-m temperature avoids problems introduced by extreme lapse rates that occur regularly very close to the surface. While the 925-mb height would work well as the upper level in the lapse-rate calculation for the central and eastern part of North Carolina, this level is actually below ground at higher elevations in the western part of the state. The 850-mb level is always well above the surface at all but the highest peaks

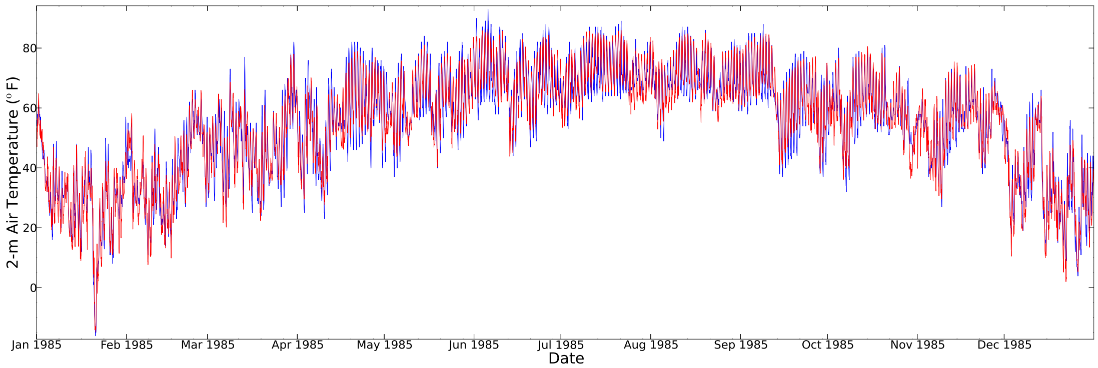

FIG. 3.2: Hourly observations (blue) and quality-controlled kriging estimates of 2-m air temperature (red) at the Asheville Regional Airport (station 03812) just south of Asheville, North Carolina, for the entire year of 1985.

in North Carolina.

Elevation does not have such a commanding and systematic influence on the moisture content of the air, so NARR dewpoint temperatures remain unadjusted for lapse rate within the kriging system. At night, temperatures tend to fall to the dewpoint temperature, but for physical reasons, the temperature cannot fall below the dewpoint temperature. In cases where the lapse rate is negative (a proxy for nocturnal boundary layer conditions; i.e., the temperature increases with height) and the temperature estimate falls below the dewpoint estimate, the algorithm raises the temperature to match the dewpoint. This produces much better estimates of temperature when compared with actual observations. Similarly, the (quality-controlled) temperature provides an upper bound for the dewpoint estimate under

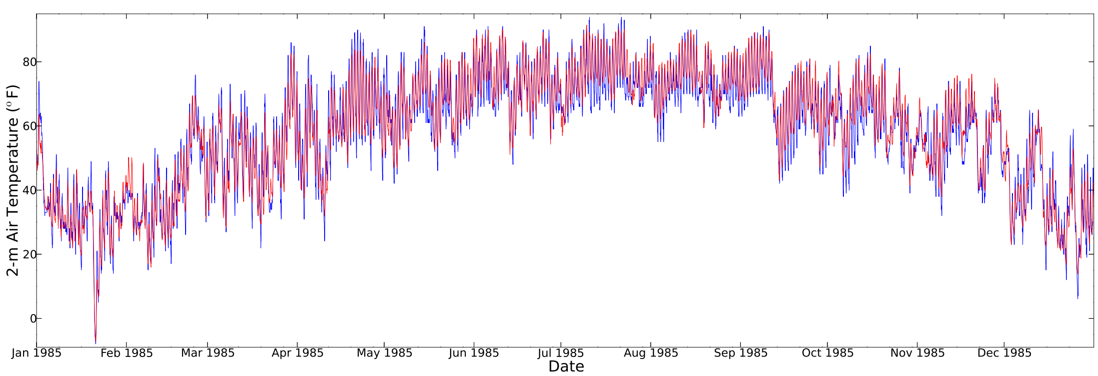

FIG. 3.3: As in Fig. 3.2, but for the Piedmont Triad International Airport (station 13723) in Greensboro, North Carolina.

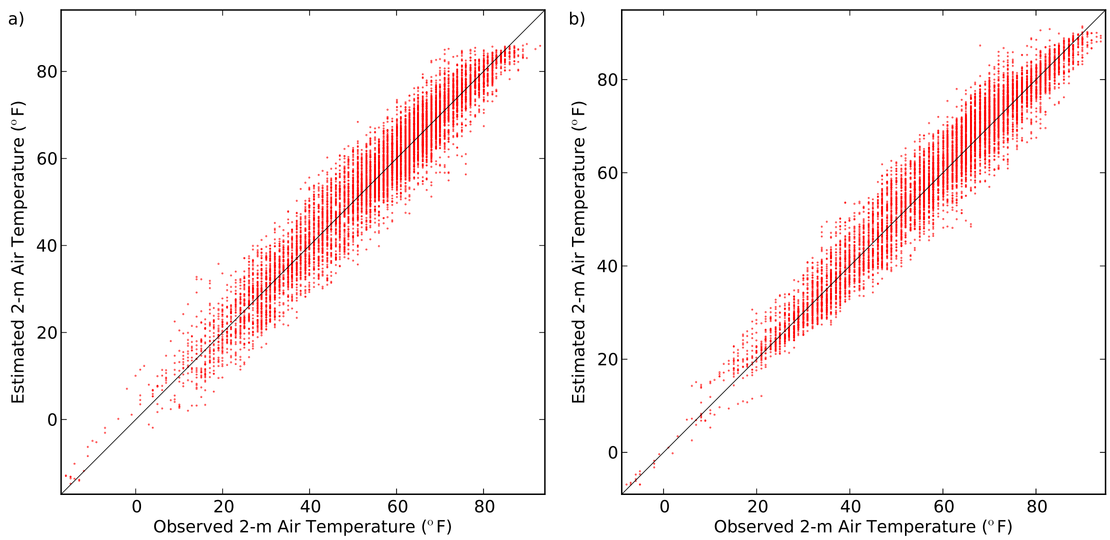

FIG. 3.4: Hourly observations plotted against quality-controlled kriging estimates of 2-m air temperature for the entire year of 1985 at a) the Asheville Regional Airport (station 03812) just south of Asheville, North Carolina, and b) the Piedmont Triad International Airport (station 13723) in Greensboro, North Carolina. The thin black line is the one-to-one line.

normal lapse rate conditions.

Figures 3.2 and 3.3 compare actual measurements of hourly air temperature with estimates obtained via ordinary kriging with the lapse-rate correction for both Asheville, NC and Greensboro, NC over the period 0000 UTC 1 January 1985 through 0000 UTC 1 January 1986. Only NARR data contribute to the spatial interpolation—no actual observations contribute to the analysis—and each hourly estimate retains independence from estimates for adjacent hours. A quality assurance algorithm (see section 4) has automatically removed any anomalous spikes. The procedure produces temperature estimates that match observations very well, including the all-time record low temperatures for Asheville and Greensboro of -16.1°F (-26.7°C) and -8.0°F (-22.2°C), respectively, both on 21 January 1985. During the warm season (April–September), temperature estimates seem to have trouble reaching the observed extremes in the diurnal cycle, though the largest absolute errors in daily maximum and minimum temperatures rarely exceed 3.6°F (2.0°C). The scatterplots in Figure 3.4 reveal the strong relationship between air temperature mea-

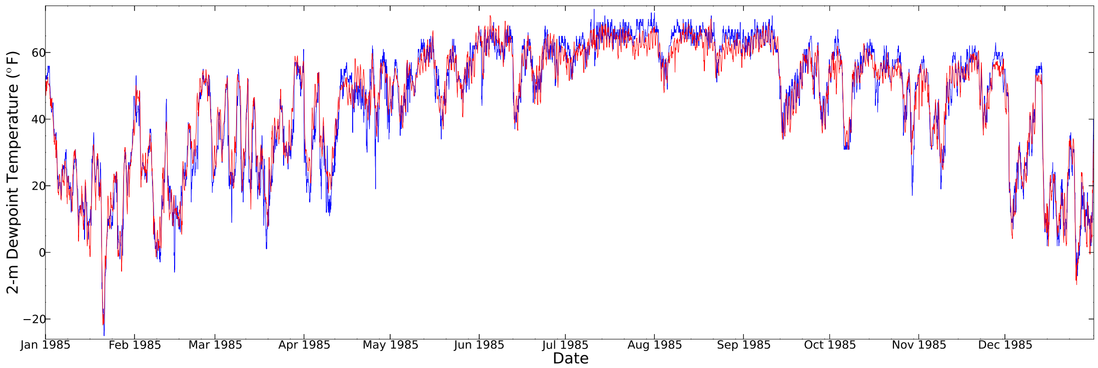

FIG. 3.5: Hourly observations (blue) and quality-controlled kriging estimates of 2-m dewpoint temperature (red) at the Asheville Regional Airport (station 03812) just south of Asheville, North Carolina, for the entire year of 1985.

surements and estimates for the entire year at both Asheville and Greensboro, where the correlation coefficients are $\rho = 0.9648$ and $\rho = 0.9723$, respectively.

Figures 3.5 and 3.6 compare actual measurements of hourly dewpoint temperature with observations at both Asheville and Greensboro. While dewpoint estimates do not (and could not) match observations exactly, there exists no clear systematic daily or seasonal bias shared by both stations. Dewpoint estimates at Greensboro show a 3.2°F (1.8°C) high bias, but this bias is not apparent at Asheville, as shown in Figure 3.7. The correlation coefficients for comparisons between dewpoint measurements and estimates are $\rho = 0.9713$ and $\rho = 0.9771$ at Asheville and Greensboro, respectively. Table 3.1 displays scalar accuracy measures for both temperature and dewpoint estimates at these two stations for all of 1985.

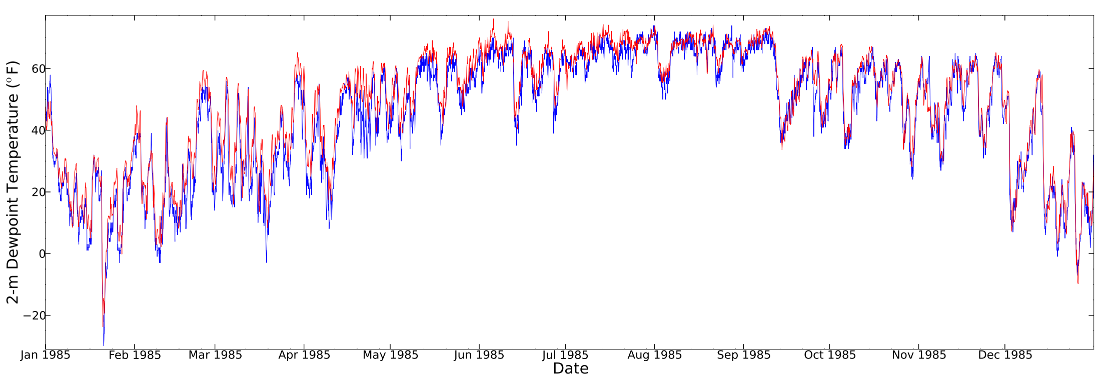

FIG. 3.6: As in Fig. 3.5, but for the Piedmont Triad International Airport (station 13723) in Greensboro, North Carolina.

TABLE 3.1: Scalar accuracy measures and correlation coefficient for hourly temperature and dewpoint estimates compared with observations for all of 1985 at Asheville, NC and Greensboro, NC.

	Temperature		Dewpoint	
	Asheville	Greensboro	Asheville	Greensboro
Mean error (°C)	0.1702	0.4105	−0.0110	1.8102
Mean absolute error (°C)	2.0271	1.8375	1.9156	2.2319
Root-mean-squared error	2.5913	2.3461	2.4903	2.9544
Pearson correlation (ρ)	0.9648	0.9723	0.9713	0.9771

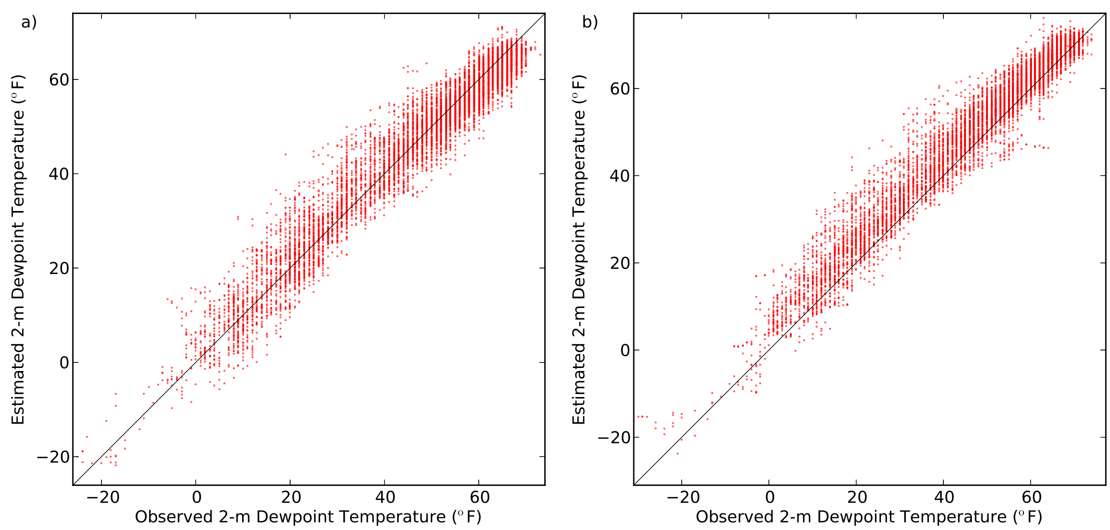

FIG. 3.7: Hourly observations plotted against quality-controlled kriging estimates of 2-m dewpoint temperature for the entire year of 1985 at a) the Asheville Regional Airport (station 03812) just south of Asheville, North Carolina, and b) the Piedmont Triad International Airport (station 13723) in Greensboro, North Carolina. The thin black line is the one-to-one line.

3.3 Relative Humidity

The relative humidity describes the moisture content of the atmosphere as a percentage of the amount of moisture required for saturation and is expressed as the ratio of the ambient vapor pressure e to the saturation vapor pressure over water e_s,

$$\mathrm{RH} = \frac{e}{e_s}. \tag{3.11}$$

The temperature uniquely determines the saturation vapor pressure. The Bolton formula (Bolton 1980) allows the calculation of the saturation vapor pressure to within 0.1% over the range −30°C to +35°C given a temperature according to

$$e_s = 611.2 \exp\left[\frac{17.67 T_C}{T_C + 243.5}\right], \tag{3.12}$$

where T_C is the temperature in degrees Celsius and e_s is in Pascals. Equation 3.12 also gives the ambient vapor pressure e by substituting the dewpoint temperature T_d for T_C. A quality assurance algorithm (see section 4) prohibits the dewpoint temperature from exceeding the temperature for physical reasons, which necessarily limits the relative humidity to the range 0% to 100%.

3.4 Wind Speed

Tests indicate that the variogram models for net 10-m wind speed produce much better estimates of the wind speed at a given station (compared with observations) than the variogram models for the individual zonal and meridional wind components. This likely stems from the fact that while the spatial distribution of wind speed can remain relatively

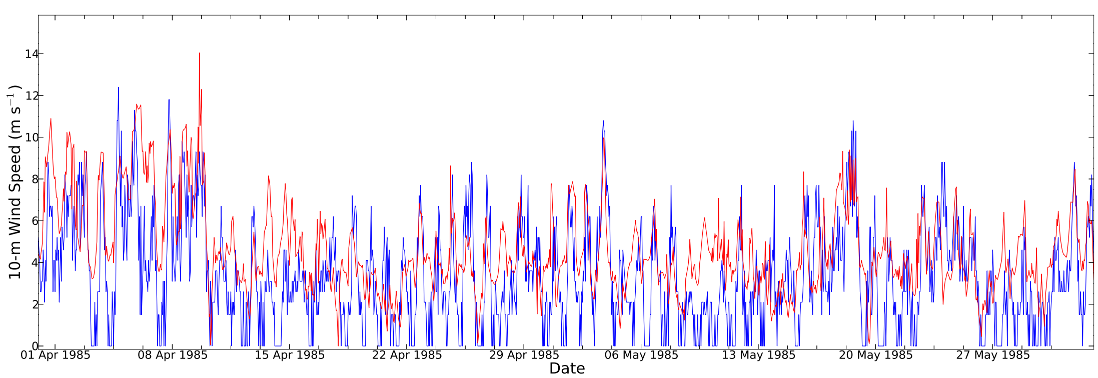

FIG. 3.8: Hourly observations (blue) and quality-controlled kriging estimates of 10-m wind speed (red) at the Asheville Regional Airport (station 03812) just south of Asheville, North Carolina, for April and May of 1985. Only two months of the year are shown for clarity.

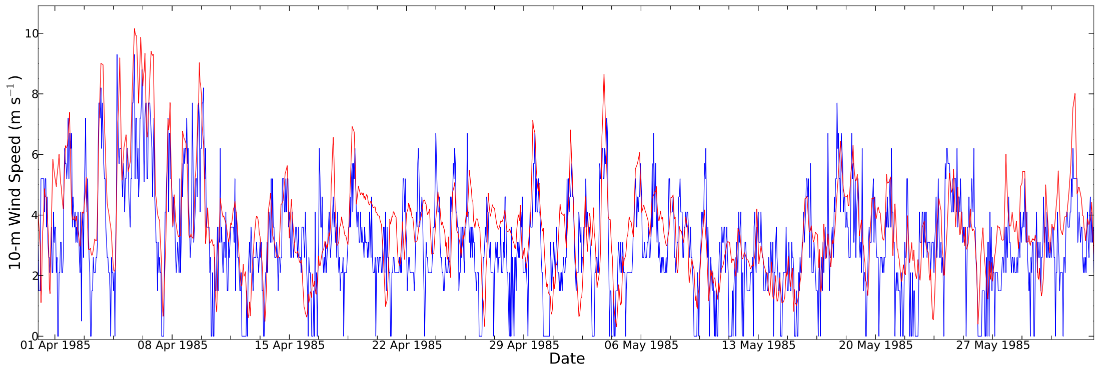

FIG. 3.9: As in Fig. 3.8, but for the Piedmont Triad International Airport (station 13723) in Greensboro, North Carolina.

smooth, slight directional changes due to terrain or mesoscale features can lead to large variations in the wind components. Slight errors in the spatial interpolation of these vector components compound when recalculating the resultant wind speed from those erroneous components. Therefore, the ordinary kriging system estimates wind speeds at each station rather than the individual wind components. However, at individual NARR grid points, the three-hourly wind components are first temporally interpolated and the resultant hourly

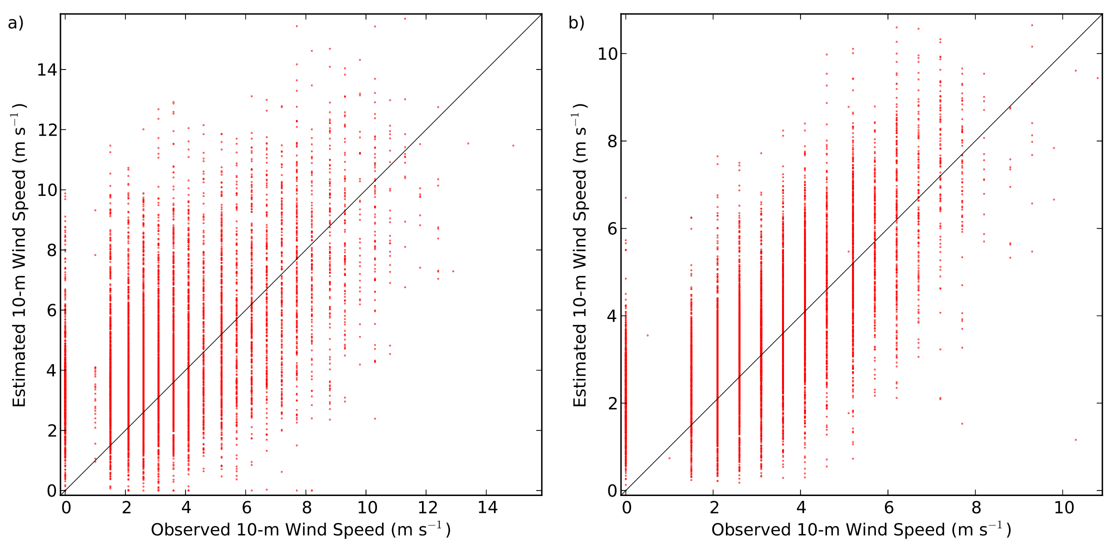

FIG. 3.10: Hourly observations plotted against quality-controlled kriging estimates of 10-m wind speed for the entire year of 1985 at a) the Asheville Regional Airport (station 03812) just south of Asheville, North Carolina, and b) the Piedmont Triad International Airport (station 13723) in Greensboro, North Carolina. The thin black line is the one-to-one line.

TABLE 3.2: Scalar accuracy measures and correlation coefficient for hourly wind speed estimates compared with observations for all of 1985 at Asheville, NC and Greensboro, NC.

	Asheville	Greensboro
Mean error (m s^{-1})	1.1229	0.5184
Mean absolute error (m s^{-1})	2.0497	1.1737
Root-mean-squared error (m s^{-1})	2.5929	1.4792
Pearson correlation, ρ	0.5168	0.6729

wind speed calculated from those components during the spatial interpolation process.

Allowing for the short-term temporal variability inherent with observed wind speeds, the 10-m wind estimates match observations fairly well for the entire year of 1985 at both Asheville and Greensboro (Figs. 3.8–3.10). Estimates tend not to drop to zero as often as the observations at each location, and some differences partially stem from the discretized measurements originally reported in whole knots, but the magnitude of the wind estimates generally compares well with the measurements. The estimates impressively capture the character of both windy and calm periods with no unphysical or outrageous outliers. Table 3.2 displays scalar accuracy measures for wind speed for the entire year of 1985 at both locations.

3.5 Cloud cover

The EICM requires hourly observations of the percentage of possible sunshine for its calculations of both net shortwave and net longwave radiation. These intermediate results affect the surface energy balance calculations that determine the temperatures throughout the pavement structure (NCHRP 2004). The input value as implemented in the EICM is actually the relative sunshine duration (i.e., the percentage of time that the Sun casts a dark shadow), specifically defined as the number of actual sunshine hours divided by the maximum possible number of sunshine hours, for use in the Ångström-Prescott formula for global solar radiation (Tahâş et al. 2011; Martínez-Lozano et al. 1984; Gueymard et al. 1995). Standard observing sites (e.g., ASOS) generally do not directly measure relative sunshine duration on an hourly basis, but instead measure cloud coverage, typically in oktas (i.e., eighths). The complement of the percentage of cloud cover, however, supplies a reasonable substitute for the relative sunshine duration per hour, even though studies have found that ground-based cloud cover observations slightly underestimate the percentage of possible sunshine (e.g., Hoyt 1977; Essa and Etman 2004) and that the relationship between cloud coverage and sunshine duration is nonlinear (see Gueymard et al. 1995). So in the absence of a concrete source for measurements of the relative sunshine duration, the present approach uses the complement of the observed fraction of the total celestial dome covered by clouds or other obscuring phenomena available from the ISD data as a proxy for the percentage of sunshine listed in the HCD files in an approach similar to that used by Heitzman et al. (2011).

Recall that the Gaussian variogram model works best for interpolating continuous data fields via ordinary kriging. Though temperature, moisture, and wind speeds tend to exhibit some spatial continuity, cloud cover may not, particularly in the vicinity of fronts or other mesoscale phenomena. The physical bounds of 0% and 100% for cloud cover compound the problems with spatial interpolation. The difficulties with the proper characterization of clouds within numerical models (Stephens 2005) such as the NARR do not help either. Indeed, tests show that cloud cover estimates via kriging do not compare well with observations. Instead of relying on geostatistical interpolation techniques to estimate hourly cloud cover values, a reasonable alternative could involve substituting the cloud cover from the nearest NARR grid point, located at most 13.8 miles (22.3 km) away from the subject station. The total sky coverage between locations separated by such a short distance should be nearly identical because they each consider almost the same sky dome. However, comparisons between observed cloud fractions at Chapel Hill, NC (station 93785) and the nearest NARR grid point at a distance of only 7.46 miles (12.01 km) show almost no qualitative association. This highlights the well-known difficulties with the proper characterization of clouds within numerical models (Stephens 2005), so the failure of the NARR cloud fields to correspond with reality is not surprising. So the question then becomes whether or not the model cloud cover accurately represents a realistic cloud cover time series.

Consider a comparison between observations at the Charlotte-Douglas International Airport (station 13881) and the nearest NARR grid point at a distance of 5.89 miles (9.48 km) to the northwest. The observations here contain all nine possible oktas (unlike some other stations) and the long observation POR provides 100,804 individual model-observation pairs when compared with the original three-hourly NARR values. The Pearson product-moment coefficient of linear correlation (ρ) and Kendall's τ can help to illuminate any positive relationship between the observed and modeled cloud cover. With the NARR cloud fractions discretized into oktas for a fair comparison with observations, the NARR data exhibit a Pearson correlation of $\rho = 0.59$, revealing a moderate positive relationship with the observations. Most applicable to this situation, however, is Kendall's τ, a robust and resistant alternative to the Pearson correlation that considers the relationship between all possible matchings of model–observation pairs (Wilks 2011). A value of $+1$ indicates strong agreement and a value of -1 indicates strong disagreement between the pairs. Since the data include many ties (because of the discretized nature of cloud cover observations), the τ_b approach is the most appropriate form (Knight 1966). Kendell's τ_b is 0.47, suggesting a weak positive monotonic relationship between the two data sets.

