AN ANALYSIS OF ATLANTA ROAD SURFACE TEMPERATURES FOR THE IMPROVEMENT OF URBAN TRANSIT

By

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(Under the Direction of J. Marshall Shepherd)

ABSTRACT

Winter provides myriad challenges for urban areas covering roads with often unseen layers of ice causing collisions and traffic jams and threatening public safety and economic sustainability. Urban transit systems are not immune to these seasonal detriments, however, these systems can provide critical services in a range of inclement weather. This study uses data from road weather sensors in North Georgia to analyze variations in road surface temperature (RST) in order to provide a scientific basis for winter transit operational policy. The research objectives are to (1) identify major physical factors in the movement and transfer of heat in and out of the road surface, (2) to understand how these physical factors interact with each other, and (3) to use the results to improve the efficiency of urban transit in winter. The major findings suggest that insolation accrued over the course of the day, moisture and precipitation, and traffic volumes all play large roles in driving variation in RST.

INDEX WORDS: Urban Transit, Winter Weather, Road Temperature, Urban Climatology

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CHAPTER 1: INTRODUCTION

Each year, winter weather affects drivers in all 50 states causing numerous car collisions and traffic jams. In fact, according to the U.S. Federal Highway Administration, between 2002 and 2012 snow, sleet, and icy pavement were blamed for an average of over 540,000 car collisions each year accounting for over 10% of all car collisions annually. This same winter weather was also blamed for almost 150,000 car-related injuries and over 1,900 automobile-related fatalities each year (How Do Weather Events Impact Roads?, 2015). These numbers show the magnitude of the problem winter weather poses for drivers.

As urbanization intensifies around the world, the need for safe, urban transportation will increase substantially (Koetse and Rietveld, 2009). This fact can either be seen as a problem or an opportunity for urban transportation. With responsible research and planning, increased urbanization can provide greater opportunities for the expansion of various public transit modes in cities across the globe. Many people are already calling for increased transit options in response to recent weather catastrophes that have crippled or completely immobilized road networks in the United States (Wiltgen, 2014; Burns, 2014).

Nick Wiltgen in a blog post on January 30, 2014 quoted fellow Weather Channel meteorologist, Carl Parker's, comments on the ensuing traffic after the Atlanta snowstorm of January 2014. "That's particularly true because of the transportation system in Atlanta, which operates at the very edge of calamity. There are no relief valves, in the form of extensive subway or commuter rail lines, which work quite well in minor winter storms.

Until that changes, I think officials should be much more cautious," in reference to public officials' winter storm management (Wiltgen, 2014).

1.1 Motivation

Progress is built on corrections and changes to older, flawed policies and practices. The progression from problem to solution motivates change and innovation within communities. The tribulations and short-comings of current transportation in winter weather fits well within this framework of a problem requiring a progressive solution. The expansion of highways and interstates since the 1940s and 1950s have created car dependencies in most American cities, especially those with population booms after World War II. These dependencies lead to diminished transit, bicycle, and pedestrian infrastructure feeding back into a political and economic cycle that promotes greater usage of cars (Burns, 2014).

While it is well known that driving on icy roads presents many challenges and is responsible for a significant number of accidents, the understanding of how road conditions deteriorate is still under much scrutiny. Questions about when, where, and how our roads ice become key to ensuring the safety of motorists across the country. Not only can the answers to these questions improve roads in winter crises, they can also be useful in designing more effective transit infrastructure as well as better utilizing existing infrastructure.

1.1.1 Atlanta ‘Snowpocalypse’

The city of Atlanta is an infamously car-dependent city with a reputation for the creation and perpetuation of urban sprawl. The United States Census Bureau estimated the population of metro Atlanta to be around 5.6 million people in 2014. The population within the city limits of Atlanta proper - where the largest central business districts are located - only accounts for about one-twelfth of that number (U.S. Census Bureau). These statistics suggest that Atlanta has a large commuter population. In fact, in 2010, the U.S Census Bureau estimated a daily population change of 273,789 people due to an influx of commuters from Atlanta suburbs. This is a 66% increase in population, the second highest daily percent increase of any metropolitan area in the United States (“Commuter Adjusted Daytime Population: 2006-2010 5-year ACS”, 2015). Approximately 82% of this enormous influx of people into the city each morning uses a personal automobile to complete their trip. As any cursory look at an Atlanta traffic map will show, these transportation patterns produce a congested traffic flow, requiring construction and expansion of more roads. In fact, in 2014 the Atlanta Metropolitan Area was estimated to have almost 20,000 miles of roads and about 3.9 million registered vehicles (Atlanta Regional Commission, 2014). This makes roads and personal automobiles a major portion of the Atlanta transportation system.

Figure 1: Traffic Map provided by AccuWeather depicting conditions at 9:30 am the morning after the storm

In January 2014, approximately 5 centimeters (2 inches) of snow brought traffic on a majority of those roads – particularly the interstates – to a complete stop. Cars and people were trapped on the roads for 12 hours or more trying to get home. Children were stranded at school as buses were unable to cut through traffic. Emergency vehicles were unable to assist those in need also due to the dysfunction of Atlanta's roads. Scenes of people walking down highways packed with motionless cars were made famous along with comparisons of these images to scenes from the apocalyptic show "The Walking Dead," (ironically filmed in Atlanta). Yet, Atlanta's simplistic rail transit system continued to operate and move people around the city, even in its spatially limited capacity.

This story, without the massive gridlock and camps of people marooned on highways, is actually quite common throughout the United States. Maybe not to the same extent as Atlanta's Snowpocalypse, but winter weather definitely impacts the efficiency of transportation systems. This begs the question, how can we design our cities to better handle this recurring threat?

1.1.2 Challenges of Urban Winters

Several studies of the climatology of freezing rain events show that while specific numbers can vary on a microscale, regional averages are available for frequency and duration of freezing rain and ice storms by number of days per year, number of hours each storm lasts, average first and last day of 'Ice Storm Season', and how these frequencies are changing over time (Cortinas et al., 2014). Houston and Changnon (2007) note that ice storm frequency in the United States increases from West to East and from South to North with New England experiencing the highest number of ice storms on average each year – as many as 12 ice storms per year. They also tend to have the longest duration of freezing rain. North Georgia, South Carolina, and central North Carolina, also show a relatively high frequency averaging approximately two observed freezing rain events per year. These storms in the southeast tend to be more damaging in terms of economic losses relative to their northeastern counterparts (Changnon, 2003).

However, Kovacik and Kloesel (2014) note changes in the regional frequencies with a westward shift of the highest frequencies. Areas of the Southern Plains, Appalachia, and the Mid Atlantic had increasing frequencies of ice storms between 2000 and 2009, while New England had decreasing frequencies. Somewhat contrastingly on a larger temporal scale, studies of freezing rain climatology in Canada have noted an east, northeasterly shift in the highest frequencies since the mid 1900s. The differences can be partially attributed to improvements in ice storm identification methods and technologies, but this should not negate the impacts of the noted trends (Cheng et al. 2007; Cheng, Shouquang, and Li 2011). All of these studies considering changes in ice storm frequency do note the overall increase in ice storm frequency and intensity over North America as a whole, the causes of which are outside the scope of this study. However, these studies warn that urban areas should be prepared for more ice per season in the coming years varying in time of year, frequency per year, duration of event, and intensity of event (Klima and Morgan, 2014; Kovacik, Hocker, and Shafer, 2011).

1.2 Transit Agency Policies

Public transit comes in many forms to serve a variety of purposes for a wide spectrum of communities and regions. The goal of a public transit system can be as simple as improving mobility for those with restricted transportation options. However, in modern cities, the concept that any system has one purpose or one goal seems naïve and misguided, not to mention inefficient. Therefore, many urban areas strive to provide transit that can help resolve multiple problems in both social and physical spheres. Considerations for people's income or race can be just as important as considerations for environmental sustainability or safety. For this reason, it is important to study transit from multiple perspectives and gain insight into solving as many problems as possible through the lens of each urban system.

One consideration for public transit and urban transportation that is lacking attention in the literature are the effects of winter weather on urban transportation and mobility outside of personal automobiles. While great efforts have been made to identify the impact various modes of urban transportation have on climate and the environment, less focus has been placed on the opposing direction of that relationship. For example, how much does the transit system efficiency vary between sunny days, rainy days, snowy days, etc.? Does the change in efficiency vary more or less depending on the modes included in a specific system? These comparisons are important to understand due to the strong relationship between mobility/accessibility and weather/climate. These are issues that every community faces on a regular basis, though their intensity and frequency vary from place to place.

The questions related to system efficiency are best introduced by looking at existing policies defined by transit agencies regarding conditions their systems operate in. Pulling (2008), which examined winter weather mitigation strategies for rail transit, notes that it is possible to operate rail transportation on a relatively efficient schedule even in winter weather. However, bus transit often faces more challenges in overcoming the same obstacles. The difference between modes can be noted in cities such as Chicago, Minneapolis, Seattle, New York, and Washington whose transit agencies specifically mention reliance on their rail system while experiencing some form of winter weather in their customer information websites. The Chicago Transit Authority (CTA) makes use of sleet scrapers and track switch heaters to ensure on-time and efficient performance by rail transit, but note that bus routes and schedules are dependent on which streets are plowed and when (“Winter Weather’s Here and CTA is Ready”). Sound Transit in Seattle states in winter weather they maintain “regular commuter schedules” for both light rail and commuter rail services. Sound Transit runs light rail trains through the night on an hourly schedule to prevent catenary wires from accumulating ice. However, the transit authority warns that many buses are likely to be rerouted or cancelled during such inclement weather (“The Ice Train Cometh”, 2015). Similarly, WMATA in Washington, D.C. notes that metrorail services can operate “very close to normal schedule in snowfall of 4 to 6 inches.” The agency also specifically identifies increased ridership due to drivers opting for transit (“Metrorail Snow Service”). This is contrasted with metrobus service which operates in up to 2” of snow and may still be subject to delays and increased headways in such conditions. They also specify that metrobus service is reduced to main roads in icy conditions until roads become unsafe (“Metrobus Snow Service”).

