Predicting Pavement-weather to Support Winter Weather Operations in Alabama

RESEARCH PROJECT #931-006

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1. Introduction

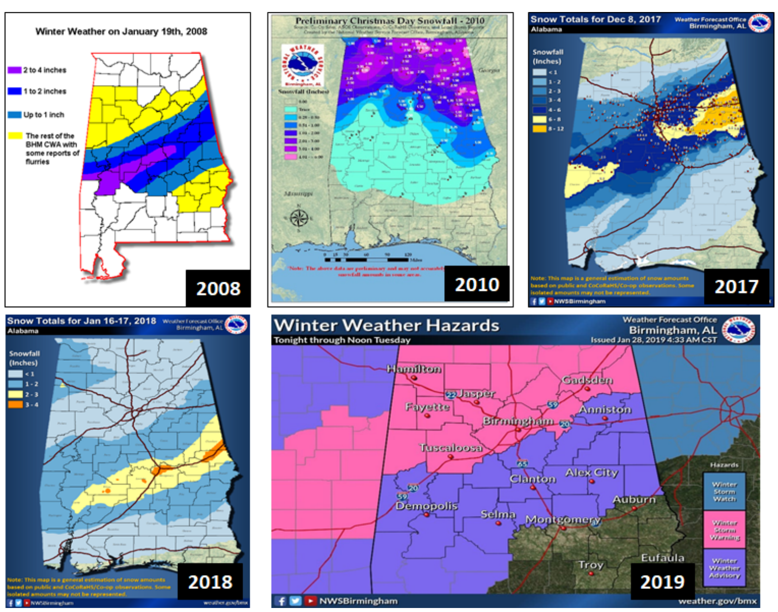
Transportation is one of the critical components of the global economy that supports a wide array of movements of passengers and goods. Therefore, it is necessary to ensure that the transportation system works efficiently. Here, the term 'efficiency' encompasses multiple aspects, ranging from serviceability of a road section/network to transport certain traffic volume (depending on the capacity), minimum delays, and safety. While it is clear that major calamities and disasters can have a considerable effect on traffic and transport systems, there is an awareness that even minor disturbances in traffic and transport systems can also play an important part in reducing their efficiency (Calvert and Snelder, 2018). Other than the human factors affecting the efficiency (e.g. driver skills, drunk status) of road network, traffic hazards that elevate the chances of disruptions in transportation system can be classified into four categories viz. 1) compromised infrastructure such as cracked pavements (Ameri et al., 2011), washouts (Hongo et al., 2013), debris flows, rock falls (Bunce et al., 1997); 2) reduced friction/control such as snowy (Weng et al., 2013), icy or wet roads (Malin et al., 2019) , asphalt bleeding during extreme heat), 3) momentary/long-duration impaired visibility such as high-intensity precipitation (Black et al., 2017), splash and spray, blowing snow, fog, dust storms haze, smog (Ashley et al. 2015; Abdel-Aty et al. 2011), and 4) decreased stability (high-velocity cross winds, buffeting). Except for the first category (compromised infrastructure), inclement weather conditions seem to be a predominant forcing in reducing traffic efficiency. Therefore, the effect of weather is probably one of the variables most commonly researched for its effect on road capacity and speed reduction (Akin et al., 2011; Chung, 2012; Chen et al., 2019). At times, the repercussions of inclement weather do not remain limited to reduced efficiency in terms of traffic delays and may result in crashes/fatalities. According to National Highway Traffic Safety Administration (NHTSA) databases, which includes the Fatality Analysis Reporting System (FARS) that contains data on all fatal traffic crashes on U.S. public roads and the General Estimates System (GES) that provides estimates based on a nationally representative sample of police-reported crashes, weather-related crashes account for around 25 percent of all crashes and 17 percent of all traffic fatalities each year (Pisano et al., 2008). Of all the weather-related crashes, 39 percent are due to winter weather controls such as snow/sleet (15%), icy pavement (13%), and snow/slush (11%) respectively.

Even though, in the USA, these inclement weather conditions are experienced almost all over the year, conditions that are encountered during winter possess high disruptive power. This is mainly because winter weather events often reduce pavement skid resistance and visibility of the drivers. Two classic examples of such events with high traffic disruptive capacity are 1) snowfall and 2) black ice formations. Heavy snowfall event is characterized by poor visibility and results in pavements covered in snow leading to reduced skid resistance even after the end of snowfall event. It is more dangerous than heavy rainfall event mainly because, unlike rain water which gets drained off guided by pavement cross slope, snow gets accumulated on the pavement unless removed. Based on the variations in temperature and precipitation, it either lingers on the pavement surface and might grow in depth in case of another snowfall event after small interval or gets converted to ice. This reduces the efficiency of the pavement and keeps it at elevated risk of accidents. Black ice, on the other hand, is thin coat of highly transparent ice. Freezing of thin layer of water or dew on the pavement are the prime causes of black ice formation. 1) Lack of any visual graphic that provides a vital lead of existence of black ice on the pavement to the drivers and 2) uncertainty associated with the locations that are conducive for black ice formation are the problems associated with it, making it difficult to negotiate. Detection of black ice is very difficult and often demand advanced technologies (Ma and Ruan, 2020; Kim et al., 2021; Cozzolino et al., 2019; Tabatabai and Aljuboori, 2017). Such winter weather events inflict heavy losses in terms of fatalities, property damages, and revenue. In order to reduce crash risks from such winter weather events and maintain uninterrupted mobility on roadways, the U.S. spends \$2.3 billion annually to just keep the roads clear of snow and ice. The smart technology that is required to detect black ice adds to this cost.