The Wilcoxon signed-rank test is a nonparametric test for paired samples, where the null hypothesis is that the data from each paired sample originate from the same population (Wilks 2011). Failing to reject the null hypothesis would provide sufficient evidence that the NARR cloud cover produces a representative meteorological time series, even though the values may not exactly match the observations at a nearby station. The results of the test indicate that, with statistical near-certainty, the discretized NARR cloud cover data do not come from the same distribution as the observations. Therefore, the nearest NARR cloud cover value is likely not a suitable replacement for an actual observation. Again, this is not entirely unexpected because of the inherent difficulty with parameterizing cloud

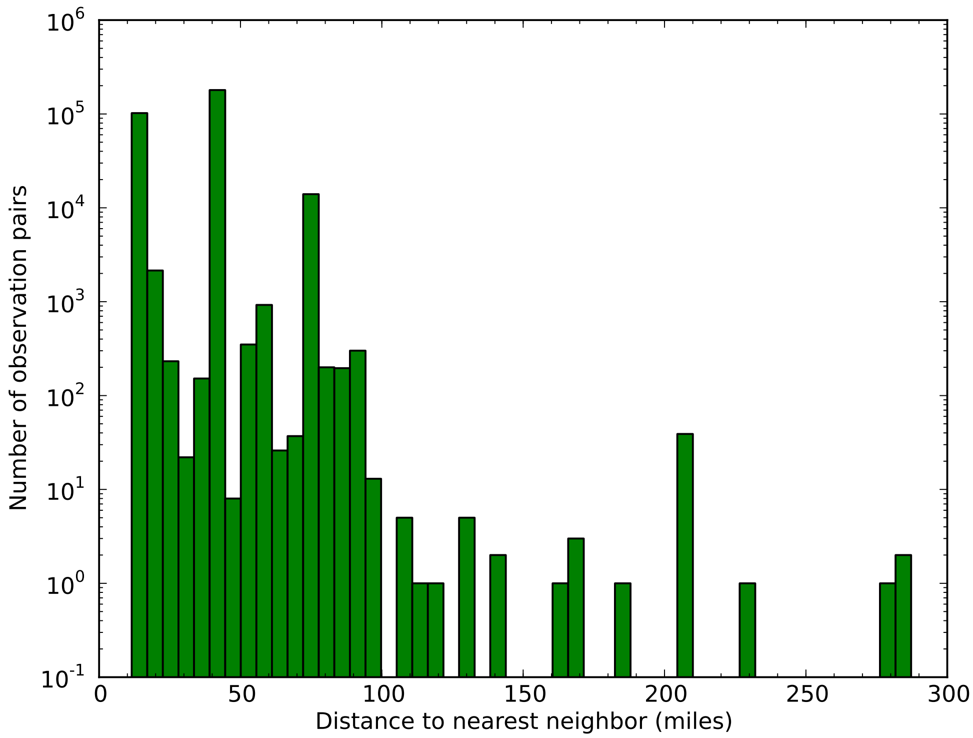

FIG. 3.11: Distance (miles) from the Charlotte-Douglas International Airport (station 13881) to the nearest ISD site for 300,586 valid observation pairs.

cover within numerical models (Stephens 2005) and, even if the model produces clouds in approximately the correct location, the character of the cloud field can differ significantly from observations.

Given the unimpressive results of both a spatial interpolation and a nearest-neighbor approach for the estimation of hourly cloud cover using NARR data, it follows that actual observations at the nearest ISD station may instead provide a useful proxy for cloud cover measurements at a given location. This at least guarantees a climatologically-appropriate time series. Over time, the distance from a particular site to the nearest ISD station fluctuates as new stations are brought online and others are decommissioned, but a histogram of the distance to the nearest station with a valid cloud cover observation indicates that, for example, roughly three quarters of the 300,586 available pairs for the Charlotte-Douglas International Airport (station 13881) fall within 62.1 miles (100 km) of the station (Fig. 3.11). In

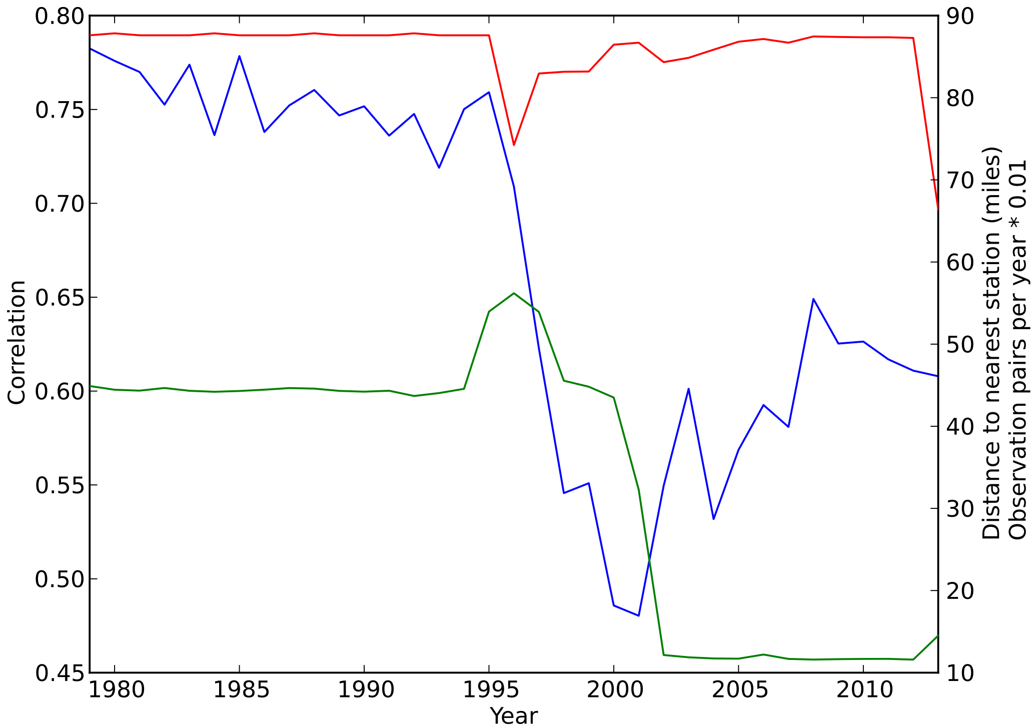

FIG. 3.12: Pearson correlation between valid cloud cover observation pairs at the Charlotte-Douglas International Airport (station 13881) and the nearest ISD station (blue; left axis), the mean annual distance to the nearest ISD station (green; right axis), and the number of valid observation pairs per year (red; right axis, scaled by a factor of 100).

a comparison between the observation pairs, Kendell's τ_b is 0.57, suggesting a strong positive monotonic relationship between the two data sets, though the Wilcoxon signed-rank test still shows that they likely did not originate from the same population. Interestingly, the Pearson correlation between observation pairs is roughly $\rho = 0.75$ through 1995, but then the correlation drops significantly for the remainder of the period of record (Fig. 3.12). This may be related to the change from human observations to automated observations from the ASOS sensor suite, which occurred across the U.S. between 1991 and 2004. The laser beam ceilometer automatically measures both the height and coverage of clouds over the station by transmitting a near-infrared laser beam vertically and timing the receipt of the return signal. Since the atmosphere typically moves, the calculation that estimates total cloud coverage is based on a 30-minute cloud-height observation period (NWS 1998). The

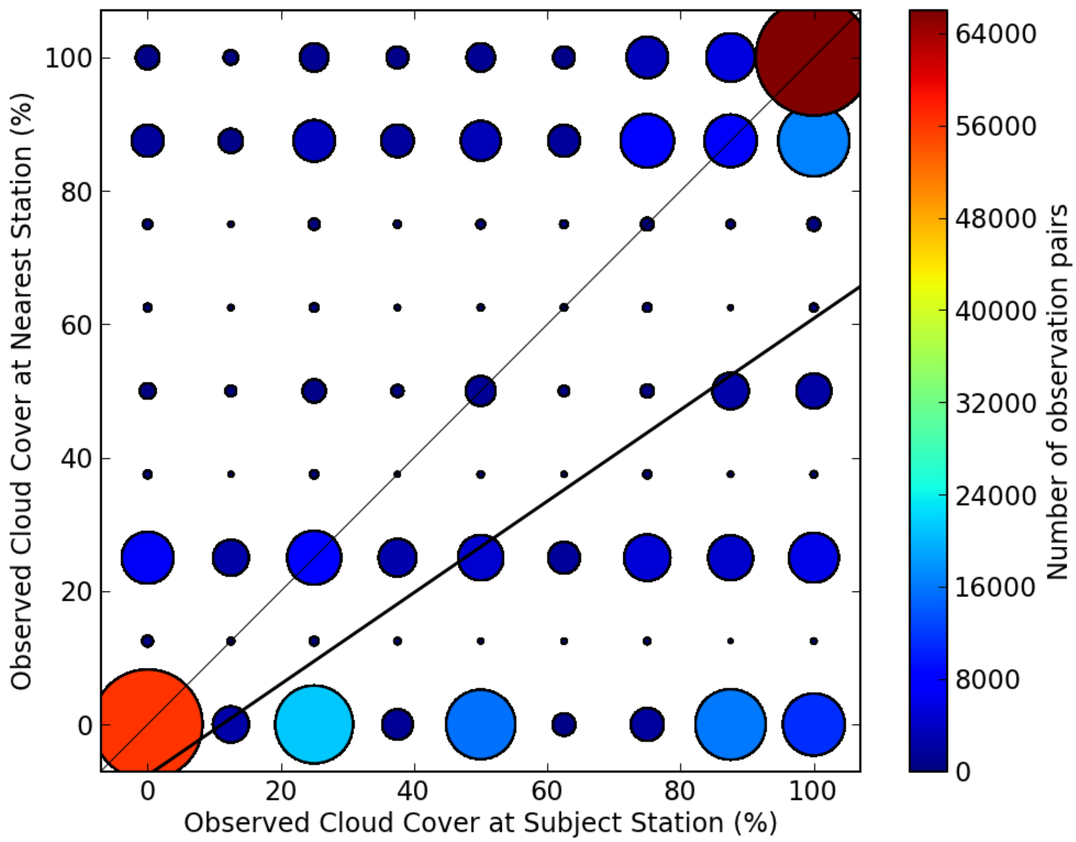

FIG. 3.13: Observed cloud cover at the Charlotte-Douglas International Airport (station 13881) compared with the observed cloud cover at the nearest ISD station. The thick black line is the linear least-squares regression line and the thin black line is the one-to-one line. Both the size and the color of the circles represents the number of observation pairs in each category.

automated measurements, therefore, may not capture cloud features that do not occur directly above the observing site, but that a human observer would report. This could account for the marked decrease in correlation coefficient as shown in Figure 3.12.

Importantly, Figure 3.13 shows that the most frequent pairs of observations between Charlotte-Douglas International Airport and adjacent stations are either both clear or both overcast. Both the colors and the relative areas of the circles in this scatterplot also indicate that if the subject station has observed clear conditions, then the nearest station is also more likely to have observed clear conditions, and vice versa. While not perfect, this provides strong evidence that a substitution of the nearest valid ISD cloud cover observation is an appropriate method for filling gaps in cloud cover measurements. The development of the final HCD files therefore relies on this approach.

A key exception to the method outlined above stems from the fact that a total of 141 hours of cloud coverage data are missing from all ISD sites simultaneously for select hours between 1998 and 2013. Occasional data outages from an upstream provider to NCDC result in large-scale gaps in coverage only for data pertaining to sky conditions. NCDC has no control over the data stream and these data are not recoverable. In the handful of cases where no ISD cloud cover data exist, estimates at subject locations instead correspond with the cloud coverage at the nearest NARR grid point.

3.6 Precipitation

Recall that the EICM accounts for precipitation on a monthly basis. Hence, daily precipitation totals would supply sufficient information to the model for Pavement ME Design pavement performance predictions. The dense GHCN-Daily network could easily provide the readily available daily precipitation totals at the subject station or nearby stations. Looking to the future, however, one could imagine that updates to the EICM could account for short-duration, heavy rainfall events or conditions where a short-lived thunderstorm drops cold rain on hot pavement. The following gap-filling procedure, therefore, attempts to produce the most likely hourly precipitation totals rather than simply placing a daily total in a single hour as currently implemented in many of the original HCD files.

The gap-filling procedure for precipitation differs from that of the temperature, dewpoint, and wind speed fields because of the inherently variable nature of precipitation on small spatial scales (e.g., Fig. 3.14). In general, no spatial interpolation technique can truly produce accurate point estimates of precipitation data, particularly for convective precipitation. The NARR often captures the presence of precipitation and, as Mesinger et al. (2006) report, the NARR precipitation field achieves very good agreement with observations, yet

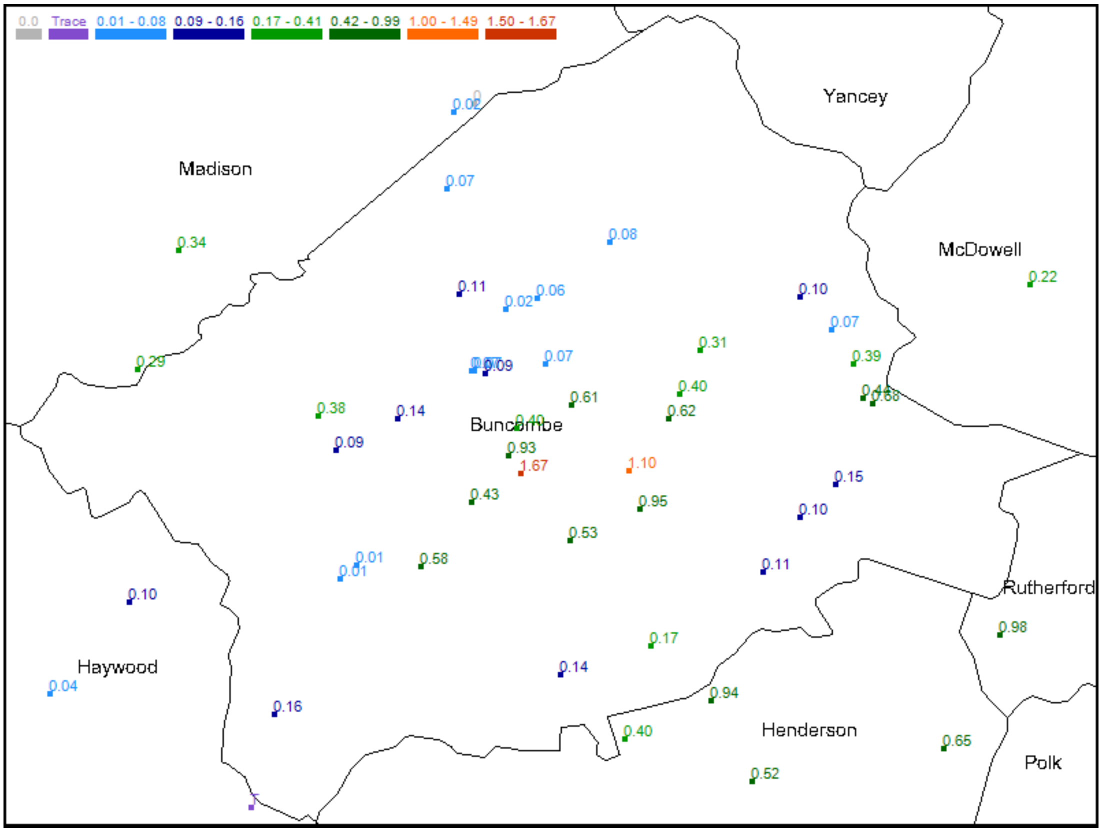

FIG. 3.14: Daily precipitation (inches) reported by volunteer observers for the CoCoRaHS network in Buncombe County, North Carolina for the 24-hr period ending at 0700 EDT 13 June 2015.

due to the nature of precipitation both in models and in reality, the quantity and location of the precipitation at point locations is still prone to large errors stemming from a number of factors (Ebert and McBride 2000). Indeed, the poor performance of the NARR cloud cover data supports the conclusion that three-hourly precipitation totals for a particular grid point may not realistically capture hourly precipitation.

A reasonable solution given sufficient spatial coverage of hourly observations could involve filling gaps in hourly precipitation data with hourly rainfall totals from the nearest ISD location with a valid hourly observation. However, the coverage of hourly observations across North Carolina remains sparse compared with the enormous spatial variability inherent in precipitation patterns, particularly early in the 1979–2013 period of record. Indeed, the state's driest and wettest locations (downtown Asheville and Lake Toxaway, respectively) are separated by only 40.6 miles (65.3 km). Considering only stations with reasonably complete observations for the entire period of record (1979–2013), the nearest ISD location to the Asheville Regional Airport (station 03812), for example, is the Greenville–Spartanburg International Airport (station 13886) in Greer, SC, a full 41.5 miles (66.8 km) away, 1198 feet (365 m) lower in elevation, and climatologically *very* different. Therefore, neither a NARR-derived precipitation estimate nor a nearest-neighbor approach using hourly observations nor spatial smoothing algorithms seem appropriate for filling gaps in hourly precipitation data.

The daily precipitation total from the GHCN-Daily data provide much better spatial coverage than the ISD data at the expense of temporal resolution. The gap-filling technique employed here involves using the daily precipitation total from the nearest GHCN-Daily station to estimate hourly precipitation with the help of the NARR data, subject to the following constraints:

1. The algorithm sets the daily rainfall total for either an entirely or partially gap-filled 24-hr period equal to the daily rainfall total at the nearest GHCN-Daily station (i.e., the new daily total may not exceed or fall short of the observed daily rainfall total at the nearest GHCN-Daily site, excluding measured hourly trace amounts). Of course, any actual measurements during the 24-hr period remain unchanged. If the nearest GHCN-Daily site measures no precipitation and no trace amount, then all of the missing hours receive estimates of zero precipitation. If the sum of the valid hourly ISD measurements during the 24-hr GHCN-Daily observation period meets or exceeds the GHCN-Daily total, the algorithm fills gaps with zero accumulation. The analysis accounts for varying observation times in the GHCN-Daily record, though it truncates the minutes in the rare instances where observations occur on the half hour (e.g., “1230 UTC” becomes “1200 UTC”).

2. Since the NARR data likely provide a fair measure of whether or not precipitation has fallen in a given three-hour period (but not necessarily the quantity), the NARR

three-hour precipitation totals help to determine the timing of the precipitation. The algorithm scales the three-hourly NARR totals (upward or downward) linearly, to the nearest hundredth of an inch, during the gap such that the daily totals in the NARR data match the GHCN-Daily observations. For example, if 40% of the daily precipitation at the nearest NARR grid point falls during the 1200–1500 UTC time frame, then the algorithm assigns 40% of the daily total observed at the nearest GHCN-Daily station to those three hours. The timing of the GHCN-Daily observations may vary, so the daily NARR totals equal the sum of the disaggregated and scaled hourly NARR values over the same 24 period as that covered by each GHCN-Daily observation.

3. For short-term gaps, if no precipitation occurred in the NARR data during the gap, but NARR precipitation fell at some point during the 24-hr period of the GHCN-Daily total, the algorithm assigns the entire difference between the GHCN-Daily total and the ISD hourly total to the last hour of the gap, filling the other hours with zeros. If the observed ISD values exceed the GHCN-Daily total during the period, the algorithm fills the entire gap with zeros.

4. If the nearest GHCN-Daily observation indicates that precipitation fell during the day, and the nearest value from a NARR grid point or ISD site does not show any precipitation during that 24-hr period, then the analysis will move to the next nearest NARR grid point or ISD site and so on through the 12th-nearest NARR grid point or ISD site until it finds a NARR period or ISD observation with precipitation. This procedure gives some allowance for the incorrect placement of precipitation in the NARR data. If no precipitation fell during that 24-hr period at any of the nearest 12 NARR grid points or ISD sites, then the entire GHCN-Daily daily total is assigned only to the 0000 UTC hour for a completely missing day or to the last hour of a short gap. The approach in this last condition is based on two plausible assumptions.

Either 1) the precipitation fell at the beginning or end of a rainfall event that occurred primarily on an adjacent day or 2) the NARR did not capture a convective event in which all of the precipitation likely fell in a single hour. Since thunderstorms tend to occur most frequently in the late afternoon, 0000 UTC is a reasonable hour in which to assign such convective precipitation. Since there remains no way to tell the difference between a multiday precipitation event (which the NARR should capture anyway) and consecutive days with afternoon thunderstorms, assigning the entire precipitation total to the 0000 UTC hour seems like a sensible approach.

5. If the scaled hourly precipitation total becomes less than 0.01 in (0.254 mm) for any non-native NARR hour (e.g., 0100, 0200, 0400, 0500, 0700, etc.), then the algorithm adds the accumulation to the next consecutive hour if it too is missing. If the next hour is not missing, the hourly result becomes a trace. The algorithm assigns a trace to accumulations remaining less than 0.01 in (0.254 mm) and ending at a native NARR hour (i.e., every third hour including 0000 UTC). For long gaps, this approach results in light or trace precipitation every three hours in the filled time series, similar to measurements by a tipping bucket rain gauge. Without this approach, small hourly totals would result in an unrealistic frequency of trace accumulations in many consecutive hours. Trace amounts do not count against the daily total precipitation estimate so that the daily total remains equal to the GHCN-Daily observation.

6. If the nearest GHCN-Daily station records a trace of precipitation, then the algorithm assigns a trace to all missing native hours with non-zero NARR precipitation and assigns zero accumulation to all other missing hours. This prevents excessive trace precipitation estimates during a single 24-hr period.

The only exception to the constraints outlined here applies to stations with missing data on the first day in the 1979–2013 period of record. Since no NARR data exist to inform the timing of precipitation prior to 0000 UTC 1 January 1979, the algorithm estimates

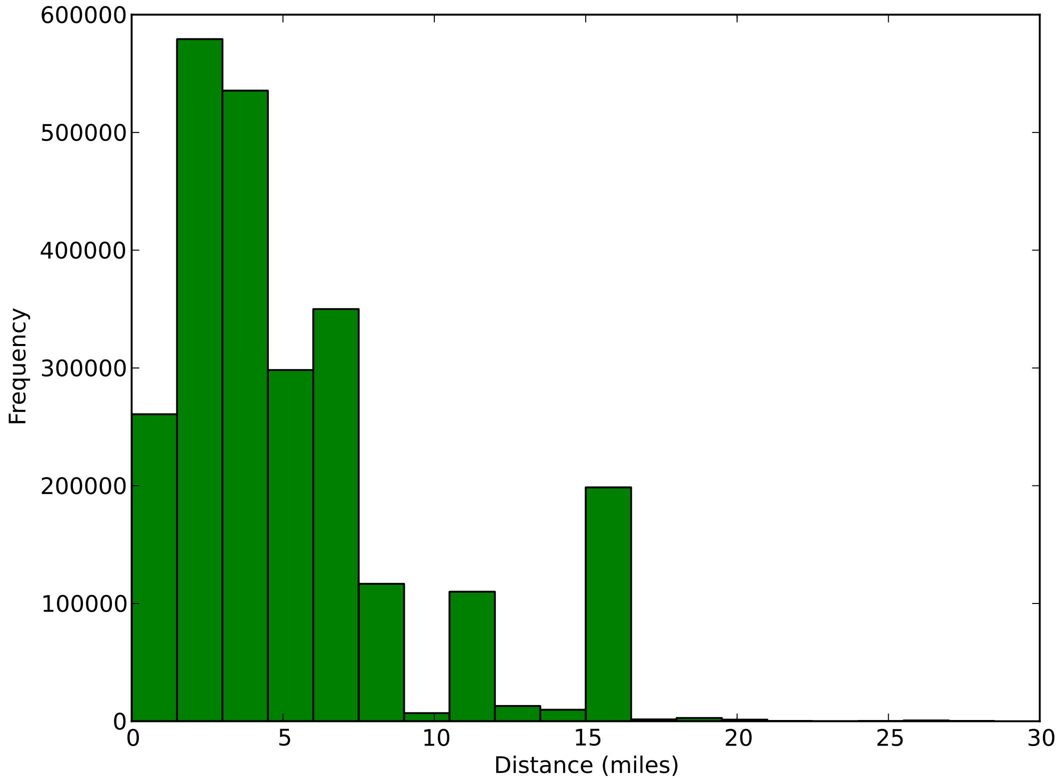

FIG. 3.15: Distance from the subject station to the nearest valid GHCN-Daily precipitation observation site for all hours with missing precipitation data at 41 stations in and near North Carolina.

precipitation by substituting unscaled NARR data from the closest NARR grid point to the subject station if the nearest GHCN-Daily site reports non-zero precipitation for this first day that exceeds the shortened NARR total.

Sometimes, the nearest available GHCN-Daily station with valid precipitation data changes and the observation time changes to a later time in the day. If this happens, an unfilled gap appears because the daily observations only cover a 24-hr period. To address this, the algorithm uses data from the previous day at the next closest station with valid data to fill in the gap for the previously-unfilled precipitation values.

Figure 3.15 illustrates the distances between subject stations and the nearest GHCN-Daily sites tapped to provide precipitation data for the gap-filling algorithm for all 41 stations included in the set of new HCD files developed here. This figure does not show a handful of outliers that extend to the farthest distance of 40 miles (64 km). The majority of nearby GHCN-Daily sites (75%) lie within 6.2 miles (10.0 km) of the subject site, which implies that the hourly precipitation estimates provide at least a reasonable representation of the actual precipitation. In Charlotte (station 13881), for example, the daily precipitation measurements only 164 feet (0.05 km) away helped to fill in all 404 missing hourly precipitation observations during the study period.

4. Quality Assurance

All climate data, whether directly observed or inferred, must undergo strict quality control procedures to check for internal consistency and extreme values before inclusion within the final HCD files. The quality assurance algorithm implemented here addresses two primary issues—errors with kriging estimates for temperature, dewpoint, and wind speed; and remaining data quality problems after the initial, less-strict quality control of each observational dataset. The procedure outlined in section 3.6 ensures high-quality precipitation data. For the remaining variables, the algorithm performs the following procedures:

1. Smooths out anomalous spikes by comparing each hourly observation with the adjacent hours, followed by a comparison with the penadjacent hours (two away on either side). The spikes mainly derive from the temporally-independent nature of the kriging estimates. Recall that each estimate is made with the help of an algorithm that automatically selects the variogram model based on the observed variogram at each hour because the millions of required estimates preclude the use of the usual hand-picked analysis parameters that work best for each individual situation. Without human intervention in the selection of the parameters for the variogram model, the resulting kriging estimates have the potential to vary widely from hour to hour. While large errors occur only for a small percentage of the total number of kriging estimates, it remains very important to correct for the unrealistic spikes that occur in the time series for each variable. For both temperature and dewpoint estimates, the threshold for identifying a spike is a rise of at least 8.1°F (4.5°C) in one hour, followed by a drop of the same magnitude in the next hour. The algorithm also checks

for unrealistic spikes in the observations, where the threshold for identifying bad values is 16.2°F (9.0°C). Intermediate thresholds catch bad temperature and dewpoint observations shortly before a sensor dies. The algorithm removes hourly wind speed estimates that increase by more than three times the previous wind speed or by 10 m s^{-1}, whichever is greater, and hourly wind speed observations that increase by the greater of either ten times the previous estimate or 30 m s^{-1}. For spikes covering two consecutive hours, the thresholds increase by a factor of 1.5. The algorithm removes bad values and replaces them with a linear interpolation between valid values before and after the run of bad data. The smoother makes three successive passes through the data, each time checking for anomalous spikes.