The transit service examples above demonstrate some of the advantages rail transit holds over bus transit in winter weather. This was noted by bloggers across the country during and after the “Snowpocalypse” of January 2014 in Atlanta. The city sees an average of 2 freezing rain events per year with each event averaging 12 hours in duration (Gay and Davis, 1993). Yet, in an event that would be regarded by many cities as “minor,” Atlanta faced severe and crippling challenge. Many public officials blamed the weather service for inaccurate predictions and late notice, but as Wiltgen (2014) and Shepherd (2014) argue, city and state officials had accurate forecasts up to 6 hours in advance. This kind of weather-related coma to which Atlanta fell victim is a direct result of poor planning and preparation. An entire city released onto roads which are incapable of handling normal traffic flows due to ice accumulation much less a load of emergency evacuees, is the result of decisions made in haste and without proper pre-planning or proper consideration of all risks. So the next question to be asked: are their physical factors which transit agencies can use to define policies that increase their system's efficiency in inclement weather?

1.3 Every Mode has its Purpose

To understand how to ensure and improve transit efficiency, it is necessary to understand why certain modes are chosen in a general planning context and what benefits or advantages they offer. These modes can vary both by their physical methods of movement as well as through more flexible means such as their scheduling, use of right of way, capacity, and more. While the list of transit modes is expanding across the globe – the use of gondolas in South America being a prime example – this thesis will consider the most common options across North American cities, namely bus and rail.

1.3.1 Trains

Rail transit has been and continues to be a popular mode of public transportation around the world. Urban metro systems form the backbone for many city's transit networks on every continent. Evolving over time, many forms of rail transit are now available including heavy rail, light rail, streetcars, trolleys, trams, etc. (American Public Transport Assoc., 2008). These modes differ in several ways, but distance, capacity, and right of way are easily the most important. Heavy rail, for instance, is the mode utilized for most metro systems and commuter rail systems. Able to carry more cars at higher speeds, this type of rail transit has the highest capacity and usually travels the farthest distances all while separated from most traffic. By contrast, streetcars tend to share segments of roadway, usually only have 1-3 cars, and are usually powered by overhead catenary wires.

While so many differences exist between types of rail transit, they all have one obvious, basic similarity: rails. Though seemingly basic, this characteristic is very different from the dynamics of a rubber tire on pavement. Greater productions of heat, smaller surfaces for water accumulation, and more intricate connections between wheel and ground all contribute to the significance of the method of propulsion defined for rail transit as these characteristics reduce the risk of ice and snow accumulation on tracks.

1.3.2 Bus Transit

Like rail transit, buses come in all shapes and sizes serving a variety of purposes. Para-transit, for example, often makes use of short shuttle buses to move small groups of people around with a more door-to-door perspective. On the opposite hand, most people are familiar with standard city buses operating on fixed routes and moving as many people as possible from one set location to another. In recent decades, more and more localities have attempted to modify this mode to better serve individual communities. This sometimes comes in the form of more capacity as the bi-articulated and double decker busses accomplish through increased seating without an increase in drivers or individual vehicles. Other times, changes in frequency or sharing of right-of-way capitalize on high ridership without requiring large amounts of capital or construction time. This increase in system rigidity and/or efficiency is often encapsulated by a form of bus service called Bus Rapid Transit (BRT).

Two types of BRT systems can be found in cities across the globe. Both types make use of rubber on pavement propulsion separating it from rail transit. This study is a direct contrast of the effects of ice on methods of propulsion. However, BRT systems are not standardized around the world. A true BRT makes use of several logistical features to mimic rail transit. These features include separation from traffic, pre-paid fares, bus floor level with station platform, priority right-of-way at traffic signals, and a limited number of permanent, pre-determined stops or stations (American Public Transport Assoc., 2008). Noting these features, method of propulsion is really the only difference between rail transit and a true BRT. However, many cities opt for what is referred to as a BRT-like system. These systems lack one or more of the features noted above while retaining the rest commonly resulting from what is known as “BRT Creep” which refers to budget shortfalls or other political resistance. Most commonly, a BRT-like system would be provided a lane on the road separated from other automobiles by lane marking but lacking a physical barrier. As demonstrated in many places currently using such a system, these bus-only lanes can often be illegally used by cars and are subject to possible collisions with reckless automobiles even when cars remain in their designated lanes. These collisions can be particularly relevant in extreme weather and/or icy conditions because these extreme scenarios are the times drivers are most likely to break rules of the road or accidents and other impediments to normal traffic flow. All of these factors affect efficiency of a system overall and should be taken into account not just during alternative analyses and environmental impact assessments, but also during operation especially in emergency policy implementation.

1.4 Research Question

While the overarching theme of this thesis is to examine urban transportation through the lens of winter, there is also a noted focus on improving existing infrastructure as well as a geographic focus on the Atlanta Metro Area. At the outset of the introduction, the concept of auto-centric cities began framing the problems urban transportation faces in America. Consequently, cities such as Atlanta face an abundance of roads and a lack of passenger-ready railways. Using these realistic constraints, this thesis can and should be more focused on improving bus transit in winter weather as buses are the most readily available mode in Atlanta's potential transit arsenal.

Considering the physical dynamics established in Section 1.3 regarding movement on roads and rails, the improvement of Atlanta's bus network is dependent on understanding the road surface. Therefore, this project will consider the major question: (1) What quantifiable factors affect Atlanta road temperatures the most? This question seeks to broadly assess when roads are more likely to freeze by investigating how road temperature varies through a series of more finite questions. How do road temperatures differ in cloudy versus sunny conditions? How does precipitation change the rate of cooling or heating of the road? Does traffic increase or decrease road temperature? How do these factors change between times of day or times of the year? A better understanding of fluctuations and changes in Road Surface Temperature (RST) will facilitate the application of techniques currently used by American transit agencies to keep bus systems running during inclement winter weather.

Based on the existing literature on road surface temperature, I hypothesize that the existence of precipitation and rate of precipitation will drastically increase the rate of change of RST. This hypothesis is due to the relatively larger heat capacity of liquid water which can absorb more heat from the road surface before changing phase. This logic can be expanded to rationalize a road surface losing more heat as the amount of precipitation making contact with the road surface increases. This first hypothesis is important as it predicts an increased impediment to tire-on-pavement based transportation which decreases the efficiency of transportation modes such as bus rapid transit. The loss in efficiency would mean all types of precipitation would require reductions in speed for vehicles without a pre-set track (rails) and whose frictional force is more variable (tire-on-pavement propulsion). The ability of forecasters and transit officials to both predict and see precipitation with certain accuracy also makes precipitation a good variable on which to base emergency transit policies. In combination with air temperature which is also easily accessible data, road temperatures should be fairly predictable. Other factors such as traffic volumes and time of day which can add or subtract heat from the road should also be good factors to consider.

CHAPTER 2: PHYSICAL THEORY AND EXISTING PREDICTIVE MODELS

Chapter 1 identified the mechanisms by which both trains and buses move and established that road and rail ice result from the simultaneous presence of cold temperatures and water. However, answering the major question posed by this thesis will mostly center on discussion of the mechanisms by which heat is transferred. As Gustavsson, Bogren, and Green (2001) point out, the transfer and movement of heat can be reduced to three physical processes: radiation, advection, and ground heat flux. Each of these processes differs by what carries the heat as well as how the carrier moves.

Radiation relies on electromagnetic particles and waves to move heat through vacuums and transparent media. Advection makes use of matter by transferring heated molecules through a fluid along a single plane. Both radiation and advection describe how heat moves from source to road surface or from road surface to sink. The final process, heat flux, simply describes how heat passes through the surface and into or out of the road. Heat flux makes use of radiation into the air and advection through water and the air treating the road as both an absorber and an emitter. Together, these physical mechanisms connect the road with heat sources and sinks that manifest simultaneously through variables such as insolation, humidity, precipitation, traffic volumes, etc.

2.1 Roads

Heat and energy movements are described on a number of different scales ranging from microscopic to urban scales or mesoscales. All of these scales contribute their own influences on road surface temperatures and subsequent ice formation. Thermal mapping has been used in road climate studies since the 1970s and is presently used to identify areas prone to ice formation or to analyze various physical features and processes' impacts on RST (Chapman and Thornes, 2005; Shao et al., 1997). These results are usually used to develop RST and road surface state prediction models such as METRo and Roadserf, most of which rely on variables such as air temperature, dewpoint, wind speed, surface temperature, and subsurface temperature (Bouilloud et al., 2009; Shao et al., 1997; Sokol et al., 2014). Production of models through thermal mapping is traditionally done by identifying neutral areas (a starting baseline location) of RST and analyzing how other locations vary with respect to neutral spots (Gustavsson 1999).

