OKLAHOMA TRANSPORTATION CENTER

ECONOMIC ENHANCEMENT THROUGH INFRASTRUCTURE STEWARDSHIP

PROACTIVE APPROACH TO TRANSPORTATION RESOURCE ALLOCATION UNDER SEVERE WINTER WEATHER EMERGENCIES

BALABHASKAR BALASUNDARAM, PH.D.
SATISH T. S. BUKKAPATNAM, PH.D.
ZHENYU KONG, PH.D.
YANG HONG, PH.D.

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Oklahoma Transportation Center
2601 Liberty Parkway, Suite 110
Midwest City, Oklahoma 73110

Phone: 405.732.6580
Fax: 405.732.6586
www.oktc.org

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16. ABSTRACT: Severe winter weather dramatically reduces road transportation infrastructure serviceability and decreases safety throughout Oklahoma. Although it has relatively mild winters when compared with northern regions of the United States, Oklahoma has reported more winter related major disaster declarations than any other state. This requires the effective monitoring of road conditions across the state in order to treat slick roadways and bridges, assist traffic control in case of accidents and other activities. To this end, in our study, we developed a transportation infrastructure specific Storm Severity Index (SSI) to quantify storm severity, built prediction models for weather parameter, including snow/ice thickness forecasting, conducted vulnerability analysis via traffic flow assignment models on the road network link, and built a conditional value at risk (CVaR) optimization model for mitigating risks via maintenance resource allocation.

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SI (METRIC) CONVERSION FACTORS

Approximate Conversions to SI Units

Symbol	When you know	Multiply by	To Find	Symbol
		LENGTH		
in	inches	25.40	millimeters	mm
ft	feet	0.3048	meters	m
yd	yards	0.9144	meters	m
mi	miles	1.609	kilometers	km
		AREA		
in^2	square inches	645.2	square millimeters	mm
ft^2	square feet	0.0929	square meters	m^2
yd^2	square yards	0.8361	square meters	m^2
ac	acres	0.4047	hectares	ha
mi^2	square miles	2.590	square kilometers	km^2
		VOLUME		
fl oz	fluid ounces	29.57	milliliters	mL
gal	gallons	3.785	liters	L
ft^3	cubic feet	0.0283	cubic meters	m^3
yd^3	cubic yards	0.7645	cubic meters	m^3
		MASS		
oz	ounces	28.35	grams	g
lb	pounds	0.4536	kilograms	kg
T	short tons (2000 lb)	0.907	megagrams	Mg
		TEMPERATURE (exact)		
°F	degrees Fahrenheit	(°F-32)/1.8	degrees Celsius	°C
		FORCE and PRESSURE or STRESS		
lbf	poundforce	4.448	Newtons	N
lbf/in^2	poundforce per square inch	6.895	kilopascals	kPa

Approximate Conversions from SI Units

Symbol	When you know	Multiply by	To Find	Symbol
		LENGTH		
mm	millimeters	0.0394	inches	in
m	meters	3.281	feet	ft
m	meters	1.094	yards	yd
km	kilometers	0.6214	miles	mi
		AREA		
mm^2	square millimeters	0.00155	square inches	in^2
m^2	square meters	10.764	square feet	ft^2
m^2	square meters	1.196	square yards	yd^2
ha	hectares	2.471	acres	ac
km^2	square kilometers	0.3861	square miles	mi^2
		VOLUME		
mL	milliliters	0.0338	fluid ounces	fl oz
L	liters	0.2642	gallons	gal
m^3	cubic meters	35.315	cubic feet	ft^3
m^3	cubic meters	1.308	cubic yards	yd^3
		MASS		
g	grams	0.0353	ounces	oz
kg	kilograms	2.205	pounds	lb
Mg	megagrams	1.1023	short tons (2000 lb)	T
		TEMPERATURE (exact)		
°C	degrees Celsius	9/5+32	degrees Fahrenheit	°F
		FORCE and PRESSURE or STRESS		
N	Newtons	0.2248	poundforce	lbf
kPa	kilopascals	0.1450	poundforce per square inch	lbf/in^2

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PROACTIVE APPROACH TO TRANSPORTATION RESOURCE ALLOCATION UNDER SEVERE WINTER WEATHER EMERGENCIES

Final Report

July 2013

Dr. Balabhaskar Balasundaram, Ph.D., Associate Professor, Oklahoma State University

Dr. Satish Bukkapatnam,, Ph.D., Professor, Oklahoma State University

Dr. Zhenyu Kong, Ph.D., Associate Professor, Oklahoma State University

Dr. Yang Hong, Ph.D., Associate Professor, The University of Oklahoma

Sponsoring Agency:

Oklahoma Transportation Center

2601 Liberty Parkway, Suite 110

Midwest City, Oklahoma 73110

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EXECUTIVE SUMMARY

Ice storms accompanied by excessive winter precipitation are high-impact weather events for the State of Oklahoma. Such hazardous conditions dramatically reduce road transportation infrastructure serviceability, and decrease safety. Consequently, these high-impact weather events are a planning and preparedness priority for the Oklahoma Department of Transportation (ODOT). Hence, the need for ODOT to monitor road conditions across the state in order to treat slick roadways and bridges, move power generators and supply potable water to regions suffering from power outages, manage debris removal in case of ice storms, and assist traffic control in case of accidents, among other activities. This Oklahoma Transportation Center (OkTC) project combines weather prediction models, risk-analysis, and optimization techniques to develop a prototype decision support system that recommends optimal resource allocation and risk mitigation strategies under severe winter weather emergencies.

The prediction of severe winter weather in the form of regional and temporal distribution of ice/snow thickness is based on *artificial neural network* approaches that include forecasts from *Short Range Ensemble Forecasting (SREF)* model as inputs. The transportation infrastructure vulnerability is estimated using passenger and freight flow on various highway segments. An appropriate loss function was developed which depends on the distribution of ice/snow thickness, and the reduction in traffic flow due to reduced system capacity. The mathematical optimization model allocates winter maintenance resources to minimize the *conditional value-at-risk* of losses, which leads to risk-averse resource allocation recommendations.

1. Introduction

Although the northern United States experiences the most severe winter weather, Oklahoma has had more declared disasters than any other state during the period 2000 to 2010. Additionally, all of Oklahoma's winter related major disasters occurred during this period. Federal aid, used as an economic baseline, was nearly 800 million dollars statewide for all winter disasters. Because of the significant transportation, economic, and social impacts of severe winter weather in Oklahoma, it is essential to understand where winter weather typically occurs in Oklahoma, what regions are most impacted by severe winter weather, and if Oklahoma's winter storms are becoming more or less frequent when compared with climatology. This was the first step prior to modeling the transportation impact of severe winter weather, and developing prediction and optimization models for allocating winter maintenance resources.

1.1 Winter Storm Data Collection and Economic Analysis

To better understand the consequences of the recent high-impact winter weather events in Oklahoma, this study compiled all United States National Weather Service (NWS) winter weather reports for the ten year period (2000 – 2010) with specific goals to determine the following.

(1) The spatial distribution of winter weather in Oklahoma during the study period,

(2) Whether the events occurred within climatological norms and,

(3) The overall socioeconomic impacts of the severe, high-impact winter weather events.

The NWS [1] classifies winter weather into five different categories (see Table 1), including Blizzard, Ice Storm, Winter Storm, Heavy Snow and Winter Snow. Oklahoma led the nation with nine winter related disaster declarations during the focus period of this study (1 November 1999 – 1 May 2010). When compared with past climatological analyses, the number and intensity of the high-impact winter weather events was anomalously large across most of Oklahoma and particularly over southern and central portions of the state. For example, central Oklahoma experienced, on average, a two-year snow event nearly every year while southwest and central Oklahoma experienced as many or more blizzards during the study period than over the previous forty-year period from 1959 – 2000. In addition, at least half of all Oklahoma counties reached or exceeded the ten-year, statewide, climatological average of catastrophic ice storms. Such ice storm events were particularly devastating across much of southern, central, and northeast Oklahoma and the results of this study demonstrated that approximately 50% of all ice storm reports occurred during disaster declaration periods. Because the number of ice storm events was anomalously large and encompassed large spatial areas during each event, the impacts frequently occurred in less prepared regions.

TABLE 1 NATIONAL WEATHER SERVICE STORM TYPE DEFINITIONS FOR OKLAHOMA

	Amarillo Forecast Office	**Norman Forecast Office**	**Tulsa Forecast Office**	**Shreveport Forecast Office**
Blizzard[1]	A blizzard means that the following conditions are expected to prevail for a period of 3 hours or longer: Sustained wind or frequent gusts to 15 ms^{-1} (35 miles per hour) or greater; Considerable falling and/or blowing snow (i.e., reducing visibility frequently to less than 0.4 km (1/4 mile).			
Ice Storm[1]	Freezing Rain Accumulations of 0.64 cm (1/4 inch) or more			
Winter Storm[2]	Snow accumulation of 15 cm (6 inches) or more in 24 hours AND/OR sleet accumulation of 5 cm (2 inches) or more	Snow accumulation of 10 cm (4 inches) or more in 12 hours OR 15 cm (6 inches) or more in 24 hours AND/OR sleet	Snow accumulation of 10 cm (4 inches) or more AND/OR sleet accumulation of 10 cm (4 inches) or more	Snow accumulation of 10 cm (4 inches) or more in 12 hours OR between 10 cm and 15 cm (4 - 6 inches) in 24 hours AND/OR sleet accumulation of 1.25 (0.5 inches) or more
Heavy Snow[1,2]	Snow accumulation of 10 cm (4 inches) or more in 12 hours OR 15 cm (6 inches) or more in 24 hours			Snow accumulation of 10 cm (4 inches) or more in 12 hours OR between 10 cm and 15 cm (4 - 6 inches) in 24 hours AND/OR sleet accumulation of 1.25 (0.5 inches) or more

	Amarillo Forecast Office	Norman Forecast Office	Tulsa Forecast Office	Shreveport Forecast Office
Winter Weather[2]	Issued for winter weather events that are of significance to the public, but do not constitute a serious enough threat to life and property to warrant a warning.			
1) NWS Glossary (http://www.weather.gov/glossary/), Accessed 2011. 2) Personal Communication with David Andra (Norman NWS Office, 2011.				

The devastating socioeconomic impact of these winter weather disasters was, in part, revealed by the federal aid distributed to regions across the state. The spatial distribution of the aid revealed that, while the two most populous counties received the most monetary aid, overall the rural counties (1) received the majority of federal aid from the disaster events and (2) yielded greater per capita cost than the more populated counties. Thus, rural regions, with fewer resources at their disposal, were more easily affected by the high-impact winter weather events and required more assistance from outside resources. The details of this study are described in Section 0. The collected storm data not only permitted an aggregate level economic analysis, but it also led us to the development of a metric to classify the severity of a storm from a transportation infrastructure perspective.

1.2 Storm Severity Index

Transportation specific *Storm Severity Index (SSI)* was developed to quantify various aspects of severe winter weather by parameters such as winter precipitation intensity, visibility, and accumulation among others. SSI was modeled for most of the winter related major disasters through Oklahoma during the study period (see Figure 1 Storm Severity Index for a winter related major disaster in December, 2009

). It is a summation of two separate indices which incorporate precipitation (*Precip index*) and non-precipitation (*Base index*) parameters. The base index consists of three important non-precipitation parameters (skin temperature, temperature trend, and wind speed), which have significant impact on winter storm severity: skin temperature indicates how close the ground is to freezing; temperature trend indicates if the temperature is decreasing (more severe) or increasing (less severe); wind speed can influence traffic conditions as it becomes more severe, it can drastically reduce visibilities due to blowing snow both during and after winter storms. The Precip index includes precipitation based parameters and their impact on transportation. The first parameter is the total precipitation accumulation, as the higher the accumulation, the more severe the impact of the storm is, and the more adverse the impact on transportation. Precipitation accumulation severity is also dependent upon the precipitation type. The second parameter describes the impact of precipitation on free flow traffic speed. This parameter incorporates precipitation type, intensity, and visibility and quantifies the cumulative effect on traffic flow. Although this second parameter combines important precipitation components, it is also useful to look at those precipitation components (Precipitation induced visibility and intensity) individually as well. SSI is also designed to be used with advanced weather prediction models to allow forecasts of winter storm severity for up to three days in advance. The SSI based classification and the results from the prediction models are utilized by a mathematical optimization model that provides winter maintenance recommendations, which is the focus of this study. The optimization based resource allocation model is designed to account for the traffic flow, storm severity (which is uncertain), winter treatment options, and resource limitations to provide tactical and operational decision-support for winter maintenance resource allocation. Details of the SSI model are provided in Section 3.

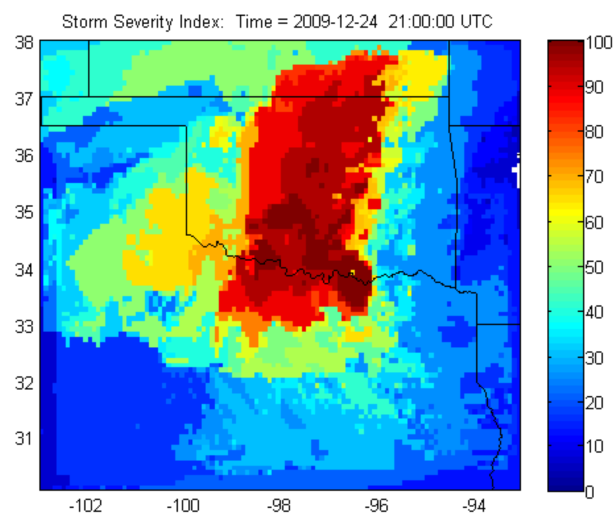

FIGURE 1 STORM SEVERITY INDEX FOR A WINTER RELATED MAJOR DISASTER IN DECEMBER, 2009

1.3 Prediction Models for Snow/Ice Thickness

The accurate prediction of weather parameters including snow/ice thickness is of great significance for SSI estimation, and also for the stochastic optimization model for maintenance resource allocation. The well-known forecasting tool, Weather Research Forecasting used by the National Weather Center uses a Gaussian process model for statistical forecasting, which assumes Normal distribution and Gaussian noise for the data. Although this model can handle the nonlinearity well, it has limitations for complex nonstationary data. Furthermore, the Gaussian assumption may not hold during storms. In order to address the challenges in the prediction of nonlinear and non-Gaussian weather parameters, a sequential Monte Carlo method, namely *Particle Filtering*, is employed in the forecast application. Other prediction models are considered for the purposes of comparison. Technical details on the prediction models developed and studied are provided in Section 4.

1.4 Vulnerability Analysis and Optimization under Weather Uncertainty

The importance of a particular link in the road network is measured as the freight plus passenger traffic flow on the link. We use a heuristic approach to model the flow assignment. Implementation of this heuristic using the mathematical programming solver IBM ILOG CPLEX® was completed and another implementation based on Dijkstra's algorithm was also completed, which was found to be more scalable than CPLEX given the massive size of the US highway network. We have further improved the Dijkstra implementation by employing some well-known graph libraries using more sophisticated data structure. An alternative to this approach for vulnerability analysis is to directly use the *annual average daily traffic flow* available from public databases for measuring vulnerability.

Because the impact of winter storm is uncertain, the winter road maintenance (WRM) recommendations both preventive and restorative should be based on a mathematical model that captures this uncertainty, in addition to modeling resource capacity/availability constraints. We develop a *conditional value-at-risk* (CVaR) optimization model for this purpose that helps us identify risk-averse maintenance resource allocation decisions. The details regarding these ideas are discussed in Section 5 of this report.

1.5 A Prototype Decision Support System

In summary, this project combines weather prediction models, risk-analysis, and optimization techniques to develop a prototype decision support system (DSS) that recommends risk-averse maintenance resource allocation strategies under severe winter weather conditions. Figure 2 Overall architecture of the prototype DSS

illustrates the overall architecture of the proof-of-concept decision support tool developed in this project. We conclude with details of this deliverable, a prototype DSS in Section 6.

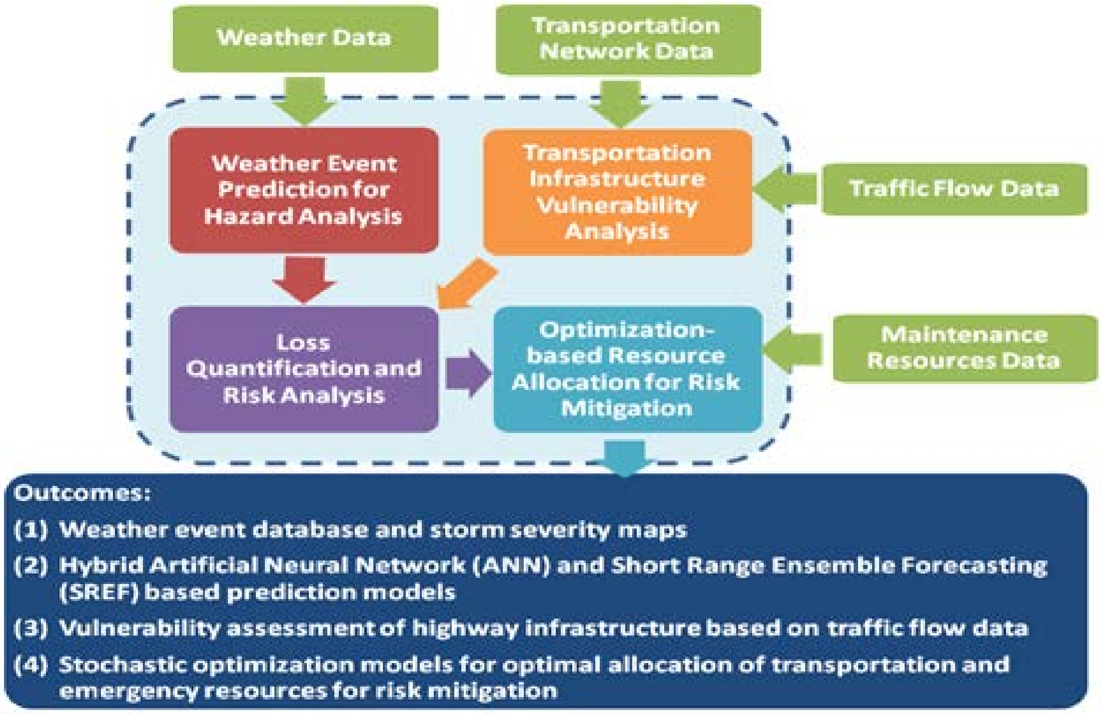

FIGURE 2 OVERALL ARCHITECTURE OF THE PROTOTYPE DSS

2. Significant Winter Weather Events and Socioeconomic Impacts

While winter weather is a common occurrence throughout many regions of the United States, the impact of significant winter storms (typically classified as snowstorms or ice storms) has yielded an increasing toll on society. For example, more winter storm related major disasters have been declared over the past decade (122 declarations during the period of 1 January 2000 – 31 December 2010) than over the previous forty seven years (1 January 1953 – 31 December 1999; 83 declarations) [2].