2. Ensuring winter weather traffic in Alabama

A harsh winter weather is more common in the high-latitude northern states of the USA, however, the southern states do experience winter storms. For example in Alabama, winter weather impacts, especially those due to freezing frost and rains, are not uncommon. Some of the instances when Alabama encountered snow storms are ‘storm of the century, 1993 (Weather, 1993), winter storm 2014 (Weather, 2014), and several snow storms in the recent past (figure 1).

Figure 1: Winter storms experienced by Alabama in the recent past (Source: national weather services)



It is definitely true that the winter storms in Alabama are not as severe as those in the northern states, however, given that the state is not accustomed to these events as its high-latitude counterparts, they tend to be much more disruptive. The contrast in the local warning criteria established by the Mobile, AL and New York, NY Weather Forecast Offices illustrate these differences clearly. For example, freezing rain with ice accumulations of ¼ inch or more is enough to trigger warning in Mobile, AL while similar warning in NY is only initiated at ½ inches. In other words, lower intensity of winter precipitation is sufficient to trigger disruption of the transportation network in Alabama.

Transportation agencies use varied winter safety and maintenance (WSM) strategies to negate deleterious impacts of winter weather, especially black-ice formation and ice-storms, on state's roadways. These include both mechanical and chemical interventions such as scraping, plowing, sanding, and application of chemicals. The methods used vary depending on the weather and pavement conditions, site-specific factors, the prescribed level of service employed by the agency, and the resource and material options available. A key component to efficiently and effectively implement WSM strategies is the knowledge of pavement-weather conditions at fine spatio-temporal resolution. This is especially relevant as most transportation agencies are under increasing pressure to maintain high levels of safety and mobility while working with limited financial and staffing resources and having to ensure more stringent environmental rules associated with chemical and material interventions. Despite its criticality, detailed information of pavement-weather conditions remains scarce.

3. Project objectives

To mitigate the challenge posed by the scarcity of pavement-weather data in Alabama, an alternative option is to model pavement-weather conditions at fine spatio-temporal resolution. In the present study, it is done using an indirect 'signature-based' approach that involves using weather data from the North American Land Data Assimilation System (NLDAS) and traffic speed data from the HERE. The aim here is to synergistically use both the datasets and identify signatures of average pavement-weather conditions in the presence of snowfall or black ice during which the transportation system is not able to work at its optimum efficiency under the influence of winter weather. The established signatures would help in finding answers for a range of questions such as 1) which regions are likely to face these signatures more frequently as compared to others, 2) what are the locations where the signatures are not true representatives of the ground realities, and 3) what are the possible solutions to fine-tune the signatures to capture actual on-ground situations. It is important to note that the term 'pavement-weather prediction' indicates predictions of ***occurrence*** of a specific pavement-weather condition 1) that is caused by winter weather event which is identified through climate variables such as precipitation, temperature etc. and 2) reveals high potential to disrupt traffic and reduce efficiency. To this end, here we outline three specific objectives of the project:

Objectives

1. Delineate detailed maps of pavement-weather signatures across the Alabama roadways.
2. Identify locations experiencing relatively high frequency of pavement-weather snow/black ice signatures.

3. Assess the predictability of the pavement-weather signatures and document possible strategies for improving predictability.

4. Data

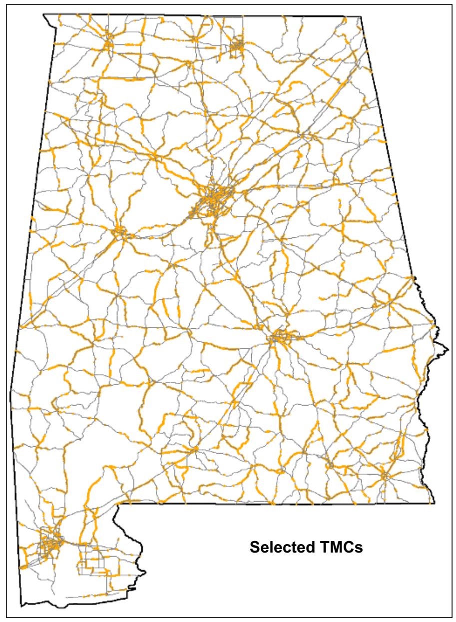
In order to identify the signatures of pavement-weather during snowfall and black ice formation, two datasets viz. HERE speed data and NLDAS climate data are used.