Many studies in thermal mapping have produced conclusions on what physical factors affect RST the most. Topography, skyview factor, screening, traffic, meteorological conditions, and the urban heat island are the most notable factors in the literature (Bogren, Gustavsson, and Karlsson, 2001; Bogren et al., 2000; Chapman, Thornes, and Bradley, 2001; Postgard, 2016; Wood and Clark, 1999). A number of studies have also focused on the specific impact that cars and traffic have on the road at various scales (Chapman and Thornes, 2005; Fujimoto, Saida, and Fukuhara, 2012; Prusa et al., 2002). However, it should be noted that there is a lack of research on the direct impacts of precipitation on RST. This is an area that this study has particular interest in exploring.

Road surface temperature alone cannot accurately predict the presence of road ice. Moisture is an obvious component that can accumulate on roadways from many sources. Two classes of road ice should be explained in order to better understand how moisture interacts with temperature on roadways. These categories are most simply differentiated by whether water appears on the roadway before or after RST drops below freezing. Rain commonly accumulates on roadways as most roads across the world are constructed of impermeable materials. This pooled rain water can stand on roadways for varying amounts of time depending on the size of the pool and the ambient conditions.

These pools accumulate from rain in the daytime while temperatures are warm and then freeze overnight if the temperatures decrease. In very humid locations, water vapor near the surface can condense onto roads that are below freezing thus causing the newly condensed moisture to freeze. This is known as frost or hoarfrost (Riehm et al., 2012) which can form black ice in areas not commonly associated with snow or ice. Both of these methods of road ice production - freezing of pooled rain water and freezing of condensed water from the air along the surface - create dangerous driving conditions outside of the setting of a winter storm or wintery precipitation. This makes the forecasting and identification of road ice formation all the more challenging.

The second category of moisture in road ice formation is made up of frozen precipitation. This is much more easily identified and usually more prominently associated with hazardous roads. This is largely due to the double threat of reduced friction between tires and the road surface and loss of vision while driving due to falling precipitation both of which contribute to modified and slower traffic flows ("How Do Weather Events Impact Roads?", 2016; Ibrahim and Hall, 1994). While sleet and snow contribute to road icing, their solid state upon reaching the ground reduces their ability to ice roads if roads are at or below freezing already. If RST is above freezing, ice would not generally form on that surface. However, freezing rain is a particularly dangerous form of precipitation as ice is formed upon impact with a surface and sticks to these various objects and surfaces (Call, 2010).

2.2 Road Ice Predictive Modelling

The use of existing road ice predictive models discussed in section 2.1 is important to consider in relation to this thesis particularly with respect to validation. As models are developed they are refined through point validation as well as thermal mapping. This is a perpetual process that is geography-dependent. Chapman and Thornes (2001) calls for integration of geographic parameters and geographic analysis to improve road ice prediction models. Similarly, Krismanc et. al (2012) concludes that further parameterization of models, in their case METRo, specifically using factors such as traffic and other anthropogenic heat sources is the best way to improve models. As Chapman and Thornes (2001) notes, much of the validation and further parameterization of road ice models relies on thermal mapping. Thermal mapping has a high spatial resolution, however, it is often only performed at night and as such has a low temporal resolution (Chapman and Thornes, 2005; Shao et al., 1997). Additionally, road ice models are complex and require further development to run faster lowering their temporal resolution as well.

Model validation using weather sensors at specific locations has a higher temporal resolution. While these sensors cannot capture the full variation of meteorological variables over space, they provide helpful insight regarding changes over time. Krismanc et. al (2012) also noted that periods of increased insolation tend to increase model error. This fact would corroborate a need for model verification in all times of day, even on a more limited spatial scale. An understanding the dynamics of meteorological variables and geographical variables and their joint analysis is necessary to more accurately apply existing models to new locations. Due to limited research in RST variation for American and low-latitude geographies, this thesis can contribute to the implementation of RST and road ice prediction models by examining some of the ways heat moves between the atmosphere and the roadway at a specific location in the Southeastern United States.

CHAPTER 3: METHODOLOGY

This study uses statistical analyses to analyze variations in road surface temperature in relation to a number of variables. The following section introduces the data used for the analysis and outlines the specific statistical tests used.

3.1 Data

Data for the road surface temperature analysis was provided by two sources. The National Weather Service shared their data from the new Road Weather Information Sensor (RWIS) network from December 2014 through July 2015. Five sensors were used for this study recording observations every 10 minutes. As shown in Figure 2, these sensors form a corridor along Interstate 85 from the northern part of the metro to the southern part of the metro. This spatial pattern allows for the analysis of the impact a variety of urban features have on road temperatures including road concentrations and traffic volumes, as well as a variety of geographic variables.

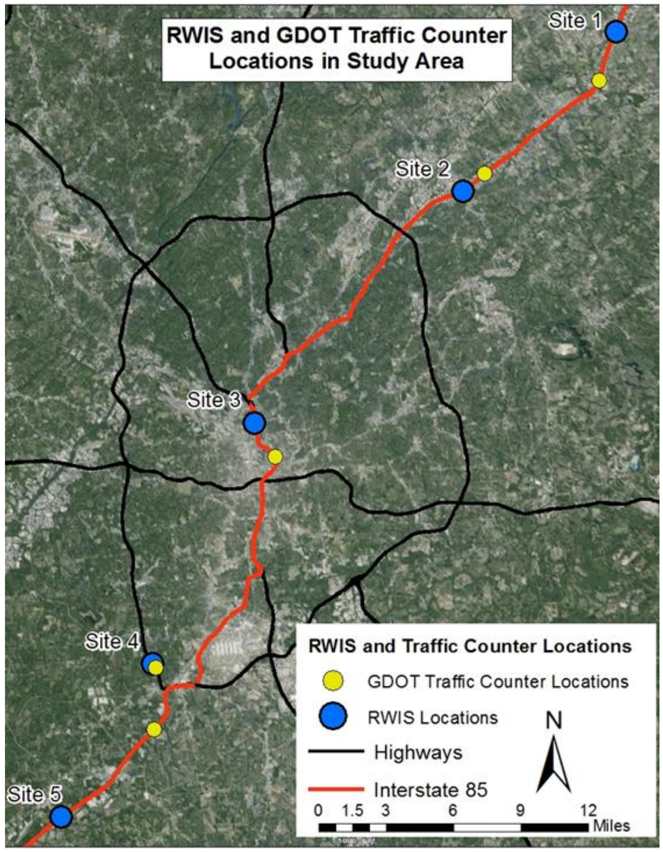

Figure 2: RWIS and traffic counter locations used

Traffic counts were acquired from the Georgia Department of Transportation (shown in yellow in Figure 2). It must be noted that it was impossible to obtain traffic counts from the same location as the weather sensors. An appropriate traffic counter was chosen using the following criteria. First and most importantly, no major highways may have merged with or split from the road on which the sensor is located. Second, the location at which the traffic is counted must have the same number of lanes as the location of the weather sensor to maintain a flow rate proportional to the number of cars counted for each instance. While this mismatch of location is not ideal, it is important to assess the approximate volume of traffic on the road at the time of each weather record to account for the impacts of anthropogenic interference caused by blockage of radiation into and out of the roadway, vehicular exhaust, and friction between tires and the road (Chapman, Lee, and Thornes 2005; Fujimoto et al. 2012). These factors all affect changes in the road surface temperature and must be accounted for.

3.1.1 Variable Descriptions

This study made use of 10 variables directly available from the RWIS dataset. Additionally, a python script was used to derive several rate of change variables to examine the magnitude and direction of the impacts one variable has on another. These rate of change variables included standard differences between two observations for temperature, humidity, and traffic counts.

The script was also used to calculate the number of consecutive observations with and without precipitation, rainLength. The larger the magnitude of a negative value, the more observations that had passed since the last precipitation event. Similarly, the larger the magnitude of a positive value, the more observations that had passed since precipitation began. The count was restarted when rain started or stopped. When a value for precipitation was missing the following record’s rainLength was reset to 0 to ensure data quality in correlation and regression analyses. Changes in phase of precipitation were not factored into the rainLength variable.

The Time/Date variable from the RWIS dataset was split into three separate variables accounting for the season, month, and time of day the observation was recorded. Winter, spring, and summer comprise the values of the season variable –

December, January, and February for winter; March, April, and May for spring; June and July for summer.

Time of Day was coded into four values: Morning, Day, Evening, and Night. Each value accounts for a 6 hour period and is based on the variation in sunrise and sunset which was important considering the RWIS observations spanned from December to July including both the longest and shortest days of the year. Day (10 a.m. – 4 p.m.) begins after Atlanta’s latest sunrise of the year and ends before Atlanta’s earliest sunset of the year including the time of day when sunlight is most direct. Night (10 p.m. – 4 a.m.) begins after Atlanta’s latest sunset and before Atlanta’s earliest sunrise. Morning and Evening occupy the other hours accordingly. The time of day was also important to account for commuting patterns when analyzing traffic counts.

To use traffic count data as a filter variable in correlation tests and for use in ANOVA tests, the data was grouped into ‘high traffic’ and ‘low traffic’. This grouping was accomplished through the use of quantiles. ‘High Traffic’ in this thesis therefore refers to the top quantile of traffic counts. Similarly, ‘Low Traffic’ in this thesis refers to the bottom quantile of traffic counts.