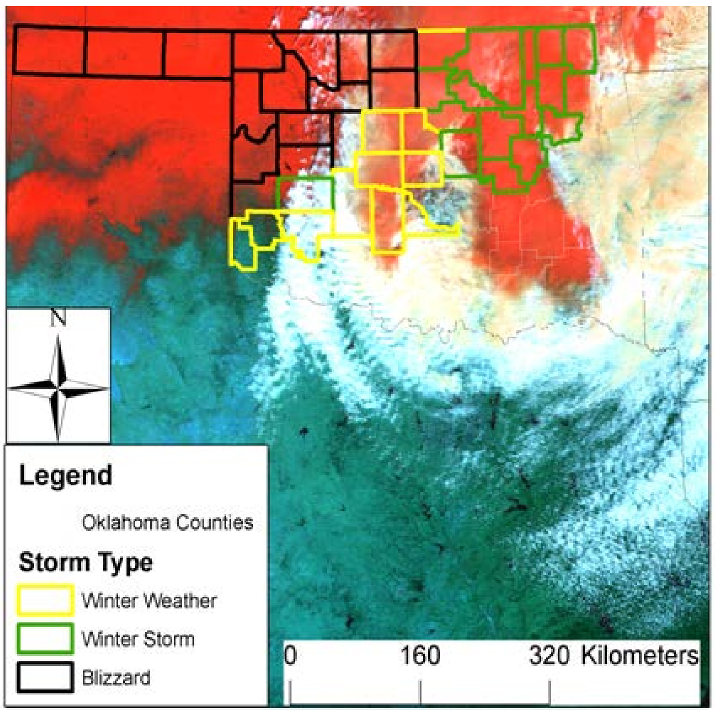

FIGURE 3 MODIS DERIVED IMAGE OF AN ONGOING BLIZZARD AFFECTING OKLAHOMA ON MARCH 27, 2009. RED REGIONS OVER NORTHWEST OKLAHOMA INDICATE SNOW ON THE GROUND. STORM TYPES (FROM STORM DATA) ARE SHOWN IN LEGEND. ACCUMULATIONS IN NORTHWEST OKLAHOMA EXCEEDED 60CM IN SOME LOCATIONS.

In terms of overall winter storms, Changnon [3] found that during the period of 1949-2003 a statistically significant decrease in the number of catastrophic winter storms (storms with at least $1 million damage) was observed across the United States, but he also claimed that a statistically significant upward trend existed in the intensity of the storms measured by monetary costs. The frequency of catastrophic winter storms decreased, but the overall events had a greater impact. Changnon [3] also reported that catastrophic winter storms were most frequent in the northeast U.S. and least frequent in the western United States. Further, despite a decreasing trend for US, Oklahoma State experienced a 105% increase in catastrophic storm incidences during the twenty year period of 1984-2003, when compared to the previous twenty year period of 1964-1983. Over the same time periods, average catastrophic storm losses increased by 291% across the South category of the United States (including Oklahoma). In terms of the regional climatology of snowstorms (defined by accumulations greater than 15.2 cm in two days or less) between 1901 and 2001, snowstorm frequency remained constant across southern Oklahoma throughout the entire period, while in northern Oklahoma the snowstorm frequency decreased over the same time period [4]. Changnon et al. [4] also showed that an average of five snowstorms occur every ten years in northwest Oklahoma while one snowstorm occurs every ten years in central and southern Oklahoma. The results of the study also noted that over the same 100-year period the snowstorms were most frequent in Oklahoma during January and February, while Changnon [5] determined that the 10-year return period for a snowstorm ranged from over 20 cm in northwest Oklahoma to just over 15 cm in southeast Oklahoma. In a statewide study, Branick [6] found that although snowfall events in Oklahoma were most numerous in January, March was the most likely time to experience 'mega snowstorms' (snowfall totals in excess of 40 cm). One such 'mega snowstorm' impacted most parts of northwest Oklahoma in March 2009 (see the satellite image shown in Figure 3 MODIS derived image of an ongoing blizzard affecting Oklahoma on March 27, 2009. Red regions over northwest Oklahoma indicate snow on the ground. Storm types (from Storm Data) are shown in legend. Accumulations in northwest Oklahoma exceeded 60cm in some locations.

) with accumulations of approximately 60 cm.

In addition to heavy snowfall events, dangerous ice storms also occur in Oklahoma. A climatological study of ice storms from 1949 to 2000 by Jones et al. [7] estimated the 50-year return period for ice storms over much of Oklahoma is 1.9 cm or greater of ice accumulation accompanied with 17 m/s wind speed values. Changnon and Karl [8] revealed that freezing rain events in the South category of the United States (including Oklahoma) were most common in December (northwest Oklahoma) and January (central/southern Oklahoma) and the number of freezing rain days steadily increased from 1985 to 2000. While winter storms, especially ice storms, are most frequent in the northeast United States [3, 8], Changnon [9] noted that in the southern United States (including Oklahoma) when freezing rain occurred, (1) it was more likely to be catastrophic and (2) the region had the greatest ice accumulations. Rauber et al. [10] explained that ice storms in the United States were most frequently caused by arctic cold fronts moving southward as warm, moist air ascends over the front. They further explained that this process was pronounced in the southern United States as the air was very warm and moist and that the arctic fronts typically slow in speed, or even stall. Such conditions can increase precipitation intensity, lengthen storm duration, and produce devastating ice accumulations.

The economic and social costs from high-impact ice storms are compounded due to (1) the infrequent nature of freezing rain events and (2) fewer resources to treat the excessive ice as it accumulates on exposed surfaces including roads, power lines, and utilities. Call [11] noted that power outages are the most adverse impact of ice storms because people have no way to heat their homes. In addition, other major impacts of ice storms include transportation disruptions, the shutdown of commercial businesses, and agricultural losses. Changnon [9] found that in the South category of the United States (including Oklahoma) the average cost for catastrophic ice storms, property losses greater than $1 million USD, occurring from 1949 - 2000 was $78 million (expressed in 2000 dollars).

Eight ice storm related major disaster declarations were received by the United States Federal Emergency Management Agency (FEMA) region VI (Louisiana, Arkansas, Oklahoma, Texas, and New Mexico) in the Southern United States from 10 January 2000 to 1 January 2010 and accounted for over a quarter of the twenty nine declared disasters nationally during the same period. Conversely, prior to 2000, the region did not experience a single ice storm event that required major disaster status [12, 13]. Yet, in the most recent decade, eight high-impact ice storms overwhelmed the ability of local government such that disaster declarations were required. The State of Oklahoma has been particularly affected by multiple high-impact winter events from 2000 to 2010 including ice storms, heavy snowfall, and blizzard conditions. At the same time, when compared to other regions of the United States, the climate of Oklahoma is defined by relatively mild winters. Yet during the study period spanning from 1 November 1999 to 1 May 2010, Oklahoma led the nation with nine winter weather related major disaster declarations [2]. To better understand the consequences of the recent high-impact winter weather events in Oklahoma, this study compiled all United States National Weather Service (NWS) winter weather reports for the 10-year period with specific goals to determine (1) the spatial distribution of winter weather in Oklahoma during the study period, (2) whether the events occurred within climatological norms and, (3) the overall socioeconomic impacts of the severe, high-impact winter weather events.

2.1 Data Collection and Collation

Data for this study consists primarily of two sources. The first is the Storm Data Publication (hence forth referred to simply as Storm Data), an official publication of the National Oceanic and Atmospheric Administration (NOAA) available from the National Climate Data Center (NCDC). The Storm Data resource contains a listing of storm occurrences and unusual weather phenomena across the United States [14]. The second dataset was obtained from FEMA and was used to identify regions affected by high-impact storms and to determine a baseline for economic impacts from each event.

All offices of the United States NWS relay confirmed winter weather reports to the NCDC for their County Warning Area (CWA), the specific geographic region for which each office is responsible for issuing forecasts, advisories and alerts. The NCDC then archives and publishes this information in a monthly publication: Storm Data. The NWS classifies winter weather into five different categories Ice Storm, Blizzard, Winter Storm, Heavy Snow, and Winter Weather (NWS 2008 [1], see Table 1 for more details). All winter events from November 1st, 1999 to May 1st, 2010 were manually archived from Storm Data. Information such as date, time, counties affected, storm type, and event summaries were recorded from Storm Data. With few exceptions, one storm report corresponded with one storm event (e.g., one Ice Storm report corresponded with one ice storm event).

With the passage of the Open Government Directive [15], FEMA posted three datasets: FEMA Disaster Declarations Summary, FEMA Public Assistance Funded Projects Summary, and FEMA Hazard Mitigation Program Summary [16-18]. When a federal disaster is declared, states may apply for monetary aid from the federal government to offset costs involved with recovery and prevention [19]. Federal aid can only be used for public infrastructure repair such as rural electric cooperatives, roads, bridges, water treatment plants, parks, and debris removal. As a result, only a fraction of total losses are covered by federal aid. Even so, a generalized assumption of this study is that public and private losses generally are greatest in the same locations, and as such, the FEMA datasets provide a proxy for economic impact on a region. Using the consumer price index, all losses were adjusted for inflation to 2010 dollars (see Table 2).

TABLE 2 COST SUMMARY FOR MAJOR DISASTER DECLARATIONS

Disaster	Size (% of counties)	Open Date	Close Date	Public Assistance 2010 Amount	Hazard Mitigation 2010 Amount	Total Cost
1355	84.42	12/25/2000	1/10/2001	$195,273,585	$58,576,438	$253,850,023

Disaster	Size (% of counties)	Open Date	Close Date	Public Assistance 2010 Amount	Hazard Mitigation 2010 Amount	Total Cost
1401	58.44	1/30/2002	1/11/2002	$135,435,131	$46,367,469	$177,802,600
1452	18.18	12/3/2002	12/4/2002	$5,142,582	$1,484,434	$6,627,016
1677	3.90	12/28/2006	12/30/2006	$7,131,386	$2,567,485	$9,698,871
1678	62.34	1/12/2007	1/26/2007	$82,643,557	$21,767,162	$104,410,720
1735	32.47	12/8/2007	1/3/2008	$103,873,997	$31,782,101	$135,656,098
1823	12.99	1/26/2009	1/28/2009	$9,479,711	$1,973,631	$11,453,341
1876	70.13	12/24/2009	12/25/2009	$18,063,800	$979,946	$19,043,746
1883	64.94	1/28/2010	1/30/2010	$75,457,829	$1,587,897	$77,045,726
			Totals	$628,501,577	$167,086,563	$795,588,140

FEMA disaster declarations summary. The Disaster Declarations Summary (Declaration) dataset lists all declared major disasters since 1950. This dataset includes the unique disaster number, dates of declaration, dates of incident, and names of counties affected.

FEMA public assistance funded projects summary. The Public Assistance Funded Projects (PA) dataset lists all of the money disbursed by the federal government due to major disasters. The PA funds offset costs to public property and interests, and do not include funds distributed by private insurance companies. Further, the PA dataset lists federal aid disbursement by agency, organization, declaration number, and county.

FEMA hazard mitigation program summary. The Hazard Mitigation Program (HM) dataset lists money disbursed by FEMA to pay for projects that will help prevent future damages from occurring. This dataset lists total costs of a project, location of project, and disaster number associated with the project.

The three FEMA datasets were used to analyze spatial patterns of major disasters in Oklahoma, as well as economic impacts on the state. Costs associated with the PA and HM datasets were combined to determine the total public costs associated with the winter weather disasters during this study. Because all of the data sources for this study reported locations by county, the spatial resolution of this study is at the county level. There are several cases where funds, sometimes considerable amounts, disbursed by the federal government were distributed statewide, as opposed to an individual county. These statewide disbursements were omitted from the county analysis, but were included when calculating overall total costs.

2.2 Results and Discussion

2.2.1 Storm Data Analysis

The FEMA datasets demonstrated that nine major disasters were declared for Oklahoma due to winter weather related conditions during the study period 2000 – 2010. In addition, the nine declarations were the greatest number of any state in the United States during the period. The counties with the most disaster declarations were oriented southwest to northeast and include southwest, central, and northeast Oklahoma as shown in Figure 4 (a) Major disaster declarations (b) total FEMA monetary aid (c) FEMA aid per capita

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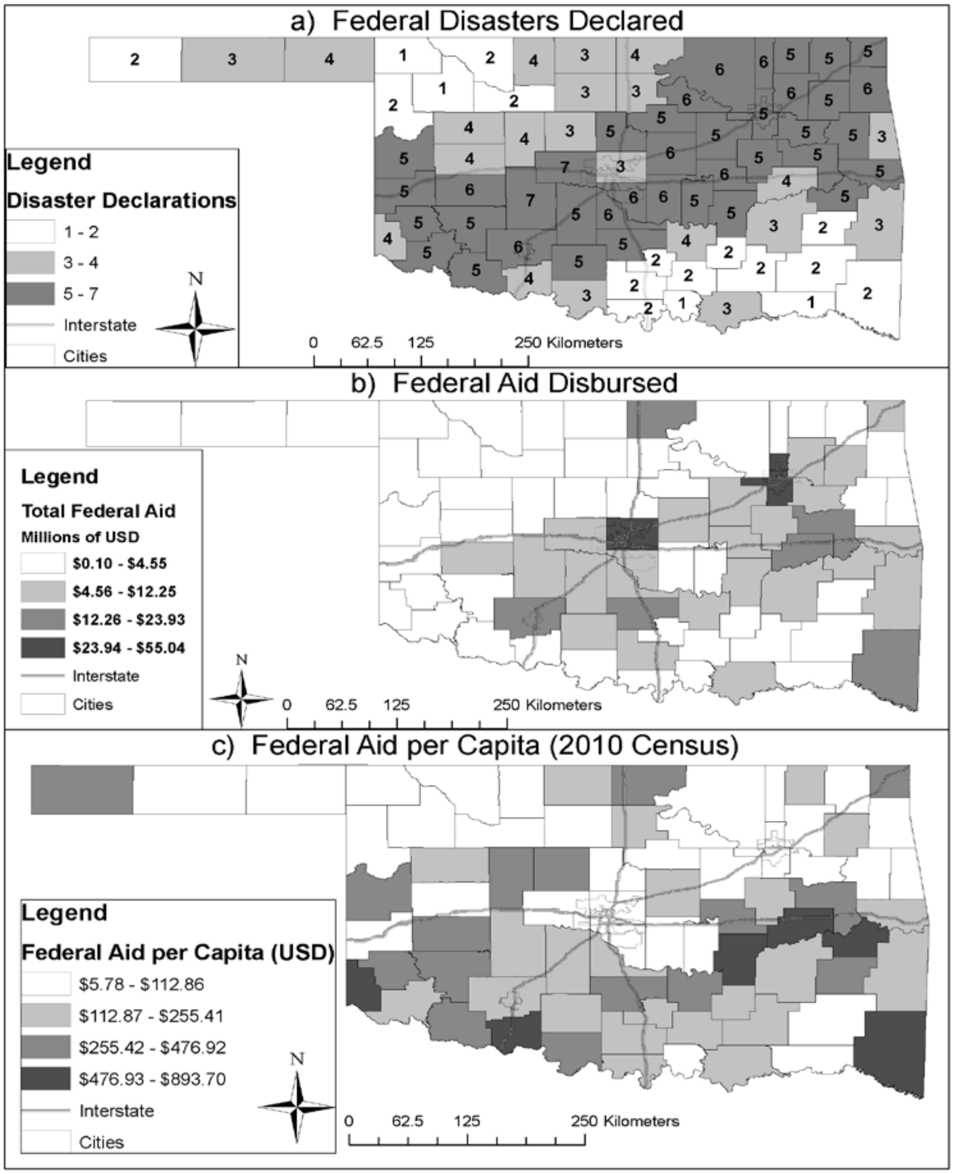