2. Ensures that all values adhere to physical bounds. The algorithm makes sure that the dewpoint remains less than or equal to the temperature after making any other necessary quality-control adjustments for temperature and that the percentage of sunshine is between 0% and 100%.

3. Checks for temporal continuity so that each time series represents all hours in the correct order.

4. Checks each observation or estimate against records of state temperature extremes observed during the month and year under consideration. The algorithm removes and linearly interpolates over any estimate or otherwise valid temperature that falls outside the bounds of an official monthly state extreme if an estimate exceeds that extreme by more than 1.8°F (1.0°C) or if an observation exceeds the official extreme by more than 3.0°F (1.7°C). Estimates of temperature that exceed a state extreme by less than 1.8°F (1.0°C) are set equal to the extreme.

5. Checks hourly temperatures against observed maximum and minimum temperatures at the nearest GHCN-Daily site. Comparisons include a very generous 8.5°C km^{-1} lapse-rate adjustment for differences in elevation and account for varying GHCN-

Daily observation times. Tests show that typical differences across North Carolina between observed daily maximum and minimum temperatures and the corresponding values at the nearest GHCN-Daily site (usually several km away) do not exceed about 5.4°F (3.0°C). Above that threshold, examples include both plausible values and clearly incorrect ones. Therefore, the algorithm removes *estimates* that exceed this threshold and linearly interpolates the adjacent valid values to fill in the gap. No adjustment is made in instances where the observed GHCN-Daily maximum temperature on a given day is less than the minimum temperature on the previous day and vice versa. The algorithm also flags as suspect any otherwise valid observations if they exceed twice this threshold at 10.8°F (6.0°C), but allows those observations to remain in the data. Even so, the algorithm flags as suspect only a small percentage of the temperature observations. At 0.1%, by far the largest percentage of suspect temperature observations occurs at Goldsboro, NC (station 13713).

6. Looks for sudden and rapid increases or decreases associated with a dying temperature or dewpoint sensor and linearly interpolates between reasonable data on either side of up to eight consecutive bad values.

7. Flags wind speeds in excess of the threshold for a category 2 hurricane (42.5 m s^{-1}) for manual inspection.

The quality assurance algorithm corrects for both inappropriate kriging estimates and poor-quality data that has passed the NCDC quality assurance algorithms, including many examples with dying sensors and sensor malfunctions. The algorithm automatically makes adjustments, but in a handful of cases, questionable ISD and GHCN-Daily observations of temperature, dewpoint, wind speed, and precipitation required manual inspection and removal.

5. Historical Climate Data Files

5.1 Notable concerns with the original HCD files

Other authors have found that environmental influences significantly impact pavement performance predictions, including Johanneck et al. (2010), who also recommend rigorous quality control and the elimination of stations with missing data within the climate database intended for use with the Pavement ME Design software. In the course of the current investigation, several specific problems emerged with respect to the original HCD files.

The original HCD files do not have observations listed at the correct times. In meteorology, both humans and automated observing systems make an hourly observation about seven minutes before the hour. For example, the conditions observed and reported at 11:53 a.m. correspond with the noon observation. The original HCD files instead truncate the minutes for each observation, such that the noon observation appears in the data as the 11 a.m. observation, even after accounting for time zones and the fact that all times refer to local standard time. This has consequences for the calculation of heat fluxes that depend upon the quantity of incoming solar radiation determined within the EICM. Correcting the HCD files by simply shifting the original data forward by one hour allows a test of the impact of this error. Comparisons between Pavement ME Design predictions with the original and corrected HCD files for various pavement types show minimal errors (Figs. 5.1–5.4). For example, the simulation for the concrete pavement project shown in Figure 5.4 yields a predicted IRI of 141.0 in/mi, mean joint faulting of 0.081 inches, and JPCP transverse cracking of 4.39% after 30 years with the original climate data. The revised climate data

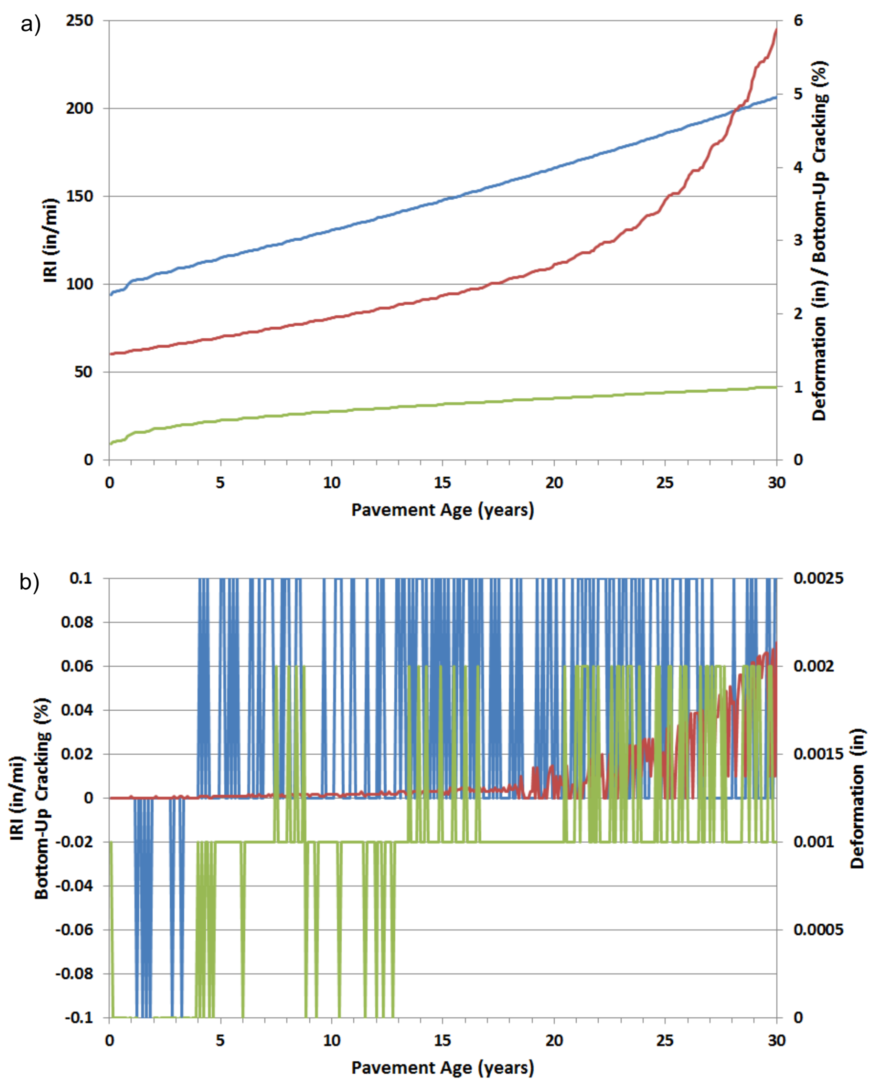

FIG. 5.1: Sensitivity of Pavement ME Design simulations to a one-hour shift in hourly climate data for an Interstate 440 project in Wake County. a) Pavement performance measures calculated with the original Raleigh-Durham HCD file (station 13722) for an aggregate base course (ABC) pavement structure and b) differences (corrected minus original) between performance measures calculated with the original and time-corrected HCD files. Both panels show IRI (blue), total pavement deformation (green), and bottom-up cracking (red).

change the results to a predicted IRI of 139.5 in/mi, mean joint faulting of 0.079 inches, and JPCP transverse cracking of 4.25% after 30 years. These reduced predicted stresses after 30 years are the same as the values produced by the simulation with the original climate data after only 29 years and 1 month.

In addition, the original HCD files contain some questionable data. For example, the

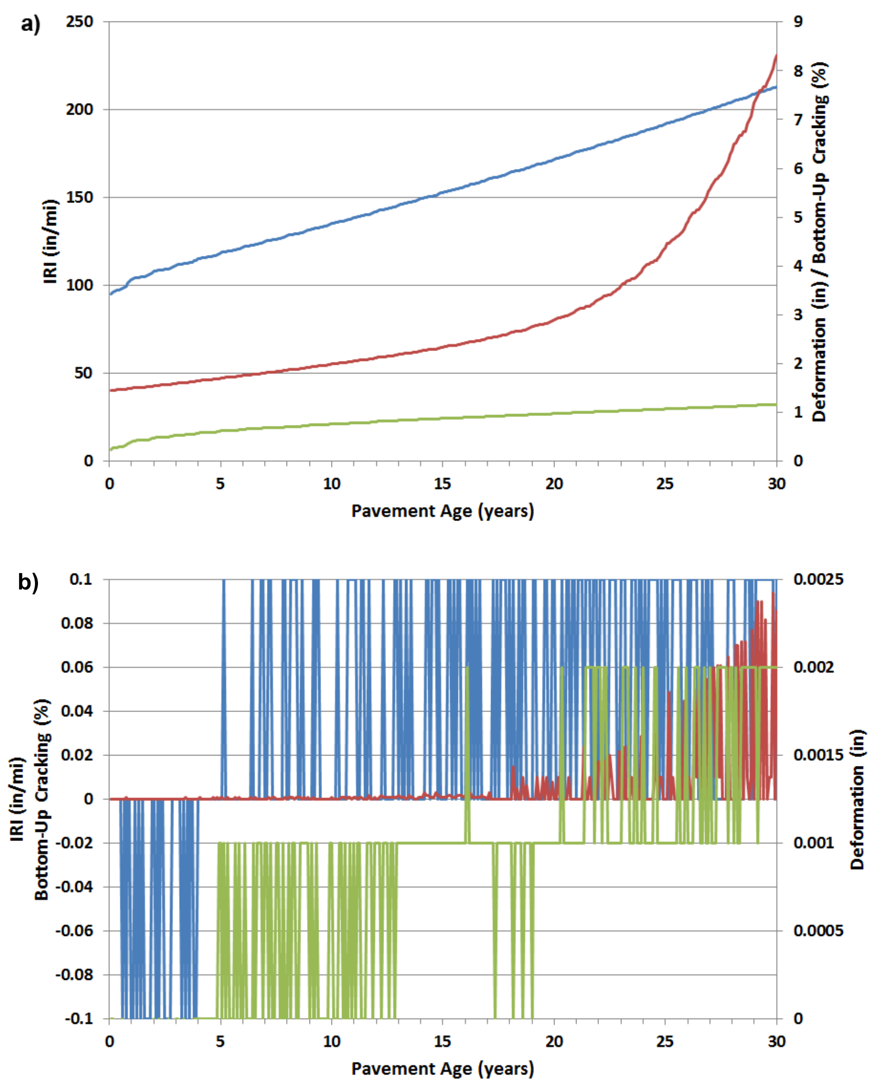

FIG. 5.2: As in Fig. 5.1, but for a cement-treated aggregate base course (CTABC) pavement structure.

relative humidity suddenly drops to unrealistic values (generally 0–13%) for 23 hours at Raleigh/Durham (station 13722) on 18 August 1996 before recovering to more reasonable values. Inspection of the ISD data indicates that this problem stems from the inclusion of both suspect and missing dewpoint observations in the construction of the original HCD time series. This problem is not unique. Unreasonable spikes also exist in the original HCD files. Examples include cases where the temperature unrealistically rises to 122°F from 57°F and falls back to 44°F before rising again to 67°F in consecutive hours at Rocky

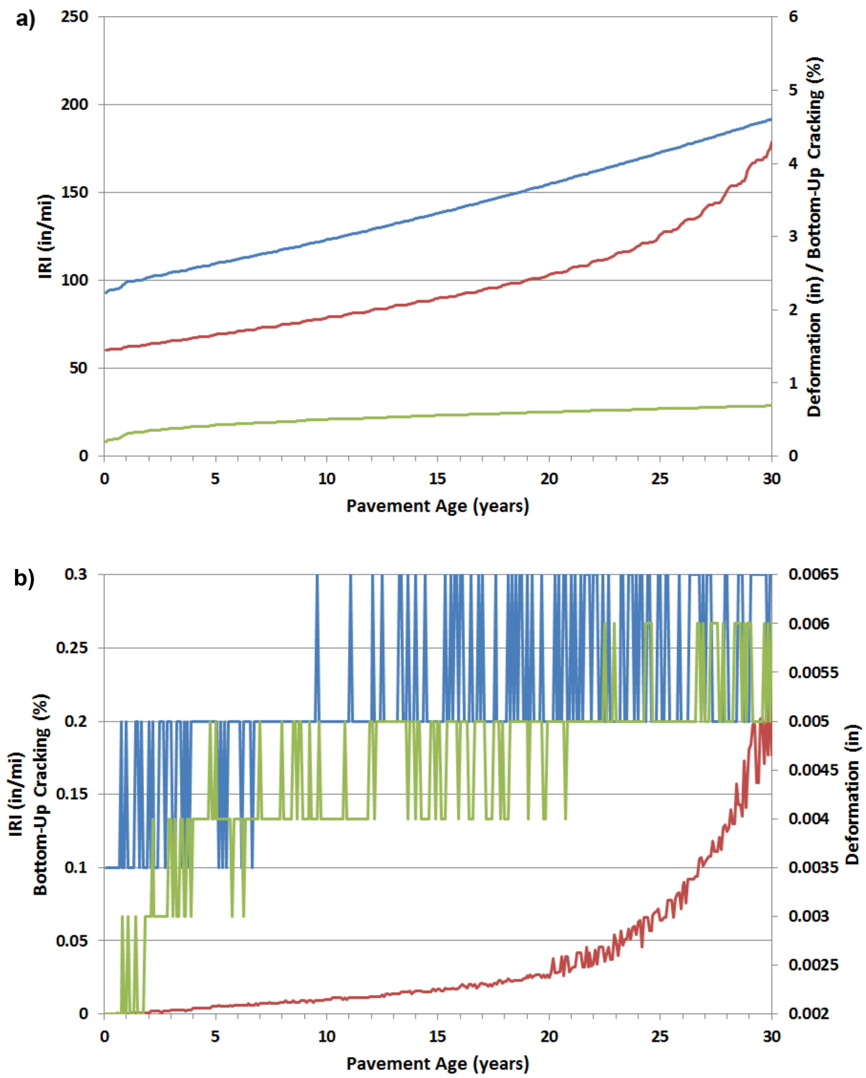

FIG. 5.3: As in Fig. 5.1, but for a full depth asphalt (FDA) pavement structure.

Mount (station 93759) on 7 March 2002 and where the temperature conspicuously drops to 0°F from 73°F before slowly recovering at Cape Hatteras (station 93729) on 15 October 2003. A wind speed value suddenly jumps from a light breeze to 74 m.p.h. and back again on 25 September 2002 at the Asheville Regional Airport (station 03812), yet the ISD data show no such gust. Hourly precipitation jumps from zero to 23 inches or more (up to 63.8 inches) and back to zero in several instances. The summary in Table A.1, described in section 5.2, contains some of these outliers.

More concerning is the lack of any temperature value at all for select hours at 15 of

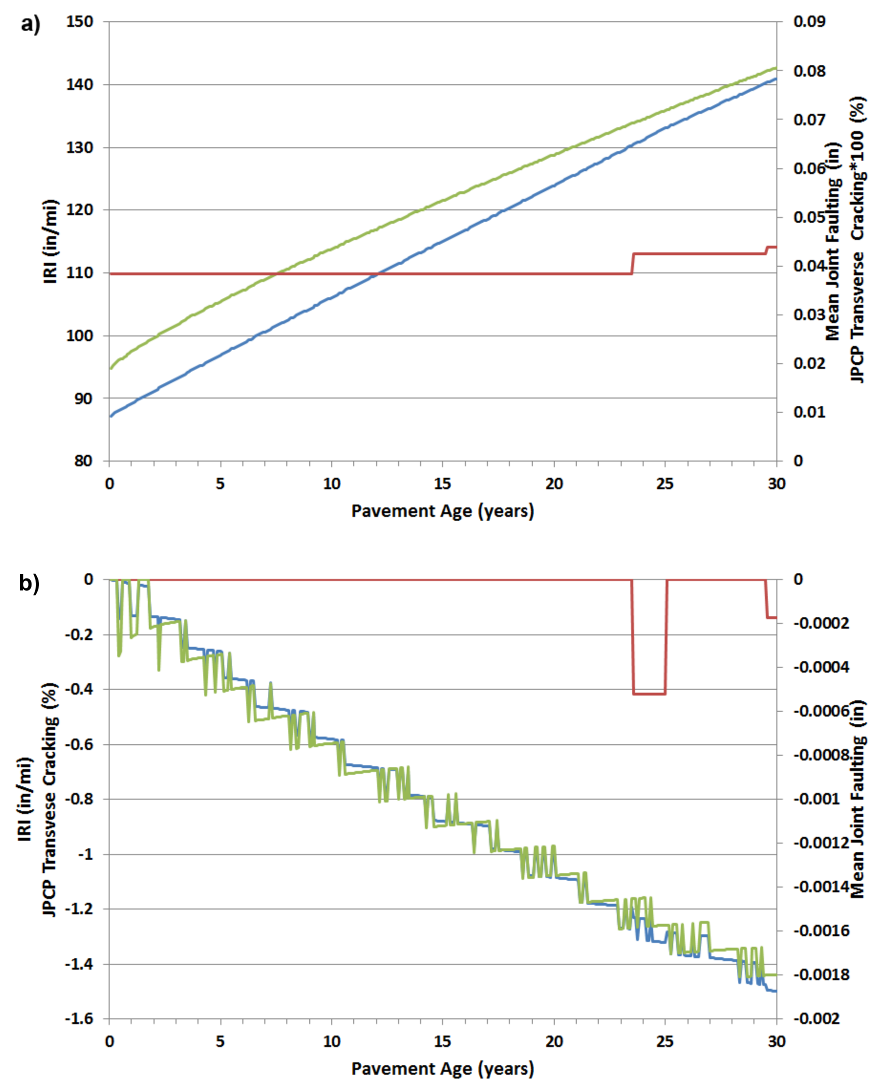

FIG. 5.4: As in Fig. 5.1, but for a concrete pavement structure. Both panels show IRI (blue), mean joint faulting (green), and JPCP transverse cracking (red).

the 30 original North Carolina and nearby station locations analyzed here. The MEPDG software most likely interprets a blank data value as 0°F, which may impact pavement performance predictions, particularly when the problem occurs in the summer when the temperature instantly drops below freezing before recovering to a very warm temperature in a subsequent hour. At Florence, SC, for example, this problem persists for 48 hours in one instance starting on 15 July 2003. Yet another concern pertains to the occasional appearance of extraneous characters in the wind data instead of numerical values. At station locations across the U.S. and Canada, 41.2% of the original 1083 HCD files contain some combination of missing temperature, relative humidity, or wind data, as well as unrealistic daily precipitation totals.

Two minor concerns arise in comparisons between the long-term HCD files developed here and the original HCD files. One discrepancy between the original HCD files and the new HCD files is that the original files contain integer wind speeds in m.p.h. that are often one m.p.h. less than in the new long-term HCD files. This likely arises because of a rounded conversation factor in the conversion from m s^{-1} to m.p.h. in the original HCD files. Another difference is that the hourly precipitation values in the original HCD files often represent daily totals, generally placed at noon local time on each day with zeros at all other times, whereas the new HCD files contain hourly accumulations distributed throughout the day as outlined in section 3.6.

Lastly, the period of record indicated in the list of stations (the station.dat file) does not necessarily reflect the actual temporal coverage of the corresponding HCD file. For example, the data for station 04734 (Maniwaki, Québec, Canada) span the period between October 1990 and September 1992, but the station.dat entry indicates a complete period of record beginning in January 1953. Future dates also appear in the station.dat file. For example, station 04712 (Montreal, Québec, Canada) has a starting date of January 2028.

All of these concerns highlight the need to develop improved environmental input to the EICM and support the effort involved with the construction of new, long-term, high-quality HCD files.

5.2 Long-term, high-quality HCD files

The procedure outlined above produced 41 HCD files containing high-quality, internally-consistent, and complete hourly meteorological data for the entire period of record from 1 January 1979 through 31 December 2013 (Fig. 5.5). Of this total, 30 files replace data for

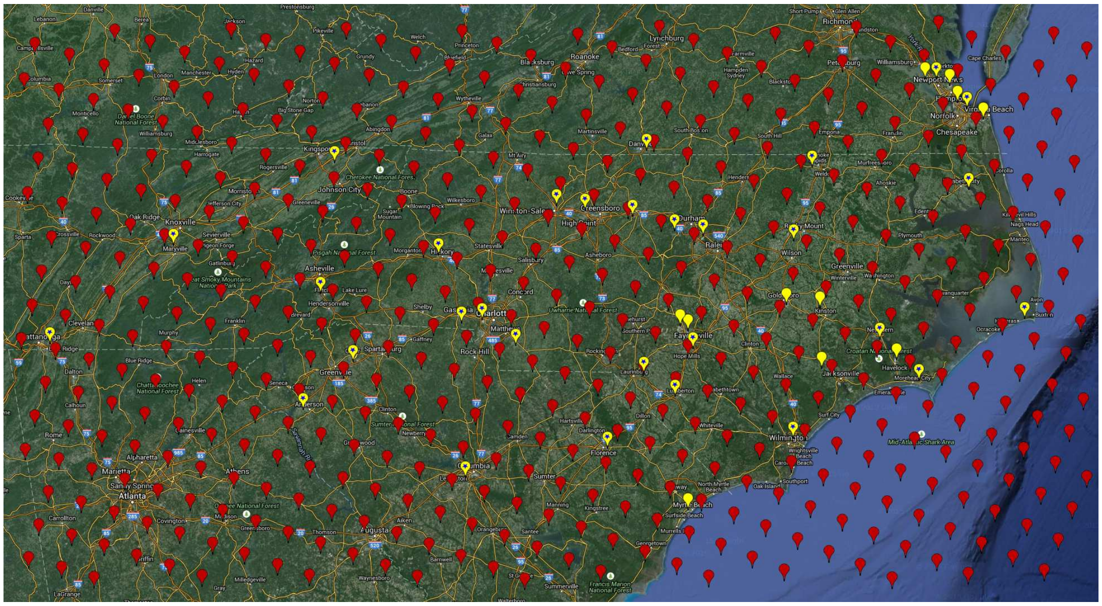

FIG. 5.5: Locations with complete HCD files for the period 1979–2013. Yellow markers indicate locations with hourly observations from meteorological measurement stations. Sites marked with a star represent stations included in the original set of HCD files accompanying the Pavement ME Design software. Data at locations marked in red are solely derived from North American Regional Reanalysis (NARR) data and represent model output with no direct observations.

existing stations in the archives distributed with the Pavement ME Design software and 11 files provide historical climate data for new locations in and near North Carolina. Though some stations are just outside the state line, 26 of the stations fall within the borders of North Carolina. The three main North Carolina climate regions consisting of the mountains, piedmont, and coastal plain each contain 1, 9, and 16 stations, respectively. Refer to Table A.2 in Appendix A for tables that provide a brief assessment of the quality of the data as measured by the percentage of direct observations that compose the entire POR for each station. Stations with a large percentage of direct measurements will likely provide a more accurate picture of the long-term climatic conditions at that location than stations with a large percentage of estimated values.

This work took place under the hypothesis that an extended time series would capture more extremes and would improve the characterization of the long-term climate at each station. Table A.1 lists statistical measures of central tendency, spread, and extremes for each variable in comparisons between the original and the new HCD files at each of the 30 original site locations. In all cases, the longer files contain more extreme values, while standard deviations remain similar between each data set.

As a supplement to the HCD files at stations where actual observations take place, 847 HCD files built solely from temporally-interpolated three-hourly NARR data can help to fill in gaps in regional coverage (Fig. 5.5). The difference between these files and those built from a combination of observations and spatial interpolations as outlined above is that both cloud cover and precipitation, as well as temperature, dewpoint, and wind speed, correspond directly with gridded NARR model output fields. Since these data files contain no actual observations, they should be used with caution and only as a supplement to the information provided by the stations marked in yellow in Figure 5.5. Pavement design locations that are relatively close to a yellow marker should use the observed data.

6. Pavement ME Design Sensitivity Analysis

Comparisons of pavement distresses and smoothness over the design life of several projects across North Carolina lend insight into the impact of the high-quality, continuous, long-term historical climate data files in the final pavement performance predictions by the AASHTOWare Pavement ME Design software (version 2.1). These sensitivity tests involve 17 unique sites (two in the mountains, eight in the piedmont, and seven in the coastal plain climate regions) in North Carolina, repeatedly drawing climate data from nine different locations, with various design selections that include eight concrete, 16 ABC, one CTABC, and 16 FDA pavement projects, for a total of 41 different design projects. In each case, the MEPDG software received both the original HCD files (hereafter referred to as “baseline” simulations) and the improved HCD files (hereafter referred to as “new” simulations) to produce pavement performance predictions.

Tables A.3, A.4, A.5, and A.6 in Appendix A detail the results of the comparisons between the baseline and new simulations of performance criteria for each project and pavement type. In each case, the design reliability indicates the probability that the actual distress levels will not exceed the pavement performance predictions over the design period (AASHTO 2008). In other words, reliability refers to the percentage of actual road samples that would not reach the predicted distress level. The target value for each performance criterion and project varies according to the requirements for each project. For example, the target distress for the X-2BB Cumberland County concrete project in Table A.3 is 15% JPCP transverse cracking at 90% reliability. These tables also list the percentage difference between the baseline and new simulations and whether or not the particular designs pass or

TABLE 6.1: Summary measures for differences (new minus baseline) in pavement distress for each pavement type. MAE refers to the mean absolute error. Two-tailed *p* values correspond with *t* distribution probabilities for differences of mean for paired samples. Bold *p* values are statistically significant at the 95% level. Performance criteria include terminal IRI (inches mile^{-1}), mean joint faulting (inches), JPCP transverse cracking (percentage of slabs), permanent deformation (inches) for both the total pavement structure and only the AC contribution, AC bottom-up and top-down fatigue cracking (feet mile^{-1}), and fatigue fracture in the chemically stabilized layer (%).