Table 1: List of Variables

Variable	Description
1. Date/Time	1. Date and time of recorded observation
2. Air Temperature	2. Temperature of the air above the road
3. Road Temperature	3. Temperature of the road skin layer
4. Subsurface Temperature	4. Temperature of the ground beneath the road
5. Dewpoint	5. Measure of absolute moisture in the air
6. Relative Humidity	6. Measure of moisture relative to air temperature
7. Wind Speed	7. Speed of the wind above the road
8. Rain/FR/Sleet/Snow	8. Physical State of precipitation if it is falling
9. Precipitation (Y/N)	9. Whether or not precipitation is falling
10. Road Surface State	10. Physical State of the road surface (dry, wet, icy)
11. Difference Values	11. Calculated difference between two observations
12. Traffic Counts	12. Number of cars passing a specific location within one hour

Four main dependent variables were selected to analyze RST sensitivity to physical and geographical factors, the Road Temperature variable being the most direct and ultimately important along with its rate of change variable, deltaRoadTemp. Additionally, a Temperature Difference variable was created by subtracting the Road Temperature variable from the Air Temperature variable. The justification for this variable is further explained in the Correlation and Regression subsections of the Results and Analyses sections. However, in general, the Road Temperature is highly dependent on the Air Temperature. Thus, analyses of the factors which impact the Temperature Difference variable are meant to examine when and why exceptions are made to the normal relationship between Road Temperature and Air Temperature. A rate of change variable, deltaTempDiff, was subsequently created as well.

One major point of this study is to better anticipate or predict road temperature values using more easily acquired or more stable physical and meteorological variables. For that reason, as will be noted at times in the Results and Analysis section, certain variables such as the subsurface temperature were not considered in-depth because they are less readily available or vary over space and time as much or more than road temperature.

Two spatial variables were used for this study, one ordinal and one ratio. The Urban Class variable assigns a number to each RWIS sensor representing urban, suburban, and exurban classes. The table below breaks down the sensors in each class referencing the sensor label in Figure 1. The Distance-To-Center variable also records the sensors' distance from the center of the city, but this variable is continuous rather than a discrete class so it can be used in regression analyses. Sensor 3 is used as the specific center of the city and the Euclidian distance is measured in miles.

Table 2: List of RWIS stations by Urban Class

Urban Class	Sensors
Urban	Site 3
Suburban	Site 2 and Site 4
Ex-urban	Site 1 and Site 5

3.1.2 Data Preparation and QA

RWIS data was received in one spreadsheet for all sensors. Using MS Access, the data were split into five tables, one for each sensor. All variables were checked for erroneous and unrealistic values. Some Time/Date values were corrected to align with correct 10-minute values, but none were changed by more than one minute either forward or backward. All observations were assigned a value for the sensor to which they belonged. The Temperature Difference variable was calculated and the data was finally exported to csv format.

A python script was written to calculate rate of change variables described in detail in the Variable Description section above. The script also coded values to be more easily understood – such as letters representing the time-of-day and a number representing the month - and performed a second check for erroneous values. After running the script, the data were placed back into the same csv file for easier analysis processing. Analysis of the data includes the statistical tests listed and described in the subsequent sections.

3.2 Correlations

Correlations were run for all continuous variables to assess their individual effects on each of the four road temperature variables. The results were organized into a matrix for each variable pair with a separate result listed for each of the five sensors, an average of those results, and a result from all five sensors combined. This matrix was then sorted based on the third class of results – the combined data set of all five sensors. Sorting was undertaken to identify correlations that were stronger in both the positive and negative directions.

A total of eleven relationships were further investigated through correlation tests. The first two – correlations between AirTemp and RoadTemp and between deltaAirTemp and deltaRoadTemp – were used to further display strong relationships and create a basis for investigating effects on RoadTemp and TempDiff in subsequent statistical tests. The last nine relationships all had correlation coefficients either above 0.2 or below -0.2. Filters were then applied to test how certain categorical variables strengthened or weakened these correlations. A set of five categorical filters were used for each of the nine strongest correlations: Time of Day, Season, Precipitation occurrence, Traffic Volumes (top 25% and bottom 25%), and spatial variables – Urban Class and Station Number. Filters were applied separately and were not overlapped.

3.3 ANOVA

Several ANOVA analyses were performed in order to investigate the direct effect of independent, categorical variables on the four dependent variables. Subsequent post-hoc tests and graphical analysis were used to identify the strength and nature of differences shown in the ANOVA analyses. The post-hoc and visual analyses were particularly important considering how large the dataset being tested was. In some cases, filters similar to those used in the correlation analyses were used to further investigate these results.

3.3.1 Seasonal Analysis

A seasonal analysis was performed using ANOVA tests to measure differences in RST by months of the year. Road Temperature and Temperature Difference were both used as dependent variables. As noted above, seasons were defined by the meteorological seasons spanning from December to July. Similar to the correlation analyses, categorical variables were used to filter the data and further tease out differences in RST. The filtering variables used include Time of Day, Precipitation (Y/N), and Precipitation start and stop.

A comparison was also made of the number of TempDiff values by sign in each season. This comparison made use of the ratio of positive TempDiff values to Negative TempDiff values in each season to better understand how the road and air temperatures relate to each other differently through the year. The number of TempDiff = 0 values were also considered with respect to the number of observations were made for each season.

3.3.2 Time of Day Analysis

ANOVA analysis was also used to examine differences in RST values by time of day. Road Temperature and TempDiff were used as dependent variables. Ratios of positive to negative TempDiff values were also compared by time of day to better understand how the road and air temperatures relate to each other differently throughout the day. The number of TempDiff = 0 values were also considered with respect to the number of observations were made for each season.

3.3.3 Spatial Analysis

A spatial analysis was also performed using ANOVA tests. The ‘Station Number’ and Urban Class variables were used as distance variables. The ‘Station Number’, which uses each station location individually - allows for conclusions based on absolute location, mainly north-south positioning while the Urban Class variable groups sensors by the relative urban density surrounding them. After initial analyses, filter variables were applied such as time of day and month to account for conditions when various types of the urban heat island would be most and least prevalent.

3.3.4 Precipitation Analysis

The precipitation analysis consisted of two independent variables. The first was the binary Precipitation variable. This allowed for the general understanding of how precipitation affects the Road Temperature, Temperature Difference, and rates of change. The second variable, deltaRain, assess how the same dependent variables change as precipitation starts and as it stops. ANOVA analysis was used for each of the independent variables in coordination with the Time of Day variable as a filter.

3.3.5 Surface State Analysis

The effects of surface state of the road on the road temperature, temperature difference, and rates of change were analyzed using ANOVA tests. Time of day filters were used to better analyze how incoming radiation changes throughout the day.

3.4 Multiple Regression

Lastly, multiple regression analysis was performed to attempt a predictive model for Road Temperature. Analysis was progressed through levels based on the number of independent variables included. The first level assessed each independent variable's individual effect on road temperature. More independent variables were added to the equation until no noticeable differences in predictive score were observed. Independent variables were selected from correlation analysis because of the similarity between the two analysis methods. R^2 values were recorded and compared to identify more and less predictive combinations.

CHAPTER 4: RESULTS

The results of all statistical tests are located in the following sections. Appendix A includes tables of results from each correlation test individually rather than by combination of variables. The results provided in the subsections of Section 4 include correlation tests, ANOVA tests, and linear regression models. More than 140,000 records were included in the main analyses. Because such a large population almost always yields p-values in excess of the 95th and even the 99th percentiles, p-values are only listed when not meeting the 95th percentile. Analysis of these results begins in Section 5.

4.1 Correlations

The correlation tests were performed on individual variable pairs to test the relevance of their relationship as well as to determine what other variables most strengthen or weaken the relationship. The listing of relationships in this subsection are in ordered from strongest positive correlation to strongest negative correlation.

An initial correlation analysis was performed to identify stronger and weaker relationships between variables. Correlation coefficients were recorded for each sensor's dataset as well as a combined dataset of all 5 sensors together. An average was taken of each of the 5 coefficients from the sensor datasets to compare with the coefficient of the combined dataset. The results of this primary analysis are shown in Table 3. The results are sorted by the average Correlation Coefficient with stronger positive correlations in green at the top and the stronger negative correlations in red at the bottom. The shading of each result coordinates with the strength of the correlation - the darker the color, the stronger the coefficient on a scale from 0 to 1 for positive correlations and 0 to -1 for negative correlations.

Based on the average coefficient column on the right, the tests resulted in 9 relationships having coefficients with magnitudes above 0.5. The variables comprising these relationships are highlighted in dark orange in the two leftmost columns. Because only two negative relationships reached the 0.5 benchmark, a lower benchmark of 0.2 was used to identify relationships with a definite, but mild correlation. This second benchmark resulted in another 7 significant relationships which are highlighted in light orange in the two leftmost columns. All 16 relationships whose averaged coefficients had absolute values above 0.2 were further researched in this study using filters in subsequent correlation tests.