4.1 HERE speed data

One of the major data sources that provides real-time traffic information is HERE (http://www.here.com). It is a commercial link-based speed dataset collected mainly from probe vehicles (Bae et al., 2018). The database can be accessed using web tools or SQL server. It provides real-time traffic information in almost 83 countries through an open application programming interface. Even though the data have a wide applicability in understanding different aspects of existing traffic network system and in decision-making, a full-fledged validation of the data against actual observations is still in progress. Validation performed by Verendel and Yeh (2019) over the selected roads in a Swedish city revealed an interesting trait of the data. During low traffic volume period, HERE data seems to miss instantaneous high speeds, however, it tends to capture the dips in the travel speed. This property is extremely useful, especially for the analysis carried out in this study which relies on capturing drop in speed.

Within the HERE database, the road sections are referred to as ‘Traffic message channels’ (TMCs). Speeds table in the database contains average speed of a fraction of vehicles on the TMC (identified by a unique TMC id) at every minute (reported with timestamp). Along with this, it also provides the free-flow speed, which indicates the speed on the segment at which vehicles are considered to be able to travel without impediment. Confidence (ranging from 0 to 1) associated with each speed record is also reported. A confidence magnitude above 0.7 indicates that the data is real time. Data pertaining to ~10,000 TMCs all over Alabama are available in the table. For computational feasibility a smaller sample set is usually desired. Selection of the sample size is guided by a) the level of precision (sampling error) desired, b) confidence level provisioned by the sample, and c) the degree of variability (Israel, 1992). A conservative estimate of sample size for population equal to ~10,000 with a precision level equal to ±3%, confidence level of 95%, and degree of variability equal to 0.5 is 1,000 (Israel, 1992). So, for the current study, a minimum sample size of 1,000 is targeted. Eventually, 1,292 TMCs are selected that are spatially distributed across Alabama and belonging to different speed classes (Figure 2). The rationale here is to have TMCs with different transportation related characteristics to remove bias in signatures.

Figure 2: Geographic locations of 1,292 TMCs selected for the pavement-weather signature analysis categorized into speed classes that are derived based on the free-flow speed.



4.2 NLDAS data

To carry out this analysis, climate data from the NLDAS project (Cosgrove et al., 2003) are used. The data are result of a collaborative endeavor of NOAA/NCEP's Environmental Modeling Center (EMC), NASA/GSFC's Hydrological Sciences Laboratory, Princeton University, the University of Washington, the NOAA/NWS Office of Hydrological Development (OHD), and the NOAA/NCEP Climate Prediction Center (CPC). These data, consisting of 10 climate variables, are available at 0.125° spatial and an hourly temporal resolution, and have been widely used in a range of disciplines such as hydrology (Pan et al., 2003; Schaake et al., 2004;, Sitterson et al., 2020; Xia et al., 2012; Xu et al., 2018; Zhang et al., 2020; Chen et al., 2020), public health (Al-Hamdan et al., 2014), and agriculture (Lewis et al., 2014). In this study, three climate variables viz. precipitation, relative humidity, and temperature data from NLDAS product are used in the process to acquire signatures of pavement weather. Relative humidity is not provided directly by NLDAS data. It is calculated using temperature, specific humidity, and pressure data provide by NLDAS dataset.