FIGURE 4 (A) MAJOR DISASTER DECLARATIONS (B) TOTAL FEMA MONETARY AID (C) FEMA AID PER CAPITA

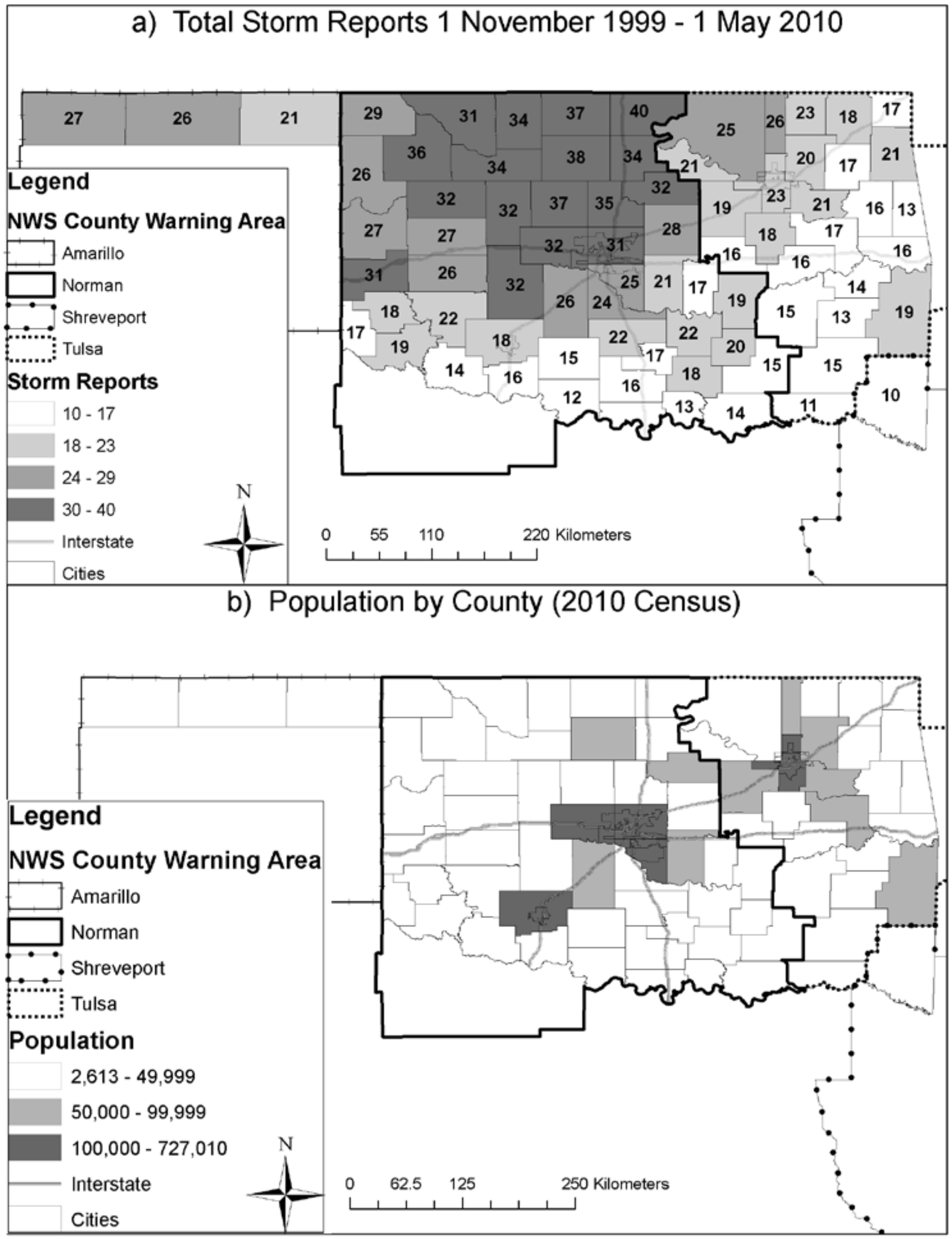

FIGURE 5 TOTAL WINTER REPORTS 1 NOVEMBER 1999 - 1 MAY 2010 (A) AND POPULATION (B) FROM 2010 CENSUS

In terms of individual storm reports, from 2000 to 2010, the highest concentration of total winter reports occurred in north central Oklahoma and the lowest concentration occurred in extreme southern and southeastern Oklahoma (see Figure 5 Total winter reports 1 November 1999 - 1 May 2010 (a) and population (b) from 2010 census

). Biases in reporting, due to population, appears to be almost nonexistent as the correlation between total storm reports and population yielded an R^2 value of 0.01. For individual storm types (Figure 6 Spatial distribution of storm types from 1 November 1999 - 1 May 2010

), Ice Storm reports were primarily concentrated in a southwest to northeast orientation, including much of southwest, central, and northeast Oklahoma. This Ice Storm pattern was significant because the state's four most populous cities (Oklahoma City, Tulsa, Norman, and Lawton) were located within this region. Heavy Snow was most frequently reported in the Oklahoma panhandle while the Winter Storm category was most frequently reported in north central Oklahoma. Blizzard reports, although few, were primarily located in the western half of Oklahoma.

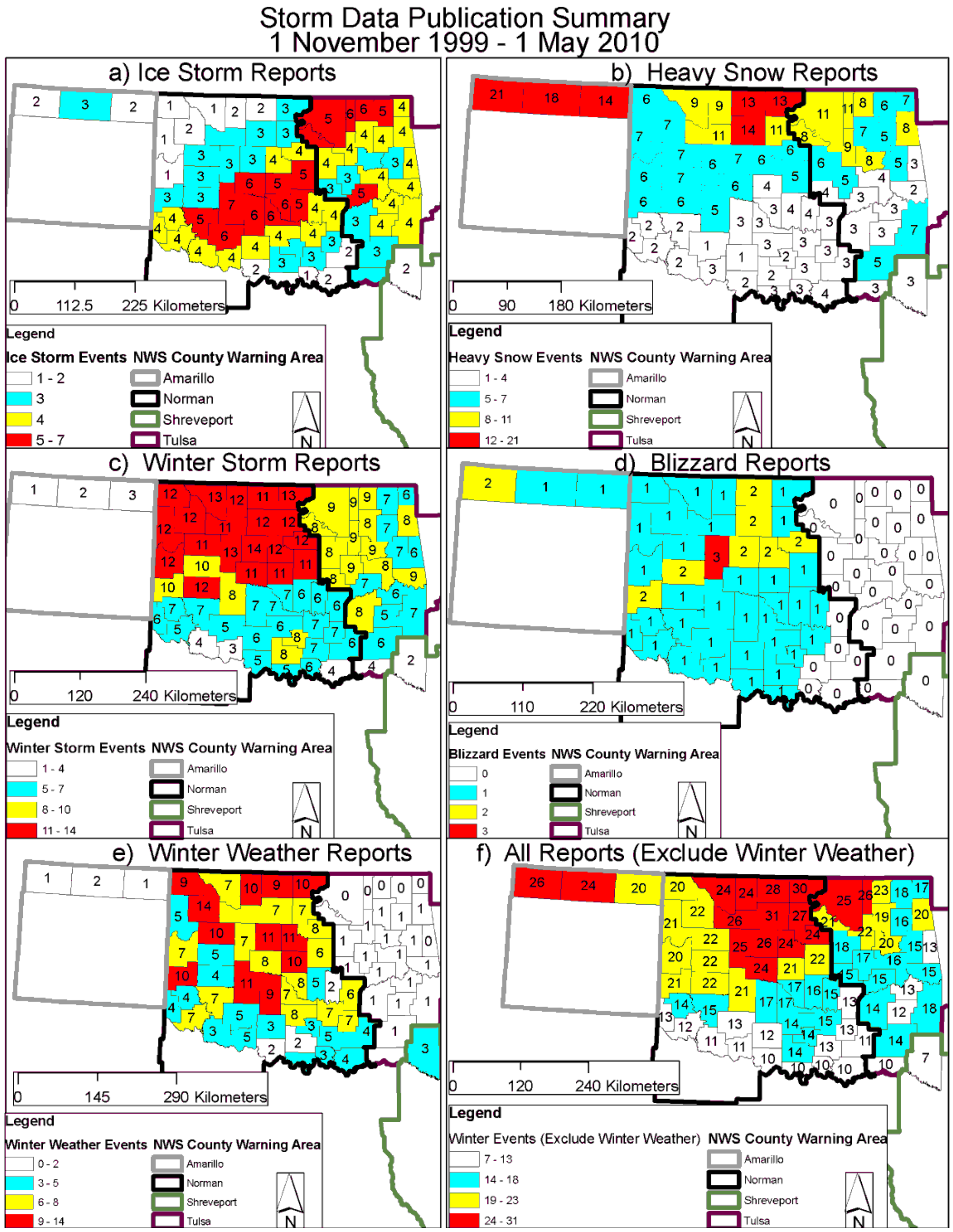

FIGURE 6 SPATIAL DISTRIBUTION OF STORM TYPES FROM 1 NOVEMBER 1999 - 1 MAY 2010

The patterns for Blizzard and Ice Storm reports, arguably the most severe winter storm types, were spatially continuous throughout the study area. However, a reporting discontinuity between NWS CWAs was evident between the Amarillo CWA and the Norman CWA for the Heavy Snow and Winter Storm classifications. Another reporting discontinuity occurred as Winter Weather reports were mostly confined to the Norman CWA and were virtually non-existent in both Tulsa and Amarillo CWAs. To account for this pattern of reporting, all winter events (2000-2010) were re-plotted without the Winter Weather reports to improve the overall consistency between NWS CWAs.

The temporal analysis of the winter events during the study period revealed that December and January received the most winter reports while the overall frequency of the reports were Winter Storm (35%), Heavy Snow (26%), Ice Storm (16%), Winter Weather (20%), and Blizzard (3%). For particular classifications, Ice Storms were most frequently reported in December, while Winter Storm and Heavy Snow were most reported in December and January.

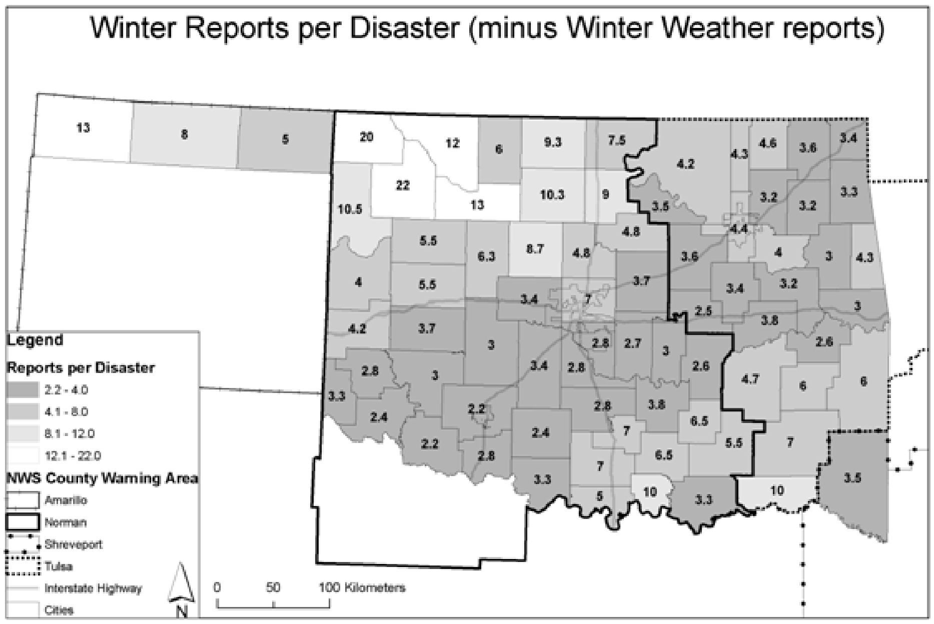

FIGURE 7 RATIO OF TOTAL WINTER REPORTS (MINUS WINTER WEATHER) TO MAJOR DISASTER DECLARATIONS

To better understand the frequency of these high impact winter events, total winter reports (minus Winter Weather reports) were normalized with the number of major disasters declared (Figure 7 Ratio of total winter reports (minus Winter Weather) to major disaster declarations

). The results yielded that southwest Oklahoma had the lowest ratio of storm reports to disasters (as low as 2.2 storm events per declared disaster), while northwest Oklahoma had the highest ratio of storms to disasters (as high as 22 storm events per declared disaster). Overall, the minimum of storm reports to disasters was located in a southwest to northeast orientation across southwest, central, and northeast Oklahoma with much of southwest Oklahoma averaging three or less storm reports per declared disaster. Further, the ratio of Ice Storm reports during disaster declarations to total Ice Storm reports (Figure 8 Ratio of Ice Storm reports during disasters to total Ice Storm reports from 1 November 1999 - 1 May 2010

) demonstrated that at least 50% of the ice storm events yielded a disaster for nearly 70% of all Oklahoma counties (more than 80% of the population). Thus, while not as frequent, when ice storm events occurred they were usually associated with disaster related conditions over widespread regions that impacted significant portions of the population. By comparison, the ratio involving the combined Blizzard, Heavy Snow, and Winter Storm reports demonstrated that while such events often encompass large areas, generally less than 30% of the events would yield a disaster (Figure 8 Ratio of Ice Storm reports during disasters to total Ice Storm reports from 1 November 1999 - 1 May 2010

).

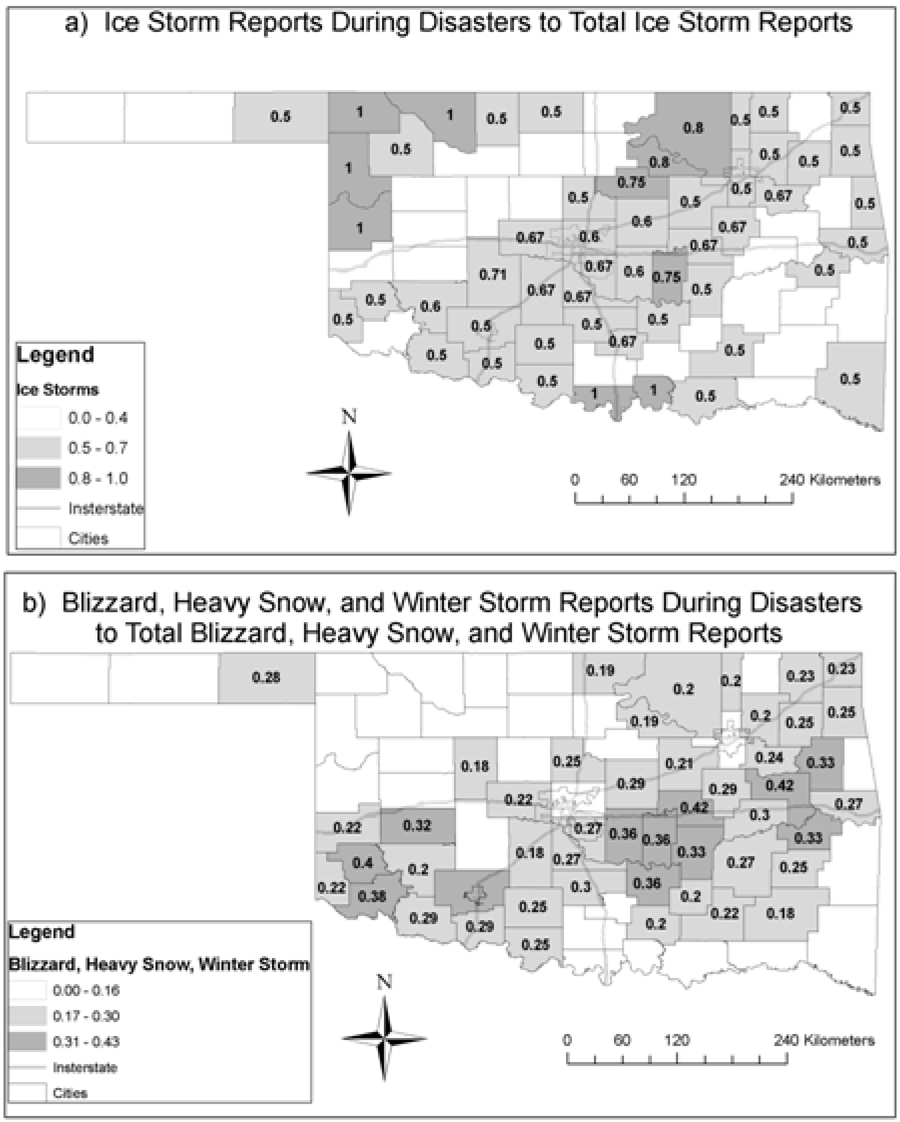

FIGURE 8 RATIO OF ICE STORM REPORTS DURING DISASTERS TO TOTAL ICE STORM REPORTS FROM 1 NOVEMBER 1999 - 1 MAY 2010

When considering total winter reports, one of the most noticeable patterns was the discontinuity of reports between NWS CWAs. For example, the discontinuity was evident in the Heavy Snow and Winter Storm reports and was especially noticeable with the Winter Weather reports. In this case, the reporting discontinuity may be due to the preferences of the local NWS office. Given the overlap of Heavy Snow and Winter Storm criteria it is possible that the Norman NWS office prefers Winter Storm over Heavy Snow, especially because it is valid for multiple precipitation types: snow for Heavy Snow and either snow or sleet for Winter Storm. Another possible reason for the discontinuity of Winter Storm and Heavy Snow reports was based on the local, physical conditions. The more frequent Heavy Snow reports in the Oklahoma panhandle may be due to a common storm track known as the Panhandle Hook, a type of cyclone which develops in the Oklahoma and Texas panhandle and typically deposits heavy snow just to the north of its track as it moves northeast [20]. The higher elevations in the Oklahoma panhandle also contribute to more frequent snow events as opposed to mixed precipitation events.

The specific discontinuity of Winter Weather reports also suggests a difference in reporting preferences of the local NWS office. For this study, Winter Weather reports were virtually non-existent in the Tulsa and Amarillo CWAs and were largely included within the Norman CWA. Winter Weather reports typically reflect minor winter precipitation events and local NWS forecast offices may not consistently report these low impact events. Branick [21] noticed reporting inconsistencies in a nationwide study of Storm Data and concluded statewide inconsistencies were possibly due to personnel at local NWS offices that have different standards of reporting.

2.2.2 Climatological Trends

Within broader climatological trends, the study period was characterized by an anomalously greater number of significant winter-weather events. Changnon [4] showed that for Oklahoma City (Oklahoma county in central Oklahoma), the two-year return period of a snow event was approximately ten centimeters of snow. Over the study period (2000 – 2010) Oklahoma County reported fifteen Heavy Snow and Winter Storm reports, each with a minimum threshold of ten centimeters of snowfall. While the Winter Storm category could be reported solely because of sleet, it is still reasonable that, many if not all Winter Storm reports met the snowfall criteria of ten centimeters of snowfall. As such, Oklahoma City experienced a two-year event more than once a year. Further, every county surrounding Oklahoma County also experienced at least ten Heavy Snow and Winter Storm reports during the study period, which indicates that the local region exceeded climatological norms for significant snowfall (2000 – 2010).

However, for all winter weather events, the results of this study noted that ice storms produce the greatest frequency of disaster conditions. During the study period, such events were most frequently reported in a southwest to northeast orientation across the central portion of the state. Such occurrences were critical given that 80% of Oklahoma's population resided in counties which recorded four or more Ice Storm reports and over 40% of the population resided in counties which recorded five or more Ice Storm reports.

Climatologically, the entire South category of the United States (including Oklahoma and surrounding states) averages five to six catastrophic (>$1 million) ice storms per decade [9]. Storm reports during all winter related disaster declarations [12] revealed that seven individual counties within Oklahoma experienced four or more catastrophic ice storm events, during the study period. As such, some individual counties in Oklahoma experienced nearly as many catastrophic ice storms in the past decade as should impact a region that spans the entire South category of the United States [9]. Further, Changnon [9] noted that over the period spanning the period of 1949- 2000, the entire state of Oklahoma experienced eleven catastrophic ice storms or approximately two per decade. Conversely, more than half of all Oklahoma counties experienced between two and five catastrophic ice storms, measured by Ice Storm reports during disaster declarations, through the study period (2000-2010).