Table 3: Table of correlation coefficients across all 5 stations for all variable pairs

V_1	V_2	Sensor 1	Sensor 2	Sensor 3	Sensor 4	Sensor 5	Combined
Road Temp	Air Temp	0.94	0.95	0.94	0.96	0.94	0.94
Air Temp	Subsurface Temp	0.89	0.89	0.9	0.88	0.88	0.89
Air Temp	Dewpoint	0.82	0.82	0.83	0.84	0.85	0.83
Subsurface Temp	Dewpoint	0.82	0.83	0.82	0.84	0.82	0.82
Road Temp	Subsurface Temp	0.81	0.82	0.81	0.82	0.82	0.81
Road Temp	Dewpoint	0.66	0.68	0.67	0.71	0.68	0.68
deltaRoadTemp	deltaAirTemp	0.64	0.7	0.62	0.64	0.62	0.64
Temp Diff	RainLength	0.28	0.2	0.21	0.09	0.25	0.2
Temp Diff	Dewpoint	0.02	0.03	0.07	0.27	0.05	0.08
Road Temp	Traffic Volume	0.14	0.06	0.03	0.08	0.11	0.08
Dewpoint	Traffic Volume	0.08	0.05	0.03	0.05	0.07	0.04
Air Temp	Traffic Volume	0.02	0	-0.03	0.02	0.01	0.01
Subsurface Temp	Traffic Volume	0	-0.03	-0.03	0	-0.02	-0.01
Temp Diff	Subsurface Temp	-0.23	-0.23	-0.19	0.03	-0.25	-0.19
Air Temp	RainLength	-0.34	-0.16	-0.2	-0.3	-0.11	-0.22
Temp Diff	Traffic Volume	-0.32	-0.18	-0.17	-0.21	-0.25	-0.21
Subsurface Temp	RainLength	-0.38	-0.19	-0.22	-0.3	-0.14	-0.24
Road Temp	RainLength	-0.38	-0.2	-0.24	-0.32	-0.18	-0.26
Temp Diff	Air Temp	-0.34	-0.34	-0.29	-0.06	-0.3	-0.28
deltaAirTemp	deltaTempDiff	-0.31	-0.41	-0.29	-0.21	-0.32	-0.31
Temp Diff	Road Temp	-0.64	-0.62	-0.6	-0.36	-0.61	-0.58
deltaRoadTemp	deltaTempDiff	-0.93	-0.94	-0.93	-0.89	-0.94	-0.93

4.1.1 Air, Road, and Ground Temperatures

The first and most important relationships to test were those between temperature readings at points above, on, and below the road surface. Because this study was primarily focused on heat transfer to and from the road surface, and because ambient air temperature and ground temperature are the most stable variables used in the study and have two of the strongest, positive correlations with road temperature, it was important to better understand these relationships.

Table 4 shows the base correlation coefficients for each of the three relationships. Road temperature and air temperature have the strongest correlation of any variable pair. It should be noted that air temperature and subsurface (ground) temperature are more strongly correlated than road temperature and subsurface temperature. As will be discussed in Section 5, these correlation values imply that road temperature is less stable and more dependent on other variables than air temperature or subsurface temperature are.

Table 4: Baseline correlations for 3 temperature variable pairs

Baseline Correlations	Air Temp Vs. Subsurface Temp	Road Temp Vs. Air Temp	Subsurface Temp Vs. Road Temp
Overall	0.89	0.94	0.81

The larger correlation coefficient between Road Temperature and Air Temperature in comparison to the other two relationships in Table 4 is repeated when the correlation is tested in addition to filters for traffic volumes, road surface state, location relative to the urban core, season, time of day, and presence of precipitation. In fact, the only sub-population in which Road Temperature and Air Temperature did not have a stronger correlation was that of “Evening” observations; Air Temperature and Subsurface temperature have a slightly stronger correlation. As was discussed in Section 3 and will be further discussed in Section 5, the proven strength of the relationship between Air Temperature and Road Temperature provides a basis for the introduction of the Temperature Difference variable – the difference between Air Temperature and Road Temperature.

In general, all three relationships were strengthened when using the mentioned filters. However, there were three exceptions. The first was the seasonal variable. All three relationships had weaker correlations when the observations were separatedby season. As Table 5 shows, the correlation coefficients for Air Temperature/Subsurface Temperature and Road Temperature/ Subsurface Temperature were weaker in summer. This result is made less significant by noting both relationships were significantly weaker than their general correlation across all seasons and showed no real temporal pattern. The Air Temperature/Road Temperature variables were also less strongly correlated when filtered by season. However, this pair of variables still maintained an objectively strong correlation and showed an unsurprising temporal trend with an increasing correlation from winter to summer.

Table 5: Table of correlations for 3 temperature pairs by season

Season	Air Temp Vs. Subsurface Temp	Road Temp Vs. Air Temp	Subsurface Temp Vs. Road Temp
Winter	0.61	0.85	0.44
Spring	0.69	0.88	0.57
Summer	0.45	0.9	0.29
Baselines	0.89	0.94	0.81

The second filter resulting in a weaker correlation was the Evening observations for the Air Temperature/Road Temperature relationship as mentioned above. Lastly, some moisture on the road surface results in a slightly weaker correlation between Air Temperature and Subsurface Temperature.

While both categorical variables involving location and urban land cover had little effect on the three relationships, a number of other variables did in fact strengthen the correlations. This was most obvious in Air Temperature/Road Temperature and Subsurface Temperature/Road Temperature. The changes in Air Temperature/Subsurface Temperature tended to be less extreme.

Table 6: Correlation coefficients for 3 temperature pairs by traffic counts

Traffic Counts	Air Temp Vs. Subsurface Temp	Road Temp Vs. Air Temp	Subsurface Temp Vs. Road Temp
Highest 25%	0.89	0.94	0.79
Lowest 25%	0.9	0.98	0.93
Baselines	0.89	0.94	0.81

Table 6 shows the correlation coefficients when filtered for the top 25% of traffic volume values and the bottom 25% of traffic volume values. Lower traffic volumes strengthened all three correlations. This resulted in a nearly perfect, positive correlation between Air Temperature and Road Temperature and correlation values over 0.9 for the other two pairs. The Subsurface Temperature/Road Temperature relationship was most strengthened in comparison to its base. This may be indicative of how little traffic influences subsurface temperature, especially with respect to road temperature.

Table 7: Correlation coefficients for 3 temperature pairs by road surface state

Road Surface	Air Temp Vs. Subsurface Temp	Road Temp Vs. Air Temp	Subsurface Temp Vs. Road Temp
Dry	0.88	0.94	0.8
Moist	0.85	0.97	0.87
Wet	0.9	0.98	0.92
Baselines	0.89	0.94	0.81

While water on the road surface has little impact on the correlation between Air Temperature and Subsurface Temperature, it has a strong positive effect on Air Temperature/Road Temperature and Subsurface Temperature/Road Temperature. Coefficients are highest when the road is wet and closest to the base coefficient when the road surface is dry. These results suggest instability and volatility in the road temperature being more subject to the effects of water.

Table 8: Correlation coefficients for 3 temperature pairs by precipitation timing

Precipitation	Air Temp Vs. Subsurface Temp	Road Temp Vs. Air Temp	Subsurface Temp Vs. Road Temp
Sust. No Precip	0.88	0.94	0.81
Precip Start	0.9	0.96	0.9
Sust. Precip	0.88	0.96	0.91
Precip Stop	0.9	0.96	0.9
Baselines	0.89	0.94	0.81

A similar trend is present when filtering for precipitation starting, stopping, and remaining sustained. Again the presence of water strengthens correlation coefficients for all three relationships. The result to note in this category, however, is that correlations remain strengthened among the sub-population composed of the first observations after precipitation has ended.

Table 9: Correlation coefficients for 3 temperature pairs by time of day

Time of Day	Air Temp Vs. Subsurface Temp	Road Temp Vs. Air Temp	Subsurface Temp Vs. Road Temp
Morning	0.92	0.99	0.96
Day	0.91	0.95	0.86
Evening	0.92	0.91	0.85
Night	0.91	0.98	0.92
Baselines	0.89	0.94	0.81

Finally, the time of day filters yielded interesting results. The strength of correlations was lower in Day and Evening observations and higher amongst Night and Morning observations. This was true for each relationship except for Air Temperature/Subsurface Temperature. All filters raised the correlation coefficient by similarly equal amounts, though none of them were significantly higher. The time of day filters did, however, register the largest increase in correlation for the Air Temperature/Road Temperature relationship as compared to its base correlation for night and morning. This alludes to the importance of insolation in driving RST variation.

4.1.2 deltaRoadTemp/deltaAirTemp

Following tests between the temperature variables, it seemed necessary to acquire a basic understanding of how the changes in temperatures correlated. The change in road temperature and the change in air temperature between each observation was measured by deltaRoadTemp and deltaAirTemp, respectively. In general, deltaRoadTemp and deltaAirTemp had a strong positive correlation coefficient of 0.64.

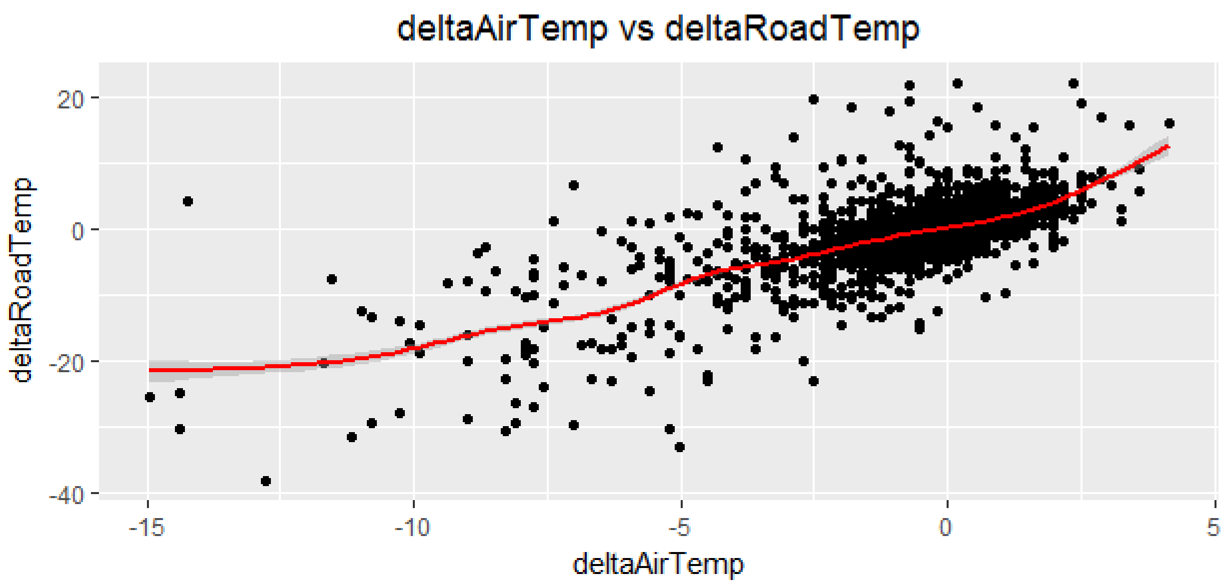

Figure 3: Graph of change in air temperature by change in road temperature

Graphing this relationship (Figure 3) shows the positive relationship as an oval centered near the origin (0,0). The nature of the oval extending from Quadrant 4 of the graph to Quadrant 1 suggests that deltaAirTemp and deltaRoadTemp are directly correlated having the same sign a majority of the time. To investigate when their signs are most likely to differ and thus weaken their correlation, the proportion of observations with one negative value and one positive value were recorded for each filter variable. It was then possible to breakdown for variables like time of day, season, location, etc. when deltaAirTemp and deltaRoadTemp were most likely to diverge.