Performance Criterion	n	Mean (bias)	MAE	Median	Sample std. dev.	*p* value
Concrete						
Terminal IRI	8	−4.057	4.815	−3.384	4.645	**0.043**
Mean joint faulting	8	−0.004	0.006	−0.003	0.007	0.110
JPCP transverse cracking	8	−2.189	2.199	−1.978	1.691	**0.008**
ABC						
Terminal IRI	16	0.720	1.797	0.699	2.493	0.266
Perm. deform. – total	16	0.010	0.026	−0.003	0.043	0.383
Perm. deform. – AC	16	0.005	0.022	−0.005	0.042	0.645
AC bottom-up fatigue	16	1.363	2.305	0.114	5.222	0.313
AC top-down fatigue	16	118.240	194.026	10.142	385.639	0.239
CTABC						
Terminal IRI	1	−0.021	0.021	−0.021	—	—
Perm. deform. – total	1	−0.006	0.006	−0.006	—	—
Perm. deform. – AC	1	−0.013	0.013	−0.013	—	—
AC bottom-up fatigue	1	−0.006	0.006	−0.006	—	—
AC top-down fatigue	1	−85.839	85.839	−85.839	—	—
Chem. stab. – fatigue	1	0.140	0.140	0.140	—	—
FDA						
Terminal IRI	16	−0.319	1.496	0.196	2.186	0.568
Perm. deform. – total	16	−0.012	0.024	−0.009	0.035	0.202
Perm. deform. – AC	16	−0.010	0.015	−0.010	0.017	**0.034**
AC bottom-up fatigue	16	−0.136	1.073	0.051	2.970	0.858
AC top-down fatigue	16	6.447	17.747	−0.253	31.578	0.427

fail based on the target criterion at the specified reliability. This analysis does not consider asphalt concrete (AC) thermal cracking predictions because the MEPDG software does not properly handle the predictions for this distress type.

The eight concrete projects generally show less distress with the new HCD files compared with the baseline simulations (Table 6.1). JPCP transverse cracking decreased in all but one project, but even where this distress increases in the I-440 Wake County project, the magnitude of the increase remains small with a change of only $+0.04\%$ of the concrete slabs, or a percentage difference of 0.80%. Similarly, terminal IRI decreases in six of the eight projects and mean joint faulting decreases in seven. In general, the few increases in pavement distress and smoothness with the new HCD files appear relatively small in magnitude compared with the large magnitude of the decreases in pavement distress and smoothness present in the simulations for these concrete projects. A hypothesis test for differences of mean for paired samples using the t distribution allows an objective assessment of these results. Table 6.1 shows that the two-tailed p values allow rejection of the null hypothesis that there is no difference between the baseline and new pavement performance predictions for both terminal IRI and JPCP transverse cracking at the 95% level. Therefore, the improved long-term climate data yield a discernable and statistically significant decrease in both smoothness and transverse cracking that implies that NCDOT may have overdesigned concrete pavement designs developed with the original HCD files.

Overall, the new HCD files have limited impact on the FDA pavement types. Decreases in AC rutting represent the only statistically significant result. Individual comparisons between the new and baseline simulations show mixed results. All performance criteria increase in four of the 16 FDA projects, all decrease in three of the projects, and the remaining nine produce a variety of increased and decreased criteria. Of the FDA projects that reach the terminal IRI target before reaching the end of the design life of the project, the MEPDG software produces both a 0.3% reduction and a 0.3% extension in the 30-year design life for the two projects in Yancey and Northampton Counties (R-2519B and R-2582A), respectively. This is equivalent to a change of only one month in design life for each.

Comparisons between the 16 ABC projects show no statistically significant differences between the baseline and new simulations for any pavement performance criterion. Pavement performance predictions for individual projects, however, can vary substantially between the baseline and new Pavement ME Design simulations, sometimes resulting in failed pavement designs that would have passed with the original HCD files (e.g., AC cracking for project R-2501C in Richmond County) and vice versa (e.g., terminal IRI for project I-3802A in Cabarrus County). Five of the comparisons for the ABC projects yield relatively large changes in predicted AC top-down fatigue with the new HCD files compared with the magnitude of the changes for the same project locations with FDA designs. Three ABC projects show increases for all pavement performance criteria and three show decreases for all criteria. Some ABC projects exhibit large changes in predicted distresses with percentage differences exceeding 40%, but other projects only exhibit small differences. Of the performance criteria that reach the target value at the specified reliability before the end of the design life for both the baseline and the new simulations, project R-3421C in Richmond County exhibits the largest difference in the percentage of the design life at failure with a reduction of 1.9% of the 34-year design life using the new HCD files, or nearly 8 months. While not statistically significant, it remains apparent that the use of the new HCD files in the MEPDG software clearly has some influence on the outcome of the predicted distresses and smoothness for individual ABC projects.

The new HCD files produce decreased pavement distresses and smoothness in the single CTABC project, though this is admittedly a very small sample size. The one exception is that the fatigue cracking in the chemically stabilized layer increases. Unfortunately, a single sample is insufficient to gauge statistical significance.

Since the climatological data vary by station, it could prove useful to compare results for different projects and pavement types that rely on data from the same single meteorological station location to determine whether or not a station influences pavement performance predictions in a systematic way. For each station, Table 6.2 shows two-tailed *p*-values corresponding with *t* distribution probabilities for differences in mean for paired samples for all of the pavement design projects that rely on historical climate data from that single location. For example, Table 6.2 indicates a statistically significant difference in terminal IRI between the baseline and new simulations at the 95% level for the one con-

TABLE 6.2: Two-tailed *p*-values corresponding with *t* distribution probabilities for differences in mean for paired samples for all of the pavement design projects that rely on historical climate data from a single location. Only pavement performance criteria with more than one sample are included. Bold *p* values are statistically significant at the 95% level. Values in parentheses indicate the number of projects included in each statistical test. Pavement performance criteria include terminal IRI (IRI), permanent deformation for both the total pavement structure (Total rutting) and only the AC contribution (AC rutting), AC bottom-up (AC bottom-up) and top-down (AC top-down) fatigue cracking, mean joint faulting (Joint), and JPCP transverse cracking (Transverse).

Station	IRI	Total rutting	AC rutting	AC bottom-up	AC top-down
Charlotte, NC (13881)	0.503 (4)	0.683 (3)	0.624 (3)	0.400 (3)	0.596 (3)
Greensboro, NC (13723)	**0.006 (3)**	0.150 (2)	0.219 (2)	0.294 (2)	0.529 (2)
Winston-Salem, NC (93807)	0.054 (2)	0.117 (2)	0.129 (2)	0.480 (2)	0.506 (2)
Wilmington, NC (13748)	**0.012 (5)**	0.384 (5)	0.294 (5)	**0.002 (5)**	0.142 (5)
Asheville, NC (03812)	0.959 (4)	**0.013 (4)**	**0.002 (4)**	0.410 (4)	0.303 (4)
Raleigh/Durham, NC (13722)	0.143 (6)	0.101 (5)	0.081 (5)	0.304 (5)	0.303 (5)
Hickory, NC (03810)	**0.035 (3)**	**0.049 (2)**	0.092 (2)	0.483 (2)	0.496 (2)
Fayetteville, NC (93740)	0.099 (6)	0.411 (4)	0.349 (4)	0.379 (4)	0.444 (4)
Maxton, NC (93782)	0.386 (2)	**0.015 (2)**	0.102 (2)	0.502 (2)	0.521 (2)

Station	Joint	Transverse
Fayetteville, NC (93740)	**0.039 (2)**	**0.042 (2)**

crete and two flexible pavement projects that rely on data from Greensboro (station 13723). Table 6.2 excludes projects that draw historical data from multiple stations in the baseline simulations due to temporal gaps in the original HCD files. The Pavement ME Design simulations call upon the data from Fayetteville (station 93740) for six projects, including four for flexible pavements. Only Fayetteville provides data for more than one concrete project, so it is the only station with *p*-values for the JPCP transverse cracking and mean joint faulting performance measures, but the statistical tests for terminal IRI include this measure from the concrete pavement projects. There exists no clear influence on any given flexible pavement performance criterion using the data from Fayetteville. Indeed, the sign of each of the changes in pavement performance predictions differs between projects. Yet the differences in JPCP transverse cracking and mean joint faulting for concrete projects that use the Fayetteville data are significant at the 95% level. Even though the four flexible pavement projects that use data from Asheville (station 03812) and the five that use data from Raleigh/Durham (13722) always produce a reduction in both total and AC rutting, as well as a reduction in AC top-down fatigue (longitudinal cracking), only the historical climate data from Asheville produce statistically significant differences in both total rutting and AC rutting. The five projects that use data from Wilmington (station 13748) all show statistically significant increases in both terminal IRI and AC bottom-up fatigue (alligator) cracking. The long-term HCD files from Charlotte (station 13881), on the other hand, do not remotely produce any statistically significant differences in pavement performance measures.

It appears that the new HCD files may in fact have the potential to influence the final pavement performance predictions for certain performance criteria, but that the magnitude, sign, and statistical significance of those changes may depend upon the HCD station selected for the analysis. A larger selection of projects that each draw climatological data from these and other sites could help to show with more certainty whether or not a particular HCD file has a systematic influence on the sign of the differences in the pavement performance criteria between the baseline and new simulations.

7. Conclusions and Recommendations

The previous sections describe the development of long-term, continuous, quality-controlled, hourly historical data for multiple locations across North Carolina for use as input to the EICM within the MEPDG software, with the goal of improving confidence in the resulting pavement performance predictions. As evidenced by the results of the automated quality assurance procedures outlined in section 5.1, the quality of the original HCD files remains sufficiently poor to warrant a recommendation that NCDOT cease further use within Pavement ME Design. These original files may adversely affect pavement performance predictions and the pavement designs based on those predictions. Tests show that similar quality concerns exist for an alarming number (41.2%) of other station locations across the United States and Canada. This conclusion alone makes the development of the improved HCD files a worthwhile effort.

The sensitivity tests in section 6 indicate that concrete pavement projects would likely benefit the most from the improved HCD files. Based on the Pavement ME Design comparisons, it appears that engineers currently overdesign such projects. NCDOT engineers could minimize costs by making small design changes such as reductions in pavement structure layer thicknesses to address this concern.

While all pavement performance predictions change with the introduction of the new HCD files within the MEPDG software, the only statistically significant differences at the 95% level for flexible pavements involve AC rutting in FDA pavement designs. As section 6 explains, the HCD station selected for use within the MEPDG software may influence the magnitude and sign of the differences in pavement performance predictions between the baseline and new simulations. For future projects, therefore, it remains important to select the station that best characterizes the climatological conditions at the project site in order to produce the most reliable predictions.

Recall that the virtual station feature of the MEPDG software allows a user to construct an hourly time series for any location based on an inverse-distance weighting algorithm and a standard tropospheric lapse-rate correction. This approach may produce a realistic time series for very closely-spaced stations, but would generally average out hourly extremes, dilute the hourly temperature gradient in the vicinity of fronts, and would produce particularly poor results in the mountains, along coasts, or across climate regions. In order to provide some guidance about when to use the virtual station feature, it seems prudent to quantify the distance from a meteorological observing station within which that station's observations provide a good representation of the regional weather. In an approach similar to Hubbard (1994), the coefficient of determination (R^2) represents the proportion of the variation at every other GHCN-Daily site that is described or accounted for by the daily observations at a given target location. Systematic errors between two sites do not affect the R^2 value, so elevation differences between sites make no difference in temperature comparisons under the assumption that the lapse rate of temperature remains constant, as in the MEPDG software. To avoid the influence of seasonality, which would artificially inflate the R^2 value, the analysis considers daily data separately for only the months of January and July, following Hubbard (1994). Figures 7.1–7.3 show R^2 values for comparisons between the quality-controlled daily observations at one existing HCD station near the center of each of North Carolina's three climate regions and the surrounding GHCN-Daily observations of maximum and minimum temperature and precipitation for a period spanning 10 years (2000–09). Spatial interpolation between two stations with some measure of confidence would require a reasonably large R^2 value in excess of 0.90, so only these regions are shaded in each subfigure. In all cases, these results show that extension of the daily precipitation beyond a few kilometers from the site would be inappropriate. Daily maximum

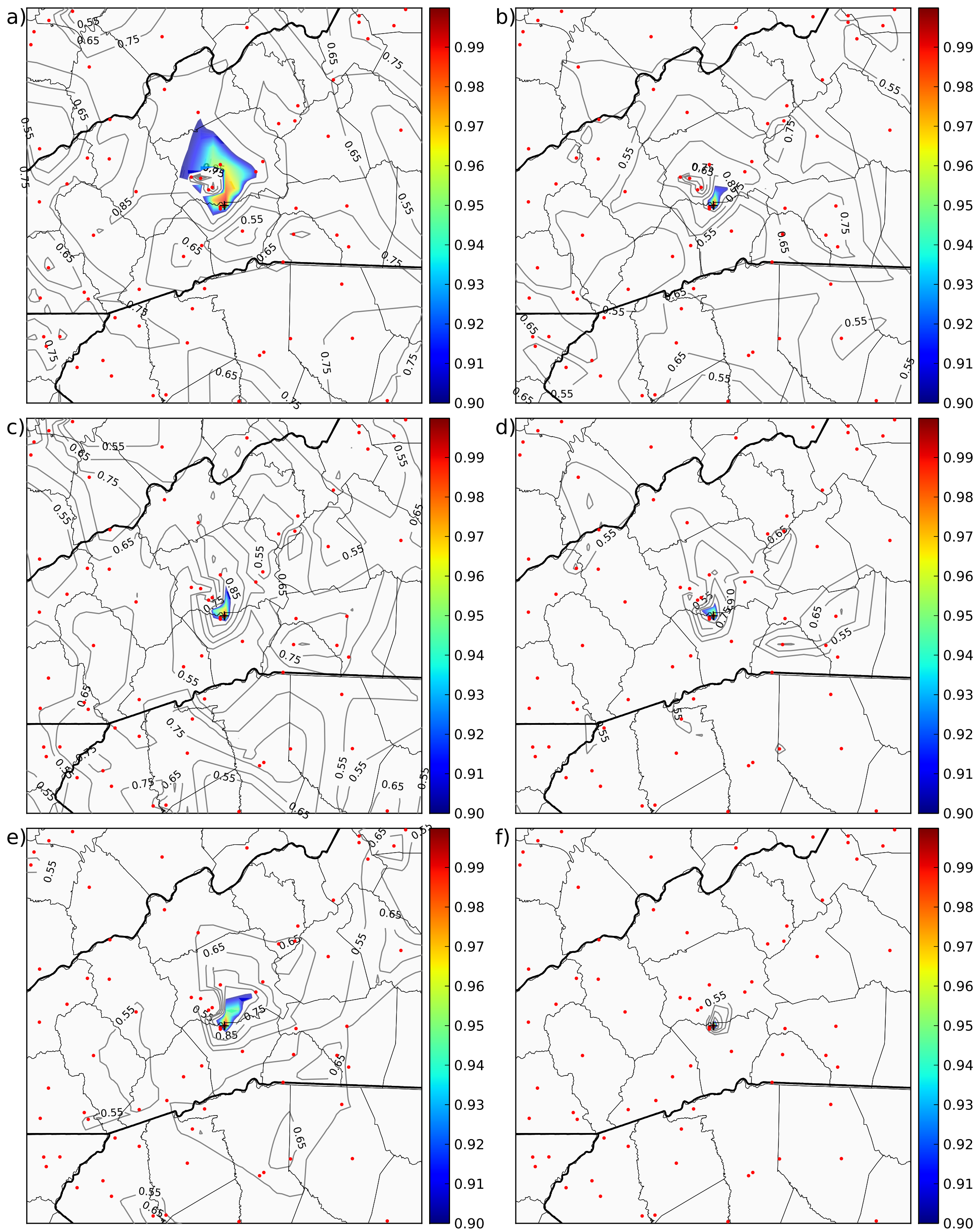

FIG. 7.1: Contoured coefficients of determination (R^2) for daily observation pairs of a) maximum temperature in January and b) July, c) minimum temperature in January and d) July, and e) precipitation in January and f) July at the Asheville Regional Airport (station 03812; '$+$' symbol) and each of the surrounding GHCN-Daily stations (red dots) over the period 2000–09. Shaded regions correspond with $R^2 \geq 0.90$.

and minimum temperatures could be spatially interpolated outward by at most a county or two with reasonable confidence.

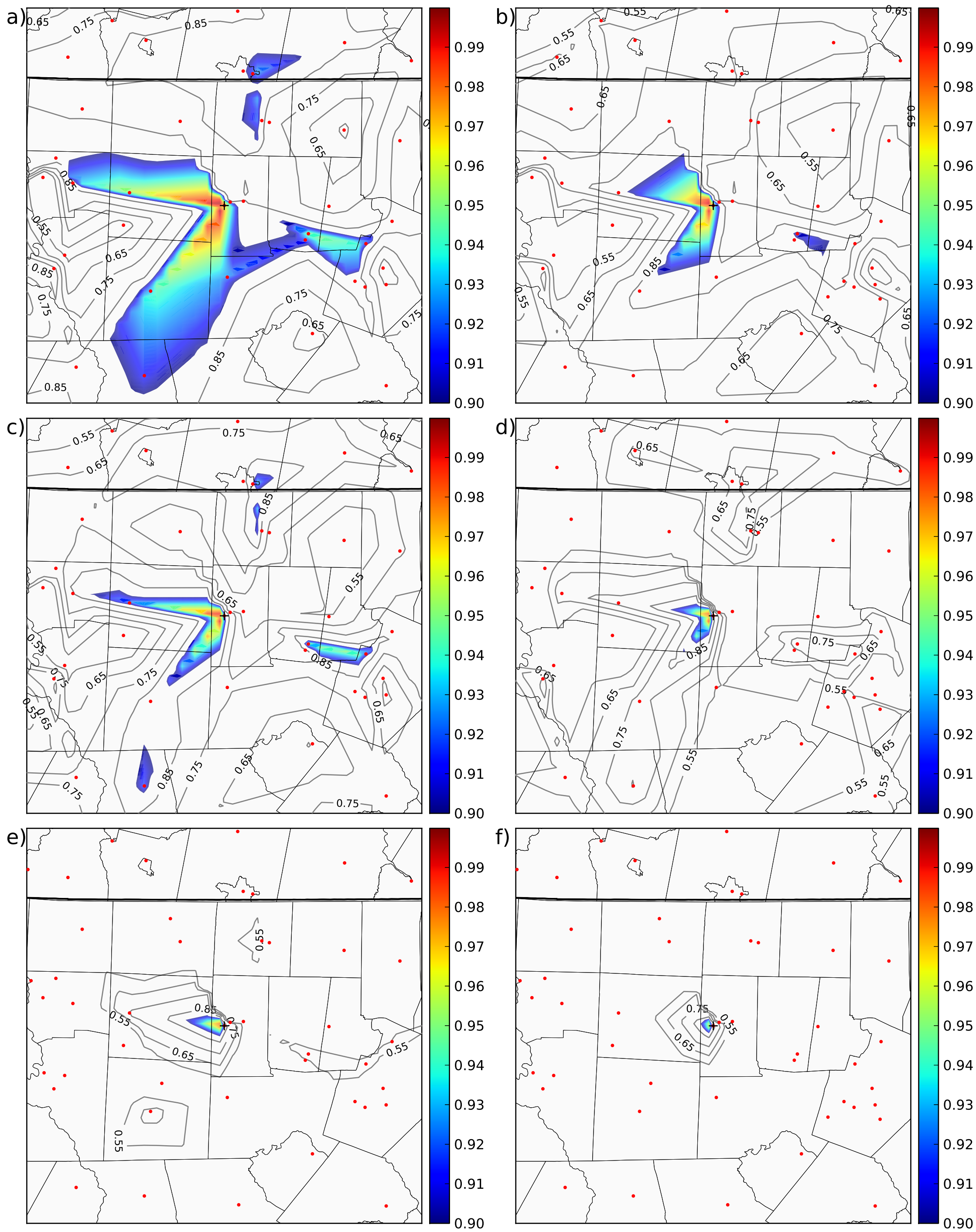

FIG. 7.2: As in Fig. 7.1, but for the Burlington Alamance Regional Airport (station 93783).

Since GHCN-Daily data do not contain information on moisture, wind speed, or cloud cover, the three-hourly gridded NARR data can provide a fair estimate of the mean distance within which the R^2 value first falls below 0.90 for these variables. Table 7.1 lists the

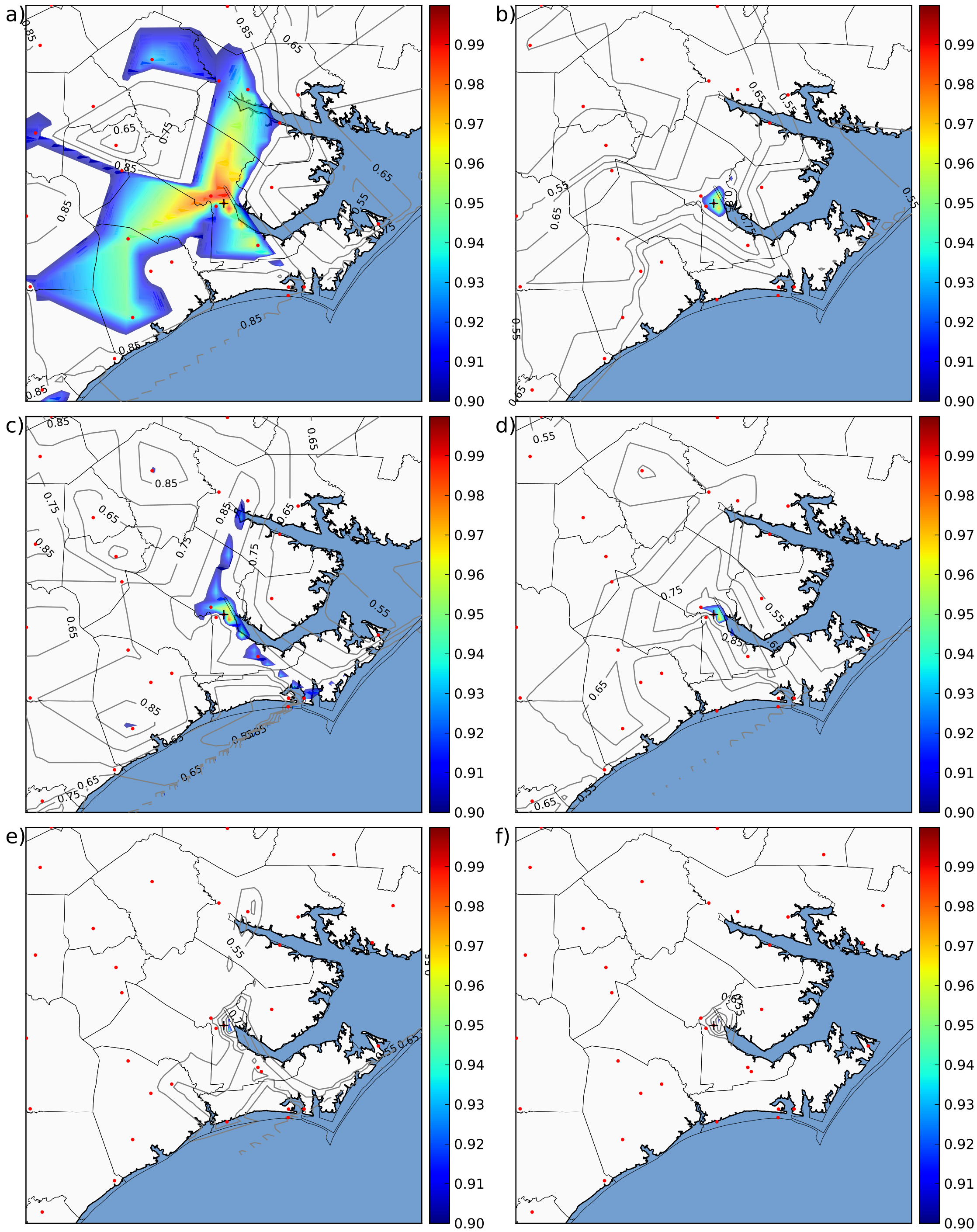

FIG. 7.3: As in Fig. 7.1, but for the New Bern Craven County Regional Airport (station 93719).

limiting distances for three NARR grid points near the approximate center of each climate region for five years of three-hourly NARR data (2000–04), again separated into only two months. For example, $R^2 = 0.862$ for all pairs of January temperatures at grid points be-

TABLE 7.1: Distances within which the coefficient of determination, R^2, first falls below 0.90 in comparisons between NARR variables at one target grid point and surrounding grid points in each of North Carolina's three climate regions. Three-hourly data pairs are grouped into 20-km distance bins for both January and July over the five-year period 2000–04.

Location: Candler, NC Climate Region: Mountains				
	January		July	
Variable	Distance (km)	R^2	Distance (km)	R^2
Temperature	40	0.862	20	0.842
Dewpoint	60	0.877	20	0.800
Wind speed	20	0.814	20	0.827
Cloud cover	40	0.883	20	0.810
Precipitation	40	0.891	20	0.769

Location: Denton, NC Climate Region: Piedmont				
	January		July	
Variable	Distance (km)	R^2	Distance (km)	R^2
Temperature	100	0.899	80	0.895
Dewpoint	120	0.878	40	0.846
Wind speed	20	0.885	20	0.861
Cloud cover	60	0.861	20	0.888
Precipitation	60	0.840	20	0.822

Location: Hookerton, NC Climate Region: Coastal Plain				
	January		July	
Variable	Distance (km)	R^2	Distance (km)	R^2
Temperature	80	0.878	80	0.865
Dewpoint	80	0.876	40	0.897
Wind speed	60	0.719	40	0.887
Cloud cover	60	0.887	20	0.870
Precipitation	60	0.833	20	0.868

tween 20–40 km away from the target grid point in the mountains. These results indicate that a long-distance spatial averaging procedure would likely fail to produce a realistic time series of hourly data. For this reason, the author recommends against the use of the virtual station feature within the MEPDG software. A better approach is to use a nearby HCD station that is climatologically similar to the desired location.

Alternatively, the large quantity of HCD files derived solely from NARR data, representing model output with no direct observations, provide a realistic picture of the climate at hundreds of sites in and near North Carolina (see Fig. 5.5). However, the impact of these HCD files on pavement performance predictions remains untested within the MEPDG software. Such tests would help to determine the feasibility of using these files in remote locations where there may exist large spatial and temporal gaps in hourly data (e.g., northern Maine, western states, Alaska, or even Western North Carolina).

The design projects analyzed in section 6 represent only a small sample for each pavement type. Ideally, a more conclusive sensitivity analysis of the differences in pavement performance predictions using the new and the original HCD files would take advantage of a large number of design projects for each pavement type and a correspondingly large number of projects using each climatological station location. With such a small sample of projects (e.g., one CTABC pavement project), it remains difficult to assess the changes in predicted pavement conditions from a statistical perspective. The use of the t distribution in statistical tests partially mitigates the problem of small sample sizes, but more projects would instill more confidence in the conclusions presented here.