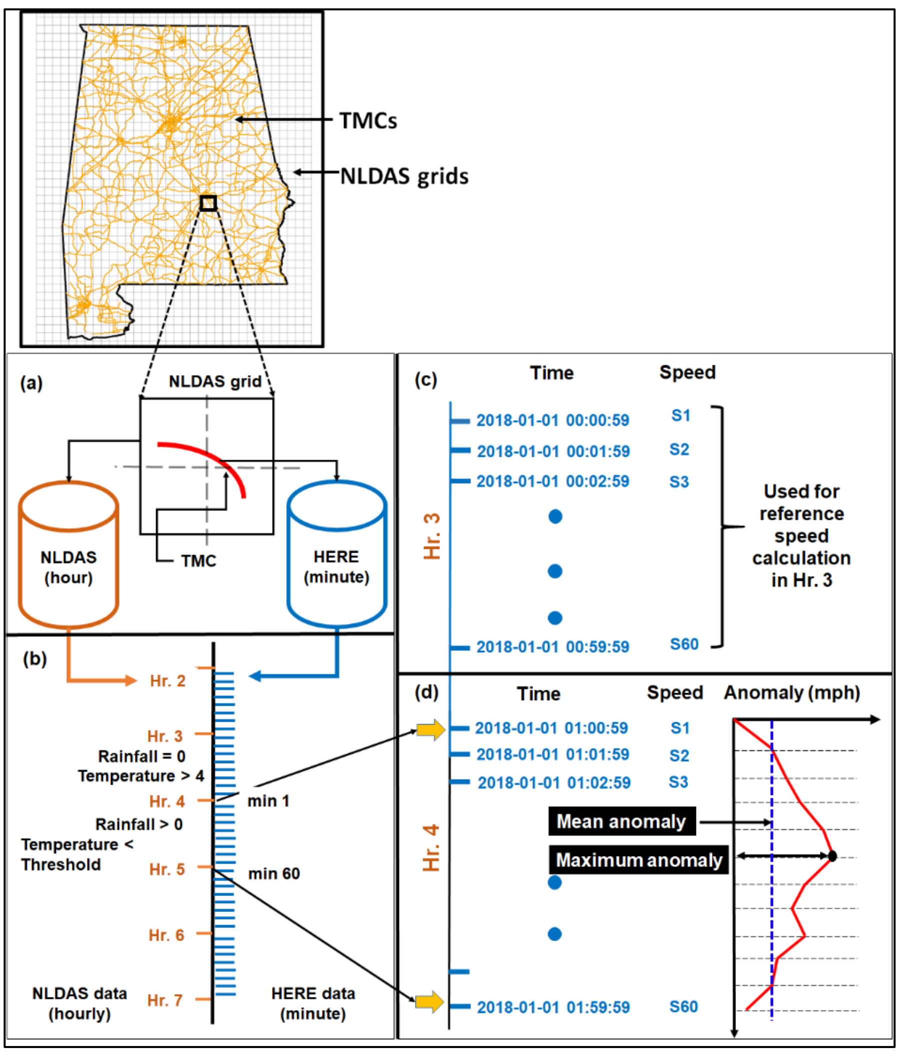
5. Methodology

A signature-based approach involves estimating pavement-weather based on the prevailing weather conditions and responses given by the vehicles on the pavement in terms of alterations in speeds. Here, the estimation of pavement-weather implies identifying the signatures of reduced efficiency of a particular TMC with the help of climate data and vehicles responses. It is conjectured that alterations in traffic speed w.r.t. speed during dry conditions carry the signatures of pavement-weather. By combining these two observations, it is possible to indirectly get glimpse of pavement weather possibly leading to disruptions in transportation. The devised methodology consists of three steps viz. 1) data formatting, 2) reference speed calculation, and 3) obtaining signatures of pavement weather.

5.1 Data formatting

1) Three impact-relevant climate variables 1) precipitation, 2) temperature, and 3) relative humidity in gridded format are obtained from NLDAS data. Relative humidity is calculated using Clausius-Clapeyron theory. Equation 1 is used to calculate relative humidity.

Figure 3: Multi-step methodology for calculating reference speed and traffic speed anomaly to winter weather event for a road section, identified by a Traffic Message Channel (TMC)



$$RH \approx 0.263 \cdot p \cdot q \cdot \left[exp\left(\frac{17.67\cdot(T-T_0)}{T-29.65}\right)\right]^{-1} \qquad \dots (1)$$

where,

q: specific humidity, p: pressure (Pa), T: temperature (K), T_0: reference temperature (typically 273.15K)

2) Meteorological data pertaining to individual TMC are extracted by identifying NLDAS grid encompassing the selected TMC (figure 3a). The overlapping operation is carried out within ArcMap 10.6.1. Meteorological data for that NLDAS grid are obtained from NLDAS database and TMC properties (actual speed, free-flow speed, confidence, and time stamp) are obtained from the HERE database. The speed data are extracted for the year 2018.

2) Both the data (NLDAS and HERE) are provided at Coordinated Universal Time (UTC), however, their temporal resolutions are different (figure 3b). HERE data at one minute resolution are mapped to the hourly NLDAS data and corresponding precipitation and temperature time series are obtained.

5.2 Reference speed calculation

A reference speed is evaluated for each TMC. Reference speed is defined as the estimated average speed of vehicles during dry pavement conditions. The dry pavement conditions are assumed to be prevalent when rainfall for that hour is equal to zero and temperature is greater than 4°C (e.g. figure 3b, hr. 3). For a given hour, if dry pavement conditions are prevalent, then the 60 speed values (one per minute) are used to calculate the reference speed (figure 3c). The speed values for which confidence is less than 0.75 are excluded from this calculation to keep the real time speed records for analysis. 'Confidence' field in HERE dataset indicates if the average speed of vehicles on that TMC is estimated with real-time traffic volume data. Higher confidence value indicates that the average speed calculations are carried out real-time.

It is to be noted that the reference speed of a TMC is not a single value. Rather, it is a matrix consisting of 7 rows and 24 columns. This is because average speed for each hour (even during dry pavement conditions) vary with day of the week and time. The speed during weekdays and peak hour might be lower than that during non-peak hours owing to low traffic volume. Hence, the reference speed is estimated for all the days of the week and all hours and expressed as a matrix with 7 rows (days of week) and 24 columns (time of day). E.g. in order to obtain reference speed for a TMC corresponding to Monday 11 AM, the speed records for all Monday 11 AM time stamps with prevailing dry pavement conditions are extracted and averaged. Also, selecting dry pavement conditions for calculating reference speed filters out effect of inclement weather conditions on traffic and hence, a fair comparison can be made between the two situations to gauge the effect of inclement weather.