Overall, the signs only diverge in approximately 15% (~20,000 out of ~140,800) of observations. The observations were split evenly for observations with positive deltaAirTemp/negative deltaRoadTemp and negative deltaAirTemp/positive deltaRoadTemp. Furthermore, no variable subset resulted in more than 20% of its observations with diverging signs for deltaAirTemp and deltaRoadTemp.

Diverging road and air temperatures are most common in the evening (30% of all diverging observations) and least common in the morning (15% of all diverging observations). This is a shift from the percentage of Evening and Morning observations in the total population; Morning and Evening observations each accounted for approximately 21% of the total number of observations in the dataset. However, Day (28.6%) and Night (26%) observations are also common times for diverging temperatures. The difference is made when comparing the number of diverging observations to non-diverging observations for each time of day. While the order of most likely to least likely times was not changed, Evening shows more potential for diverging temperature values with 21% of all Evening observations having opposite signs for deltaRoadTemp and deltaAirTemp.

The breakdown between observations with positive deltaAirTemp/negative deltaRoadTemp and negative deltaAirTemp/positive deltaRoadTemp further explained some of the trend in overall diverging observations. Evening and Day observations were more likely to have an increasing air temperature (positive deltaAirTemp) and decreasing road temperature. Observations with diverging temperatures and positive deltaAirTemp values accounted for 8% of all Day observations and 13% of all Evening observations. Whereas Night and Morning observations were more likely to have a decreasing air temperature and increasing road temperature when temperature values were diverging. It should be noted that Day observations were most likely to have increasing air temperatures while road temperatures were decreasing, and Night observations were most likely to have decreasing air temperatures while road temperatures were increasing.

In general, the proportion of Precipitation observations to Non-Precipitation observations did not change significantly within the subset of diverging temperature observations. In the total population of observations, approximately 10.6% were taken while precipitation was falling. Within the subset of observations with diverging temperatures, approximately 9.9% were taken when precipitation was falling.

The same was true when considering the beginning and ending of a period of precipitation. The only exception was found in observations taken when precipitation began falling. These observations make up only 1.23% of the total dataset, but decrease in percentage for the subpopulation of observations with diverging temperatures (0.85% of the subpopulation). Furthermore, their percentage is lowest in the subpopulation of observations taken as air temperature decreased and road temperature increased – they made up 0.63% of observations in that subset. This shows tendency for road and air temperature to converge as precipitation begins to fall.

4.1.2.1 Correlations

After the above exploration of factors causing road and air temperatures to diverge, correlation coefficients were generated to further test the previous analysis and to test the effect of other variables on this relationship. To be explicit, variable values with lower percentages/counts in the above examination of observations with diverging temperature values should have stronger correlations in this analysis.

The presence of precipitation most significantly affected the correlation between deltaAirTemp and deltaRoadTemp. In general, precipitation strengthened the correlation to 0.66 from 0.64. However, filtering for the start of a precipitation event (the first observation after precipitation begins) raises the coefficient to 0.85 while filtering for sustained rain lowers the coefficient to 0.56.

Figure 4 below shows the distribution of deltaAirTemp values separated by whether precipitation has just begun (blue curve) or has been sustained (pink curve). The object of note in this figure is the long tail on the left side of the graph showing a lot of outliers, especially for the beginning of precipitation events. This was considered when noticing the disparity between correlation coefficients for sustained precipitation and beginning precipitation. However, removing outliers from the top and bottom of the deltaAirTemp distribution only slightly lowered the coefficient for the start of precipitation events.

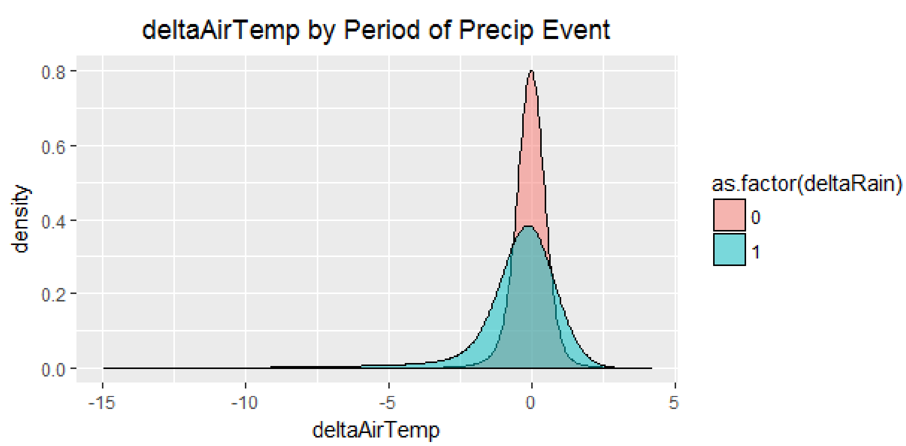

Figure 4: Smoothed histogram of change in air temperature

The ending of a precipitation event slightly lowers the correlation to 0.61. Observations taken outside of a precipitation event made up the vast majority of the distribution and produced a correlation equal to the base correlation.

The time of day had less of an impact on the correlation strength. Morning, Day, and Evening observations were not significantly different – 0.61, 0.63, and 0.65 respectively. Night observations had a lower correlation at 0.55. Some of the heat addition and removal that occurred at night with regard to traffic levels helps this weaker correlation and is discussed in Section 5.

Surface state values produced similar results as the time of day values. Dry, Not Dry, and Wet all resulted in coefficients similar to the base – 0.64, 0.65, and 0.64 respectively. Moist road surfaces resulted in a stronger correlation of 0.73. Though not a large increase in the coefficient, the absence of a trend from dry to wet makes this result notable.

4.1.3 TempDiff/RainLength

Section 4.1.2 notes the sizeable impact precipitation has on the correlation between the change in road temperature and the change in air temperature. This study made use of a derived variable called "TempDiff" which was simply the result of subtracting road temperature from air temperature for each observation. This relationship further describes how precipitation affects the transfer of energy between the air and road surface.

The main table of base correlations between variables notes that TempDiff and rainLength have a weaker correlation (~0.21) than the relationships examined in the previous two sections. It was hypothesized that much of the weakness might be explained by accounting for the duality of the rainLength variable. While the domain of the variable was continuous, this variable would be better described, from a chronological perspective, as operating in two domains as shown in Figure 5: a continuous positive domain describing a period where precipitation is present (shown in blue) and a continuous negative domain describing a period where precipitation is not present (shown in pink). The correlation analyses performed attempted to take this logic into consideration by performing tests for each positive and negative rainLength values.

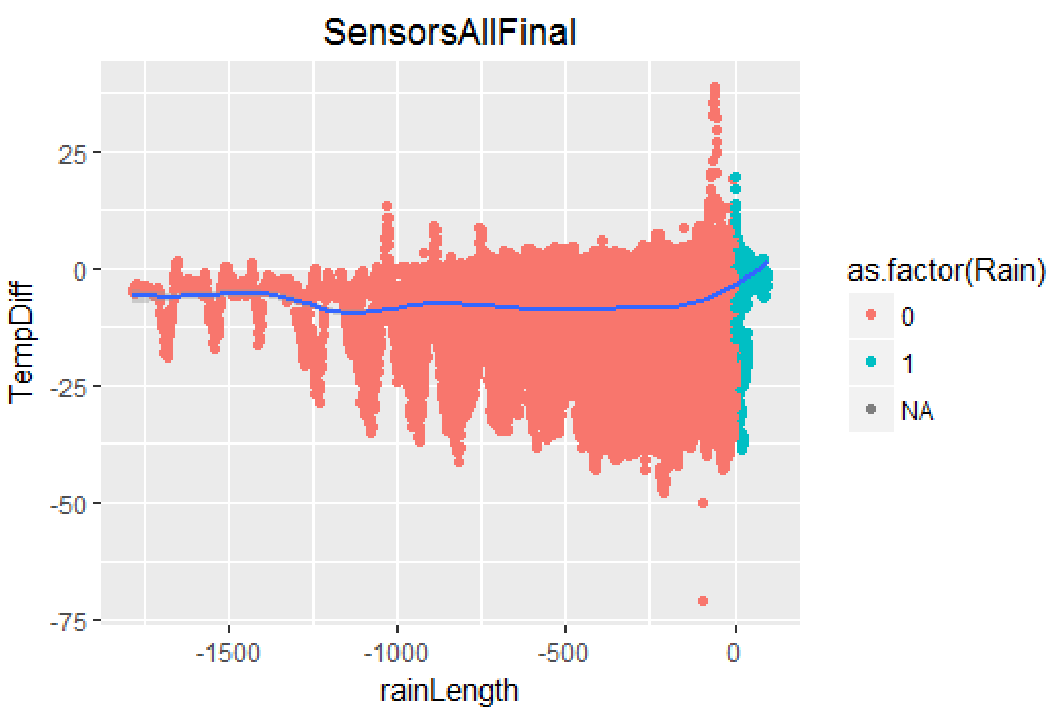

Figure 5: Graph of # of observations taken during precipitation (blue) or dry conditions (pink) by the Temperature Difference

Dividing rainLength into positive and negative domains, two base correlations can be generated. Surprisingly, both are lower than the overall base coefficient. Positive rainLength values and TempDiff have a correlation coefficient of 0.05 while negative rainLength values and TempDiff have a slightly higher coefficient of 0.15.