Similar to Ice Storm reports, Blizzard reports were continuous across the state, further demonstrating that the highest impact storms were consistently reported between NWS forecast offices. Because Blizzards include wind criteria and climatologically stronger winds are located across the western portion of the state [22], such reports were generally isolated to the western half of Oklahoma. Schwartz and Schmidlin [23] analyzed blizzards across the United States from 1959 to 2000 and noted that during that 40-year period, only northwest Oklahoma experienced any blizzards; approximately ten blizzards were reported in the Oklahoma Panhandle and up to three in the northwest quarter of Oklahoma. However, from 2000 - 2010, the counties with the most Blizzard reports were not located within the panhandle region, but across central and southwest Oklahoma. Such results were significant given that the southwest quarter of Oklahoma, a region which climatologically experienced no blizzards within the Schwartz and Schmidlin's study [23], had more Blizzard reports within the study period (2000 – 2010) than the entire forty years previous (1959 – 2000). Further, when compared to the Schwartz and Schmidlin [23] climatology, as many Blizzard reports occurred during the study period (2000 – 2010) over the northwest quarter of Oklahoma as were recorded over the previous forty years (1959 – 2000).

2.2.3 FEMA Analysis

Although Oklahoma typically experiences less winter storms than other regions of the United States, the occurrence of high impact storms, as defined by disaster declarations, were numerous during the study period. As such, with nine disasters statewide from 1 November 1999 – 1 May 2010, Oklahoma led the nation in winter weather related declarations and the areal coverage of these events were large with the average winter related disaster encompassed approximately 45% of the 77 counties in Oklahoma while the largest encompassed nearly 85% of all counties. Further, over 60% of Oklahoma's population resided in counties which had at least five declarations during the study period and half of all Oklahoma counties were declared disasters at least five times. Within a larger perspective, from 1 November 1999 to 1 May 2010, such frequent local occurrences were greater than those for 43 entire states in the United States. The total aid (PA & HM) allocated to the State of Oklahoma resulting from these disasters was approximately 800 million USD (as shown in Table 2 Cost summary for major disaster declarations).

The purpose for gauging high impact winter storms using disaster declarations (and allocated Federal resources) is that it serves as a reliable proxy for estimating monetary damages associated with these storms and associated socioeconomic impacts. While the total monetary disbursements to Oklahoma from FEMA totaled near $800 million, the most populous counties, Oklahoma and Tulsa counties, received the most monetary aid from the federal government, when compared to other counties in the state. However, whereas 49% of Oklahoma's population resides in five counties (each with populations over 100,000 residents), these counties only accounted for 30% of federal disbursements due to disasters. As such, 70% of federal funds were disbursed to the remaining 72, more rural, counties (which included 51% of the population) during the winter weather disasters. Thus, when associated disbursements were normalized to population, the highest cost per capita occurred in rural counties outside of the main population centers. Statistically, counties in the upper 50th percentile of disbursement per county (≥ $142 per capita) accounted for 25% of the population and counties which had higher than the 75th percentile (≥ $284 per capita) accounted for only 10% of the population.

The allocation of federal resources in this manner demonstrates that although the most populous counties received the greatest sum total of funds, the rural locales were most affected by the high-impact winter storms and required more aid per given population base due to prolonged impact on local infrastructure. The results are consistent with Call [24], who noted that rural regions are more likely to suffer from prolonged power outages as utilities initially focus on regions with higher numbers of customers. In addition, rural counties are less likely to have the resources (personnel and updated technology) of more populated counties. Thus, when a wide-spread, high-impact winter weather event occurs, rural areas require more external assistance than the local tax base can accommodate.

For the study period, the highest cost per capita of federal funds due to disasters is located across the southern half of Oklahoma, particularly southwest Oklahoma, which was also the region of some of the lowest storm report per disaster ratios. As such, southwest Oklahoma, which was largely rural, was particularly vulnerable to the frequent, high impact winter events that occurred during the period and relied on increased external sources to assist the recovery.

2.3 Conclusion

Oklahoma led the nation with nine winter related disaster declarations during the focus period of this study (1 November 1999 – 1 May 2010) which accounted for nearly 800 Million USD in total aid from the United States Federal Government. When compared with past climatological analyses, the number and intensity of the high-impact winter weather events was anomalously large across most of Oklahoma and particularly over southern and central portions of the state. For example, central Oklahoma experienced, on average, a two-year snow event nearly every year while southwest and central Oklahoma experienced as many as or more Blizzards during the study period than over the previous forty-year period from 1959 – 2000 [23]. In addition, at least half of all Oklahoma counties reached or exceeded the ten-year, statewide, climatological average of catastrophic ice storms [9]. Such ice storm events were particularly devastating across much of southern, central, and northeast Oklahoma and the results of this study demonstrated that statewide approximately 50% of all Ice Storm reports occurred during disaster declaration periods. Because the number of Ice Storm events was anomalously large and encompassed large spatial areas during each event, the impacts frequently occurred in less prepared regions.

The devastating socioeconomic impacts of these winter weather disasters was, in part, revealed by the federal aid distributed to regions across the state. The spatial distribution of the aid revealed that, while the two most populous counties received the most monetary aid, overall the rural counties (1) received the majority of federal aid from the disaster events and (2) yielded greater per capita cost than the more populated counties. Thus, rural regions, with fewer resources at their disposal, were more impacted by the high-impact winter weather events and required more assistance from outside resources.

The contents of this section have appeared in, T. Grout, Y. Hong, J. Basara, B. Balasundaram, S. T. S. Bukkapatnam and Z. Kong. Severe winter weather climatology and socioeconomic impact in Oklahoma: 2000-2010. Journal of Weather, Climate, and Society, 2011, DOI 10.1175/WCAS-D-11-00057.1.

3. Development and Implementation of a Storm Severity Index

During the past 50 years large-scale disruptions due to extreme winter weather events, especially ice storms, have cost in excess of $45 billion on the nation's infrastructure, and winter maintenance approximately accounts for 25% of State Departments of Transportation (DOTs) budgets [25]. Nationally, there have been 33 Presidential disasters declared because of snow and ice since 2000 [12]. According to Federal Highway Administration (FHWA) statistics [26], State and local agencies spend more than $2.5 billion on snow and ice control operations and more than $5 billion to repair infrastructure damage caused by ice and snow. In the period of 1995–2004, more than 389,000 crashes occurred in winter weather (6% of all crashes), more than 133,000 persons were injured in winter weather (more than 4% of all crash injuries) and more than 1,500 people were killed in crashes during winter weather (more than 3% of all crash fatalities). Adverse weather is recognized as one of the leading causes of non-recurrent congestion, and in particular winter precipitation alone can cause 15% of non-recurring delay. The cost of congestion related travel delays on an economy is significant. It has been estimated that in metropolitan areas, truckers lose about $3.4 billion (about 32 million hours) stuck in weather-related traffic delays. A one-day highway shutdown can cost a metropolitan area up to $76 million in lost time, wages, and productivity [27]. Consequently, various state DoTs have been striving for effective maintenance and response policies to mitigate hazard in the event of extreme winter weather as part of their winter preparedness programs [28-33].

Weather data is essential to the decision making processes during severe winter weather. To make effective decisions over large geographic regions, weather data must be gridded instead of point based. To maximize preparedness, we need to forecast weather information (data) up to some reasonable time scale into the future (2-3 days), which can be done through advanced weather prediction models, such as the Weather Research and Forecasting model (WRF) and the Short Range Ensemble Forecasting (SREF) model. Although these weather prediction models are ideal for improving preparedness, they also require extensive background knowledge in meteorology to be useful. It is important to present the model output clearly so that transportation managers can focus on making decisions instead of learning those complex models. This goal can be accomplished by developing winter severity indices tied to specific sectors of the economy.

There have been several indices developed recently and Maze et al. [34] contains a brief summary of many of these. Many indices rank entire winter seasons using daily temperature and snow data [35-37]. Some of these indices even factor in multiple precipitation types [38-40]. Nearly all of these storm indices were developed using observed data and were applied to the entire winter season. Maze et al. [34] notes a more recent index [41], which is storm based and includes factors such as temperature, wind, and storm behavior. Other storm based indices have been developed for specific types of precipitation such as the Nor'easter intensity index [42] or the Sperry-Piltz [43] ice accumulation index which categorizes ice storms according to ice accumulation and wind. Many of the existing indices are applied to winter seasons and not applied to individual storms or they are based on observed data and not advanced numerical weather prediction models. Furthermore, these indices are static and are not designed to be updated dynamically as the storm data is gathered and forecasts are updated. Because winter storms affect different sectors of the economy differently, it is important to tune an index to a specific sector. For example, the Sperry-Piltz ice accumulation index applies to the electrical grid and utility infrastructures and is hence used by utility managers. There are no known indices which utilize advanced numerical weather prediction models and are tailored specifically to transportation maintenance operations to classify individual storms.

3.1 Storm Severity Index Development

A transportation-specific, storm-based, and dynamic Storm Severity Index (SSI), which accounts for all major winter precipitation types (rain, snow, sleet, and freezing rain), was developed in this study. It was designed to be compatible with multiple forecasting models such as the Weather Research and Forecasting model (WRF) [44] or the Short-Range Ensemble and Forecast (SREF) model [45]. Both of these models are advanced weather prediction models, which predict weather conditions two to three days in advance. The WRF model has a higher resolution, more frequent time steps and produces forecasts out of two days. The SREF is an ensemble model consisting of over a dozen weather models and the mean of these models is used for the calculation of the SSI. It has a coarser resolution compared to the WRF, but it forecasts for up to three days in advance.

Using weather parameters produced by weather prediction models, the SSI is specifically formulated for transportation by accounting for precipitation intensity and visibility, precipitation accumulation, as well as other non-precipitation hazards such as the winds, temperature, and temperature trend. The SSI was developed similar to Boselly et al.'s work [36] with weather parameters assigned categorical scores and then weighted relative to other parameters. The SSI is composed of two sub-indices, which rate important non-precipitation parameters (Base Index) and important precipitation parameters (Precip Index). The Base Index parameters are skin temperature, temperature trend, and wind speed; while the Precip Index parameters are precipitation impact on free flow traffic speed (a function of precipitation type, intensity, and visibility) and precipitation accumulation. The total SSI is then the sum of both indexes. This SSI is unique because it is a dynamic and gridded storm based index, which is tailored specifically to transportation.

The SSI quantifies weather impacts on free flow traffic speed caused by both precipitation intensity and precipitation accumulation. In addition, it can be used with multiple advanced numerical weather prediction models (WRF or SREF), which can be used for both forecasting and hindcasting purposes. Because this SSI is used with numerical weather models, it has the same time step (typically 3 hours) and resolution (as low as 1km) as the weather prediction model used. All parameters in both indices are divided into categories with each parameter category assigned a score (from 0 to 1) based on severity. Additionally, each parameter is given a weight (from 0 to 100%) so that they can be given a relative significance compared to other parameters within each index. All parameter weights within an index must sum up to 100%, thus the index score can have a maximum score of 100. The index score is the sum of the products of the parameter's categorical scores' and that parameter's weight. The mathematical formula (shown as Eq. 1) for each index is represented as:

$$\text{Index(maximum 100)} = \sum[(\text{Parameter category score}) \times (\text{Parameter Weight})] \qquad (1)$$

The SSI is only calculated during storm conditions, or when precipitation is forecast to begin until 24 hours after all precipitation has ended. Once a storm is over, the SSI is reset to zero and is not calculated until precipitation is predicted to begin again. The 24 hour period assumes that the emergency response to high-impact winter storms will be completed within 24 hours after the last predicted winter precipitation falls.

3.1.1 Base Index

The first index is the Base index (see Table 3 Base index description , adapted from Kyte et al. [46], who quantified wind effects on driving conditions in free flow speed), which consists of three important non–precipitation parameters (surface temperature, temperature trend, and wind speed) that impact winter storm severity.

TABLE 3 BASE INDEX DESCRIPTION

Index	Parameter	Weight (%)	Score (0 - 1)
BASE	Temperature	40	Above Freezing (1), Below Freezing (0)
	Temperature Trend	10	Increasing (0), Decreasing (1)

Index	Parameter	Weight (%)	Score (0 - 1)
	Windspeed[1]	50	Windspeed < 10 mph (0); 16mph ≤ Windspeed ≤ 20 mph (0.33) 20 mph < Windspeed ≤ 30 mph (0.66) Windspeed > 30 mph (1)

Surface temperature is important because it is the ground temperature and thus the closest approximation to the pavement temperature. Temperature trend is important because it indicates if the temperature is decreasing (more severe) or increasing (less severe). Finally, wind speed is included because it can influence traffic conditions as velocities increase. Calculation of the base index involves assigning a score to each weather parameter (between 0 and 1) as well as a parameter weight (summed to 1) (see Figure 9 Flowchart for Base Index: Base index score is calculated by multiplying the parameter weight with the parameter score. Max score is 100.

for details).

3.1.2 Precip Index

The Precip index (see Figure 10 Flowchart for Precip Index: Precip index score is calculated by multiplying the parameter weight with the parameter score. Max score is 100.

) consists of important precipitation based parameters and their impact on transportation. The first parameter is storm total precipitation accumulation. Precipitation accumulation severity is dependent upon the precipitation type; one inch of snow is not as severe as one inch of ice. The second parameter describes the impact of precipitation on free flow traffic speed. This parameter incorporates precipitation type, intensity and visibility, and quantifies the impact on traffic flow.

The Precip index consists of two parameters: precipitation accumulation and precipitation intensity effect on free flow traffic speed. The scores and weights assigned each parameter are explained in the following.

Precipitation Accumulation: Accumulation scores were adapted or slightly modified from Nixon and Qiu [41], who quantified the relative impact of winter storm accumulations on transportation for different precipitation types. All precipitation estimates are calculated using liquid equivalent amounts. All freezing rain amounts are radial equivalent accumulations according to the method described by Jones [47]. Snow and sleet amounts were derived using general conversions from liquid equivalent amounts [48, 49].

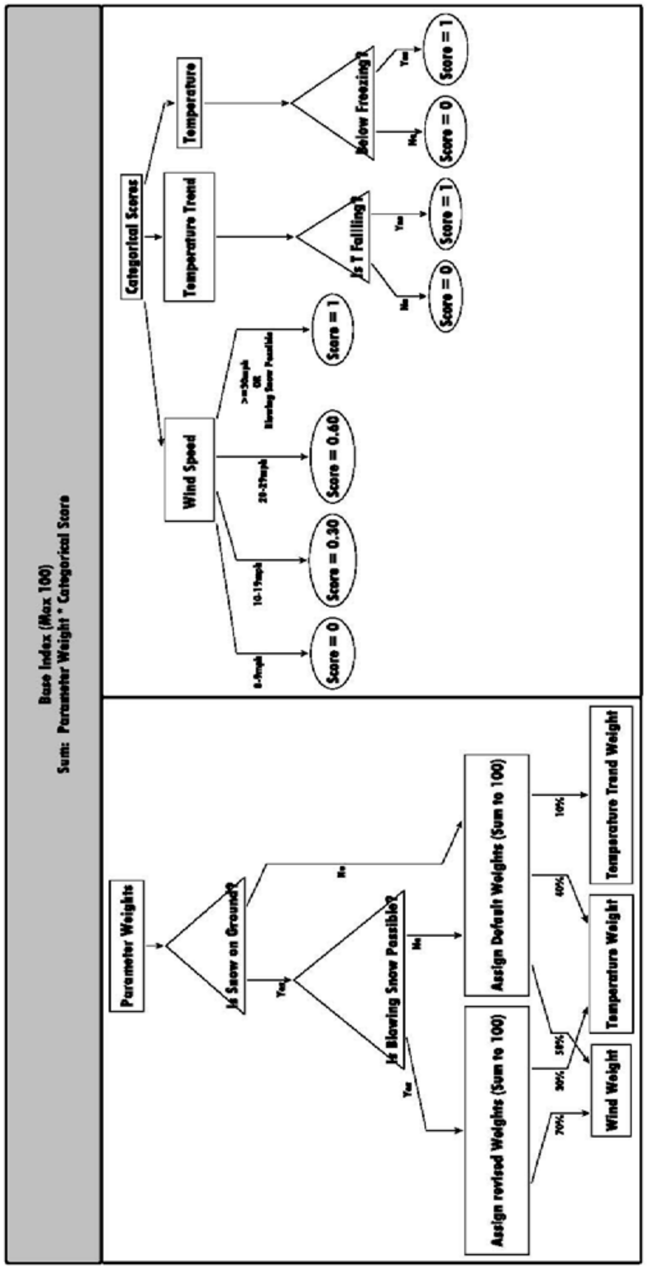

FIGURE 9 FLOWCHART FOR BASE INDEX: BASE INDEX SCORE IS CALCULATED BY MULTIPLYING THE PARAMETER WEIGHT WITH THE PARAMETER SCORE. MAX SCORE IS 100.