Lastly, a word of caution is warranted regarding the interpretation of the results of the sensitivity analysis. Model developers often calibrate models to produce reasonable results for test cases. The parameters selected for use with the MEPDG software are no exception. Even with an improved characterization of certain parameters, such as climatological data, the resulting predictions by the model can suffer negative impacts and even diverge from reality under the influence of the modified input values. Though one would hope that improving the HCD files would instill more confidence in the pavement performance predictions, one must interpret these results through a lens of healthy skepticism.

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Appendix A. Supplemental Tables

TABLE A.1: Statistical measures for each meteorological time series for both the original (Old) and the new (New) HCD files at each of the 30 original Pavement ME Design site locations. Variables include 2-m air temperature (TAIR, °F), 10-m wind speed (WSPD, m s^{-1}), percentage of possible sunshine (PSUN, %), daily precipitation totals ending at midnight local standard time (PREC, in), and relative humidity (RELH, %). Parentheses indicate removal of missing temperatures, assumed zero, with value shown giving the next lowest temperature in the record. Asterisks (*) indicate unreasonable values in the record. The new 35-yr HCD files have a period of record from 1 January 1979 to 31 December 2013.

Station 03812 (Asheville, NC)										
Original period of record: 1 July 1996–28 February 2006 (9.66 years)										
	TAIR		WSPD		PSUN		PREC		RELH	
	Old	New	Old	New	Old	New	Old	New	Old	New
Maximum	93.9	98.1	74.0*	48.0	100.0	100.0	4.42	4.47	100.0	100.0
Minimum	5.0	−16.1	0.0	0.0	0.0	0.0	0.00	0.00	0.0	8.0
Mean	55.4	55.3	5.3	6.8	59.6	50.0	0.12	0.13	73.8	73.4
25th percentile	43.0	43.0	0.0	3.0	0.0	0.0	0.00	0.00	58.0	57.0
Median	57.0	57.0	5.0	6.0	75.0	50.0	0.00	0.00	79.0	78.0
75th percentile	68.0	68.0	8.0	10.0	100.0	100.0	0.07	0.05	93.0	93.0
Sample std. dev.	16.0	16.4	4.8	5.6	43.8	43.7	0.33	0.35	21.1	21.5

Station 13723 (Greensboro, NC)										
Original period of record: 1 July 1996–28 February 2006 (9.66 years)										
	TAIR		WSPD		PSUN		PREC		RELH	
	Old	New	Old	New	Old	New	Old	New	Old	New
Maximum	97.0	102.9	34.0	47.0	100.0	100.0	4.16	5.11	100.0	100.0
Minimum	7.0	−8.0	0.0	0.0	0.0	0.0	0.00	0.00	11.0	8.0
Mean	58.6	58.6	6.0	7.1	48.9	47.7	0.11	0.11	69.3	67.3
25th percentile	46.0	45.0	4.0	5.0	0.0	0.0	0.00	0.00	53.0	51.0
Median	60.1	60.1	6.0	7.0	50.0	50.0	0.00	0.00	71.0	69.0
75th percentile	72.0	72.0	8.0	9.0	100.0	100.0	0.04	0.03	89.0	86.0
Sample std. dev.	16.6	17.0	4.0	4.4	40.6	42.3	0.32	0.33	21.0	21.1

TABLE A.1: *(Continued)*

Station 13882 (Chattanooga, TN)										
Original period of record: 1 July 1996–28 February 2006 (9.66 years)										
	TAIR		WSPD		PSUN		PREC		RELH	
	Old	New	Old	New	Old	New	Old	New	Old	New
Maximum	100.0	106.0	27.0	46.0	100.0	100.0	5.24	9.49	100.0	100.0
Minimum	7.0	−9.9	0.0	0.0	0.0	0.0	0.00	0.00	0.0	10.0
Mean	60.7	60.4	4.2	5.1	60.3	47.4	0.15	0.15	71.4	70.4
25th percentile	48.0	46.9	0.0	0.0	25.0	0.0	0.00	0.00	56.0	55.0
Median	63.0	62.1	4.0	5.0	75.0	50.0	0.00	0.00	75.0	74.0
75th percentile	73.9	73.9	7.0	8.0	100.0	100.0	0.06	0.06	90.0	89.0
Sample std. dev.	16.8	17.3	4.1	4.7	41.0	42.1	0.37	0.39	20.4	20.5

Station 13744 (Florence, SC)										
Original period of record: 1 April 1999–28 February 2006 (6.91 years)										
	TAIR		WSPD		PSUN		PREC		RELH	
	Old	New	Old	New	Old	New	Old	New	Old	New
Maximum	102.9	106.0	33.0	64.0	100.0	100.0	4.22	4.26	100.0	100.0
Minimum	(9.8)	0.1	0.0	0.0	0.0	0.0	0.00	0.00	11.0	9.0
Mean	63.1	63.3	6.0	7.2	68.8	55.7	0.10	0.05	70.8	69.9
25th percentile	51.0	51.1	4.0	5.0	25.0	12.0	0.00	0.00	54.0	53.0
Median	66.0	64.9	6.0	7.0	100.0	75.0	0.00	0.00	74.0	73.0
75th percentile	75.0	75.0	8.0	10.0	100.0	100.0	0.02	0.00	90.0	89.0
Sample std. dev.	16.1	16.3	3.9	4.5	41.4	43.7	0.32	0.24	21.7	21.2

Station 13877 (Bristol/Johnson City/Kingsport, TN)										
Original period of record: 1 July 1996–28 February 2006 (9.66 years)										
	TAIR		WSPD		PSUN		PREC		RELH	
	Old	New	Old	New	Old	New	Old	New	Old	New
Maximum	99.0	102.0	31.0	62.0	100.0	100.0	3.50	3.50	103.0	100.0
Minimum	5.0	−20.0	0.0	0.0	0.0	0.0	0.00	0.00	0.0	8.0
Mean	55.6	55.6	3.6	4.7	53.6	43.0	0.12	0.11	73.9	71.8
25th percentile	42.1	42.1	0.0	0.0	0.0	0.0	0.00	0.00	59.0	57.0
Median	57.0	57.0	3.0	5.0	50.0	25.0	0.00	0.00	78.0	75.0
75th percentile	69.0	69.1	6.0	7.0	100.0	88.0	0.08	0.08	92.0	89.0
Sample std. dev.	17.1	17.4	4.1	4.7	41.8	41.4	0.29	0.27	19.8	19.9

Station 13722 (Raleigh/Durham, NC)										
Original period of record: 1 July 1996–28 February 2006 (9.66 years)										
	TAIR		WSPD		PSUN		PREC		RELH	
	Old	New	Old	New	Old	New	Old	New	Old	New
Maximum	102.9	105.1	42.0	54.0	100.0	100.0	5.33	5.64	100.0	100.0
Minimum	8.0	−7.1	0.0	0.0	0.0	0.0	0.00	0.00	0.0	8.0
Mean	59.9	60.0	5.2	6.7	45.5	42.3	0.13	0.12	71.3	69.4
25th percentile	46.9	46.9	3.0	3.0	0.0	0.0	0.00	0.00	54.0	52.0
Median	62.0	62.1	5.0	7.0	25.0	25.0	0.00	0.00	74.0	72.0
75th percentile	73.0	73.0	8.0	9.0	75.0	75.0	0.04	0.04	91.0	89.0
Sample std. dev.	16.9	17.1	4.0	4.4	38.9	40.4	0.36	0.33	21.6	21.4

TABLE A.1: *(Continued)*

Station 93785 (Chapel Hill, NC)										
Original period of record: 1 July 1999–28 February 2006 (6.66 years)										
	TAIR		WSPD		PSUN		PREC		RELH	
	Old	New	Old	New	Old	New	Old	New	Old	New
Maximum	100.0	103.2	24.0	36.0	100.0	100.0	5.28	5.23	100.0	100.0
Minimum	(5.1)	−6.1	0.0	0.0	0.0	0.0	0.00	0.00	0.0	10.0
Mean	59.1	59.6	3.8	6.7	70.3	51.7	0.11	0.12	71.1	70.2
25th percentile	46.0	46.4	0.0	4.0	25.0	0.0	0.00	0.00	54.0	57.0
Median	61.0	61.1	4.0	6.0	100.0	50.0	0.00	0.00	74.0	72.0
75th percentile	72.0	73.4	6.0	9.0	100.0	100.0	0.03	0.06	91.0	86.0
Sample std. dev.	16.9	17.2	3.3	4.4	41.2	43.5	0.31	0.34	21.5	17.9

Station 93765 (Beaufort, NC)										
Original period of record: 1 May 2000–28 February 2006 (5.83 years)										
	TAIR		WSPD		PSUN		PREC		RELH	
	Old	New	Old	New	Old	New	Old	New	Old	New
Maximum	94.0	98.1	39.0	48.0	100.0	100.0	5.52	7.89	100.0	100.0
Minimum	(9.0)	8.6	0.0	0.0	0.0	0.0	0.00	0.00	16.0	14.0
Mean	63.4	66.0	8.4	10.9	67.9	51.9	0.15	0.15	77.7	77.2
25th percentile	52.0	57.2	5.0	7.0	25.0	12.0	0.00	0.00	69.0	70.0
Median	66.0	68.0	8.0	10.0	100.0	50.0	0.00	0.00	81.0	79.0
75th percentile	76.0	77.0	11.0	14.0	100.0	100.0	0.05	0.09	90.0	87.0
Sample std. dev.	15.0	12.9	4.8	5.6	39.5	40.7	0.43	0.42	16.0	12.8

Station 03810 (Hickory, NC)										
Original period of record: 1 January 1998–28 February 2006 (8.16 years)										
	TAIR		WSPD		PSUN		PREC		RELH	
	Old	New	Old	New	Old	New	Old	New	Old	New
Maximum	100.9	102.9	25.0	69.0	100.0	100.0	6.31	6.31	100.0	100.0
Minimum	(3.2)	−7.8	0.0	0.0	0.0	0.0	0.00	0.00	0.0	6.0
Mean	58.5	58.7	4.3	5.5	68.3	54.4	0.12	0.07	69.1	68.4
25th percentile	46.0	46.0	0.0	3.0	25.0	0.0	0.00	0.00	51.0	51.0
Median	60.0	60.1	4.0	6.0	100.0	75.0	0.00	0.00	71.0	70.0
75th percentile	71.0	72.0	6.0	8.0	100.0	100.0	0.04	0.00	90.0	88.0
Sample std. dev.	16.3	16.7	3.6	4.2	42.0	44.5	0.34	0.26	21.8	21.9

Station 93740 (Fayetteville, NC)										
Original period of record: 1 April 1998–28 February 2006 (7.91 years)										
	TAIR		WSPD		PSUN		PREC		RELH	
	Old	New	Old	New	Old	New	Old	New	Old	New
Maximum	102.0	109.0	40.0	63.0	100.0	100.0	4.93	4.33	100.0	100.0
Minimum	13.0	−2.7	0.0	0.0	0.0	0.0	0.00	0.00	0.0	7.0
Mean	62.5	62.2	6.4	7.1	68.7	56.4	0.11	0.09	70.0	69.9
25th percentile	50.0	49.7	4.0	5.0	25.0	12.0	0.00	0.00	53.0	53.0
Median	64.9	64.2	6.0	7.0	100.0	75.0	0.00	0.00	72.3	73.0
75th percentile	75.0	75.0	9.0	9.0	100.0	100.0	0.02	0.01	90.0	89.0
Sample std. dev.	16.4	16.7	3.9	4.4	41.6	43.1	0.34	0.30	21.9	21.7

TABLE A.1: *(Continued)*

Station 13881 (Charlotte, NC)										
Original period of record: 1 July 1998–28 February 2006 (7.66 years)										
	TAIR		WSPD		PSUN		PREC		RELH	
	Old	New	Old	New	Old	New	Old	New	Old	New
Maximum	100.0	102.9	34.0	63.0	100.0	100.0	4.14	6.33	100.0	100.0
Minimum	10.0	−5.1	0.0	0.0	0.0	0.0	0.00	0.00	11.0	6.0
Mean	60.4	60.8	4.9	6.6	41.1	41.6	0.11	0.11	69.6	66.6
25th percentile	48.0	48.0	3.0	5.0	0.0	0.0	0.00	0.00	52.0	50.0
Median	62.1	63.0	5.0	6.0	25.0	25.0	0.00	0.00	71.0	68.0
75th percentile	73.0	73.0	7.0	9.0	75.0	75.0	0.03	0.03	90.0	86.0
Sample std. dev.	16.3	16.6	3.4	4.2	37.3	40.5	0.31	0.33	21.7	21.3

Station 93719 (New Bern, NC)										
Original period of record: 1 October 1997–28 February 2006 (8.41 years)										
	TAIR		WSPD		PSUN		PREC		RELH	
	Old	New	Old	New	Old	New	Old	New	Old	New
Maximum	100.0	100.9	32.0	70.0	100.0	100.0	6.52	9.73	100.0	100.0
Minimum	(4.0)	−3.8	0.0	0.0	0.0	0.0	0.00	0.00	0.0	11.0
Mean	61.6	62.4	5.8	6.7	66.3	54.4	0.14	0.08	75.4	73.6
25th percentile	49.0	50.0	3.0	4.0	25.0	0.0	0.00	0.00	61.0	60.0
Median	64.0	64.9	6.0	7.0	100.0	75.0	0.00	0.00	80.0	78.0
75th percentile	74.0	75.0	8.0	9.0	100.0	100.0	0.06	0.00	93.0	90.0
Sample std. dev.	16.0	16.1	4.1	4.6	41.7	43.9	0.40	0.33	19.4	19.5

Station 93807 (Winston-Salem, NC)										
Original period of record: 1 December 1998–28 February 2006 (7.24 years)										
	TAIR		WSPD		PSUN		PREC		RELH	
	Old	New	Old	New	Old	New	Old	New	Old	New
Maximum	98.1	102.0	25.0	63.0	100.0	100.0	5.52	5.52	100.0	100.0
Minimum	(9.4)	−8.1	0.0	0.0	0.0	0.0	0.00	0.00	0.0	5.0
Mean	58.9	58.8	4.8	6.3	66.3	52.7	0.12	0.09	67.1	67.4
25th percentile	46.0	45.7	3.0	3.0	25.0	0.0	0.00	0.00	50.0	53.0
Median	61.0	60.5	5.0	6.0	100.0	75.0	0.00	0.00	67.5	69.0
75th percentile	72.0	72.2	7.0	8.0	100.0	100.0	0.04	0.01	87.0	84.0
Sample std. dev.	16.5	16.9	3.6	4.2	43.0	44.2	0.32	0.28	21.7	19.8

Station 13776 (Lumberton, NC)										
Original period of record: 1 March 1999–28 February 2006 (7.00 years)										
	TAIR		WSPD		PSUN		PREC		RELH	
	Old	New	Old	New	Old	New	Old	New	Old	New
Maximum	102.0	106.0	34.0	38.0	100.0	100.0	7.62	7.41	100.0	100.0
Minimum	13.0	−0.2	0.0	0.0	0.0	0.0	0.00	0.00	13.0	10.0
Mean	62.1	62.5	5.4	7.3	69.5	56.9	0.11	0.12	73.1	73.4
25th percentile	50.0	50.0	3.0	5.0	25.0	12.0	0.00	0.00	57.0	60.0
Median	65.0	64.4	5.0	7.0	100.0	75.0	0.00	0.00	78.0	76.0
75th percentile	75.0	75.4	8.0	10.0	100.0	100.0	0.03	0.04	93.0	89.0
Sample std. dev.	16.5	16.6	4.2	4.5	41.3	43.2	0.37	0.34	21.0	18.2

TABLE A.1: *(Continued)*

Station 13737 (Norfolk, VA)										
Original period of record: 1 July 1996–28 February 2006 (9.66 years)										
	TAIR		WSPD		PSUN		PREC		RELH	
	Old	New	Old	New	Old	New	Old	New	Old	New
Maximum	100.0	104.0	41.0	68.0	100.0	100.0	6.23	8.93	100.0	100.0
Minimum	(8.3)	−2.9	0.0	0.0	0.0	0.0	0.00	0.00	13.0	9.0
Mean	60.4	60.5	7.9	9.8	58.1	50.6	0.13	0.13	73.2	69.8
25th percentile	47.0	46.9	5.0	6.0	25.0	0.0	0.00	0.00	60.0	56.0
Median	62.0	62.1	7.0	9.0	75.0	50.0	0.00	0.00	76.0	72.0
75th percentile	73.9	73.9	11.0	13.0	100.0	100.0	0.04	0.04	89.0	86.0
Sample std. dev.	16.0	16.4	4.8	5.5	38.3	41.5	0.37	0.39	18.5	18.7

Station 93783 (Burlington, NC)										
Original period of record: 1 July 1998–28 February 2006 (7.66 years)										
	TAIR		WSPD		PSUN		PREC		RELH	
	Old	New	Old	New	Old	New	Old	New	Old	New
Maximum	100.0	104.0	28.0	32.0	100.0	100.0	4.10	4.69	100.0	100.0
Minimum	(1.7)	−5.3	0.0	0.0	0.0	0.0	0.00	0.00	0.0	7.0
Mean	58.9	59.2	4.6	7.0	68.7	51.2	0.11	0.12	68.7	69.9
25th percentile	46.0	45.8	0.0	5.0	25.0	0.0	0.00	0.00	51.0	57.0
Median	61.0	60.8	4.0	7.0	100.0	50.0	0.00	0.00	72.0	72.0
75th percentile	72.0	73.2	7.0	9.0	100.0	100.0	0.04	0.05	89.0	85.0
Sample std. dev.	17.3	17.3	3.9	4.3	41.9	43.7	0.33	0.33	21.8	18.1

Station 93782 (Maxton, NC)										
Original period of record: 1 June 1998–28 February 2006 (7.75 years)										
	TAIR		WSPD		PSUN		PREC		RELH	
	Old	New	Old	New	Old	New	Old	New	Old	New
Maximum	102.0	107.1	33.0	40.0	100.0	100.0	4.47	5.72	100.0	100.0
Minimum	(9.1)	−0.3	0.0	0.0	0.0	0.0	0.00	0.00	0.0	8.0
Mean	61.9	62.1	5.6	6.8	70.0	56.7	0.09	0.12	72.5	72.7
25th percentile	49.0	49.4	3.0	4.0	25.0	12.0	0.00	0.00	56.0	60.0
Median	64.0	64.0	5.0	6.0	100.0	75.0	0.00	0.00	77.0	76.0
75th percentile	75.0	75.2	8.0	9.0	100.0	100.0	0.02	0.04	93.0	89.0
Sample std. dev.	16.9	16.7	4.0	4.2	41.5	43.1	0.32	0.33	21.5	18.5

Station 13728 (Danville, VA)										
Original period of record: 1 August 2000–28 February 2006 (5.58 years)										
	TAIR		WSPD		PSUN		PREC		RELH	
	Old	New	Old	New	Old	New	Old	New	Old	New
Maximum	100.0	102.9	28.0	63.0	100.0	100.0	3.12	5.81	100.0	100.0
Minimum	6.0	−9.0	0.0	0.0	0.0	0.0	0.00	0.00	11.0	6.0
Mean	57.2	58.5	4.9	6.4	67.2	51.1	0.11	0.10	70.5	68.4
25th percentile	43.0	44.6	3.0	4.0	25.0	0.0	0.00	0.00	52.0	51.0
Median	59.0	60.1	5.0	6.0	100.0	62.0	0.00	0.00	74.0	71.0
75th percentile	71.0	72.0	7.0	9.0	100.0	100.0	0.04	0.03	92.0	88.0
Sample std. dev.	17.4	17.5	3.9	4.2	42.5	44.3	0.28	0.30	22.3	21.4

TABLE A.1: *(Continued)*

Station 93759 (Rocky Mount, NC)										
Original period of record: 1 October 2000–28 February 2006 (5.41 years)										
	TAIR		WSPD		PSUN		PREC		RELH	
	Old	New	Old	New	Old	New	Old	New	Old	New
Maximum	122.0*	104.0	36.0	66.0	100.0	100.0	4.39	7.53	100.0	100.0
Minimum	(3.9)	−3.8	0.0	0.0	0.0	0.0	0.00	0.00	7.0	8.0
Mean	58.8	60.3	5.2	7.0	70.1	54.0	0.09	0.12	74.6	72.4
25th percentile	45.0	46.9	3.0	5.0	25.0	0.0	0.00	0.00	57.0	57.0
Median	61.0	62.1	5.0	7.0	100.0	75.0	0.00	0.00	79.0	77.0
75th percentile	73.0	73.9	8.0	9.0	100.0	100.0	0.02	0.04	94.0	90.0
Sample std. dev.	17.5	17.2	4.1	4.5	41.0	43.9	0.29	0.33	21.6	20.3

Station 93846 (Anderson, SC)										
Original period of record: 1 November 1998–28 February 2006 (7.33 years)										
	TAIR		WSPD		PSUN		PREC		RELH	
	Old	New	Old	New	Old	New	Old	New	Old	New
Maximum	100.9	106.0	31.0	68.0	100.0	100.0	5.68	4.85	100.0	100.0
Minimum	9.0	−4.9	0.0	0.0	0.0	0.0	0.00	0.00	0.0	9.0
Mean	60.5	61.3	5.1	6.5	69.4	56.8	0.12	0.09	70.6	69.2
25th percentile	48.0	48.9	3.0	3.0	25.0	0.0	0.00	0.00	53.0	52.0
Median	62.0	63.0	5.0	6.0	100.0	75.0	0.00	0.00	74.0	72.0
75th percentile	73.0	73.9	8.0	9.0	100.0	100.0	0.03	0.00	90.0	89.0
Sample std. dev.	16.1	16.5	4.2	4.8	41.9	44.1	0.37	0.29	21.6	21.6

Station 53870 (Gastonia, NC)										
Original period of record: 1 February 1999–28 February 2006 (7.07 years)										
	TAIR		WSPD		PSUN		PREC		RELH	
	Old	New	Old	New	Old	New	Old	New	Old	New
Maximum	100.0	105.1	22.0	31.0	100.0	100.0	3.31	4.70	100.0	100.0
Minimum	5.0	−2.1	0.0	0.0	0.0	0.0	0.00	0.00	0.0	7.0
Mean	60.2	60.3	3.7	6.0	73.1	51.5	0.11	0.12	70.2	70.7
25th percentile	48.0	47.2	0.0	3.0	50.0	0.0	0.00	0.00	53.0	57.0
Median	62.0	61.9	4.0	6.0	100.0	50.0	0.00	0.00	73.0	73.0
75th percentile	72.0	73.7	6.0	8.0	100.0	100.0	0.03	0.04	90.0	86.0
Sample std. dev.	16.3	16.8	3.3	3.9	39.8	43.5	0.30	0.32	21.8	18.3

Station 13748 (Wilmington, NC)										
Original period of record: 1 July 1996–28 February 2006 (9.66 years)										
	TAIR		WSPD		PSUN		PREC		RELH	
	Old	New	Old	New	Old	New	Old	New	Old	New
Maximum	102.9	102.9	51.0	62.0	100.0	100.0	6.77	13.50	100.0	100.0
Minimum	14.0	1.0	0.0	0.0	0.0	0.0	0.00	0.00	14.0	10.0
Mean	63.4	63.4	6.6	7.8	69.3	56.8	0.15	0.15	75.1	73.3
25th percentile	52.0	52.0	4.0	5.0	25.0	0.0	0.00	0.00	62.0	60.0
Median	66.0	66.0	6.0	8.0	100.0	75.0	0.00	0.00	79.0	78.0
75th percentile	75.9	75.9	9.0	11.0	100.0	100.0	0.06	0.05	90.0	90.0
Sample std. dev.	15.5	15.7	4.6	5.1	41.1	43.7	0.46	0.48	19.0	19.2

TABLE A.1: *(Continued)*

Station 93729 (Cape Hatteras, NC)										
Original period of record: 1 July 1996–28 February 2006 (9.66 years)										
	TAIR		WSPD		PSUN		PREC		RELH	
	Old	New	Old	New	Old	New	Old	New	Old	New
Maximum	92.0	98.1	46.0	68.0	100.0	100.0	58.10*	11.42	104.0	100.0
Minimum	(4.1*)	6.1	0.0	0.0	0.0	0.0	0.00	0.00	0.0	12.0
Mean	62.9	63.2	8.3	10.0	71.5	57.9	0.17	0.16	77.7	76.2
25th percentile	52.0	52.0	5.0	7.0	25.0	0.0	0.00	0.00	67.0	65.0
Median	64.0	64.9	8.0	9.0	100.0	75.0	0.00	0.00	81.0	79.0
75th percentile	75.0	75.0	11.0	13.0	100.0	100.0	0.06	0.05	90.0	89.0
Sample std. dev.	14.0	14.3	4.2	5.1	40.4	43.7	1.07	0.49	15.9	15.8

Station 13891 (Knoxville, TN)										
Original period of record: 1 July 1996–28 February 2006 (9.66 years)										
	TAIR		WSPD		PSUN		PREC		RELH	
	Old	New	Old	New	Old	New	Old	New	Old	New
Maximum	96.1	105.1	38.0	43.0	100.0	100.0	3.70	5.75	104.0	100.0
Minimum	5.0	−23.1	0.0	0.0	0.0	0.0	0.00	0.00	0.0	11.0
Mean	59.1	58.8	5.3	6.0	50.0	46.0	0.14	0.13	72.5	71.5
25th percentile	46.0	45.0	3.0	3.0	0.0	0.0	0.00	0.00	58.0	57.0
Median	61.0	61.0	5.0	6.0	50.0	50.0	0.00	0.00	75.0	74.0
75th percentile	72.0	72.0	7.0	8.0	100.0	100.0	0.08	0.07	89.0	89.0
Sample std. dev.	16.8	17.3	4.3	4.7	39.7	41.7	0.34	0.34	19.0	19.5

Station 13883 (Columbia, SC)										
Original period of record: 1 July 1996–28 February 2006 (9.66 years)										
	TAIR		WSPD		PSUN		PREC		RELH	
	Old	New	Old	New	Old	New	Old	New	Old	New
Maximum	104.0	108.0	34.0	62.0	100.0	100.0	5.17	6.45	100.0	100.0
Minimum	13.0	−0.0	0.0	0.0	0.0	0.0	0.00	0.00	11.0	8.0
Mean	63.6	63.4	5.2	6.3	55.5	48.0	0.11	0.09	69.1	68.8
25th percentile	51.1	51.1	3.0	3.0	25.0	0.0	0.00	0.00	51.0	51.0
Median	66.0	66.0	5.0	6.0	50.0	50.0	0.00	0.00	73.0	73.0
75th percentile	76.0	75.9	8.0	9.0	100.0	100.0	0.02	0.00	89.0	89.0
Sample std. dev.	16.4	16.8	4.0	4.6	41.0	41.7	0.33	0.30	21.7	22.1