Using the time of day as a filter, correlation is again stronger when treating rainLength as one domain. Evening produced a stronger correlation at 0.33 while Day observations produced a weaker correlation of 0.2 which is slightly lower than the base correlation. When filtering for positive rainLength values, coefficients were weakened to the single digits for all times of day.

Filtering for negative rainLength values produced mixed results. Evening (0.27) and Morning (0.22) observations somewhat strengthened the correlation, while, Night (0.18) and Day (0.16) slightly weakened the correlation. All positive rainLength values resulted in correlations between 0 and 0.1.

Seasonal differences in correlation followed suit with all values tested in one domain resulting in higher values than testing individually for positive and negative rainLengths. Under one domain, correlations were stronger in summer (0.22) and spring (0.21) and weaker in winter (0.12). For negative rainLength values only, correlation rose from 0.05 to 0.19 from winter to summer while positive rainLengths resulted in correlations between -0.03 and 0.05.

4.1.4 AirTemp/RainLength

There was a moderate negative correlation between the air temperature variable and the RainLength variable (-0.23). This means the longer precipitation fell, the colder the air became which was expected. However, the correlation is not tremendously useful past this main conclusion which is generally understood and now statistically supported. A lack of precipitation lowers the magnitude of the correlation slightly (around -0.19).

Temporal variables tended to have a larger effect on this relationship with correlation magnitudes increasing in the Evening (-0.29) and Night (-0.24) using the Time of Day variable. Correlations also increased in the summer (-0.4) and spring (-0.31) using the Seasonal variable. Contrastingly, correlations were lowered from the base value in Day (-0.21) and Morning (-0.17) using the Time of Day variable and in winter (-0.08) using the Seasonal variable. The dichotomy created between increased correlations in seasons with greater insolation and increased correlations during times of day with increased insolation was of note.

4.1.5 TempDiff/Traffic Volume

Temperature Difference and Traffic Volume have a negative correlation with a base coefficient of approximately -0.23. Precipitation does weaken the correlation (-0.15) with the end of precipitation further weakening the correlation (-0.11). This wet/dry dichotomy was replicated using the Surface State variable as a filter where wet (-0.15) roads weakened correlations in comparison to dry (-0.24) and moist (-0.23) road surfaces.

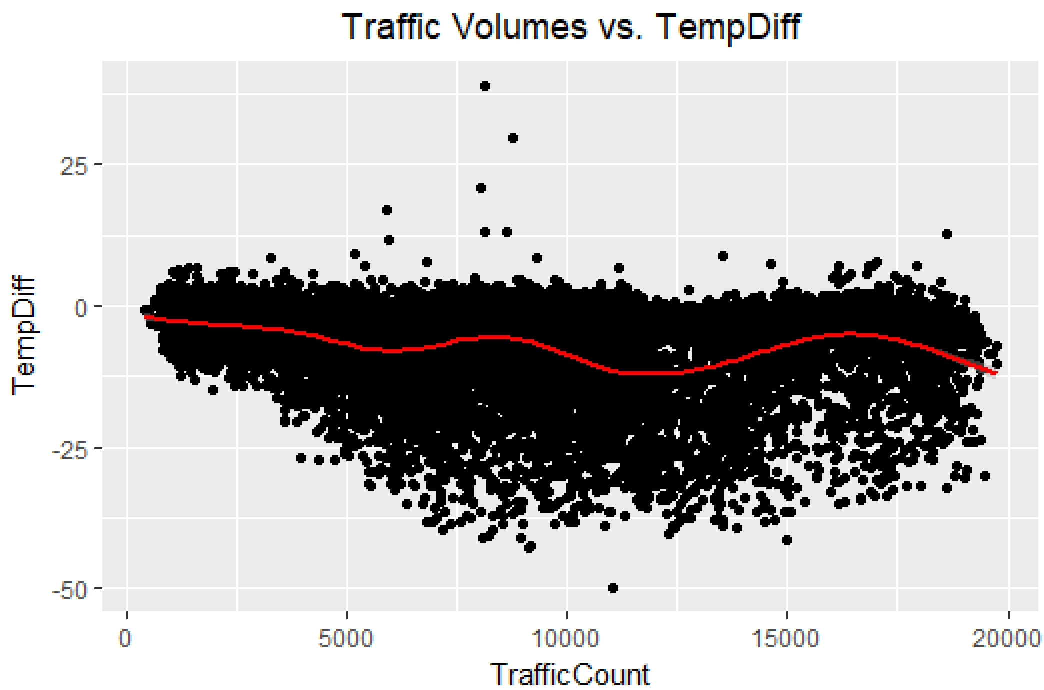

Figure 6: Graph of Temperature Difference vs. Traffic Volumes

Insolation also shows a slight effect on this relationship as correlations were weaker in Day (-0.11) and Morning (-0.05) than in Evening (-0.23) and Night (-0.5). However, a longer timescale variable such as Season, does not have as much impact on correlation values which ranged between -0.19 and -0.21 from winter to summer.

The spatial variable filters showed greater variation with less urban sensors having stronger correlations than more urban ones. Urban Classes 1 and 2 were virtually equivalent with coefficients of -0.17 and -0.18, respectively. However, class 3 shows a significant increase in magnitude (-0.3). These results are repeated when considering stations individually. Station 3, the most urban and central station, had a weaker correlation (-0.17) while stations 1 and 5, the most rural stations, had much stronger correlations of -0.32 and -0.25, respectively.

Finally, filtering for high and low traffic observations yielded interesting results. Observations with the top 25% of traffic counts had a similar magnitude coefficient as the base correlation, but the sign was opposite (0.23). Contrastingly, filtering for observations with the bottom 25% of traffic counts resulted in a coefficient with a slightly lower magnitude than the base coefficient (-0.16). The range of Temperature Difference values on the graph of each filtered relationship also deserves attention. While the top 25% of traffic counts produced a similar magnitude of correlation, the range of potential TempDiff values for each Traffic Count value is much larger than that of the bottom 25% of traffic counts (Figure 6). The wider range of TempDiff values in high traffic volumes suggest traffic works in combination with a heat source or sink to affect RST values.

4.1.6 RoadTemp/RainLength

The correlation of Road Temperature and rainLength can say a lot about the direct effects of precipitation on RST. The base correlation over all rainLength values at -0.26 was stronger than the coefficient over only positive (-0.25) or negative (-0.22) values on their own. This range of base coefficients can be explained by the spikes near rainLength = 0 in Figure 7. As mentioned previously, these spikes can create linear discontinuities that are overlooked when the domain does not begin or end at 0.

Once again time of day affected the magnitude of correlations across all three domains. Across all rainLength values, Evening (-0.37) had the strongest correlation by far. Night (-0.27) and Day (-0.25) were weaker, but still stronger than Morning (-0.2). This ranking was the same across negative rainLength values with slightly weaker magnitudes. Positive rainLength values resulted in weaker correlations and a new ranking of times of day. For this domain, Night (-0.32) produced a stronger correlation while Day (-0.14) produced a weaker one. Evening (-0.26) and Morning (-0.21) were more similar. For all three domain a clear separation existed between transitional times of day (Morning and Evening) and more stable times (Day and Night).

Seasonality resulted in more interesting trends with correlations generally weaker in winter and stronger in summer for all three rainLength domains. The difference lies in correlation during the months of spring. When considering all rainLength values, spring (-0.33) and summer (-0.35) have similar correlations which are much stronger than in winter months (-0.13). The correlations stay the same relative to each other with a slightly lower magnitude for the negative rainLength domain. However, only taking into account positive rainLength values (observations taken during precipitation events), winter (-0.04) and spring (-0.07) are more similar while summer (-0.26) remains the stronger correlation. Correlation values in all seasons are lower when only considering precipitation observations reinforcing the importance of this variable to the relationship between road temperature and precipitation.

Surface State values proved to be impactful filters, especially across rainLength domains. This is most likely due to surface state's semi-dependence upon precipitation. Across all domains, 'Moist' roads had weaker correlations ranging from 0.02 to -0.09. For observations taken outside of precipitation events (negative rainLength), 'Dry' (-0.18) surfaces had a stronger correlation between road temperatures and rainLength while 'Wet' (0.09) roads had a weaker correlation. This was also true when including both positive and negative rainLength values at the same time. Conversely, 'Wet' (-0.34) roads had stronger correlations among observations taken during precipitation events while ‘Dry’ (-0.13) had weaker ones. For these filters, ‘Wet’ roads among observations outside of precipitation and ‘Dry’ roads amongst observations during precipitation become a proxy for the beginning and ending of precipitation as the water begins to pool on or evaporate from the road surface.