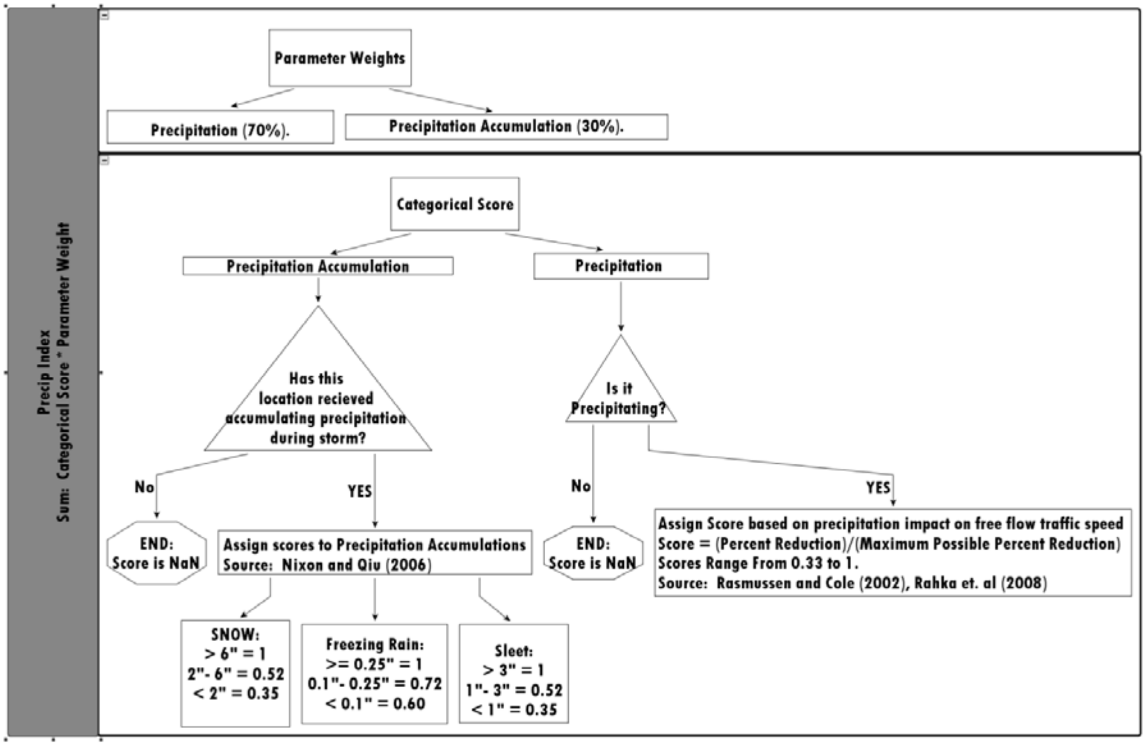

FIGURE 10 FLOWCHART FOR PRECIP INDEX: PRECIP INDEX SCORE IS CALCULATED BY MULTIPLYING THE PARAMETER WEIGHT WITH THE PARAMETER SCORE. MAX SCORE IS 100.

Precipitation impact on Free Flow Traffic Speed: This parameter incorporates precipitation intensity and visibility. Categories for this parameter are numerous but they are all based upon visibility, intensity, and precipitation type. This parameter is weighted more than accumulation as precipitation intensity is more impactful on transportation than storm accumulations.

Snow and Sleet: Snow and sleet have the highest impact on visibility. Average liquid-equivalent hourly snowfall/sleet rates are calculated from model output and intensities are assigned according to Rasmussen and Cole [50]. Visibility (a function of precipitation intensity), temperature, and time of day, were assigned according to Rasmussen and Cole [50]. Rakha et al. [51] studied how precipitation impacts free-flow traffic speed; it is a function of precipitation intensity and visibility. Intensities and visibilities determined from Rasmussen and Cole [50] were applied to Rakha et al [51] to determine the impact of precipitation intensity on free flow traffic speed. Scoring was the ratio of the impact on free-flow traffic speed to the maximum possible impact on free-flow traffic speed.

Rain/Freezing Rain: According to Rassmussen and Cole [50], liquid precipitation does not impact visibilities near as much as snowfall. Rakha et al. [51] does quantify rainfall intensities on free flow traffic speed. Unfortunately, freezing rain's impact on free flow traffic speed is not well studied and accurate impacts on free flow traffic speed are not available. To account for freezing rain it was assumed that for any three hour period, or time step of the model, if a location was forecast to experience freezing rain with radial ice accumulations greater than .01” then that location would receive a maximum score of 1. This may be excessive, but the impact of freezing rain cannot be overemphasized.

3.2 SSI Implementation and Preliminary Evaluation

The SSI is implemented over the winter seasons of 2000-2010. A WRF model was run in-house for all winter seasons (December to March) from 2000- 2010 for central Oklahoma. SSI scores for each grid were accumulated on a 12 hourly and daily basis and they yielded a log-normal distribution (see Figure 11 and Figure 12). In addition, a statewide WRF model was run for some major disaster storms of the past decade in Oklahoma.

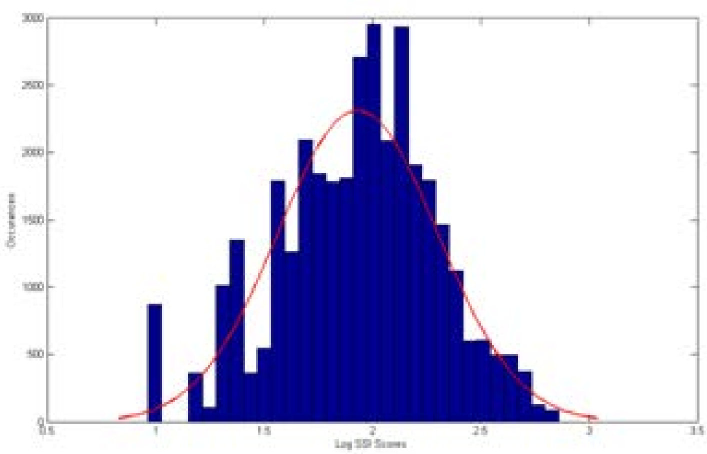

FIGURE 11 LOG SSI DISTRIBUTION ON A 12 HOUR BASIS

To evaluate the SSI, daily accident data including injuries and fatalities, for Oklahoma county for 10 winter months (from 2000 – 2010) was obtained from the Oklahoma Department of Transportation [52]. These accident statistics spanned some of Oklahoma’s most severe winter weather including many of the winter related major disasters. A statistical validation of the SSI is underway at the time of this writing and is expected to be a part of a future research publication that is planned, based on this work.

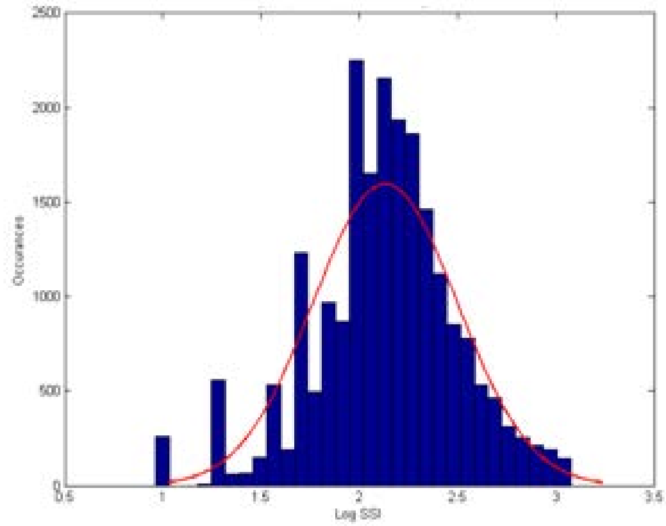

FIGURE 12 LOG SSI DISTRIBUTION OF SSI SCORES ON A DAILY BASIS

3.3 Conclusion

A storm severity index was developed geared specifically toward transportation. The SSI provides a user-friendly approach to enable transportation officials to be better informed with regards to impending winter weather. This approach is an improvement over other severity indices because it is transportation specific, storm based, and it is both (spatially) gridded and dynamic. The SSI incorporates multiple weather parameters that influence transportation safety. In addition, using advanced weather prediction models enables the SSI to be calculated for both past and present winter events. By using a gridded and predictive SSI, transportation planning managers can anticipate severe winter weather and specifically its potential impact on transportation infrastructure. In rapidly changing weather conditions, as the weather models update, SSI can also be updated dynamically. As weather prediction models improve in accuracy so will the SSI. The SSI shows some preliminary statistical evidence of being a better indicator of transportation specific storm severity than simpler indicators like predicted snow/ice thickness or precipitation depth alone. The results of this research are currently being prepared for publication.

4. Nonlinear Bayesian Analysis for Snow/Ice Thickness Prediction

Predicting weather parameters including ice/snow thickness is key to accurately forecasting SSI and it is also needed in the stochastic optimization model for maintenance resource allocation. The methodological contributions in this regard are detailed in this section. These numerical prediction models are complementary to WRF/SREF models employed in the development of SSI as they offer higher resolution, are relatively easier to work with from a computational perspective, and enable probabilistic forecasts as opposed to point estimates of weather parameters, when compared to WRF/SREF models that employ physics models and need supercomputing resources.

Probabilistic forecast of weather parameters has many advantages over the non-probabilistic forecast techniques in aiding weather related decision making processes [53]. An emergency manager can better decide whether to use anti-icing treatments or de-icing treatments based on the probability of icing on the road. Physical forecast models do not consider uncertainties in both initial conditions and model formulation [54], a drawback that can be addressed by probabilistic models. Previous research shows that, decision-makers provided with information about uncertainty can make better decisions compared to those who do not have this information [55]. In addition, classifying storms into different categories in terms of their severity is essential for the optimization based resource allocation decision support system. In order to classify upcoming storms, we need accurate forecast of weather parameters. In this study we develop such a probabilistic forecast system that incorporates outputs of physical models and historical data.

4.1 Literature Review

Time series models such as autoregressive moving average (ARMA) models are widely used in weather forecasting. ARMA models assume a linear relationship between current data and past data. While they are effective for stationary and linear systems, they are not best suited for predicting weather parameters. ARMA models use iterative methods to find the optimal model parameters which makes them computationally demanding. For example, an ARMA model is constructed by Torres et al. to forecast short term average wind speed in [56]. To overcome the challenge of seasonality difference in their study, ARMA models are developed for each month. Burlando et al. [57] employed ARMA models for rainfall forecasting by investigating all rainfall occurrences in a period and using an event based approach.

Kalman filtering is an online forecasting method in which measurements are used to update the model sequentially by assuming linear dynamics and Gaussian noise. An autoregressive (AR) model is proposed by Huang and Chalabi [58] to forecast average wind speed by adjusting the model parameters with Kalman filtering over time. Details about forecasting of time series by using ARMA model and Kalman filtering are investigated in [59]. Ensemble Kalman filtering method is suitable for geophysical models that use partial differential equations [60-62].

Extended Kalman Filter (EKF) is a nonlinear adaptation of Kalman Filter (KF) [61, 63]. Artificial Neural Networks are also a relevant alternative for this purpose. Various statistical forecasting techniques including ARMA models, Neural Network and Adaptive Neuro-Fuzzy Inference Systems are compared in their ability to predict hourly average wind speed [64]. Application of Neural Network models in forecasting of weather parameters is also investigated in [65, 66].

As a non-parametric model, Gaussian process models can capture nonlinearity in the system with a probabilistic approach although it assumes stationarity. In Ref. [67], energy system models are optimized using forecast information from a Gaussian process model. Gaussian process model is constructed to model a wind field in Ref. [68]. In this study, we employ a sequential Monte Carlo method called particle filtering in order to model nonlinear and nonstationary weather parameters as detailed next.

4.2 Methodology

Previous studies show that weather parameters such as temperature, pressure, wind speed and wind direction strongly relate to the amount of snow fall [69-71]. Thus, snow fall can be quantitatively be related to the weather parameters by using nonlinear regression analysis such as artificial neural network. Weather parameters are forecasted using nonlinear Bayesian analysis, and then forecasted values of weather parameters are input to a neural network model, as summarized in Figure 13 Flowchart of the particle filter forecast model

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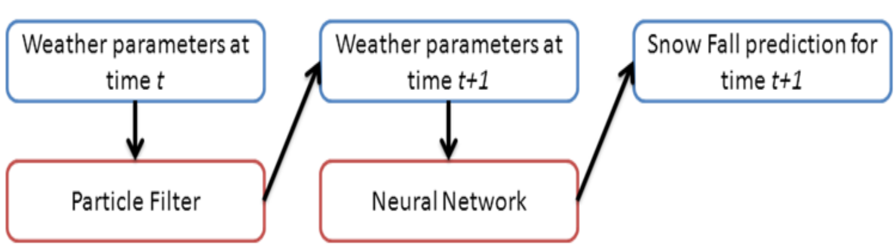

FIGURE 13 FLOWCHART OF THE PARTICLE FILTER FORECAST MODEL

During severe storm conditions, weather parameters changes rapidly. Thus, we need to run the physical models frequently to get accurate forecast. Because physical models are computationally intensive, it is not preferable to use them for short term forecasting. Statistical methods can be useful since they are fast and accurate. WRF model itself for example uses Gaussian process models for statistical forecasting. While they can handle the nonlinearity well, Gaussian assumption restricts its application in the forecasting of weather data. In addition, Gaussian process model assumes stationarity (the covariance structure is time independent), which may not hold under storm conditions. In order to address this problem, a sequential Monte Carlo method, namely Particle Filtering (PF) is utilized in this study to forecast the weather parameters. PF method is also compared against other widely used techniques, including Kalman filtering (KF) and Gaussian Process.

In order to demonstrate the advantage of particle filtering model over Kalman filtering and Gaussian process, the models are applied to temperature data for one-hour ahead forecasting as shown in Figure 14 Comparison of various forecasting methods for one-step ahead temperature prediction

. The data is obtained from MESONET [72]. The accuracy of the different methods, defined in Eq. 2 (also known as R^2), is compared in

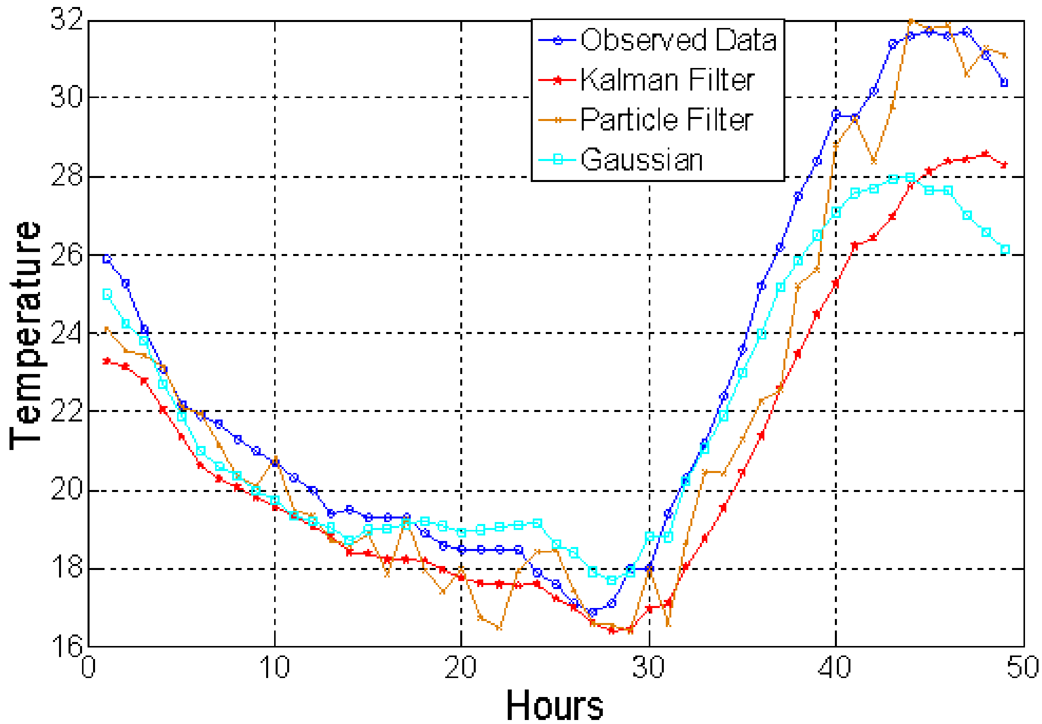

FIGURE 14 COMPARISON OF VARIOUS FORECASTING METHODS FOR ONE-STEP AHEAD TEMPERATURE PREDICTION

$$\text{Accuracy} = \left(1 - \frac{\text{Mean Square Error}}{\text{Variance of Data}}\right) \times 100 \qquad (2)$$

TABLE 4 ACCURACY OF DIFFERENT FORECASTING METHODS

FORECASTING METHOD	**ACCURACY (R^2)**
KALMAN FILTER	78.56%
GAUSSIAN PROCESS	86.37%
PARTICLE FILTER	92.35%

In addition to air temperature (at the height of 1.5 m), relative humidity, solar radiation, air pressure, average wind speed, wind direction, temperature (at 9 m) parameters are also forecasted in order to predict snow fall. Figure 15 One Step Ahead Forecast of Relative Humidity (%) (top) and Solar Radiation W/m^2 (bottom)

, Figure 16 One Step Ahead Forecast of Air Pressure (mbar)(top) and Air Temperature at 9 m

, and Figure 17 One Step Ahead Forecast of Average Wind Speed (m/s) (top) and Wind Direction (degree) (bottom)

illustrate the prediction results for these parameters. The blue lines are actual observations and red lines are forecasted values acquired from particle filtering method.