Station 53872 (Monroe, NC)										
Original period of record: 1 February 1999–28 February 2006 (7.07 years)										
	TAIR		WSPD		PSUN		PREC		RELH	
	Old	New	Old	New	Old	New	Old	New	Old	New
Maximum	100.0	104.1	34.0	39.0	100.0	100.0	4.06	6.98	100.0	100.0
Minimum	10.0	−0.8	0.0	0.0	0.0	0.0	0.00	0.00	4.0	4.0
Mean	60.1	60.8	5.3	6.9	68.1	50.8	0.10	0.12	70.1	70.6
25th percentile	48.0	48.0	3.0	5.0	25.0	0.0	0.00	0.00	53.0	58.0
Median	62.0	62.4	5.0	7.0	100.0	50.0	0.00	0.00	72.0	72.0
75th percentile	72.0	74.1	8.0	9.0	100.0	100.0	0.02	0.04	90.0	86.0
Sample std. dev.	16.3	16.7	3.8	4.1	42.1	43.2	0.30	0.33	21.8	18.0

TABLE A.1: *(Continued)*

Station 93781 (Roanoke Rapids, NC)										
Original period of record: 1 November 1998–28 February 2006 (7.33 years)										
	TAIR		WSPD		PSUN		PREC		RELH	
	Old	New	Old	New	Old	New	Old	New	Old	New
Maximum	101.0	107.0	32.0	38.0	100.0	100.0	191.40*	6.95	100.0	100.0
Minimum	(6.6)	−4.6	0.0	0.0	0.0	0.0	0.00	0.00	3.0	9.0
Mean	59.1	59.5	4.5	7.4	66.9	54.0	0.18	0.12	70.7	72.7
25th percentile	46.0	46.0	0.0	5.0	25.0	0.0	0.00	0.00	54.0	60.0
Median	61.0	60.8	4.0	7.0	100.0	75.0	0.00	0.00	73.0	75.0
75th percentile	72.0	73.4	7.0	10.0	100.0	100.0	0.02	0.05	90.0	88.0
Sample std. dev.	16.8	17.4	3.6	4.4	42.8	44.4	3.73	0.34	21.1	18.2

Station 93741 (Newport News, VA)										
Original period of record: 1 December 2000–28 February 2006 (5.24 years)										
	TAIR		WSPD		PSUN		PREC		RELH	
	Old	New	Old	New	Old	New	Old	New	Old	New
Maximum	102.0	105.1	40.0	70.0	100.0	100.0	4.15	7.18	100.0	100.0
Minimum	(9.6)	0.2	0.0	0.0	0.0	0.0	0.00	0.00	12.0	8.0
Mean	58.6	59.4	6.4	8.2	66.8	52.3	0.11	0.05	72.2	70.9
25th percentile	44.6	46.0	4.0	5.0	25.0	0.0	0.00	0.00	56.0	56.0
Median	60.0	61.0	6.0	8.0	100.0	75.0	0.00	0.00	75.0	74.0
75th percentile	73.0	73.4	9.0	11.0	100.0	100.0	0.03	0.00	90.0	88.0
Sample std. dev.	17.4	17.2	4.3	4.9	42.8	43.5	0.33	0.25	20.6	19.9

Station 13786 (Elizabeth City, NC)										
Original period of record: 1 March 1998–28 February 2006 (8.00 years)										
	TAIR		WSPD		PSUN		PREC		RELH	
	Old	New	Old	New	Old	New	Old	New	Old	New
Maximum	98.1	102.0	43.0	63.0	100.0	100.0	4.40	7.56	100.0	100.0
Minimum	(2.4)	2.9	0.0	0.0	0.0	0.0	0.00	0.00	16.0	8.0
Mean	60.7	61.4	8.0	9.1	66.8	53.5	0.12	0.12	76.9	75.5
25th percentile	48.0	49.2	5.0	6.0	25.0	0.0	0.00	0.00	64.0	65.0
Median	63.0	63.0	8.0	9.0	100.0	75.0	0.00	0.00	80.0	79.0
75th percentile	74.0	74.0	11.0	12.0	100.0	100.0	0.04	0.06	93.0	89.0
Sample std. dev.	16.4	15.5	4.7	5.0	41.8	42.6	0.34	0.33	18.0	16.4

Station 03870 (Greer, SC)										
Original period of record: 1 July 1996–28 February 2006 (9.66 years)										
	TAIR		WSPD		PSUN		PREC		RELH	
	Old	New	Old	New	Old	New	Old	New	Old	New
Maximum	102.9	106.0	28.0	63.0	100.0	100.0	4.68	9.32	100.0	100.0
Minimum	(4.9)	−4.0	0.0	0.0	0.0	0.0	0.00	0.00	7.0	4.0
Mean	60.6	60.3	5.5	6.7	66.0	55.3	0.13	0.13	69.4	68.0
25th percentile	48.0	48.0	3.0	3.0	25.0	0.0	0.00	0.00	53.0	51.0
Median	62.0	62.1	5.0	6.0	100.0	75.0	0.00	0.00	71.0	70.0
75th percentile	73.0	73.0	8.0	9.0	100.0	100.0	0.05	0.04	89.0	87.0
Sample std. dev.	15.9	16.3	3.9	4.5	43.1	44.3	0.37	0.37	21.4	21.7

TABLE A.2: Percentages of the complete 35-year time series of hourly data at each station categorized by the source and disposition of the observations and estimates for 2-m air temperature (TAIR), 2-m dewpoint temperature (DEWP), 10-m wind speed (WSPD), cloud cover (CLCV), and precipitation (PREC). Direct observations refer to unmodified measurements at the given station, but may include short-term temporal gaps of two hours or less filled via linear interpolation for air temperature, dewpoint temperature, and wind speed measurements. Values in parentheses indicate the number of hours (observations) in each category.

Station 03812 (Asheville, NC)			
	TAIR	DEWP	WSPD
Direct observations	99.967% (306739)	99.938% (306651)	99.971% (306751)
Estimates	0.031% (94)	0.055% (168)	0.029% (89)
Quality-controlled observations	0.001% (3)	0.001% (4)	0.000% (0)
Quality-controlled estimates	0.000% (0)	0.006% (17)	0.000% (0)
Suspect estimates	0.001% (4)	0.000% (0)	
Suspect observations	0.000% (0)	0.000% (0)	
	CLCV	PREC	
Direct observations	97.720% (299845)	99.843% (306357)	
Linearly-interpolated observations	0.843% (2587)	0.015% (46)	
Nearest observations	1.053% (3230)		
Linearly-interpolated nearest observations	0.338% (1037)		
Nearest NARR grid point	0.046% (141)		
GHCN-Daily/NARR filled		0.142% (437)	
Total direct observations 99.488%	**(1526343)**		
Total other 0.512%	**(7857)**		

Station 93765 (Beaufort, NC)			
	TAIR	DEWP	WSPD
Direct observations	35.047% (107539)	35.051% (107552)	35.055% (107563)
Estimates	64.357% (197474)	64.877% (199068)	64.945% (199277)
Quality-controlled observations	0.002% (7)	0.001% (3)	0.000% (0)
Quality-controlled estimates	0.009% (27)	0.071% (217)	0.000% (0)
Suspect estimates	0.584% (1793)	0.000% (0)	
Suspect observations	0.000% (0)	0.000% (0)	
	CLCV	PREC	
Direct observations	33.418% (102539)	34.041% (104450)	
Linearly-interpolated observations	0.843% (2587)	1.068% (3278)	
Nearest observations	61.835% (189736)		
Linearly-interpolated nearest observations	3.858% (11837)		
Nearest NARR grid point	0.046% (141)		
GHCN-Daily/NARR filled		64.891% (199112)	
Total direct observations 34.522%	**(529643)**		
Total other 65.478%	**(1004557)**		

TABLE A.2: *(Continued)*

Station 93783 (Burlington, NC)			
	TAIR	DEWP	WSPD
Direct observations	35.076% (107626)	35.062% (107584)	34.625% (106242)
Estimates	64.661% (198407)	64.892% (199116)	65.375% (200598)
Quality-controlled observations	0.002% (7)	0.000% (1)	0.000% (0)
Quality-controlled estimates	0.001% (3)	0.045% (139)	0.000% (0)
Suspect estimates	0.260% (797)	0.000% (0)	
Suspect observations	0.000% (0)	0.000% (0)	
	CLCV	PREC	
Direct observations	33.852% (103870)	33.759% (103587)	
Linearly-interpolated observations	0.445% (1366)	1.275% (3912)	
Nearest observations	64.501% (197915)		
Linearly-interpolated nearest observations	1.156% (3548)		
Nearest NARR grid point	0.046% (141)		
GHCN-Daily/NARR filled		64.966% (199341)	
Total direct observations **34.475%**	**(528909)**		
Total other **65.525%**	**(1005291)**		

Station 93729 (Cape Hatteras, NC)			
	TAIR	DEWP	WSPD
Direct observations	99.597% (305602)	98.821% (303223)	98.978% (303704)
Estimates	0.342% (1048)	0.925% (2839)	1.022% (3136)
Quality-controlled observations	0.058% (178)	0.005% (14)	0.000% (0)
Quality-controlled estimates	0.000% (1)	0.249% (764)	0.000% (0)
Suspect estimates	0.004% (11)	0.000% (0)	
Suspect observations	0.000% (0)	0.000% (0)	
	CLCV	PREC	
Direct observations	93.718% (287565)	97.296% (298542)	
Linearly-interpolated observations	1.360% (4174)	2.332% (7154)	
Nearest observations	4.453% (13663)		
Linearly-interpolated nearest observations	0.423% (1297)		
Nearest NARR grid point	0.046% (141)		
GHCN-Daily/NARR filled		0.373% (1144)	
Total direct observations **97.682%**	**(1498636)**		
Total other **2.318%**	**(35564)**		

TABLE A.2: *(Continued)*

Station 93785 (Chapel Hill, NC)			
	TAIR	DEWP	WSPD
Direct observations	34.588% (106131)	34.482% (105804)	34.033% (104427)
Estimates	65.182% (200004)	65.482% (200926)	65.967% (202413)
Quality-controlled observations	0.008% (26)	0.002% (7)	0.000% (0)
Quality-controlled estimates	0.000% (0)	0.034% (103)	0.000% (0)
Suspect estimates	0.221% (679)	0.000% (0)	
Suspect observations	0.000% (0)	0.000% (0)	
	CLCV	PREC	
Direct observations	32.942% (101078)	33.719% (103464)	
Linearly-interpolated observations	0.624% (1914)	0.891% (2733)	
Nearest observations	65.522% (201048)		
Linearly-interpolated nearest observations	0.867% (2659)		
Nearest NARR grid point	0.046% (141)		
GHCN-Daily/NARR filled		65.390% (200643)	
Total direct observations 33.953%	**(520904)**		
Total other 66.047%	**(1013296)**		

Station 13881 (Charlotte, NC)			
	TAIR	DEWP	WSPD
Direct observations	99.987% (306799)	99.987% (306799)	99.987% (306799)
Estimates	0.013% (41)	0.013% (41)	0.013% (41)
Quality-controlled observations	0.000% (0)	0.000% (0)	0.000% (0)
Quality-controlled estimates	0.000% (0)	0.000% (0)	0.000% (0)
Suspect estimates	0.000% (0)	0.000% (0)	
Suspect observations	0.000% (0)	0.000% (0)	
	CLCV	PREC	
Direct observations	97.975% (300627)	99.864% (306423)	
Linearly-interpolated observations	1.381% (4237)	0.004% (13)	
Nearest observations	0.540% (1658)		
Linearly-interpolated nearest observations	0.058% (177)		
Nearest NARR grid point	0.046% (141)		
GHCN-Daily/NARR filled		0.132% (404)	
Total direct observations 99.560%	**(1527447)**		
Total other 0.440%	**(6753)**		

TABLE A.2: *(Continued)*

Station 13786 (Elizabeth City, NC)			
	TAIR	DEWP	WSPD
Direct observations	55.084% (169019)	54.904% (168467)	55.285% (169637)
Estimates	44.791% (137438)	45.059% (138260)	44.715% (137203)
Quality-controlled observations	0.004% (12)	0.015% (47)	0.000% (0)
Quality-controlled estimates	0.000% (0)	0.022% (66)	0.000% (0)
Suspect estimates	0.112% (343)	0.000% (0)	
Suspect observations	0.009% (28)	0.000% (0)	
	CLCV	PREC	
Direct observations	52.252% (160331)	53.015% (162671)	
Linearly-interpolated observations	1.661% (5096)	2.140% (6566)	
Nearest observations	43.573% (133700)		
Linearly-interpolated nearest observations	2.468% (7572)		
Nearest NARR grid point	0.046% (141)		
GHCN-Daily/NARR filled		44.845% (137603)	
Total direct observations **54.108%**	**(830125)**		
Total other **45.892%**	**(704075)**		

Station 93740 (Fayetteville, NC)			
	TAIR	DEWP	WSPD
Direct observations	89.016% (273136)	88.433% (271349)	89.684% (275187)
Estimates	10.916% (33496)	11.383% (34928)	10.316% (31653)
Quality-controlled observations	0.018% (55)	0.022% (66)	0.000% (0)
Quality-controlled estimates	0.002% (6)	0.162% (497)	0.000% (0)
Suspect estimates	0.044% (135)	0.000% (0)	
Suspect observations	0.004% (12)	0.000% (0)	
	CLCV	PREC	
Direct observations	85.900% (263576)	81.248% (249301)	
Linearly-interpolated observations	2.836% (8702)	8.311% (25500)	
Nearest observations	10.823% (33208)		
Linearly-interpolated nearest observations	0.395% (1213)		
Nearest NARR grid point	0.046% (141)		
GHCN-Daily/NARR filled		10.442% (32039)	
Total direct observations **86.856%**	**(1332549)**		
Total other **13.144%**	**(201651)**		

TABLE A.2: *(Continued)*

Station 53870 (Gastonia, NC)			
	TAIR	DEWP	WSPD
Direct observations	34.986% (107352)	34.976% (107321)	34.694% (106456)
Estimates	64.601% (198221)	64.932% (199237)	65.306% (200384)
Quality-controlled observations	0.001% (4)	0.000% (0)	0.000% (0)
Quality-controlled estimates	0.002% (6)	0.092% (282)	0.000% (0)
Suspect estimates	0.409% (1256)	0.000% (0)	
Suspect observations	0.000% (1)	0.000% (0)	
	CLCV	PREC	
Direct observations	33.832% (103809)	33.763% (103597)	
Linearly-interpolated observations	0.460% (1410)	1.235% (3789)	
Nearest observations	64.796% (198819)		
Linearly-interpolated nearest observations	0.867% (2661)		
Nearest NARR grid point	0.046% (141)		
GHCN-Daily/NARR filled		65.003% (199454)	
Total direct observations 34.450%	**(528535)**		
Total other 65.550%	**(1005665)**		

Station 13723 (Greensboro, NC)			
	TAIR	DEWP	WSPD
Direct observations	99.986% (306798)	99.986% (306798)	99.986% (306798)
Estimates	0.014% (42)	0.014% (42)	0.014% (42)
Quality-controlled observations	0.000% (0)	0.000% (0)	0.000% (0)
Quality-controlled estimates	0.000% (0)	0.000% (0)	0.000% (0)
Suspect estimates	0.000% (0)	0.000% (0)	
Suspect observations	0.000% (0)	0.000% (0)	
	CLCV	PREC	
Direct observations	96.480% (296038)	99.836% (306338)	
Linearly-interpolated observations	1.713% (5255)	0.021% (64)	
Nearest observations	1.601% (4913)		
Linearly-interpolated nearest observations	0.161% (493)		
Nearest NARR grid point	0.046% (141)		
GHCN-Daily/NARR filled		0.143% (438)	
Total direct observations 99.255%	**(1522770)**		
Total other 0.745%	**(11430)**		

TABLE A.2: *(Continued)*

Station 03810 (Hickory, NC)			
	TAIR	DEWP	WSPD
Direct observations	88.834% (272579)	88.778% (272407)	88.843% (272605)
Estimates	11.125% (34137)	10.992% (33727)	11.157% (34235)
Quality-controlled observations	0.001% (4)	0.006% (19)	0.000% (0)
Quality-controlled estimates	0.000% (0)	0.224% (687)	0.000% (0)
Suspect estimates	0.037% (112)	0.000% (0)	
Suspect observations	0.003% (8)	0.000% (0)	
	CLCV	PREC	
Direct observations	84.841% (260327)	77.564% (237998)	
Linearly-interpolated observations	2.463% (7557)	10.989% (33718)	
Nearest observations	12.256% (37606)		
Linearly-interpolated nearest observations	0.394% (1209)		
Nearest NARR grid point	0.046% (141)		
GHCN-Daily/NARR filled		11.447% (35124)	
Total direct observations **85.772%**	**(1315916)**		
Total other **14.228%**	**(218284)**		

Station 13776 (Lumberton, NC)			
	TAIR	DEWP	WSPD
Direct observations	41.459% (127214)	41.428% (127118)	40.854% (125357)
Estimates	58.216% (178630)	58.529% (179589)	59.146% (181483)
Quality-controlled observations	0.001% (2)	0.000% (1)	0.000% (0)
Quality-controlled estimates	0.001% (3)	0.043% (132)	0.000% (0)
Suspect estimates	0.323% (991)	0.000% (0)	
Suspect observations	0.000% (0)	0.000% (0)	
	CLCV	PREC	
Direct observations	39.886% (122385)	39.717% (121868)	
Linearly-interpolated observations	0.858% (2633)	1.705% (5233)	
Nearest observations	56.477% (173293)		
Linearly-interpolated nearest observations	2.734% (8388)		
Nearest NARR grid point	0.046% (141)		
GHCN-Daily/NARR filled		58.577% (179739)	
Total direct observations **40.669%**	**(623942)**		
Total other **59.331%**	**(910258)**		

TABLE A.2: *(Continued)*

Station 93782 (Maxton, NC)			
	TAIR	DEWP	WSPD
Direct observations	41.710% (127982)	41.705% (127968)	41.362% (126916)
Estimates	58.121% (178339)	58.252% (178739)	58.638% (179924)
Quality-controlled observations	0.003% (8)	0.000% (1)	0.000% (0)
Quality-controlled estimates	0.001% (3)	0.043% (132)	0.000% (0)
Suspect estimates	0.166% (508)	0.000% (0)	
Suspect observations	0.000% (0)	0.000% (0)	
	CLCV	PREC	
Direct observations	40.358% (123833)	40.009% (122765)	
Linearly-interpolated observations	0.658% (2020)	1.663% (5104)	
Nearest observations	56.466% (173259)		
Linearly-interpolated nearest observations	2.473% (7587)		
Nearest NARR grid point	0.046% (141)		
GHCN-Daily/NARR filled		58.327% (178971)	
Total direct observations **41.029%**	**(629464)**		
Total other **58.971%**	**(904736)**		

Station 53872 (Monroe, NC)			
	TAIR	DEWP	WSPD
Direct observations	35.134% (107806)	35.134% (107804)	34.917% (107140)
Estimates	64.688% (198489)	64.845% (198970)	65.083% (199700)
Quality-controlled observations	0.002% (7)	0.001% (2)	0.000% (0)
Quality-controlled estimates	0.001% (3)	0.021% (64)	0.000% (0)
Suspect estimates	0.173% (530)	0.000% (0)	
Suspect observations	0.002% (5)	0.000% (0)	
	CLCV	PREC	
Direct observations	34.053% (104487)	33.902% (104026)	
Linearly-interpolated observations	0.402% (1234)	1.211% (3716)	
Nearest observations	64.639% (198339)		
Linearly-interpolated nearest observations	0.860% (2639)		
Nearest NARR grid point	0.046% (141)		
GHCN-Daily/NARR filled		64.887% (199098)	
Total direct observations **34.628%**	**(531263)**		
Total other **65.372%**	**(1002937)**		

TABLE A.2: *(Continued)*

Station 93719 (New Bern, NC)			
	TAIR	DEWP	WSPD
Direct observations	96.871% (297239)	96.851% (297179)	96.872% (297242)
Estimates	2.901% (8901)	2.611% (8013)	3.118% (9567)
Quality-controlled observations	0.002% (7)	0.001% (2)	0.000% (0)
Quality-controlled estimates	0.170% (521)	0.536% (1646)	0.010% (31)
Suspect estimates	0.056% (172)	0.000% (0)	
Suspect observations	0.000% (0)	0.000% (0)	
	CLCV	PREC	
Direct observations	92.741% (284566)	85.659% (262836)	
Linearly-interpolated observations	2.484% (7623)	10.972% (33668)	
Nearest observations	4.427% (13583)		
Linearly-interpolated nearest observations	0.302% (927)		
Nearest NARR grid point	0.046% (141)		
GHCN-Daily/NARR filled		3.369% (10336)	
Total direct observations 93.799%	**(1439062)**		
Total other 6.201%	**(95138)**		

Station 13722 (Raleigh/Durham, NC)			
	TAIR	DEWP	WSPD
Direct observations	99.965% (306733)	99.955% (306703)	99.968% (306743)
Estimates	0.035% (107)	0.043% (131)	0.032% (97)
Quality-controlled observations	0.000% (0)	0.000% (1)	0.000% (0)
Quality-controlled estimates	0.000% (0)	0.002% (5)	0.000% (0)
Suspect estimates	0.000% (0)	0.000% (0)	
Suspect observations	0.000% (0)	0.000% (0)	
	CLCV	PREC	
Direct observations	97.069% (297845)	99.802% (306231)	
Linearly-interpolated observations	0.779% (2390)	0.024% (75)	
Nearest observations	1.821% (5587)		
Linearly-interpolated nearest observations	0.286% (877)		
Nearest NARR grid point	0.046% (141)		
GHCN-Daily/NARR filled		0.174% (534)	
Total direct observations 99.352%	**(1524255)**		
Total other 0.648%	**(9945)**		

TABLE A.2: *(Continued)*

Station 93781 (Roanoke Rapids, NC)			
	TAIR	DEWP	WSPD
Direct observations	28.694% (88044)	28.687% (88024)	28.220% (86590)
Estimates	70.920% (217610)	71.211% (218503)	71.780% (220250)
Quality-controlled observations	0.001% (2)	0.001% (3)	0.000% (0)
Quality-controlled estimates	0.003% (8)	0.101% (310)	0.000% (0)
Suspect estimates	0.383% (1176)	0.000% (0)	
Suspect observations	0.000% (0)	0.000% (0)	
	CLCV	PREC	
Direct observations	28.156% (86394)	27.133% (83255)	
Linearly-interpolated observations	0.522% (1601)	1.582% (4855)	
Nearest observations	68.176% (209192)		
Linearly-interpolated nearest observations	3.100% (9512)		
Nearest NARR grid point	0.046% (141)		
GHCN-Daily/NARR filled		71.285% (218730)	
Total direct observations **28.178%**	**(432307)**		
Total other **71.822%**	**(1101893)**		

Station 93759 (Rocky Mount, NC)			
	TAIR	DEWP	WSPD
Direct observations	68.087% (208919)	67.992% (208626)	67.669% (207635)
Estimates	31.777% (97506)	31.905% (97896)	32.330% (99200)
Quality-controlled observations	0.009% (29)	0.011% (34)	0.000% (0)
Quality-controlled estimates	0.021% (65)	0.093% (284)	0.002% (5)
Suspect estimates	0.099% (304)	0.000% (0)	
Suspect observations	0.006% (17)	0.000% (0)	
	CLCV	PREC	
Direct observations	64.806% (198850)	60.301% (185027)	
Linearly-interpolated observations	2.223% (6820)	6.883% (21119)	
Nearest observations	32.091% (98469)		
Linearly-interpolated nearest observations	0.834% (2560)		
Nearest NARR grid point	0.046% (141)		
GHCN-Daily/NARR filled		32.816% (100694)	
Total direct observations **65.771%**	**(1009057)**		
Total other **34.229%**	**(525143)**		

TABLE A.2: *(Continued)*

Station 13748 (Wilmington, NC)			
	TAIR	DEWP	WSPD
Direct observations	99.959% (306713)	99.944% (306669)	99.970% (306749)
Estimates	0.038% (116)	0.049% (149)	0.030% (91)
Quality-controlled observations	0.003% (9)	0.001% (2)	0.000% (0)
Quality-controlled estimates	0.001% (2)	0.007% (20)	0.000% (0)
Suspect estimates	0.000% (0)	0.000% (0)	
Suspect observations	0.000% (0)	0.000% (0)	
	CLCV	PREC	
Direct observations	96.954% (297494)	99.729% (306008)	
Linearly-interpolated observations	0.946% (2902)	0.110% (338)	
Nearest observations	1.992% (6112)		
Linearly-interpolated nearest observations	0.062% (191)		
Nearest NARR grid point	0.046% (141)		
GHCN-Daily/NARR filled		0.161% (494)	
Total direct observations 99.311%	**(1523633)**		
Total other 0.689%	**(10567)**		

Station 93807 (Winston-Salem, NC)			
	TAIR	DEWP	WSPD
Direct observations	67.344% (206638)	59.868% (183698)	73.827% (226530)
Estimates	32.549% (99874)	39.562% (121393)	26.173% (80310)
Quality-controlled observations	0.033% (100)	0.024% (74)	0.000% (0)
Quality-controlled estimates	0.004% (12)	0.546% (1675)	0.000% (0)
Suspect estimates	0.070% (216)	0.000% (0)	
Suspect observations	0.000% (0)	0.000% (0)	
	CLCV	PREC	
Direct observations	70.537% (216437)	68.270% (209481)	
Linearly-interpolated observations	2.799% (8587)	5.571% (17095)	
Nearest observations	25.840% (79286)		
Linearly-interpolated nearest observations	0.779% (2389)		
Nearest NARR grid point	0.046% (141)		
GHCN-Daily/NARR filled		26.158% (80264)	
Total direct observations 67.969%	**(1042784)**		
Total other 32.031%	**(491416)**		