5.3 Anomaly: responses of vehicles to pavement-weather

The fluctuations in the vehicle speed are inevitable even during dry pavement period. However, in case of inclement weather conditions, most of the vehicles travel with reduced speed to ensure safety. These fluctuations are termed as anomalies. These are calculated by subtracting actual vehicle speeds from the reference speed. This means that if during inclement weather, vehicle's speed drops below the reference speed, anomalies will be positive. These anomalies are the responses given to the prevailing pavement-weather e.g. if there is a snowfall event depositing 0.5 inch of snowfall on the pavement, the vehicles will probably move with lower speed as long as snow depositions are there on the pavement (even after the end of the event). Overall, the winter weather events are identified based on the climate variable data (figure 3b) and responses of vehicles to those events are captured by mean and maximum anomalies (figure 3d). In this study, mean anomalies are used to gauge the responses pertaining to the snowfall and maximum anomalies are used to gauge the responses during black ice. This is explained in the later sections.

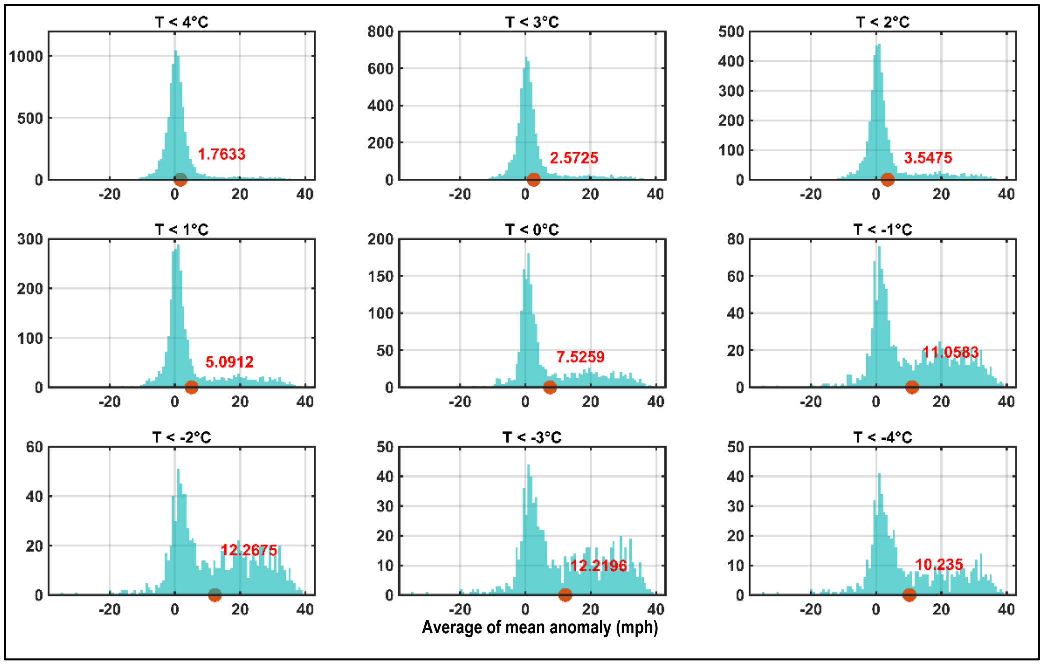
Using the approach discussed, pavement weather signals are obtained for two forms of winter events. Here, two terminologies are defined and used throughout next sections. 'Signatures of pavement-weather snowfall' implies responses of vehicles in terms of anomalies to pavement-weather that is influenced by a snowfall event indicating reduced efficiency. 'Signatures of pavement-weather black ice' is exact counterpart of previous term when pavement surface is covered with black ice.

6. Results and discussion

6.1 Signatures of pavement-weather snowfall

Snow often remains on the pavement unless melted down because of increase in temperature or removed by scraping/chemicals. If not removed, it may remain on the pavement event after the snowfall stops. A common reaction by the drivers on receiving visual signal of falling/retained snow on the pavement is to reduce the vehicle speed and continue driving at a lower speed as compared to that on a clean and dry pavement. This brings down the average speed of vehicle with which it is moving. Hence, the response of vehicles will be better captured by mean anomaly (as compared to maximum anomaly). Precipitation data consist of snow events or events with a combination of snow and rain. In order to separate and extract solid phase from the precipitation data, a temperature-based filter is applied (Auer Jr, 1974; Dai, 2008). There is a fair amount of uncertainty associated with the temperature threshold, as different methods (Auer Jr, 1974; Dai, 2008; Marks et al., 2013; Jennings et al., 2018) point to different temperature values associated with rainfall vs. snowfall. As per Dai (2008), the phase transfer occurs over a fairly large range of temperature −2°C to +4°C. Since, the pavement has higher thermal capacity than air, it is able to more effectively hold cold and heat than the air above it. Therefore, multiple temperature thresholds are considered for the analysis. The **average speed anomalies** are obtained for the selected TMCs where precipitation is greater than zero and temperature less than the threshold. The threshold temperature is assumed to vary from 4°C to -4°C. The frequency distribution of average speed anomalies during snowfall (precipitation > 0 and temperature < threshold) are compared for different temperature thresholds (figure 4). Frequency distributions illustrated by histogram and representative average speed anomalies (mean anomalies shown by orange dot) reveal two important observations.