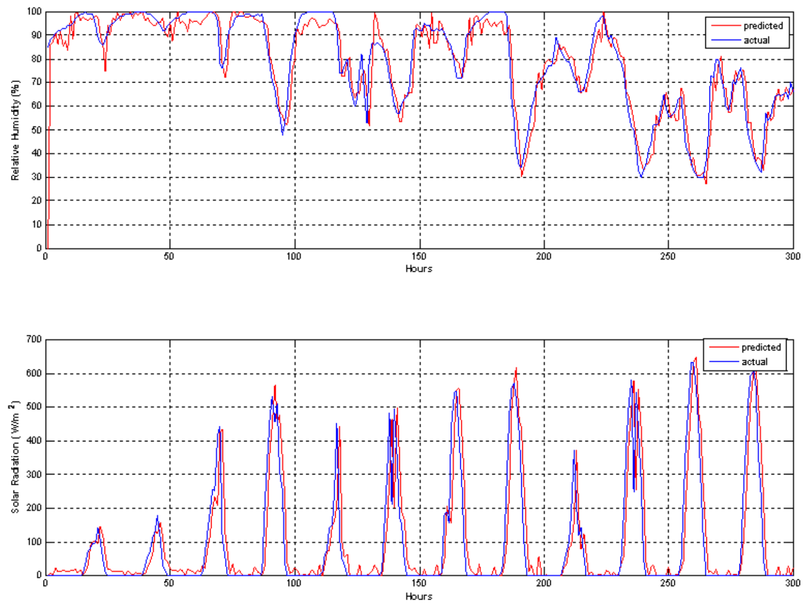

FIGURE 15 ONE STEP AHEAD FORECAST OF RELATIVE HUMIDITY (%) (TOP) AND SOLAR RADIATION $\mathbf{W/m^2}$ (BOTTOM)

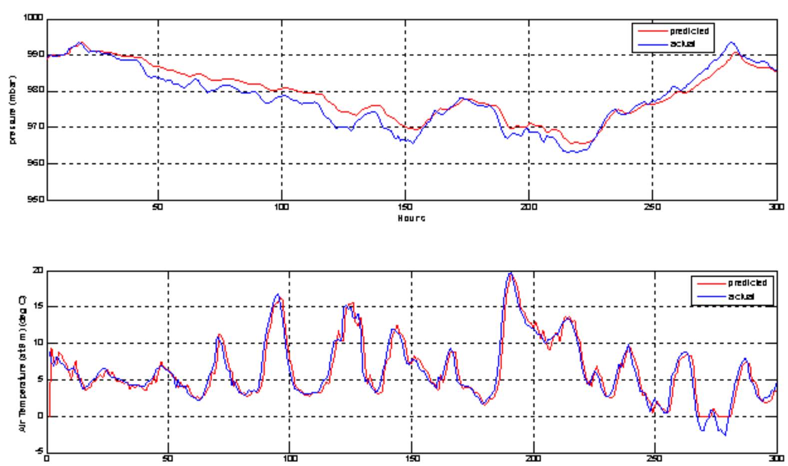

FIGURE 16 ONE STEP AHEAD FORECAST OF AIR PRESSURE (MBAR)(TOP) AND AIR TEMPERATURE AT 9 M

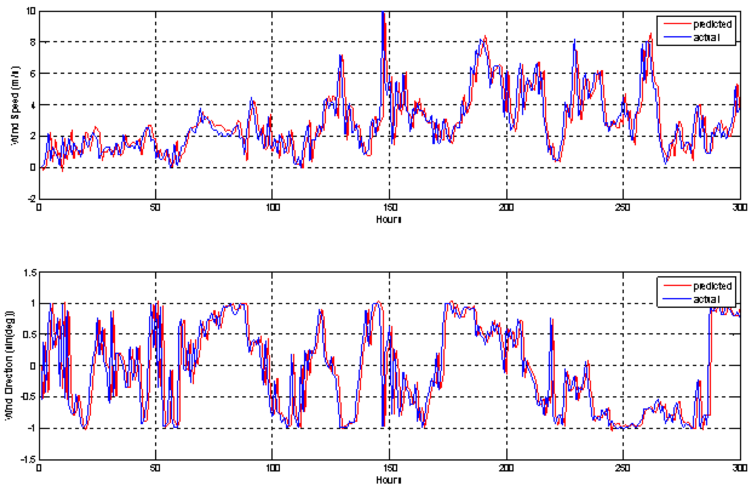

FIGURE 17 ONE STEP AHEAD FORECAST OF AVERAGE WIND SPEED (M/S) (TOP) AND WIND DIRECTION (DEGREE) (BOTTOM)

TABLE 5 ACCURACY RESULTS FOR FORECAST OF WEATHER PARAMETERS

Weather Parameter	**Accuracy (R^2)**
Relative Humidity	91.36%
Solar radiation	86.32%
Air Pressure	88.24%
Air Temperature (at 9m)	92.25%
Average Wind Speed	89.58%
Wind Direction	87.46%

Table 5 shows R^2 values for one step ahead forecasting of different weather parameters by using particle filtering. All the values are above 85% accuracy which can be used for accurate snow depth prediction.

4.3 Predicting Snow Depth Using Artificial Neural Networks

After the prediction of the weather parameters (relative humidity, solar radiation, air pressure, average wind speed, wind direction, temperature) using particle filtering method, these are input to a neural network model to predict snow/ice thickness, as illustrated in Figure 18 Flowchart for snow depth forecasting using the predicted weather parameters

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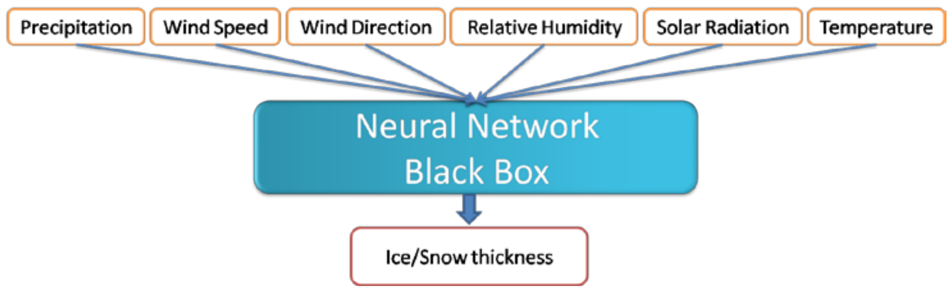

FIGURE 18 FLOWCHART FOR SNOW DEPTH FORECASTING USING THE PREDICTED WEATHER PARAMETERS

A feed forward neural network with 2 layers and 20 neurons is used for snow depth prediction. Out of 130 data points; 64 data points are used for training, 33 used for validation and 33 used for testing. Prediction accuracy of snow depth is 80%. Comparison of observation and prediction of the snow depth is illustrated in Figure 19 Comparison of observation and prediction of the snow depth using Neural Network model

, which indicates the high accuracy of the neural network model.

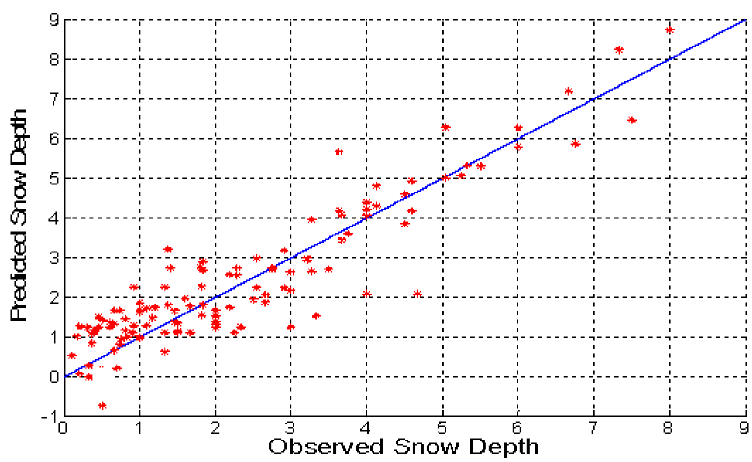

FIGURE 19 COMPARISON OF OBSERVATION AND PREDICTION OF THE SNOW DEPTH USING NEURAL NETWORK MODEL

4.4 Conclusion

This section surveyed various numerical prediction models available in the literature, specifically ones used to predict weather parameters. A particle filter method is developed to predict several weather parameters that are subsequently used in the prediction of snow/ice thickness using an artificial neural network. Preliminary experiments indicate that this technique is better suited to predict nonlinear and nonstationary weather parameters and snow/ice depth frequently over short ranges with reasonable computational effort. The parameters predicted using the particle filter method and the snow/ice depth predictions using the neural network model are used in the SSI model to predict the SSI for future time periods during a storm event, which is used subsequently in the stochastic optimization model for resource allocation.

5. Optimization Model for Resource Allocation and Risk Mitigation

In the United States, winter road maintenance (WRM) operations take up significant portion of annual operating budgets in many states [73]. Under severe winter weather, the State DOTs are typically responsible for different transportation risk mitigation activities such as *plowing* (removal of snow and ice from the road using specially equipped trucks), *anti-icing* (preventing ice formation on the road by treating with sodium chloride or rock salt, other compounds such as calcium chloride, magnesium chloride are also used combined with road-bonding agents to enhance corrosion inhibition properties), *de-icing* (if ice forms on the road, it is treated with chemicals to keep it from compacting and bonding to the road surface, this facilitates plowing), and *spreading abrasives* (chemically wetted sand is spread at turns, intersections, gradients on the road to improve traction). The State DOT's responsibilities during emergencies may also include moving power generators to hospitals and other critical places that are suffering from power outage, restoring utility poles that are down, moving potable water in tankers to small towns where water supply has been cut-off due to utilities being incapacitated, removing debris in the wake of ice storms, setting up portable message boards warning commuters of frozen roads or other hazards as they develop.

Clearly, the maintenance operations are complicated, and their effectiveness depends on the availability of appropriate resources at the appropriate time and place, which in turn is complicated by the uncertainty in the severity of the winter storm hazard in addition to resource and capacity limitations. The maintenance resource allocation decisions have to be made under limited capacity/resource availability, and uncertain information, and needs to be done *a priori* to allow the development of a maintenance operational plan. It is hence, important to employ a suitable optimization model that captures uncertainty and resource limitations, with an objective which drives decisions leading to a desirable system behavior. We discuss some relevant concepts prior to developing such a mathematical model in Section 5.2.

5.1 Hazard, Vulnerability and Risk

Vulnerability analysis deals with the ``cost of an emergency," that is, the value of service provided by the transportation system, or infrastructure. In contrast, hazard analysis deals with the "likelihood of an emergency." Risk, is the probability that more than a threshold level of service-reduction is sustained by a transportation system, or infrastructure. That is, risk is a measure of combined effects of vulnerability and hazard probability. Consider the following examples for illustration purposes. Suppose a segment of a bridge is missing due to construction delays. This is poses a hazard- certain catastrophe for any traffic ``on that segment." If this bridge is closed to traffic, there is no service provided and hence, it is not vulnerable. Thus, a hazardous highway segment poses no risk, if it is closed for service. On the other hand, consider a major highway segment that serves a large volume of traffic, hence, it is a vulnerable asset. It would be considered hazardous if its structural integrity is questionable, and it would then be considered risky. If it is reinforced structurally, it is less hazardous and hence, it becomes less risky, even though it is still equally vulnerable. If traffic flow is reduced by newly developed alternate routes, this highway segment is less risky as it is now less vulnerable, although it is equally hazardous.

The importance of a particular link in a road network is measured as the normalized freight plus passenger flow (rate) on the link, which can either be obtained directly from public databases or by heuristically solving a *freight flow assignment* model. We use a heuristic approach to flow assignment, illustrated in

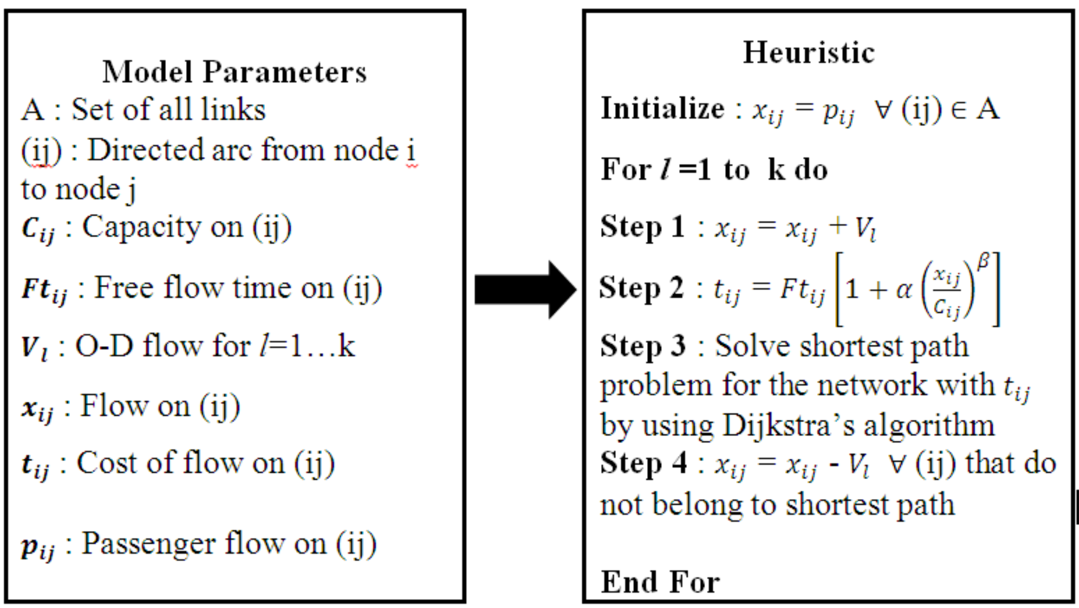

Figure 20 Heuristic algorithm for freight flow assignment

, developed as a part of the Freight Movement Model project completed recently by Drs. Kamath and Ingalls at OSU in collaboration with OU. Implementation of this heuristic using the mathematical programming solver IBM ILOG CPLEX® was completed and another implementation based on our implementation of Dijkstra's algorithm was also completed, which was found to scale better than CPLEX given the massive size of the US highway network under consideration. Hence, we further improved the Dijkstra implementation by employing some well-known graph libraries that implement the algorithm using more sophisticated data structures.

Model Parameters

A : Set of all links

(ij) : Directed arc from node i to node j

C_{ij} : Capacity on (ij)

Ft_{ij} : Free flow time on (ij)

V_l : O-D flow for l=1…k

x_{ij} : Flow on (ij)

t_{ij} : Cost of flow on (ij)

p_{ij} : Passenger flow on (ij)

Heuristic

Initialize : $x_{ij} = p_{ij} \;\; \forall$ (ij) ∈ A

For l =1 to k do

Step 1 : $x_{ij} = x_{ij} + V_l$

Step 2 : $t_{ij} = Ft_{ij}\left[1 + \alpha\left(\frac{x_{ij}}{C_{ij}}\right)^{\beta}\right]$

Step 3 : Solve shortest path problem for the network with t_{ij} by using Dijkstra's algorithm

Step 4 : $x_{ij} = x_{ij}$ - $V_l \;\; \forall$ (ij) that do not belong to shortest path

End For

FIGURE 20 HEURISTIC ALGORITHM FOR FREIGHT FLOW ASSIGNMENT

5.2 Optimization of Conditional Value-at-Risk (CVaR)

The modeling approach employed in this study is the optimization of Conditional Value-at-Risk (CVaR). Rockafellar and Uryasev pioneered the work [74, 75] on developing the general methodology of optimization of CVaR and applying it to portfolio optimization problems. The notion of Value-at-risk (VaR) is well-known in financial applications, and the related notion of CVaR as a downside measure of risk is fast gaining acceptance in finance due its many desirable properties. In this study we develop CVaR optimization models to identify maintenance resource allocation decisions that minimize the risk of high-losses under probabilistic storm severity information.

The general framework is as follows. Assume, that L(x,Y) is the loss in a system associated with the decision vector x and the random vector Y representing uncertain parameters involved in the operations of a system. In our case, x represents the resource allocation decisions and y is a vector of random variables indicating the severity of the storm event. For each x, the loss L(x,Y) is a random variable having a distribution induced by that of Y. However, an analytical expression the loss distribution is not needed for the implementation of this approach.

The β-Value-at-Risk (VaR) is the β-quantile ($\beta \in (0,1)$) of the loss distribution $\psi(x,l)$ for each fixed x given by,

$$\beta - \mathrm{VaR}[L(x,Y)] = \beta - \mathrm{VaR}(x) = \inf\{l: \psi(x,l) \geq \beta\} \quad (3)$$

The β-Conditional Value-at-Risk is the conditional expectation of the tail loss given by Eq. 4,

$$\beta - \mathrm{CVaR}[L(x,Y)] = \beta - \mathrm{CVaR}(x) = E[L(x,Y) \mid L(x,Y) \geq \beta - \mathrm{VaR}(x)] \quad (4)$$

We want to find a decision x that minimizes the average losses in the worst $1 - \beta$ percentile of cases, thereby identifying a "robust" or "risk-averse" solutions. CVaR aggregates various losses under uncertainty into a single coherent measure of downside risk and it is more conservative than VaR [75]. From an optimization point of view, CVaR is convex in x if $L(x,Y)$ is convex in x. Moreover, it is not necessary to have a closed form expression for the distribution of $L(x,Y)$. As shown by Rockafellar and Urysev [74, 75], the convex function shown in Eq. 5 can be used instead of the CVaR function, which can further approximated by sampling scenarios.

$$F_\beta(x,\zeta) = \zeta + \frac{1}{1-\beta} E[(L(x,Y) - \zeta)^+] \quad (5)$$

5.2.1 A CVaR Model

The mathematical optimization model for WRM operations is used to determine the types and amount of different treatments applied to a highway link, while accounting for the resources consumed in the application of the different treatments. We use the following notations.

Notations.

- $G(N,A)$ is the highway network of Oklahoma modeled as a directed graph;
- R is the index set of resource types consumed by winter maintenance actions, indexed by j;
- W is the index set of treatments (and associated piece of equipment), such as deicing, plowing, gritting, and so on, indexed by k;
- $T_{uv} \in W$ is the set of mutually exclusive treatments for link $(uv) \in A$;
- f_{uv} is the flow across arc $(uv) \in A$ - this is deterministic, or at least estimated from historical data;
- h_{uv} is the state of arc $(uv) \in A$ after a winter storm;

- ρ_{uv}^{k} is the percentage improvement in condition that treatment $k \in W$ restores to link $(uv) \in A$;
- r_{uv}^{jk} is the amount of winter road maintenance resources of type $j \in R$ consumed by one unit of WRM equipment or crew for treatment $k \in W$ on link $(uv) \in A$. If resource $j \in R$ is not used for treatment $k \in W$, then $r_{uv}^{jk} = 0$;
- r_{tot}^{j} is the total amount of resource $j \in R$ currently in inventory;
- u^{j} is the upper bound on the amount of resource $j \in R$ available for purchase;
- C_{uv}^{k} is the cost per unit of equipment to apply treatment $k \in W$ to arc $(uv) \in A$;
- d^{j} is cost to buy or rent one unit of resource $j \in R$;
- b is the total budget;
- m_{uv}^{k} is the maximum units of treatment $k \in W$ that can be applied to link $(uv) \in A$;
- S is the index set of scenarios, indexed by s;
- h_{uv}^{s} is the condition of link $(uv) \in A$ in scenario $s \in S$;
- β is the percentile of the loss distribution;
- p_s is the probability of scenario $s \in S$
- $[\theta]^{+} = \max(0, \theta)$.

Decision variables.

- x_{uv}^{k} is the units of WRM treatment $k \in W$ applied to arc $(uv) \in A$;
- w_{uv}^{k} is 1 if treatment $k \in W$ is applied to arc $(uv) \in A$, and 0 otherwise.