TABLE A.2: *(Continued)*

Station 13877 (Bristol/Johnson City/Kingsport, TN)			
	TAIR	DEWP	WSPD
Direct observations	99.963% (306726)	99.942% (306661)	99.992% (306816)
Estimates	0.037% (114)	0.050% (154)	0.008% (24)
Quality-controlled observations	0.000% (0)	0.002% (5)	0.000% (0)
Quality-controlled estimates	0.000% (0)	0.007% (20)	0.000% (0)
Suspect estimates	0.000% (0)	0.000% (0)	
Suspect observations	0.000% (0)	0.000% (0)	
	CLCV	PREC	
Direct observations	96.237% (295293)	99.646% (305753)	
Linearly-interpolated observations	0.828% (2540)	0.220% (675)	
Nearest observations	2.559% (7852)		
Linearly-interpolated nearest observations	0.330% (1014)		
Nearest NARR grid point	0.046% (141)		
GHCN-Daily/NARR filled		0.134% (412)	
Total direct observations 99.156%	**(1521249)**		
Total other 0.844%	**(12951)**		

Station 13728 (Danville, VA)			
	TAIR	DEWP	WSPD
Direct observations	85.789% (263236)	85.447% (262185)	85.501% (262352)
Estimates	14.160% (43449)	14.483% (44439)	14.499% (44488)
Quality-controlled observations	0.014% (43)	0.010% (31)	0.000% (0)
Quality-controlled estimates	0.004% (11)	0.060% (185)	0.000% (0)
Suspect estimates	0.028% (85)	0.000% (0)	
Suspect observations	0.005% (16)	0.000% (0)	
	CLCV	PREC	
Direct observations	80.436% (246810)	75.258% (230923)	
Linearly-interpolated observations	3.292% (10100)	10.221% (31361)	
Nearest observations	15.835% (48587)		
Linearly-interpolated nearest observations	0.392% (1202)		
Nearest NARR grid point	0.046% (141)		
GHCN-Daily/NARR filled		14.521% (44556)	
Total direct observations 82.486%	**(1265506)**		
Total other 17.514%	**(268694)**		

Table A.2: *(Continued)*

Station 13882 (Chattanooga, TN)			
	TAIR	DEWP	WSPD
Direct observations	99.982% (306785)	99.977% (306768)	99.993% (306817)
Estimates	0.018% (55)	0.021% (65)	0.007% (23)
Quality-controlled observations	0.000% (0)	0.002% (7)	0.000% (0)
Quality-controlled estimates	0.000% (0)	0.000% (0)	0.000% (0)
Suspect estimates	0.000% (0)	0.000% (0)	
Suspect observations	0.000% (0)	0.000% (0)	
	CLCV	PREC	
Direct observations	96.752% (296875)	99.838% (306342)	
Linearly-interpolated observations	0.811% (2488)	0.009% (27)	
Nearest observations	2.002% (6143)		
Linearly-interpolated nearest observations	0.389% (1193)		
Nearest NARR grid point	0.046% (141)		
GHCN-Daily/NARR filled		0.154% (471)	
Total direct observations 99.308%	**(1523587)**		
Total other 0.692%	**(10613)**		

Station 13891 (Knoxville, TN)			
	TAIR	DEWP	WSPD
Direct observations	99.996% (306827)	99.987% (306799)	99.997% (306832)
Estimates	0.004% (13)	0.011% (35)	0.003% (8)
Quality-controlled observations	0.000% (0)	0.000% (1)	0.000% (0)
Quality-controlled estimates	0.000% (0)	0.002% (5)	0.000% (0)
Suspect estimates	0.000% (0)	0.000% (0)	
Suspect observations	0.000% (0)	0.000% (0)	
	CLCV	PREC	
Direct observations	97.038% (297751)	99.859% (306408)	
Linearly-interpolated observations	1.391% (4267)	0.006% (19)	
Nearest observations	1.409% (4323)		
Linearly-interpolated nearest observations	0.117% (358)		
Nearest NARR grid point	0.046% (141)		
GHCN-Daily/NARR filled		0.135% (413)	
Total direct observations 99.375%	**(1524617)**		
Total other 0.625%	**(9583)**		

TABLE A.2: *(Continued)*

Station 93741 (Newport News, VA)			
	TAIR	DEWP	WSPD
Direct observations	98.126% (301090)	97.095% (297927)	98.244% (301451)
Estimates	1.835% (5632)	2.690% (8253)	1.756% (5389)
Quality-controlled observations	0.009% (27)	0.007% (22)	0.000% (0)
Quality-controlled estimates	0.003% (9)	0.208% (638)	0.000% (0)
Suspect estimates	0.002% (7)	0.000% (0)	
Suspect observations	0.024% (75)	0.000% (0)	
	CLCV	PREC	
Direct observations	92.794% (284730)	84.889% (260473)	
Linearly-interpolated observations	4.106% (12600)	12.930% (39674)	
Nearest observations	2.699% (8281)		
Linearly-interpolated nearest observations	0.355% (1088)		
Nearest NARR grid point	0.046% (141)		
GHCN-Daily/NARR filled		2.181% (6693)	
Total direct observations **94.230%**	**(1445671)**		
Total other **5.770%**	**(88529)**		

Station 13737 (Norfolk, VA)			
	TAIR	DEWP	WSPD
Direct observations	99.977% (306770)	99.881% (306475)	99.967% (306739)
Estimates	0.021% (65)	0.077% (236)	0.033% (101)
Quality-controlled observations	0.002% (5)	0.001% (3)	0.000% (0)
Quality-controlled estimates	0.000% (0)	0.041% (126)	0.000% (0)
Suspect estimates	0.000% (0)	0.000% (0)	
Suspect observations	0.000% (0)	0.000% (0)	
	CLCV	PREC	
Direct observations	97.736% (299894)	99.817% (306279)	
Linearly-interpolated observations	1.031% (3165)	0.021% (63)	
Nearest observations	1.133% (3475)		
Linearly-interpolated nearest observations	0.054% (165)		
Nearest NARR grid point	0.046% (141)		
GHCN-Daily/NARR filled		0.162% (498)	
Total direct observations **99.476%**	**(1526157)**		
Total other **0.524%**	**(8043)**		

TABLE A.2: *(Continued)*

Station 13744 (Florence, SC)			
	TAIR	DEWP	WSPD
Direct observations	99.003% (303781)	98.879% (303399)	99.131% (304173)
Estimates	0.984% (3020)	1.092% (3352)	0.869% (2667)
Quality-controlled observations	0.003% (10)	0.004% (12)	0.000% (0)
Quality-controlled estimates	0.003% (8)	0.025% (77)	0.000% (0)
Suspect estimates	0.005% (15)	0.000% (0)	
Suspect observations	0.002% (6)	0.000% (0)	
	CLCV	PREC	
Direct observations	94.365% (289550)	86.826% (266418)	
Linearly-interpolated observations	3.439% (10553)	12.023% (36891)	
Nearest observations	1.881% (5772)		
Linearly-interpolated nearest observations	0.269% (824)		
Nearest NARR grid point	0.046% (141)		
GHCN-Daily/NARR filled		1.151% (3531)	
Total direct observations 95.641%	**(1467321)**		
Total other 4.359%	**(66879)**		

Station 03870 (Greer, SC)			
	TAIR	DEWP	WSPD
Direct observations	99.969% (306745)	99.959% (306715)	99.968% (306742)
Estimates	0.031% (95)	0.039% (119)	0.032% (98)
Quality-controlled observations	0.000% (0)	0.000% (1)	0.000% (0)
Quality-controlled estimates	0.000% (0)	0.002% (5)	0.000% (0)
Suspect estimates	0.000% (0)	0.000% (0)	
Suspect observations	0.000% (0)	0.000% (0)	
	CLCV	PREC	
Direct observations	97.890% (300365)	99.671% (305830)	
Linearly-interpolated observations	1.127% (3457)	0.178% (546)	
Nearest observations	0.855% (2625)		
Linearly-interpolated nearest observations	0.082% (252)		
Nearest NARR grid point	0.046% (141)		
GHCN-Daily/NARR filled		0.151% (464)	
Total direct observations 99.491%	**(1526397)**		
Total other 0.509%	**(7803)**		

TABLE A.2: *(Continued)*

Station 13883 (Columbia, SC)			
	TAIR	DEWP	WSPD
Direct observations	99.921% (306598)	99.917% (306585)	99.992% (306814)
Estimates	0.079% (241)	0.082% (251)	0.008% (26)
Quality-controlled observations	0.000% (0)	0.000% (1)	0.000% (0)
Quality-controlled estimates	0.000% (1)	0.001% (3)	0.000% (0)
Suspect estimates	0.000% (0)	0.000% (0)	
Suspect observations	0.000% (0)	0.000% (0)	
	CLCV	PREC	
Direct observations	97.129% (298030)	93.139% (285789)	
Linearly-interpolated observations	0.696% (2136)	6.798% (20860)	
Nearest observations	1.907% (5851)		
Linearly-interpolated nearest observations	0.222% (682)		
Nearest NARR grid point	0.046% (141)		
GHCN-Daily/NARR filled		0.062% (191)	
Total direct observations 98.020%	**(1503816)**		
Total other 1.980%	**(30384)**		

Station 93846 (Anderson, SC)			
	TAIR	DEWP	WSPD
Direct observations	91.605% (281082)	91.517% (280810)	91.603% (281074)
Estimates	8.359% (25648)	8.456% (25945)	8.397% (25766)
Quality-controlled observations	0.005% (15)	0.008% (25)	0.000% (0)
Quality-controlled estimates	0.001% (2)	0.020% (60)	0.000% (0)
Suspect estimates	0.030% (93)	0.000% (0)	
Suspect observations	0.000% (0)	0.000% (0)	
	CLCV	PREC	
Direct observations	86.806% (266354)	82.780% (254003)	
Linearly-interpolated observations	3.508% (10764)	8.346% (25609)	
Nearest observations	9.215% (28274)		
Linearly-interpolated nearest observations	0.426% (1307)		
Nearest NARR grid point	0.046% (141)		
GHCN-Daily/NARR filled		8.874% (27228)	
Total direct observations 88.862%	**(1363323)**		
Total other 11.138%	**(170877)**		

TABLE A.2: *(Continued)*

Station 13750 (Norfolk, VA)			
	TAIR	DEWP	WSPD
Direct observations	99.544% (305441)	99.458% (305176)	99.659% (305793)
Estimates	0.420% (1289)	0.500% (1535)	0.341% (1047)
Quality-controlled observations	0.004% (12)	0.003% (8)	0.000% (0)
Quality-controlled estimates	0.000% (0)	0.039% (121)	0.000% (0)
Suspect estimates	0.002% (6)	0.000% (0)	
Suspect observations	0.030% (92)	0.000% (0)	
	CLCV	PREC	
Direct observations	96.806% (297039)	89.100% (273393)	
Linearly-interpolated observations	1.525% (4680)	10.525% (32295)	
Nearest observations	1.198% (3676)		
Linearly-interpolated nearest observations	0.425% (1304)		
Nearest NARR grid point	0.046% (141)		
GHCN-Daily/NARR filled		0.375% (1152)	
Total direct observations 96.913%	**(1486842)**		
Total other 3.087%	**(47358)**		

Station 93735 (Fort Eustis, VA)			
	TAIR	DEWP	WSPD
Direct observations	60.193% (184695)	60.039% (184225)	59.983% (184052)
Estimates	39.702% (121823)	39.853% (122285)	40.017% (122788)
Quality-controlled observations	0.001% (3)	0.016% (50)	0.000% (0)
Quality-controlled estimates	0.000% (0)	0.091% (280)	0.000% (0)
Suspect estimates	0.101% (310)	0.000% (0)	
Suspect observations	0.003% (9)	0.000% (0)	
	CLCV	PREC	
Direct observations	58.532% (179601)	53.957% (165563)	
Linearly-interpolated observations	0.630% (1932)	6.147% (18862)	
Nearest observations	38.591% (118414)		
Linearly-interpolated nearest observations	2.200% (6752)		
Nearest NARR grid point	0.046% (141)		
GHCN-Daily/NARR filled		39.895% (122415)	
Total direct observations 58.541%	**(898136)**		
Total other 41.459%	**(636064)**		

TABLE A.2: *(Continued)*

Station 13769 (Virginia Beach, VA)			
	TAIR	DEWP	WSPD
Direct observations	99.451% (305156)	99.310% (304724)	99.565% (305504)
Estimates	0.540% (1656)	0.619% (1900)	0.435% (1336)
Quality-controlled observations	0.006% (18)	0.005% (15)	0.000% (0)
Quality-controlled estimates	0.001% (2)	0.066% (201)	0.000% (0)
Suspect estimates	0.001% (2)	0.000% (0)	
Suspect observations	0.002% (6)	0.000% (0)	
	CLCV	PREC	
Direct observations	96.652% (296568)	88.946% (272923)	
Linearly-interpolated observations	1.434% (4400)	10.578% (32457)	
Nearest observations	1.453% (4458)		
Linearly-interpolated nearest observations	0.415% (1273)		
Nearest NARR grid point	0.046% (141)		
GHCN-Daily/NARR filled		0.476% (1460)	
Total direct observations 96.785%	**(1484875)**		
Total other 3.215%	**(49325)**		

Station 13702 (Hampton, VA)			
	TAIR	DEWP	WSPD
Direct observations	98.725% (302928)	98.802% (303165)	98.925% (303540)
Estimates	1.185% (3635)	1.191% (3653)	1.075% (3300)
Quality-controlled observations	0.002% (5)	0.001% (4)	0.000% (0)
Quality-controlled estimates	0.000% (0)	0.006% (18)	0.000% (0)
Suspect estimates	0.010% (31)	0.000% (0)	
Suspect observations	0.079% (241)	0.000% (0)	
	CLCV	PREC	
Direct observations	96.848% (297169)	87.741% (269223)	
Linearly-interpolated observations	0.822% (2522)	11.244% (34502)	
Nearest observations	1.896% (5817)		
Linearly-interpolated nearest observations	0.388% (1191)		
Nearest NARR grid point	0.046% (141)		
GHCN-Daily/NARR filled		1.015% (3115)	
Total direct observations 96.208%	**(1476025)**		
Total other 3.792%	**(58175)**		

TABLE A.2: *(Continued)*

Station 93737 (Fort Bragg, NC)			
	TAIR	DEWP	WSPD
Direct observations	93.731% (287604)	93.718% (287565)	93.261% (286162)
Estimates	6.242% (19153)	6.278% (19262)	6.739% (20678)
Quality-controlled observations	0.003% (9)	0.004% (12)	0.000% (0)
Quality-controlled estimates	0.000% (0)	0.000% (1)	0.000% (0)
Suspect estimates	0.024% (74)	0.000% (0)	
Suspect observations	0.000% (0)	0.000% (0)	
	CLCV	PREC	
Direct observations	91.803% (281688)	82.418% (252890)	
Linearly-interpolated observations	0.941% (2887)	11.409% (35008)	
Nearest observations	6.836% (20977)		
Linearly-interpolated nearest observations	0.374% (1147)		
Nearest NARR grid point	0.046% (141)		
GHCN-Daily/NARR filled		6.173% (18942)	
Total direct observations 90.986%	**(1395909)**		
Total other 9.014%	**(138291)**		

Station 13713 (Goldsboro, NC)			
	TAIR	DEWP	WSPD
Direct observations	95.233% (292214)	95.299% (292416)	95.023% (291569)
Estimates	4.448% (13648)	4.228% (12972)	4.973% (15258)
Quality-controlled observations	0.002% (5)	0.001% (3)	0.000% (0)
Quality-controlled estimates	0.159% (487)	0.472% (1449)	0.004% (13)
Suspect estimates	0.056% (172)	0.000% (0)	
Suspect observations	0.102% (314)	0.000% (0)	
	CLCV	PREC	
Direct observations	93.165% (285869)	84.071% (257964)	
Linearly-interpolated observations	1.005% (3083)	11.262% (34555)	
Nearest observations	5.382% (16515)		
Linearly-interpolated nearest observations	0.402% (1232)		
Nearest NARR grid point	0.046% (141)		
GHCN-Daily/NARR filled		4.667% (14321)	
Total direct observations 92.558%	**(1420032)**		
Total other 7.442%	**(114168)**		

TABLE A.2: *(Continued)*

Station 13754 (Havelock, NC)			
	TAIR	DEWP	WSPD
Direct observations	99.560% (305490)	99.393% (304977)	99.618% (305667)
Estimates	0.395% (1211)	0.484% (1484)	0.382% (1173)
Quality-controlled observations	0.018% (55)	0.002% (7)	0.000% (0)
Quality-controlled estimates	0.017% (52)	0.121% (372)	0.000% (0)
Suspect estimates	0.001% (4)	0.000% (0)	
Suspect observations	0.009% (28)	0.000% (0)	
	CLCV	PREC	
Direct observations	96.843% (297154)	88.341% (271067)	
Linearly-interpolated observations	1.660% (5094)	11.204% (34377)	
Nearest observations	1.181% (3624)		
Linearly-interpolated nearest observations	0.270% (827)		
Nearest NARR grid point	0.046% (141)		
GHCN-Daily/NARR filled		0.455% (1396)	
Total direct observations 96.751%	**(1484355)**		
Total other 3.249%	**(49845)**		

Station 93753 (Jacksonville, NC)			
	TAIR	DEWP	WSPD
Direct observations	57.048% (175045)	56.809% (174314)	61.309% (188120)
Estimates	42.655% (130882)	42.946% (131774)	38.691% (118720)
Quality-controlled observations	0.048% (147)	0.152% (467)	0.000% (0)
Quality-controlled estimates	0.002% (7)	0.093% (285)	0.000% (0)
Suspect estimates	0.188% (577)	0.000% (0)	
Suspect observations	0.059% (182)	0.000% (0)	
	CLCV	PREC	
Direct observations	50.009% (153447)	54.567% (167434)	
Linearly-interpolated observations	4.587% (14075)	5.955% (18273)	
Nearest observations	44.412% (136274)		
Linearly-interpolated nearest observations	0.946% (2903)		
Nearest NARR grid point	0.046% (141)		
GHCN-Daily/NARR filled		39.478% (121133)	
Total direct observations 55.948%	**(858360)**		
Total other 44.052%	**(675840)**		

TABLE A.2: *(Continued)*

Station 93726 (Kinston, NC)			
	TAIR	DEWP	WSPD
Direct observations	73.098% (224293)	72.765% (223273)	76.205% (233828)
Estimates	26.319% (80757)	26.193% (80370)	23.782% (72974)
Quality-controlled observations	0.010% (30)	0.019% (59)	0.000% (0)
Quality-controlled estimates	0.270% (828)	1.023% (3138)	0.012% (38)
Suspect estimates	0.257% (788)	0.000% (0)	
Suspect observations	0.047% (144)	0.000% (0)	
	CLCV	PREC	
Direct observations	71.197% (218462)	67.844% (208172)	
Linearly-interpolated observations	4.016% (12324)	8.323% (25537)	
Nearest observations	24.145% (74085)		
Linearly-interpolated nearest observations	0.596% (1828)		
Nearest NARR grid point	0.046% (141)		
GHCN-Daily/NARR filled		23.834% (73131)	
Total direct observations **72.222%**	**(1108028)**		
Total other **27.778%**	**(426172)**		

Station 13714 (Pope Field, NC)			
	TAIR	DEWP	WSPD
Direct observations	98.777% (303088)	98.765% (303052)	98.837% (303271)
Estimates	1.203% (3691)	1.228% (3767)	1.163% (3569)
Quality-controlled observations	0.001% (4)	0.001% (3)	0.000% (0)
Quality-controlled estimates	0.001% (3)	0.006% (18)	0.000% (0)
Suspect estimates	0.006% (18)	0.000% (0)	
Suspect observations	0.012% (36)	0.000% (0)	
	CLCV	PREC	
Direct observations	96.536% (296211)	87.282% (267817)	
Linearly-interpolated observations	1.082% (3321)	11.555% (35456)	
Nearest observations	2.055% (6306)		
Linearly-interpolated nearest observations	0.281% (861)		
Nearest NARR grid point	0.046% (141)		
GHCN-Daily/NARR filled		1.162% (3567)	
Total direct observations **96.040%**	**(1473439)**		
Total other **3.960%**	**(60761)**		

TABLE A.2: *(Continued)*

Station 13717 (Myrtle Beach, SC)			
	TAIR	DEWP	WSPD
Direct observations	76.346% (234261)	76.076% (233433)	79.931% (245259)
Estimates	22.695% (69638)	23.107% (70903)	20.058% (61547)
Quality-controlled observations	0.088% (269)	0.210% (644)	0.000% (0)
Quality-controlled estimates	0.278% (853)	0.606% (1860)	0.011% (34)
Suspect estimates	0.538% (1652)	0.000% (0)	
Suspect observations	0.054% (167)	0.000% (0)	
	CLCV	PREC	
Direct observations	67.753% (207892)	66.526% (204128)	
Linearly-interpolated observations	6.267% (19231)	13.382% (41060)	
Nearest observations	24.469% (75081)		
Linearly-interpolated nearest observations	1.465% (4495)		
Nearest NARR grid point	0.046% (141)		
GHCN-Daily/NARR filled		20.093% (61652)	
Total direct observations **73.326%**	**(1124973)**		
Total other **26.674%**	**(409227)**		

TABLE A.3: Comparison of Pavement ME Design pavement distress results at the specified reliability (%) for baseline simulations (Baseline) and simulations using the new long-term climate data files (New) for a selection of concrete projects. Performance criteria include terminal IRI (inches mile^{-1}), JPCP transverse cracking (percentage of slabs), and mean joint faulting (inches).

Project/location: X-2BB Cumberland Co. Pavement type: Concrete
Primary data source: Fayetteville, NC (93740)
Design life: 30.0 years

			Predicted Stress			Pass/Fail	
Performance Criterion	Reliability	Target	Baseline	New	% Diff	Baseline	New
Terminal IRI	90	172.00	142.98	133.78	−6.44	Pass	Pass
Mean joint faulting	90	0.12	0.10	0.09	−10.83	Pass	Pass
JPCP transverse cracking	90	15.00	11.57	6.76	−41.60	Pass	Pass

Project/location: I-3802A Cabarrus Co. Pavement type: Concrete
Primary data source: Charlotte, NC (13881)
Design life: 30.0 years

			Predicted Stress			Pass/Fail	
Performance Criterion	Reliability	Target	Baseline	New	% Diff	Baseline	New
Terminal IRI	90	185.00	158.49	159.77	0.80	Pass	Pass
Mean joint faulting	90	0.15	0.11	0.12	6.51	Pass	Pass
JPCP transverse cracking	90	10.00	6.95	4.25	−38.84	Pass	Pass

Project/location: R-2554BB Wayne Co. Pavement type: Concrete
Primary data source: Fayetteville, NC (93740)
Design life: 30.0 years

			Predicted Stress			Pass/Fail	
Performance Criterion	Reliability	Target	Baseline	New	% Diff	Baseline	New
Terminal IRI	90	172.00	142.60	133.17	−6.62	Pass	Pass
Mean joint faulting	90	0.12	0.10	0.09	−12.23	Pass	Pass
JPCP transverse cracking	90	15.00	10.59	6.38	−39.80	Pass	Pass

Project/location: I-5110 Guilford Co. Pavement type: Concrete
Primary data source: Greensboro, NC (13723)
Design life: 30.0 years

			Predicted Stress			Pass/Fail	
Performance Criterion	Reliability	Target	Baseline	New	% Diff	Baseline	New
Terminal IRI	90	185.00	151.25	153.00	1.16	Pass	Pass
Mean joint faulting	90	0.15	0.10	0.10	−0.25	Pass	Pass
JPCP transverse cracking	90	10.00	5.84	5.41	−7.34	Pass	Pass

TABLE A.3: *(Continued)*

Project/location: I-440, Wake Co.							Pavement type: Concrete
Primary data source: Raleigh/Durham, NC (13722)							
Design life: 30.0 years							
			Predicted Stress			Pass/Fail	
Performance Criterion	Reliability	Target	Baseline	New	% Diff	Baseline	New
Terminal IRI	90	172.00	144.50	143.32	−0.82	Pass	Pass
Mean joint faulting	90	0.12	0.09	0.09	−2.56	Pass	Pass
JPCP transverse cracking	90	15.00	5.11	5.15	0.80	Pass	Pass

Project/location: R-3421C, Richmond Co.							Pavement type: Concrete
Primary data source: Maxton, NC (93782)							
Secondary data sources for baseline simulation: Monroe, NC (53872); Fayetteville, NC (93740)							
Design life: 34.0 years							
			Predicted Stress			Pass/Fail	
Performance Criterion	Reliability	Target	Baseline	New	% Diff	Baseline	New
Terminal IRI	90	172.00	99.37	95.39	−4.01	Pass	Pass
Mean joint faulting	90	0.12	0.02	0.02	−4.59	Pass	Pass
JPCP transverse cracking	90	10.00	8.69	6.80	−21.75	Pass	Pass

Project/location: R-2303D, Sampson Co.							Pavement type: Concrete
Primary data source: Fayetteville, NC (93740)							
Secondary data sources for baseline simulation: Lumberton, NC (13776); Wilmington, NC (13748)							
Design life: 30.0 years							
			Predicted Stress			Pass/Fail	
Performance Criterion	Reliability	Target	Baseline	New	% Diff	Baseline	New
Terminal IRI	90	172.00	146.00	143.22	−1.91	Pass	Pass
Mean joint faulting	90	0.12	0.10	0.10	−4.23	Pass	Pass
JPCP transverse cracking	90	15.00	12.03	10.59	−11.93	Pass	Pass

Project/location: R-3100A Catawba Co.							Pavement type: Concrete
Primary data source: Hickory, NC (03810)							
Design life: 30.0 years							
			Predicted Stress			Pass/Fail	
Performance Criterion	Reliability	Target	Baseline	New	% Diff	Baseline	New
Terminal IRI	90	172.00	140.85	131.95	−6.32	Pass	Pass
Mean joint faulting	90	0.15	0.08	0.07	−15.85	Pass	Pass
JPCP transverse cracking	90	10.00	8.49	6.42	−24.33	Pass	Pass

TABLE A.4: Comparison of Pavement ME Design pavement distress results at the specified reliability (%) for baseline simulations (Baseline) and simulations using the new long-term climate data files (New) for a selection of ABC projects. Performance criteria include terminal IRI (inches mile^{-1}), permanent deformation (inches) for both the total pavement structure and only the AC contribution, and AC bottom-up and top-down fatigue cracking (feet mile^{-1}). AC thermal cracking is not included here due to its incorrect representation within Pavement ME Design. Values in parentheses in the pass/fail column indicate the percentage of the design life at the point when the distress at the specified reliability reaches the indicated target value (percentages not available for AC rutting).