Figure 4: Histograms showing frequency distribution and average of mean anomaly (orange dot) during snowfall events with different temperature thresholds for partitioning precipitation into rainfall and snowfall

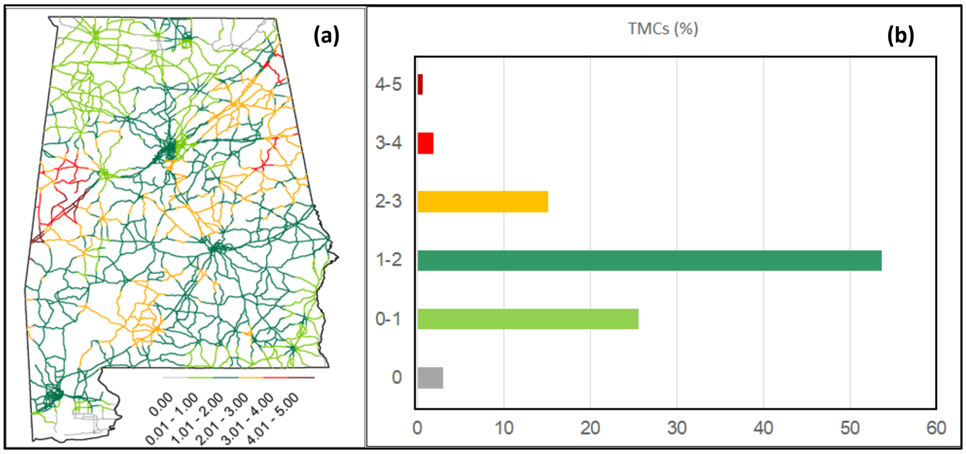


Representative average anomalies increase in magnitude with reduction in the temperature threshold. This pattern is visible till temperature threshold equal to -2°C. As the temperature reduces further, reduction in representative average anomaly is encountered. It is to be noted that all of the representative average anomalies during snowfall are significantly different from that during dry period (precipitation = 0 and temperature > 4°C). Since, temperature threshold equal to -2°C is the one with maximum representative average anomaly, it may be stated with high confidence that during these prevailing conditions (precipitation = 0 and temperature < -2°C), pavement is covered by snow and hence, signatures of pavement-weather snowfall are the highest.

6.2 Average instances of pavement-weather snowfall signatures

Based on the previous analysis, it is clear that transportation system gets highly disrupted by during snowfall, when temperature is less than -2°C. This information can be used to identify the locations where these signatures are observed frequently. Three years of NLDAS climate data (2017-2019) are used for this purpose. Important reason behind selecting three years to identify prominent locations of the signature can be explained as follows. By selecting years from the recent past, it is made sure that fluctuations in the traffic volume will not affect the analysis significantly. Also, under non-stationary climatic conditions, there are possibilities that longer datasets might introduce biases in the statistical properties of climate variables. Average frequency of pavement-weather snowfall signatures encountered during three years (figure 4) shows most of the TMCs (by count ~97%) within Alabama have faced snowfall at least once in three years. Out of all, ~94% of TMCs encounter the snowfall signatures up to 3 time per year. Interestingly, the TMCs encountering relatively high signatures are **NOT** along the northern part of Alabama, however, along the southeast direction going through the central part of Alabama.

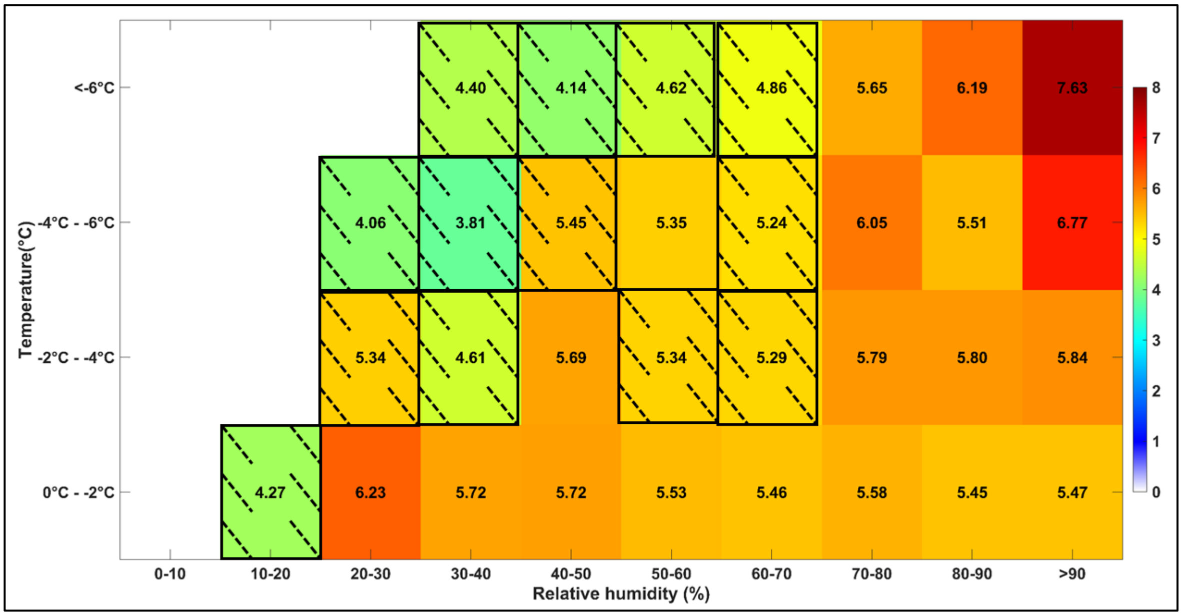
Figure 5: Spatial distribution (a) and fraction of total TMCs (b) experiencing different magnitudes of average snowfall signatures encountered during 2017-2019.