Loss function.

Loss function that is used in this model is described according to Eq. 6.

$$L(x, h^{s}) = \sum_{(uv)\in A} f_{uv}\left[h_{uv}^{s} - \sum_{k\in W} \rho_{uv}^{k} x_{uv}^{k}\right]^{+} \tag{6}$$

Model.

Minimize $\zeta + \frac{1}{1-\beta}\left[\sum_{s\in S} p_s \left(L(x, h_{uv}^{s}) - \zeta\right)^{+}\right]$

Subject to:

$$\sum_{k\in W}\sum_{(uv)\in A} r_{uv}^{jk} x_{uv}^{k} \leq r_{tot}^{j} + u^{j} \quad \forall j \in R \tag{7}$$

$$\sum_{k\in W}\sum_{(uv)\in A} C_{uv}^{k} x_{uv}^{k} + \sum_{j\in R} d^{j} \left[\sum_{k\in W}\sum_{(uv)\in A} r_{uv}^{jk} x_{uv}^{k} - r_{tot}^{j}\right]^{+} \leq b \tag{8}$$

$$x_{uv}^{k} \leq m_{uv}^{k} w_{uv}^{k} \quad \forall (uv) \in A, k \in W \tag{9}$$

$$\sum_{k\in T_{uv}} w_{uv}^{k} \leq 1 \quad \forall (uv) \in A \tag{10}$$

$$x_{uv}^{k} \geq 0 \text{ and integer; } w_{uv}^{k} \in \{0,1\} \quad \forall (uv) \in A, \text{and } k \in W \tag{11}$$

Constraint (7) indicates that the amount of resources used should not exceed availability, including what is immediately available and what can be purchased or rented. Constraint (8) ensures that all expenditures are less than the total budget. Constraint (9) states that each link cannot get assigned more units than the maximum that can be allocated to that link. Constraint (10) ensures that at most one kind of treatment among the group of mutually exclusive treatments associated with a link can be used on that link.

5.3 Results from Numerical Experiments

This model was implemented in C++ using IBM ILOG CPLEX® libraries for solving the mixed integer optimization problem. The experiments were conducted on a Windows XP PC with 2.26 GHz i3 CPU and 4.00 GB of RAM. The following combination of real-life data and synthetic data was used in our preliminary experiments to validate this proof-of-concept model.

- Highway network of Oklahoma
- Vulnerability of links measured as annual average daily traffic flow rates
- Amount of resources used by each treatment.
- Maximum available amount of resources and maximum amount can be rented.
- Unit cost to apply each treatment.
- Unit cost to rent each resource.
- Percentages of improvement when one unit of each treatment is applied to a link.

Table 6 Amount of resources used by each treatment - Table 10 show the synthetic data that was generated for experimental purposes.

TABLE 6 AMOUNT OF RESOURCES USED BY EACH TREATMENT

	Resource 1	Resource 2	Resource 3	Resource 4	Resource 5
Treatment 1	2	3	2	0	3
Treatment 2	0	2	1	3	1
Treatment 3	3	1	0	2	4
Treatment 4	2	0	3	1	2
Treatment 5	4	3	5	2	0

TABLE 7 MAXIMUM AMOUNT OF RESOURCES AVAILABLE

Resource number	In inventory	Available to rent
1	50000	50000
2	20000	80000
3	60000	40000
4	80000	20000
5	40000	60000

TABLE 8 UNIT COST TO APPLY EACH TREATMENT

Treatment number	Costs
1	200
2	180
3	300
4	80
5	120

TABLE 9 UNIT COST TO RENT EACH RESOURCE

Resource number	Costs
1	250

Resource number	Costs
2	210
3	380
4	140
5	150

TABLE 10 PERCENTAGE IMPROVEMENT FROM UNIT APPLICATION OF A TREATMENT

Treatment number	% improvement
1	5
2	10
3	8
4	9
5	10

The Oklahoma highway network and traffic flow data used in our experiments was obtained from the *Freight Analysis Framework* database maintained by the Federal Highway Administration. It has 2806 nodes, and we only consider class 1, class 2, and class 3 highways resulting in 3303 links. This corresponds to an optimization model with 198, 236 decision variables and 350, 179 constraints and solving this model to optimality takes more than 1 hour. So, we terminate the algorithm when the optimality gap (tolerance) reduced below 10%, which happens in under 400 seconds. Another aspect of solving this problem concerns scenario generation or sampling. We solved the model with 50 scenarios generated by particle filtering, discussed in Section 4.

Particle filtering gives us probability of each weather parameters at time (t+s) given those at time t. Then forecasted weather parameters are plugged into the SSI model discussed in Section 3 to predict SSI values at the time (t+s). This process was repeated for all 120 mesonet stations in Oklahoma and 100,000 scenarios are randomly generated. From these 100,000 randomly generated scenarios, 50 scenarios with the highest probability were selected. Finally, the probabilities were normalized to ensure that the summation of probabilities for all 50 scenarios is equal to 1.

The goal of this model is to improve the link conditions under uncertain severe winter weather by allocating maintenance resources to minimize the conditional-value-at-risk of losses. Figure 21 Vulnerability analysis before assignment

and Figure 22 Vulnerability analysis after assignment illustrate the link conditions before and after assignment respectively. That is, comparing the performance of the solution found by the model against the same CVaR objective when no resources are allocated. This is an extreme comparison, however, it does provide a baseline for us to assess the extent of the impact in the absence of any treatment, to the one recommended by the model. One of the future tasks is to validate the model and its performance against simple greedy heuristics that mimic the decision making process of a maintenance manager in the absence of any sophisticated mathematical model to aid their decisions. As shown in Figure 21 Vulnerability analysis before assignment

and Figure 22 Vulnerability analysis after assignment

, before assignment, flows on almost all links are reduced by more than the Beta value (0.95) due to severe weather. But after assignment, link conditions are improved for most of the links.

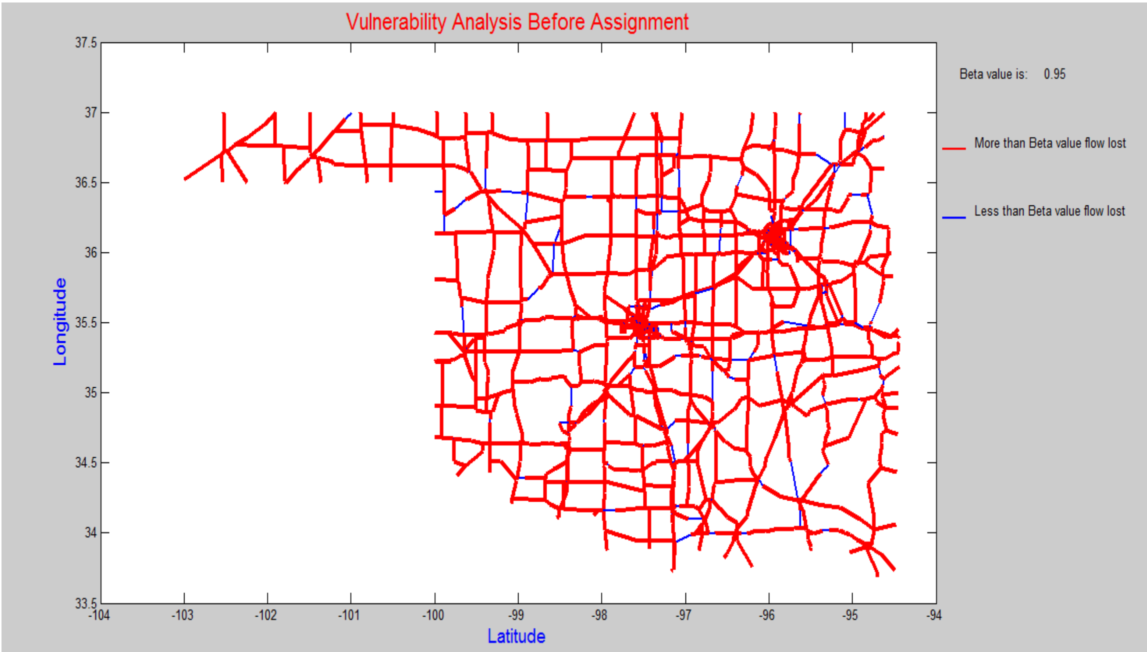

FIGURE 21 VULNERABILITY ANALYSIS BEFORE ASSIGNMENT

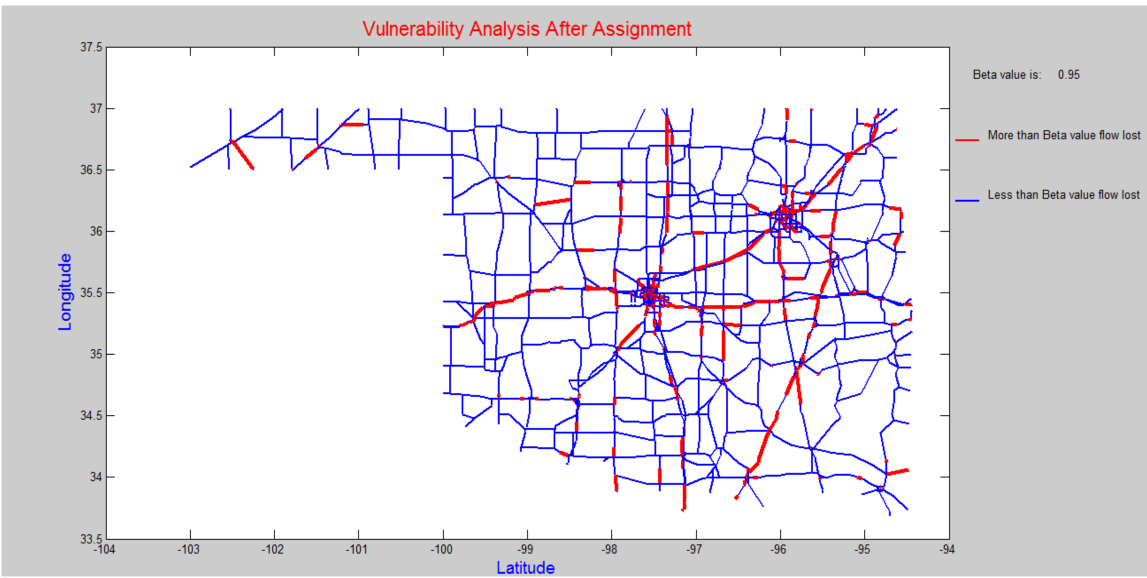

FIGURE 22 VULNERABILITY ANALYSIS AFTER ASSIGNMENT

6. Deliverable: Prototype DSS Implementation

The technical results and conlusions from the SSI model, prediction models and the CVaR optimization model were discussed at the end of the respective sections. However, the overall goal of this two year project was the development of a prototype DSS that combines each module (SSI, prediction and optimization) into a single user-friendly interface along with pertinent data, to generate visualizations and other numerical outputs that aid a maintenance manager. We conclude this report with a discussion of such an implementation which is available upon request from the research team. The DSS developed is a proof-of-concept demonstrating the feasibility of integrating sophisticated mathematical models into a system that enables informed decision-making. Our results demonstrate the potential advantages of developing our research results into professional software packages that ODOT could employ.

The prototype DSS is called the *Winter Resource Allocation & Maintenance: Decision Support System (WinRAM DSS)* and it has been implemented using Microsoft Visual Studio® and it utilizes Matlab®, and IBM ILOG CPLEX® optimization engine for its various functions. Visualization is done using the GIS software TransCAD®**.** WinRAM DSS has four tabs, namely, *SSI Analysis* tab, *Prediction Model* tab, *Optimization Model* tab, and an *About* tab. All SSI analysis, prediction model and optimization model tabs follow the same input procedure. They read information from a working folder, set the parameters, check all input files, run models, and visualize results. Also in those tabs, you can copy some files from another folder to the working folder, if it is needed. This was done to faciliate "what-if" analyses where different what-if test cases stored in different folders are automatically copied into the working folder with a single button click to make them easier to run.

6.1 SSI Analysis Tab

SSI Analysis tab can be used to generate color-coded maps of SSI for different storms including future storms, based on the forecasts. To generate the color maps, two models (SREF or WRF) are used. After a model is chosen, the date of the storm event must be chosen. After a model is chosen, the event for that model will be shown in a drop-down box and other inapplicable events are deactivated. Other inputs for the SSI model are accumulation and quantile. Both precipitation accumulation and intensity are used to calculate the SSI, and the relative weights of their importance must be provided. Default is 30% for accumlation with intensity accounting for 70%. This is useful as sometimes intensity is more important, for example when if there is a heavy snow squall which is brief but very intense. The accumulation would not be very significant but the intensity would be very important as it would impact transportation. The quantile is provided so that the SSI quantile score at three hour intervals can be generated for every event. The median and maximum SSI are especially useful to see how severe the storm is on average and how intense the storm will be at its worst. After all input files are confirmed, a chosen model can be run. Outputs can be shown in detail or summary. The detailed plot output is a three hour SSI model for the entire event. The summary plot is a quantile summaries for the entire storm.

Screenshot of the SSI tab is given in Figure 23 and a sample output from running the SSI model with SREF is shown in Figure 24 for illustration purposes.

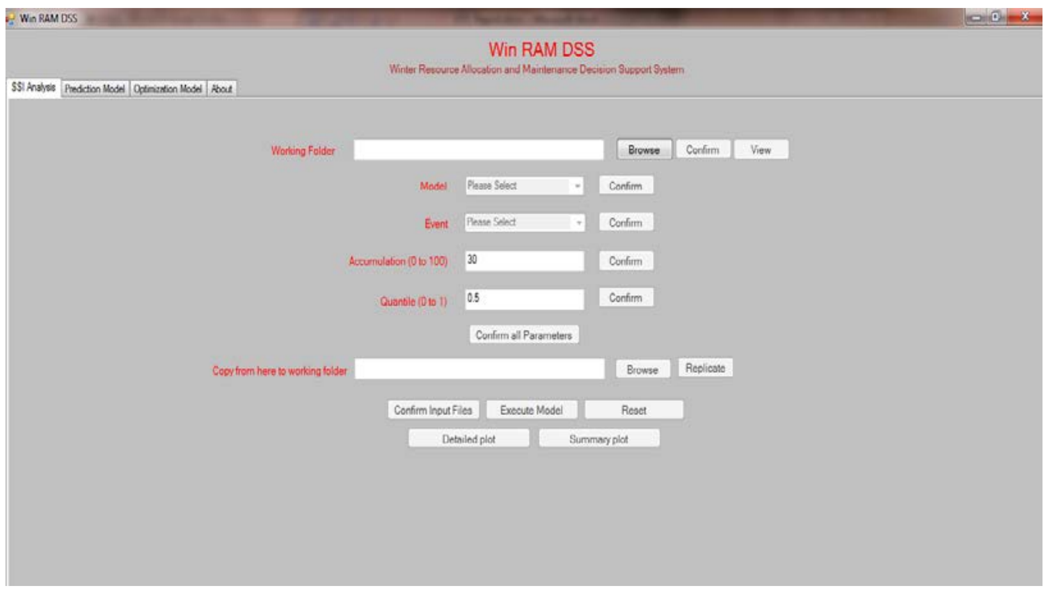

FIGURE 23 SSI TAB SCREENSHOT

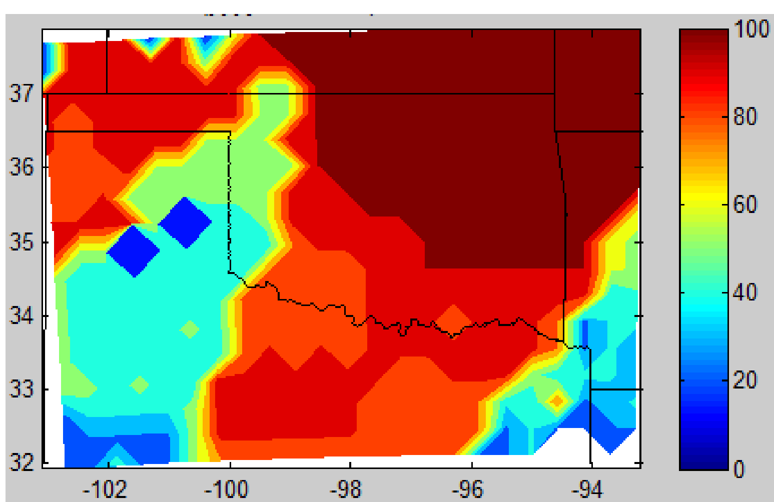

FIGURE 24 SSI OUTPUT ILLUSTRATION

6.2 Prediction Model Tab

The Prediction tab can be used to access and run the models for forecasting the weather parameters, including temperature, relative humidity, wind speed and air pressure. The predicted weather parameters are then used to calculate SSI as discussed in the previous section. The weather condition as quantified by the SSI is separated into three classes, namely, low, medium and severe. The probabilities of belonging to different categories are illustrated as color-coded map throughout the state of Oklahoma. Predicted weather parameters are also used to generate visualizations.

Particle filtering technique is employed here for the weather parameters forecasting. Historical data files are extracted directly from MESONET website [72] which allows us to update the model dynamically. The DSS requests two input parameters (number of particles, noise level) from the user. Large number of particles can better approximate the distribution of weather parameters, which can improve forecasting accuracy, but requires more computational effort. There is a trade-off between computational time and accuracy controlled by the number of particles chosen. The default particle number value is set as 100.

Second parameter is the noise level, which is relates to data quality. Especially during severe weather conditions, the quality of data collected is questionable as the measurements under these conditions may no longer be as reliable, requiring us filter out the noise in data. The default value for noise level is set at 0.01 which means that 1% of data is assumed to be noise.