Project/location: R-2303D, Sampson Co. Pavement type: ABC
Primary data source: Fayetteville, NC (93740)
Secondary data sources for baseline simulation: Lumberton, NC (13776); Wilmington, NC (13748)
Design life: 20.0 years

			Predicted Stress			Pass/Fail	
Performance Criterion	Reliability	Target	Baseline	New	% Diff	Baseline	New
Terminal IRI	90	172.00	139.81	140.93	0.79	Pass	Pass
Perm. deform. – total	90	0.75	0.39	0.41	6.71	Pass	Pass
Perm. deform. – AC	90	0.25	0.18	0.18	2.45	Pass	Pass
AC bottom-up fatigue	90	25.00	6.88	12.14	76.54	Pass	Pass
AC top-down fatigue	90	2000.00	832.61	891.43	7.07	Pass	Pass

Project/location: R-3421C, Richmond Co. Pavement type: ABC
Primary data source: Maxton, NC (93782)
Secondary data sources for baseline simulation: Monroe, NC (53872); Fayetteville, NC (93740)
Design life: 34.0 years

			Predicted Stress			Pass/Fail	
Performance Criterion	Reliability	Target	Baseline	New	% Diff	Baseline	New
Terminal IRI	90	172.00	187.21	190.14	1.56	Fail (88.2%)	Fail (86.3%)
Perm. deform. – total	90	0.75	0.40	0.45	11.94	Pass	Pass
Perm. deform. – AC	90	0.25	0.27	0.30	13.00	Fail	Fail
AC bottom-up fatigue	90	25.00	2.39	2.96	24.06	Pass	Pass
AC top-down fatigue	90	2000.00	286.39	299.32	4.51	Pass	Pass

Project/location: R-4047 Haywood Co. Pavement type: ABC
Primary data source: Asheville, NC (03812)
Design life: 20.0 years

			Predicted Stress			Pass/Fail	
Performance Criterion	Reliability	Target	Baseline	New	% Diff	Baseline	New
Terminal IRI	90	172.00	137.73	137.89	0.11	Pass	Pass
Perm. deform. – total	90	0.75	0.25	0.23	−5.26	Pass	Pass
Perm. deform. – AC	90	0.25	0.11	0.09	−16.61	Pass	Pass
AC bottom-up fatigue	90	25.00	2.04	2.21	8.24	Pass	Pass
AC top-down fatigue	90	2000.00	1296.22	1232.28	−4.93	Pass	Pass

TABLE A.4: *(Continued)*

Project/location: R-2501C, Richmond Co.							Pavement type: ABC
Primary data source: Maxton, NC (93782)							
Design life: 30.0 years							
			Predicted Stress			Pass/Fail	
Performance Criterion	Reliability	Target	Baseline	New	% Diff	Baseline	New
Terminal IRI	90	172.00	164.16	167.44	2.00	Pass	Pass
Perm. deform. – total	90	0.50	0.47	0.45	−3.67	Pass	Pass
Perm. deform. – AC	90	0.40	0.26	0.23	−9.15	Pass	Pass
AC bottom-up fatigue	90	15.00	3.38	22.86	577.15	Pass	Fail (56.4%)
AC top-down fatigue	90	2000.00	1941.83	3287.02	69.27	Pass	Fail (26.7%)

Project/location: R-3432, Brunswick Co.							Pavement type: ABC
Primary data source: Wilmington, NC (13748)							
Design life: 20.0 years							
			Predicted Stress			Pass/Fail	
Performance Criterion	Reliability	Target	Baseline	New	% Diff	Baseline	New
Terminal IRI	90	172.00	127.06	128.29	0.97	Pass	Pass
Perm. deform. – total	90	0.75	0.21	0.22	4.13	Pass	Pass
Perm. deform. – AC	90	0.25	0.08	0.07	−4.14	Pass	Pass
AC bottom-up fatigue	90	25.00	1.72	1.84	7.22	Pass	Pass
AC top-down fatigue	90	2000.00	1017.74	1232.18	21.07	Pass	Pass

Project/location: U-2707, Forsyth Co.							Pavement type: ABC
Primary data source: Winston-Salem, NC (93807)							
Design life: 30.0 years							
			Predicted Stress			Pass/Fail	
Performance Criterion	Reliability	Target	Baseline	New	% Diff	Baseline	New
Terminal IRI	90	172.00	171.49	169.80	−0.98	Pass	Pass
Perm. deform. – total	90	0.75	0.29	0.27	−5.23	Pass	Pass
Perm. deform. – AC	90	0.25	0.11	0.10	−10.02	Pass	Pass
AC bottom-up fatigue	90	25.00	2.60	2.36	−9.31	Pass	Pass
AC top-down fatigue	90	2000.00	1658.06	1685.91	1.68	Pass	Pass

Project/location: X-2BB Cumberland Co.							Pavement type: ABC
Primary data source: Fayetteville, NC (93740)							
Design life: 30.0 years							
			Predicted Stress			Pass/Fail	
Performance Criterion	Reliability	Target	Baseline	New	% Diff	Baseline	New
Terminal IRI	90	172.00	169.92	170.93	0.60	Pass	Pass
Perm. deform. – total	90	0.75	0.43	0.45	4.24	Pass	Pass
Perm. deform. – AC	90	0.25	0.30	0.31	2.81	Fail	Fail
AC bottom-up fatigue	90	25.00	3.05	5.75	88.75	Pass	Pass
AC top-down fatigue	90	2000.00	540.77	797.33	47.44	Pass	Pass

TABLE A.4: *(Continued)*

Project/location: R-2519B, Yancey Co. Pavement type: ABC
Primary data source: Asheville, NC (03812)
Design life: 30.0 years

Performance Criterion	Reliability	Target	Predicted Stress Baseline	Predicted Stress New	Predicted Stress % Diff	Pass/Fail Baseline	Pass/Fail New
Terminal IRI	90	172.00	181.21	180.71	−0.28	Fail (91.9%)	Fail (92.5%)
Perm. deform. – total	90	0.75	0.43	0.42	−4.06	Pass	Pass
Perm. deform. – AC	90	0.25	0.14	0.12	−12.75	Pass	Pass
AC bottom-up fatigue	90	25.00	18.10	14.48	−19.98	Pass	Pass
AC top-down fatigue	90	2000.00	1060.10	576.40	−45.63	Pass	Pass

Project/location: R-3100A Catawba Co. Pavement type: ABC
Primary data source: Hickory, NC (03810)
Design life: 20.0 years

Performance Criterion	Reliability	Target	Predicted Stress Baseline	Predicted Stress New	Predicted Stress % Diff	Pass/Fail Baseline	Pass/Fail New
Terminal IRI	90	172.00	144.71	139.30	−3.74	Pass	Pass
Perm. deform. – total	90	0.75	0.34	0.30	−10.92	Pass	Pass
Perm. deform. – AC	90	0.25	0.17	0.15	−15.10	Pass	Pass
AC bottom-up fatigue	90	25.00	16.72	13.53	−19.08	Pass	Pass
AC top-down fatigue	90	2000.00	1258.28	1794.99	42.65	Pass	Pass

Project/location: I-4733 Catawba Co. Pavement type: ABC
Primary data source: Charlotte, NC (13881)
Design life: 30.0 years

Performance Criterion	Reliability	Target	Predicted Stress Baseline	Predicted Stress New	Predicted Stress % Diff	Pass/Fail Baseline	Pass/Fail New
Terminal IRI	90	172.00	182.96	183.34	0.21	Fail (90.8%)	Fail (90.6%)
Perm. deform. – total	90	0.50	0.40	0.39	−1.38	Pass	Pass
Perm. deform. – AC	90	0.25	0.23	0.22	−2.34	Pass	Pass
AC bottom-up fatigue	90	10.00	22.12	22.03	−0.38	Fail (56.9%)	Fail (57.5%)
AC top-down fatigue	90	1000.00	2247.42	2221.28	−1.16	Fail (18.3%)	Fail (20.8%)

Project/location: I-3802A Cabarrus Co. Pavement type: ABC
Primary data source: Charlotte, NC (13881)
Design life: 30.0 years

Performance Criterion	Reliability	Target	Predicted Stress Baseline	Predicted Stress New	Predicted Stress % Diff	Pass/Fail Baseline	Pass/Fail New
Terminal IRI	90	185.00	181.21	187.45	3.44	Pass	Fail (98.3%)
Perm. deform. – total	90	0.75	0.40	0.55	37.55	Pass	Pass
Perm. deform. – AC	90	0.25	0.24	0.39	64.41	Pass	Fail
AC bottom-up fatigue	90	10.00	18.54	18.24	−1.60	Fail (80.0%)	Fail (82.5%)
AC top-down fatigue	90	1000.00	287.09	294.45	2.56	Pass	Pass

TABLE A.4: *(Continued)*

Project/location: R-2582A, Northampton Co.							Pavement type: ABC
Primary data source: Raleigh/Durham, NC (13722)							
Design life: 30.0 years							
			Predicted Stress			Pass/Fail	
Performance Criterion	Reliability	Target	Baseline	New	% Diff	Baseline	New
Terminal IRI	90	172.00	175.83	175.59	−0.14	Fail (96.7%)	Fail (96.9%)
Perm. deform. – total	90	0.75	0.38	0.37	−1.85	Pass	Pass
Perm. deform. – AC	90	0.25	0.15	0.14	−3.94	Pass	Pass
AC bottom-up fatigue	90	10.00	2.58	2.52	−2.22	Pass	Pass
AC top-down fatigue	90	500.00	310.79	306.70	−1.32	Pass	Pass

Project/location: R-2554BB Wayne Co.							Pavement type: ABC
Primary data source: Fayetteville, NC (93740)							
Design life: 30.0 years							
			Predicted Stress			Pass/Fail	
Performance Criterion	Reliability	Target	Baseline	New	% Diff	Baseline	New
Terminal IRI	90	172.00	167.17	166.40	−0.46	Pass	Pass
Perm. deform. – total	90	0.75	0.38	0.36	−4.57	Pass	Pass
Perm. deform. – AC	90	0.25	0.25	0.24	−6.64	Fail	Pass
AC bottom-up fatigue	90	25.00	2.03	1.99	−2.15	Pass	Pass
AC top-down fatigue	90	2000.00	368.07	349.84	−4.95	Pass	Pass

Project/location: U-3338B, New Hanover Co.							Pavement type: ABC
Primary data source: Wilmington, NC (13748)							
Design life: 30.0 years							
			Predicted Stress			Pass/Fail	
Performance Criterion	Reliability	Target	Baseline	New	% Diff	Baseline	New
Terminal IRI	90	172.00	162.30	164.13	1.13	Pass	Pass
Perm. deform. – total	90	0.75	0.25	0.27	4.93	Pass	Pass
Perm. deform. – AC	90	0.25	0.14	0.14	0.41	Pass	Pass
AC bottom-up fatigue	90	25.00	1.66	1.76	6.27	Pass	Pass
AC top-down fatigue	90	2000.00	511.72	550.00	7.48	Pass	Pass

Project/location: I-440, Wake Co.							Pavement type: ABC
Primary data source: Raleigh/Durham, NC (13722)							
Design life: 30.0 years							
			Predicted Stress			Pass/Fail	
Performance Criterion	Reliability	Target	Baseline	New	% Diff	Baseline	New
Terminal IRI	90	185.00	181.25	181.50	0.14	Pass	Pass
Perm. deform. – total	90	0.50	0.40	0.40	−0.01	Pass	Pass
Perm. deform. – AC	90	0.25	0.24	0.23	−1.59	Pass	Pass
AC bottom-up fatigue	90	10.00	3.85	4.55	18.34	Pass	Pass
AC top-down fatigue	90	1000.00	281.36	277.56	−1.35	Pass	Pass

TABLE A.4: *(Continued)*

Project/location: I-5110 Guilford Co.						Pavement type: ABC	
Primary data source: Greensboro, NC (13723)							
Design life: 30.0 years							
			Predicted Stress			Pass/Fail	
Performance Criterion	Reliability	Target	Baseline	New	% Diff	Baseline	New
Terminal IRI	90	185.00	186.47	188.19	0.92	Fail (98.9%)	Fail (97.5%)
Perm. deform. – total	90	0.75	0.49	0.51	4.24	Pass	Pass
Perm. deform. – AC	90	0.50	0.32	0.33	3.85	Pass	Pass
AC bottom-up fatigue	90	10.00	21.53	21.75	1.02	Fail (67.5%)	Fail (67.8%)
AC top-down fatigue	90	1000.00	335.71	329.33	−1.90	Pass	Pass

TABLE A.5: Comparison of Pavement ME Design pavement distress results at the specified reliability (%) for baseline simulations (Baseline) and simulations using the new long-term climate data files (New) for a CTABC project. Performance criteria include terminal IRI (inches mile^{-1}), permanent deformation (inches) for both the total pavement structure and only the AC contribution, AC bottom-up and top-down fatigue cracking (feet mile^{-1}), and fatigue fracture in the chemically stabilized layer (%). AC thermal cracking is not included here due to its incorrect representation within Pavement ME Design.

Project/location: I-440, Wake Co.						Pavement type: CTABC	
Primary data source: Raleigh/Durham, NC (13722)							
Design life: 30.0 years							
			Predicted Stress			Pass/Fail	
Performance Criterion	Reliability	Target	Baseline	New	% Diff	Baseline	New
Terminal IRI	90	185.00	182.14	182.12	−0.01	Pass	Pass
Perm. deform. – total	90	0.50	0.45	0.44	−1.27	Pass	Pass
Perm. deform. – AC	90	0.25	0.33	0.32	−3.89	Fail	Fail
AC bottom-up fatigue	90	10.00	1.52	1.51	−0.40	Pass	Pass
AC top-down fatigue	90	1000.00	387.07	301.23	−22.18	Pass	Pass
Chem. stab. – fatigue	–	25.00	0.96	1.10	14.58	Pass	Pass

TABLE A.6: Comparison of Pavement ME Design pavement distress results at the specified reliability (%) for baseline simulations (Baseline) and simulations using the new long-term climate data files (New) for a selection of FDA projects. Performance criteria include terminal IRI (inches mile^{-1}), permanent deformation (inches) for both the total pavement structure and only the AC contribution, and AC bottom-up and top-down fatigue cracking (feet mile^{-1}). AC thermal cracking is not included here due to its incorrect representation within Pavement ME Design. Values in parentheses in the pass/fail column indicate the percentage of the design life at the point when the distress at the specified reliability reaches the indicated target value (percentages not available for AC rutting).

Project/location: I-3802A Cabarrus Co. Pavement type: FDA
Primary data source: Charlotte, NC (13881)
Design life: 30.0 years

			Predicted Stress			Pass/Fail	
Performance Criterion	Reliability	Target	Baseline	New	% Diff	Baseline	New
Terminal IRI	90	185.00	182.85	180.42	−1.33	Pass	Pass
Perm. deform. – total	90	0.75	0.46	0.40	−12.35	Pass	Pass
Perm. deform. – AC	90	0.50	0.30	0.26	−14.57	Pass	Pass
AC bottom-up fatigue	90	10.00	13.27	3.89	−70.71	Fail (93.1%)	Pass
AC top-down fatigue	90	1000.00	257.63	257.41	−0.09	Pass	Pass

Project/location: R-3421C, Richmond Co. Pavement type: FDA
Primary data source: Maxton, NC (93782)
Secondary data sources for baseline simulation: Monroe, NC (53872); Fayetteville, NC (93740)
Design life: 34.0 years

			Predicted Stress			Pass/Fail	
Performance Criterion	Reliability	Target	Baseline	New	% Diff	Baseline	New
Terminal IRI	90	172.00	175.43	178.75	1.89	Fail (97.1%)	Fail (94.4%)
Perm. deform. – total	90	0.75	0.39	0.44	12.33	Pass	Pass
Perm. deform. – AC	90	0.25	0.24	0.27	12.49	Pass	Fail
AC bottom-up fatigue	90	25.00	4.29	10.95	155.41	Pass	Pass
AC top-down fatigue	90	2000.00	398.85	464.69	16.51	Pass	Pass

Project/location: R-3432, Brunswick Co. Pavement type: FDA
Primary data source: Wilmington, NC (13748)
Design life: 20.0 years

			Predicted Stress			Pass/Fail	
Performance Criterion	Reliability	Target	Baseline	New	% Diff	Baseline	New
Terminal IRI	90	172.00	126.15	127.23	0.86	Pass	Pass
Perm. deform. – total	90	0.75	0.19	0.20	3.35	Pass	Pass
Perm. deform. – AC	90	0.25	0.06	0.06	−5.22	Pass	Pass
AC bottom-up fatigue	90	25.00	1.67	1.74	4.20	Pass	Pass
AC top-down fatigue	90	2000.00	1070.44	1159.25	8.30	Pass	Pass

TABLE A.6: *(Continued)*

Project/location: R-4047 Haywood Co. Pavement type: FDA
Primary data source: Asheville, NC (03812)
Design life: 20.0 years

Performance Criterion	Reliability	Target	Predicted Stress Baseline	Predicted Stress New	Predicted Stress % Diff	Pass/Fail Baseline	Pass/Fail New
Terminal IRI	90	172.00	137.76	137.88	0.09	Pass	Pass
Perm. deform. – total	90	0.75	0.24	0.23	−4.79	Pass	Pass
Perm. deform. – AC	90	0.25	0.08	0.07	−16.74	Pass	Pass
AC bottom-up fatigue	90	25.00	1.72	1.76	2.27	Pass	Pass
AC top-down fatigue	90	2000.00	347.24	333.70	−3.90	Pass	Pass

Project/location: U-3338B, New Hanover Co. Pavement type: FDA
Primary data source: Wilmington, NC (13748)
Design life: 30.0 years

Performance Criterion	Reliability	Target	Predicted Stress Baseline	Predicted Stress New	Predicted Stress % Diff	Pass/Fail Baseline	Pass/Fail New
Terminal IRI	90	172.00	161.52	163.34	1.13	Pass	Pass
Perm. deform. – total	90	0.75	0.23	0.25	5.15	Pass	Pass
Perm. deform. – AC	90	0.25	0.12	0.12	0.59	Pass	Pass
AC bottom-up fatigue	90	25.00	1.71	1.84	7.61	Pass	Pass
AC top-down fatigue	90	2000.00	562.46	591.76	5.21	Pass	Pass

Project/location: R-3100A Catawba Co. Pavement type: FDA
Primary data source: Hickory, NC (03810)
Design life: 20.0 years

Performance Criterion	Reliability	Target	Predicted Stress Baseline	Predicted Stress New	Predicted Stress % Diff	Pass/Fail Baseline	Pass/Fail New
Terminal IRI	90	172.00	139.68	134.68	−3.58	Pass	Pass
Perm. deform. – total	90	0.75	0.26	0.23	−12.29	Pass	Pass
Perm. deform. – AC	90	0.25	0.13	0.11	−15.01	Pass	Pass
AC bottom-up fatigue	90	25.00	1.83	1.75	−4.70	Pass	Pass
AC top-down fatigue	90	2000.00	306.04	309.69	1.19	Pass	Pass

Project/location: X-2BB Cumberland Co. Pavement type: FDA
Primary data source: Fayetteville, NC (93740)
Design life: 30.0 years

Performance Criterion	Reliability	Target	Predicted Stress Baseline	Predicted Stress New	Predicted Stress % Diff	Pass/Fail Baseline	Pass/Fail New
Terminal IRI	90	172.00	168.48	163.83	−2.76	Pass	Pass
Perm. deform. – total	90	0.75	0.41	0.30	−26.11	Pass	Pass
Perm. deform. – AC	90	0.25	0.19	0.18	−2.11	Pass	Pass
AC bottom-up fatigue	90	25.00	1.76	1.80	2.74	Pass	Pass
AC top-down fatigue	90	2000.00	266.44	267.91	0.55	Pass	Pass

TABLE A.6: *(Continued)*

Project/location: I-440, Wake Co. Pavement type: FDA
Primary data source: Raleigh/Durham, NC (13722)
Design life: 30.0 years

			Predicted Stress			Pass/Fail	
Performance Criterion	Reliability	Target	Baseline	New	% Diff	Baseline	New
Terminal IRI	90	185.00	179.86	179.08	−0.43	Pass	Pass
Perm. deform. – total	90	0.50	0.36	0.34	−6.90	Pass	Pass
Perm. deform. – AC	90	0.25	0.20	0.18	−14.11	Pass	Pass
AC bottom-up fatigue	90	10.00	3.51	3.76	7.11	Pass	Pass
AC top-down fatigue	90	1000.00	269.23	265.43	−1.41	Pass	Pass

Project/location: R-2303D, Sampson Co. Pavement type: FDA
Primary data source: Fayetteville, NC (93740)
Secondary data sources for baseline simulation: Lumberton, NC (13776); Wilmington, NC (13748)
Design life: 20.0 years

			Predicted Stress			Pass/Fail	
Performance Criterion	Reliability	Target	Baseline	New	% Diff	Baseline	New
Terminal IRI	90	172.00	135.33	135.90	0.42	Pass	Pass
Perm. deform. – total	90	0.75	0.30	0.32	7.02	Pass	Pass
Perm. deform. – AC	90	0.25	0.12	0.13	2.38	Pass	Pass
AC bottom-up fatigue	90	25.00	1.92	2.03	5.79	Pass	Pass
AC top-down fatigue	90	2000.00	283.36	287.56	1.48	Pass	Pass

Project/location: R-2519B, Yancey Co. Pavement type: FDA
Primary data source: Asheville, NC (03812)
Design life: 30.0 years

			Predicted Stress			Pass/Fail	
Performance Criterion	Reliability	Target	Baseline	New	% Diff	Baseline	New
Terminal IRI	90	172.00	175.11	175.38	0.15	Fail (97.5%)	Fail (97.2%)
Perm. deform. – total	90	0.75	0.33	0.32	−1.99	Pass	Pass
Perm. deform. – AC	90	0.25	0.09	0.08	−12.94	Pass	Pass
AC bottom-up fatigue	90	25.00	2.00	1.91	−4.29	Pass	Pass
AC top-down fatigue	90	2000.00	277.92	270.77	−2.57	Pass	Pass

Project/location: R-2582A, Northampton Co. Pavement type: FDA
Primary data source: Raleigh/Durham, NC (13722)
Design life: 30.0 years

			Predicted Stress			Pass/Fail	
Performance Criterion	Reliability	Target	Baseline	New	% Diff	Baseline	New
Terminal IRI	90	172.00	173.63	173.38	−0.14	Fail (98.6%)	Fail (98.9%)
Perm. deform. – total	90	0.75	0.33	0.32	−2.13	Pass	Pass
Perm. deform. – AC	90	0.25	0.10	0.10	−3.72	Pass	Pass
AC bottom-up fatigue	90	10.00	2.35	2.31	−1.68	Pass	Pass
AC top-down fatigue	90	500.00	273.82	273.46	−0.13	Pass	Pass

TABLE A.6: *(Continued)*

Project/location: U-2707, Forsyth Co.							Pavement type: FDA
Primary data source: Winston-Salem, NC (93807)							
Design life: 30.0 years							
			Predicted Stress			Pass/Fail	
Performance Criterion	Reliability	Target	Baseline	New	% Diff	Baseline	New
Terminal IRI	90	172.00	166.82	165.41	−0.85	Pass	Pass
Perm. deform. – total	90	0.75	0.19	0.18	−5.44	Pass	Pass
Perm. deform. – AC	90	0.25	0.08	0.07	−10.10	Pass	Pass
AC bottom-up fatigue	90	25.00	1.49	1.48	−0.51	Pass	Pass
AC top-down fatigue	90	2000.00	260.03	259.75	−0.11	Pass	Pass

Project/location: I-5110 Guilford Co.							Pavement type: FDA
Primary data source: Greensboro, NC (13723)							
Design life: 30.0 years							
			Predicted Stress			Pass/Fail	
Performance Criterion	Reliability	Target	Baseline	New	% Diff	Baseline	New
Terminal IRI	90	185.00	177.68	179.04	0.77	Pass	Pass
Perm. deform. – total	90	0.75	0.32	0.33	4.00	Pass	Pass
Perm. deform. – AC	90	0.50	0.16	0.17	3.52	Pass	Pass
AC bottom-up fatigue	90	10.00	2.60	2.67	2.83	Pass	Pass
AC top-down fatigue	90	1000.00	257.44	257.73	0.11	Pass	Pass

Project/location: R-3601 Brunswick Co.							Pavement type: FDA
Primary data source: Wilmington, NC (13748)							
Design life: 20.0 years							
			Predicted Stress			Pass/Fail	
Performance Criterion	Reliability	Target	Baseline	New	% Diff	Baseline	New
Terminal IRI	90	172.00	130.41	130.69	0.21	Pass	Pass
Perm. deform. – total	90	0.75	0.29	0.28	−5.08	Pass	Pass
Perm. deform. – AC	90	0.25	0.16	0.13	−19.97	Pass	Pass
AC bottom-up fatigue	90	25.00	1.83	1.89	3.17	Pass	Pass
AC top-down fatigue	90	2000.00	290.10	277.20	−4.45	Pass	Pass

Project/location: R-2501C, Richmond Co.							Pavement type: FDA
Primary data source: Maxton, NC (93782)							
Design life: 30.0 years							
			Predicted Stress			Pass/Fail	
Performance Criterion	Reliability	Target	Baseline	New	% Diff	Baseline	New
Terminal IRI	90	172.00	158.87	159.46	0.37	Pass	Pass
Perm. deform. – total	90	0.50	0.35	0.33	−4.68	Pass	Pass
Perm. deform. – AC	90	0.40	0.19	0.17	−9.14	Pass	Pass
AC bottom-up fatigue	90	15.00	2.53	2.47	−2.42	Pass	Pass
AC top-down fatigue	90	2000.00	588.55	543.30	−7.69	Pass	Pass

TABLE A.6: *(Continued)*

Project/location: R-2554BB Wayne Co.							Pavement type: FDA
Primary data source: Fayetteville, NC (93740)							
Design life: 30.0 years							
			Predicted Stress			Pass/Fail	
Performance Criterion	Reliability	Target	Baseline	New	% Diff	Baseline	New
Terminal IRI	90	172.00	174.34	174.33	−0.00	Fail (98.1%)	Fail (98.1%)
Perm. deform. – total	90	0.75	0.49	0.49	0.00	Pass	Pass
Perm. deform. – AC	90	0.25	0.26	0.24	−4.92	Fail	Pass
AC bottom-up fatigue	90	25.00	20.44	20.49	0.27	Pass	Pass
AC top-down fatigue	90	2000.00	518.62	511.72	−1.33	Pass	Pass