6.3 Pavement-weather black ice signatures

Black ice formation on the top surface of the pavement can be triggered by different possible combinations of climate variables e.g. 1) melting of deposited snow on the top of the pavement and freezing of that liquid because of temperature drop, 2) icy rainfall falling on the pavement with subzero pavement temperature, 3) lowering of temperature (mainly in the morning) below dew point resulting in condensation and freezing of water vapor. This indicates it not absolutely necessary to have icy rain/snowfall to have situations conducive for black ice formation. Therefore, black ice signatures can be captured by looking at the variations in temperature and relative humidity (instead of precipitation). However, it is necessary to check that snowfall has not occurred for last five hours. Now it is important to understand the possible reaction of the drivers when they encounter black ice on road. As discussed before, it is very difficult to identify that the pavement is covered with black ice because of its transparent nature. Hence, whenever, a black ice patch is encountered (possibly vehicle loses traction momentarily), the vehicles' speeds are reduced by the drivers. Unlike snowfall, black ice formations are not spatially extensive and hence, once the vehicle moves out of the patch, drives increase the speed. Therefore, in order to capture the signatures of black ice, variations in the maximum anomalies with respect to different combinations of temperature and relative humidity are required to be considered (instead of mean anomalies).

Figure 6: Average of maximum anomaly (mph) during black ice signatures categorized into different ranges of temperature and relative humidity. (White squared: data not available, crossed squares: average of maximum anomaly during black ice signatures is not significantly different from average of maximum anomaly during dry pavement signatures)

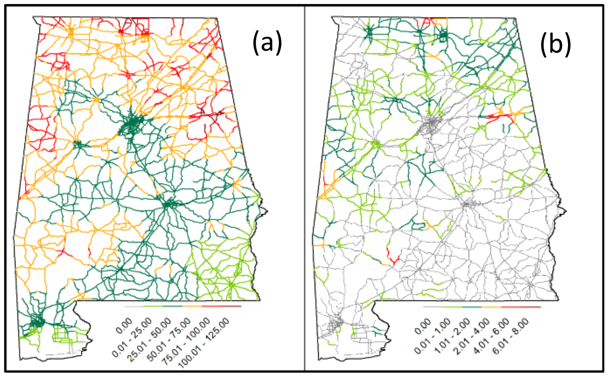


Averages of maximum anomalies for all the TMCs for different categories of temperature and relative humidity (figure 6) indicate that as there is increase in the relative humidity and reduction in temperature, anomalies increase in magnitude. Two specific situations viz. 1) relative humidity > 70% and temperature < -2°C [mild signature] and 2) relative humidity > 90% and temperature < -4°C [strong signatures] result in relatively high (higher for second combination) average of maximum anomalies that are significantly different from those during their warmer counterpart (temperature > 4°C). These two combinations of relative humidity and temperature are the possible signatures of pavement-weather black ice. These are analyzed further in the next section.

6.4 Average instances of pavement-weather black ice signatures

As compared to the frequency of average occurrences of signatures of pavement-weather snowfall, black ice signatures are more frequently encountered during 2017-2019 (figure 7). High average occurrences of mild (figure 7a) and strong signatures (figure 7b) are observed mainly in the northern part and across western border of Alabama. These results actually bring out the threat associated with black ice formations on the TMCs within Alabama mainly because of higher frequencies of occurrences. About 43% of TMCs within Alabama encounter mild signature of black ice more than 50 times per year. 39% of TMCs encounter at least one strong signature of black ice. On the first glance, the magnitude of average frequencies of black ice signatures (strong) may seem low. However, considering high percentage of TMCs affected by these and the threat it poses to the number of cars moving on those TMCs, the situation demands serious attention.