Forecasted weather parameters are plugged into the SSI model to get predicted SSI values. According to SSI values, weather condition is categorized as low (SSI<50), medium (50<SSI<75), severe (SSI>75). The probabilities for each condition are calculated. Given these probabilities, the most probable 30 weather scenarios for Oklahoma network is generated and given as an input for resource allocation optimization model. A snapshot of the prediction tab is shown in Figure 25 Prediction model tab screenshot

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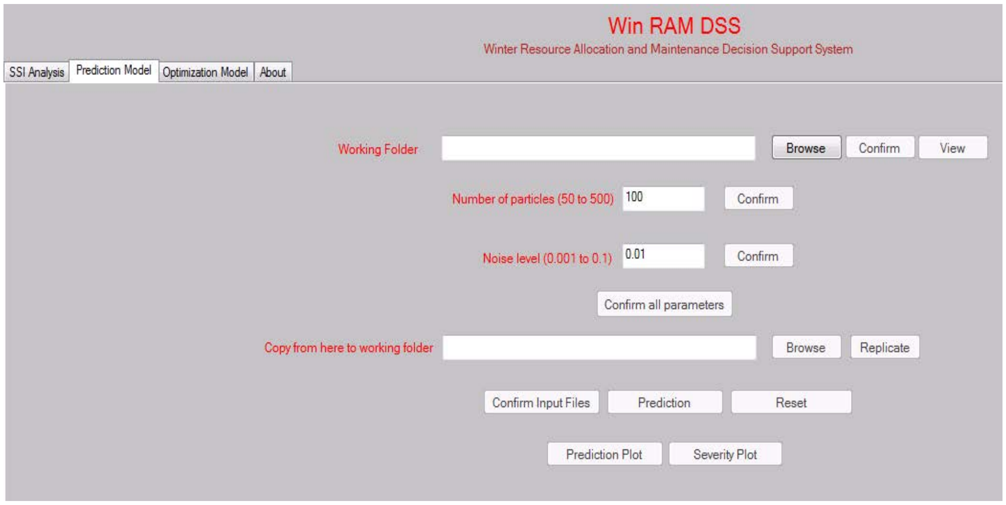

FIGURE 25 PREDICTION MODEL TAB SCREENSHOT

One example for the prediction model is demonstrated. February 2nd is selected for the demonstration. Number of particles is chosen as 100 and the noise level is set to 0.01. The prediction of different weather parameters are shown in Figure 26 Forecast of temperature (degree ℃)

- Figure 29 Forecast of air pressure (mbar)

. You can select different radio buttons to see forecast of different weather parameters for the state of Oklahoma.

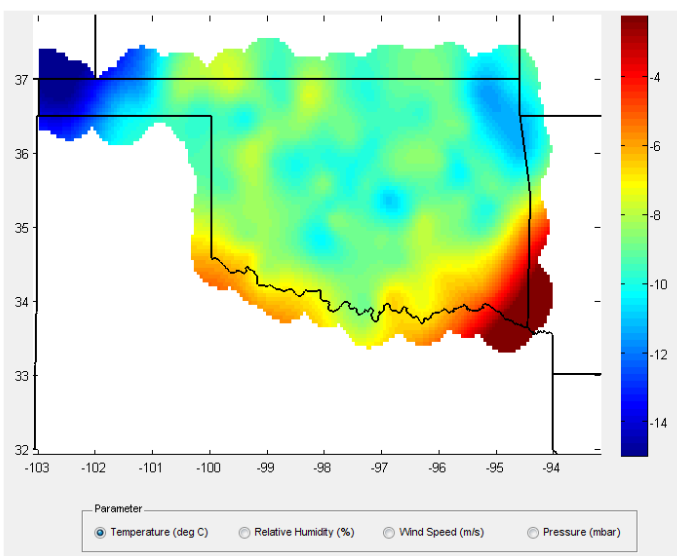

FIGURE 26 FORECAST OF TEMPERATURE (DEGREE ℃)

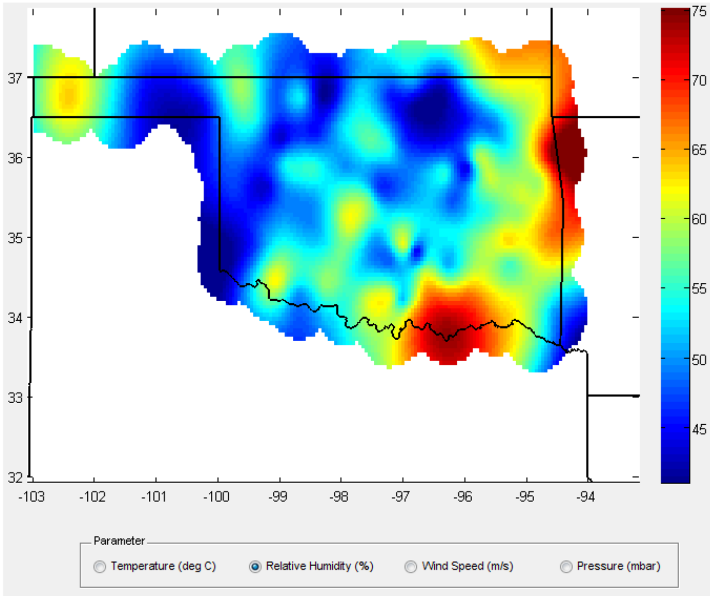

FIGURE 27 FORECAST OF RELATIVE HUMIDITY (%)

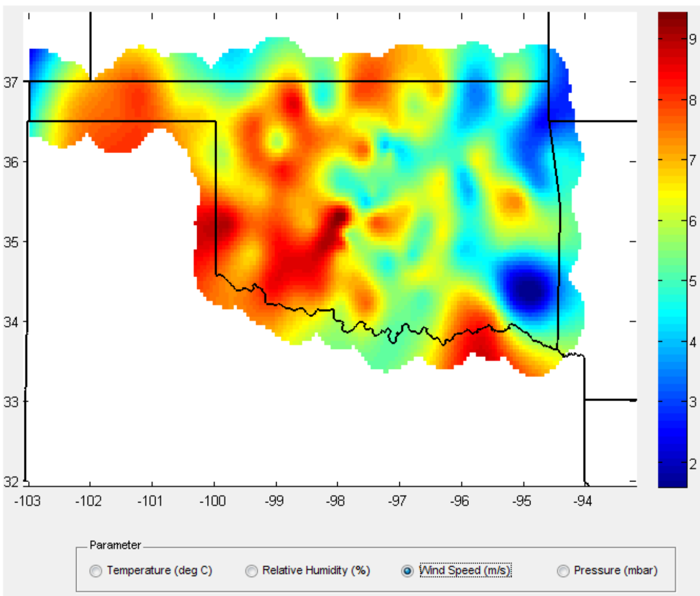

FIGURE 28 FORECAST OF WIND SPEED (M/S)

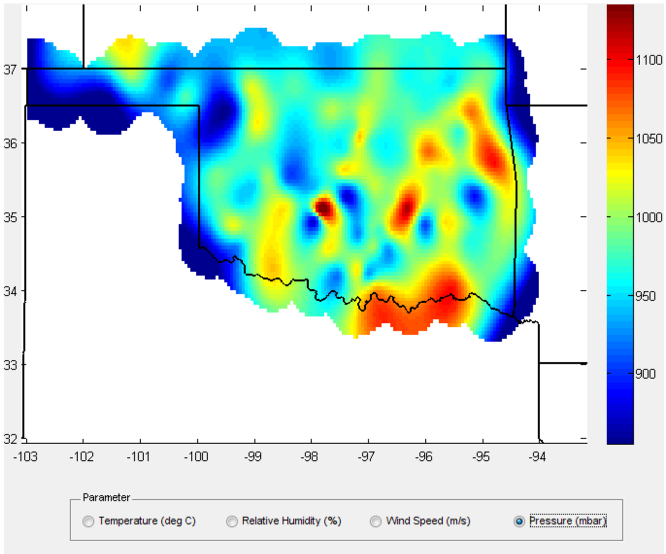

FIGURE 29 FORECAST OF AIR PRESSURE (MBAR)

After the weather parameters are predicted, we can visualize the probability of each weather condition (low, medium and severe weather conditions) based on the predicted SSI (see Figure 30 Probability map of low severity weather condition

- Figure 32 Probability map of high severity weather condition

for example). In the weather condition probability map, the red areas show high probability for the corresponding weather conditions (up to 1) and blue areas show low probability.

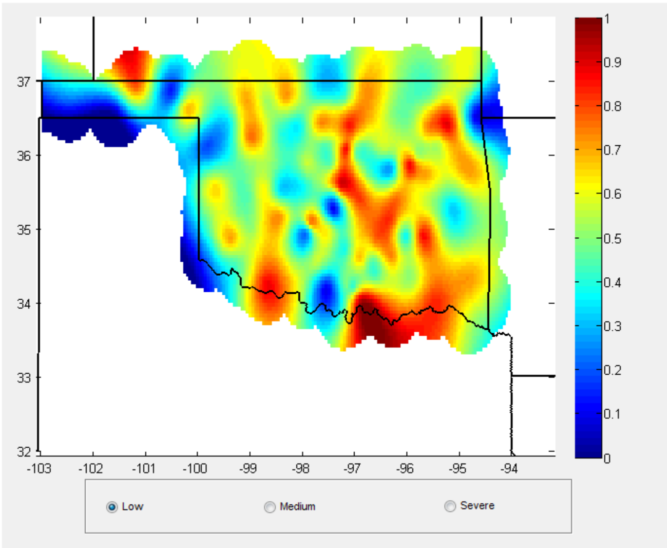

FIGURE 30 PROBABILITY MAP OF LOW SEVERITY WEATHER CONDITION

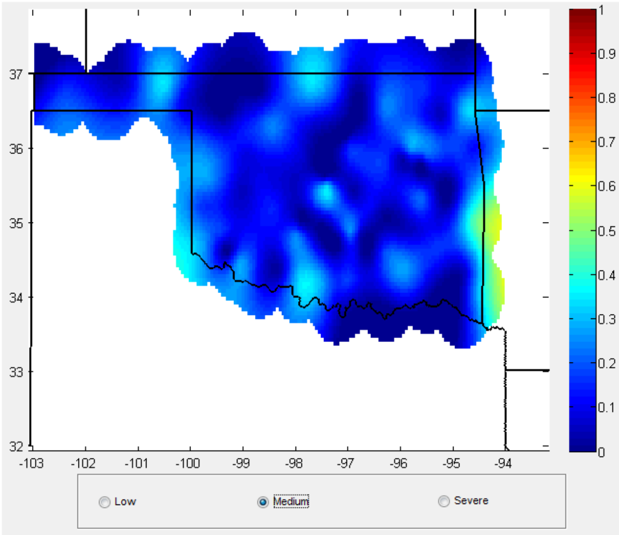

FIGURE 31 PROBABILITY MAP OF MEDIUM SEVERITY WEATHER CONDITION

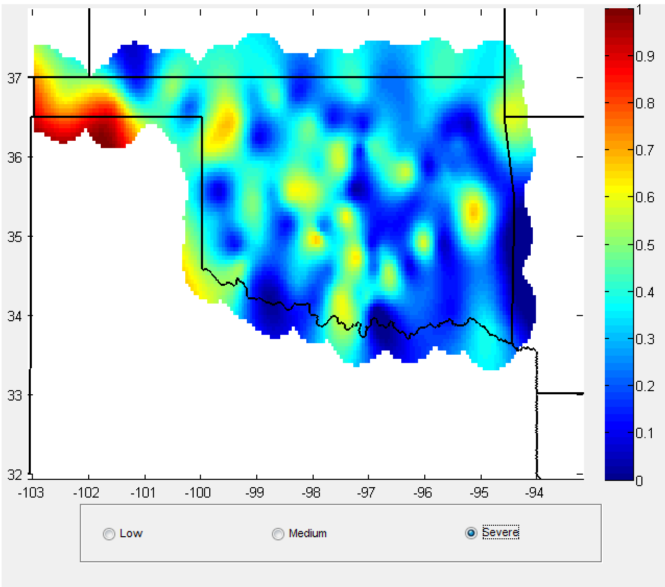

FIGURE 32 PROBABILITY MAP OF HIGH SEVERITY WEATHER CONDITION

6.3 Optimization Model Tab

This tab allows the user to access the optimization models, set parameters, and generate detailed output identifying maintenance resource allocation recommendations, as well as help visualize the solution. Input files for this tab are similar to the input files for optimization model. Parameters that should be set in the optimization tab are:

- β value that can vary from 0 to 1.
- Maximum budget.
- Maximum time the model is allowed to run can be set as a parameter.

The check box in front of the maximum budget parameter will allow us to remove the budget constraint from our model. The maximum time limit provided can result in suboptimal solutions, but given the intractability of such large-scale stochastic optimization models, this is necessary for the graceful termination of the optimization algorithm. A screenshot of the optimization model tab is shown in Figure 33 and Figure 34 depicts the assignment of different treatments on to the links.

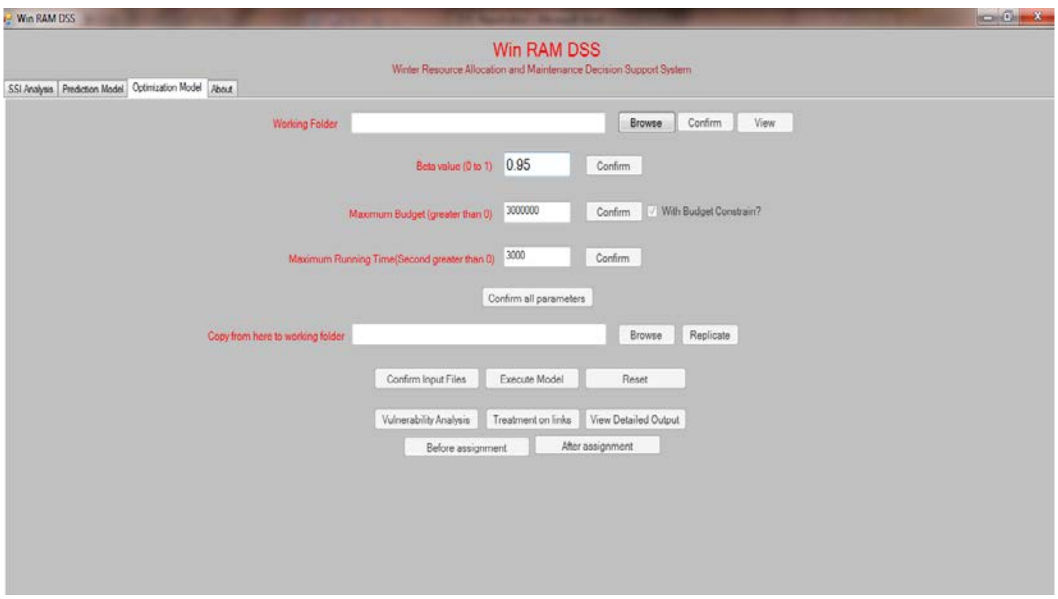

FIGURE 33 OPTIMIZATION TAB SCREENSHOT

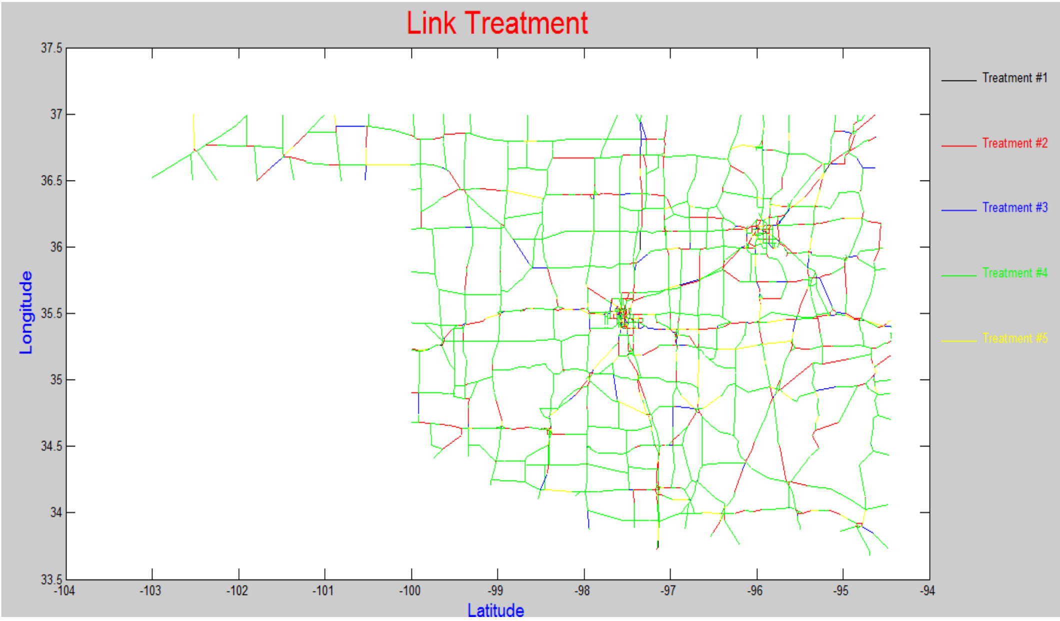

FIGURE 34 ILLUSTRATION OF LINK TREATMENTS FOUND BY THE OPTIMIZATION MODEL

6.4 Concluding Comments

Ice storms accompanied by excessive winter precipitation are high-impact weather events for the State of Oklahoma. Such hazardous conditions dramatically reduce road transportation infrastructure serviceability, and decrease safety. Consequently, these high-impact weather events are a planning and preparedness priority for ODOT. This OkTC project combines weather prediction models, risk-analysis, and optimization techniques to develop a prototype decision support system that recommends optimal resource allocation and risk mitigation strategies under severe winter weather emergencies.

The prediction of severe winter weather in the form of regional and temporal distribution of ice/snow thickness is based on *artificial neural network* and particle filtering approaches that include forecasts from SREF model as inputs. An appropriate loss function was developed which depends on the distribution of ice/snow thickness, and the reduction in traffic flow due to reduced system capacity. A stochastic optimization mode is developed that allocates winter maintenance resources to minimize the *conditional value-at-risk* of losses, which leads to risk-averse resource allocation recommendations.

The mathematical models developed to quantify storm severity, predict transportation specific weather conditions, and to optimally allocate maintenance resources have been implemented in a prototype decision support system and tested on a combination of real and synthetic data. The deliverable developed and its individual modules show the potential for sophisticated models in better aiding transportation decision-making. They also helped us identify several basic research challenges in modeling and methodology that need to be addressed to expand the scalability and resolution of the approaches developed in this project. This project has laid the foundation for future studies along these lines, and has produced a useful and comprehensive deliverable developed over its two year duration.

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