Figure 7: Average frequency of mild (a) and strong (b) black ice pavement-weather signatures experienced during 2017-2019



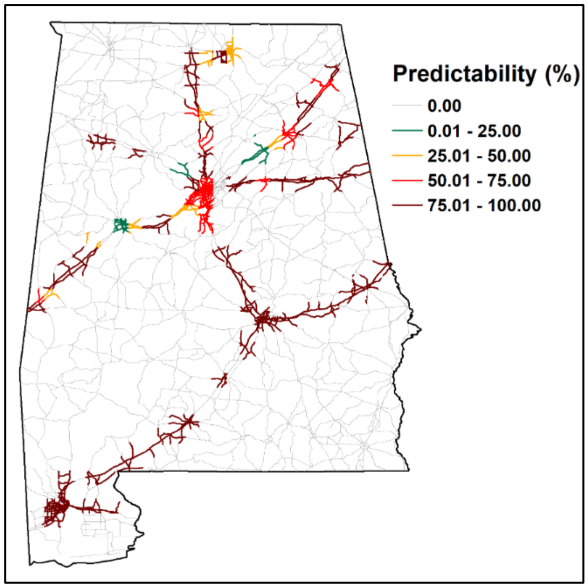
6.5 Predictability of pavement-weather snowfall

The term predictability is usually defined as degree to which a correct prediction or forecast of a system's state can be made, either qualitatively or quantitatively. Present study assumes different connotation associated with this term. First of all, the prediction of pavement weather do not mean estimation of temporal evolution of pavement weather. Rather it is the identification of 1) signatures of snow/black ice depositions on the pavement surface leading to reduced efficiency of transportation system and 2) possible hot spots (locations with high possibility of traffic disruptions because of snowfall/black ice formations). Similarly, predictability is quantified as the fraction of instances (represented in terms of percentage) when the TMCs reveal positive anomalies (reduced speed) when snowfall/black ice signatures are encountered. There are possibilities that even if the pavement-weather signatures for snow/black ice are encountered, anomalies still remain negative (no reduction in speed). This might happen for a number of reasons e.g. driver does not reduce the speed during low intensity snowfall or he/she might be driving on TMCs within the city where low speed limits are assigned to the roads and hence, he/she continue to drive with the same speed. The approach used to quantify the predictability can be explained as follows. Consider, a single NLDAS grid encompassing 'n' TMCs. Assume that the number of times the signature of snowfall (e.g. precipitation > 0 and temperature < threshold) encountered are 'm'. Under ideal conditions, all the anomalies for 'n' TMCs experiencing 'm' signatures (total events = m×n) should be positive. In reality, say 'p' instances reveal positive anomalies.

$$\text{Predictability} = (p \times 100)/ (m \times n) \qquad \ldots (1)$$

Predictability plot for the signatures of snowfall (figure 8) with temperature threshold of -2°C reveal high predictability except for the central Alabama. Even within the central Alabama, predictability is between 50-70% which is reasonably good. The results vouch for the robustness of the signature based approach.

Figure 8: Predictability of snowfall pavement-weather signature pertaining to threshold temperature -2°C for the selected TMCs



7. Key findings and possible improvements

This report presents a signature based approach to identify signatures of snow/black ice on the pavement and indirectly predict pavement weather conditions leading to reduced efficiency of transportation system. It is carried out using two datasets NLDAS and HERE over Alabama. The weather data and speed data are used in combinations to establish the signature of pavement weather. In this context, a question may arise that, if based on weather data, one can check the occurrence of snowfall on the TMC, then why to obtain the signatures by looking at speed data. The answer to this question is that the rationale of this study is to predict pavement weather during which traffic efficiency gets affect because of inclement winter weather. This cannot be achieved by merely looking at the weather data. To get exact idea of pavement weather, it is necessary to look at the reaction of traffic moving on that road e.g. in case of precipitation event when the temperature is less than 4°C, precipitation may be in the form of icy water/snow and this will get deposited on the pavement. However, it may not lead to total disruption of traffic and reduced efficiently. Here the aim is to predict that pavement weather condition, which will considerably reduce the efficiency of the system. Based on the study, following are the important observations/inferences.

1. Strong signature of snowfall on the pavement affecting efficiency of the system are observed during precipitation event with temperature < -2°C
2. The TMCs within the central Alabama along the southeast direction are likely to get affected by snow. It may be because that is the usual path of the snow storm encountered by Alabama in the recent past.
3. High possibilities of black ice formations are encountered when temperature drops below -4°C and relative humidity exceeds 90%.
4. These instances are frequently encountered within Alabama mainly in the northern part.

5. For the selected TMCs and encompassing NLDAS grids, high predictability is observed for central to southern Alabama.

While the signature based approach and the results look promising and provide some guidelines (such as information about hotspots) about winter weather operations, there is definitely a scope for improvement. Since, the approach relies on establishing pavement-weather signatures based on anomalies, considering all the TMCs (~10,000) data (instead of samples) for all the available years (2017-mid 2020) in order to obtain signatures will help to fine-tune the analysis. NLDAS data provide climate variables at 1/8° spatial resolution. However, considering the lengths of TMCs, a finer spatial resolution data may be more helpful in extracting realistic signatures.

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