The effect of traffic volumes on this relationship was somewhat dependent upon the rainLength domain used in the evaluation. Across all 3 domains, low traffic volumes resulted in a stronger correlation than higher traffic volumes. This correlation was stronger for both high (-0.27) and low (-0.31) traffic volumes when considering positive and negative rainLength values together. The contrast between coefficients produced by high (-0.16) and low (-0.29) traffic was greatest when only considering positive rainLength values (observations taken during precipitation events).

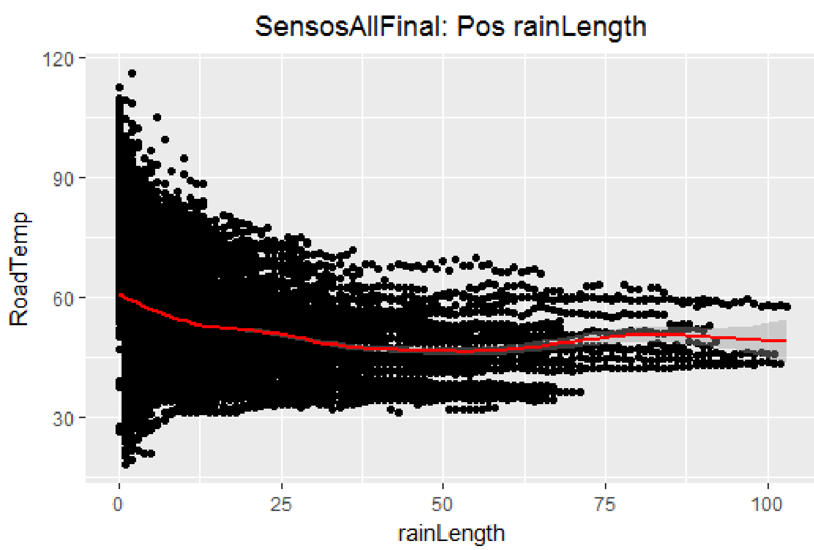

Figure 7: Road temperature by time in precipitation

4.1.7 AirTemp/TempDiff

Air Temperature and Temperature Difference had a base correlation coefficient of -0.27. Recalling that Temperature Difference in this study was calculated by subtracting Air Temperature from Road Temperature, this negative correlation was not surprising given the heat accumulated within road surfaces over the course of a day, especially in southern cities. A graph of these two variables (Figure 8) provided an interesting observation regarding range of values. As Air Temperature increased, the range of Temperature Difference values seemed to increase as well. As mentioned in the introduction and methodology portions of this thesis, road temperature was usually less stable than air temperature. This graph seems to suggest that this fact is especially true when Air Temperatures are higher.

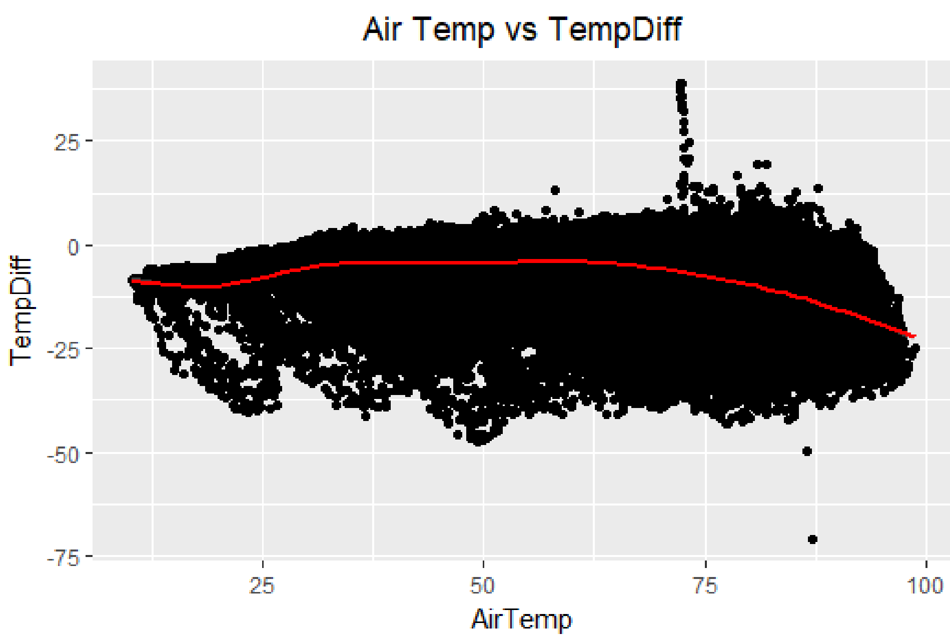

Figure 8: Graph of Air Temperature vs the Temperature Difference

Precipitation also decreased the predictability of the Temperature difference. Filtering for observations taken in precipitation events resulted in a lower and opposite signed correlation coefficient (0.18) than observations taken when no precipitation was falling. Furthermore, filtering for observations taken immediately after precipitation began produced the strongest correlation (0.33) which was also positive. Observations taken immediately after precipitation events finished results in a weaker correlation (0.08). Graphing this relationship using precipitation start and stop as filters resulted in observations clustered around the 0 degree Temperature Difference mark (Figure 9).

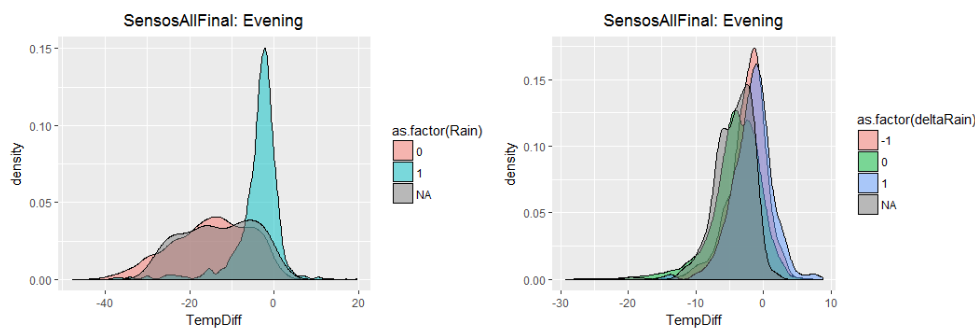

Figure 9: Smoothed histograms of Temperature Difference in Evening
(Left) 1 is in precipitation and 0 is out of precipitation
(Right) -1 is the end of precip, 0 is sustained precip or no precip, 1 is the start of precip

Seasonality was a large factor for this relationship which is mostly explained by Air Temperature's dependency on seasons (even in a more moderate region like the southeastern U.S.). Winter observations resulted in a slight positive correlation (0.14). Spring (-0.33) and summer (-0.6) both had negative correlations. This particularly true for summer observations.

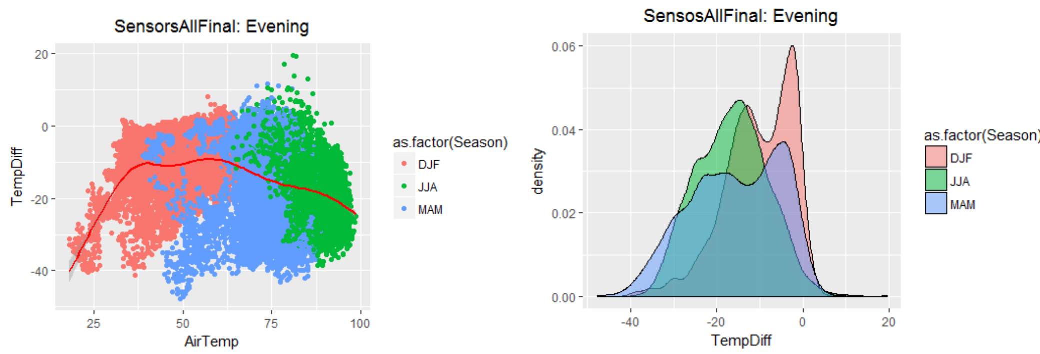

Figure 10: Graphs of variable relationship by Season
(Left) Graph of Air Temperature by Temperature Difference
(Right) Smoothed histogram of Temperature Difference

Filtering for Surface State affected correlation values but not on a wet to dry scale. ‘Dry’ (-0.27) observations produced the only negative correlation which was slightly stronger than the base correlation. Contrastingly, ‘Moist’ (0.28) and ‘Wet’ (0.13) roads resulted in positive correlations. Thinking of ‘Moist’ roads as being in flux between wet and dry, this could make sense in the context of energy transfer from air to road or vice versa. More conclusions could and will be drawn in the context of other variable relationships in the ‘Analysis’ section of this thesis.

Traffic Volumes also impacted correlation strength with correlation increasing as traffic volumes increased. The top 25% of observations by traffic volume produced a stronger correlation (-0.39) than the base while the bottom 25% of observations by traffic volume resulted in a much weaker correlation (-0.11).

4.1.8 deltaAirTemp/deltaTempDiff

The relationship between deltaAirTemp and deltaTempDiff describes how a change in air temperature relates to a change in the Temperature Difference. The baseline correlation for this relationship was -0.31. Expressed verbally, an increase in Air

Temperature often decreases the Temperature Difference. Conversely, a decrease in air temperature is often accompanied by an increase in the Temperature Difference. The four graphs below show how the relationship changes based on three Temperature Difference domains and the unfiltered relationship.

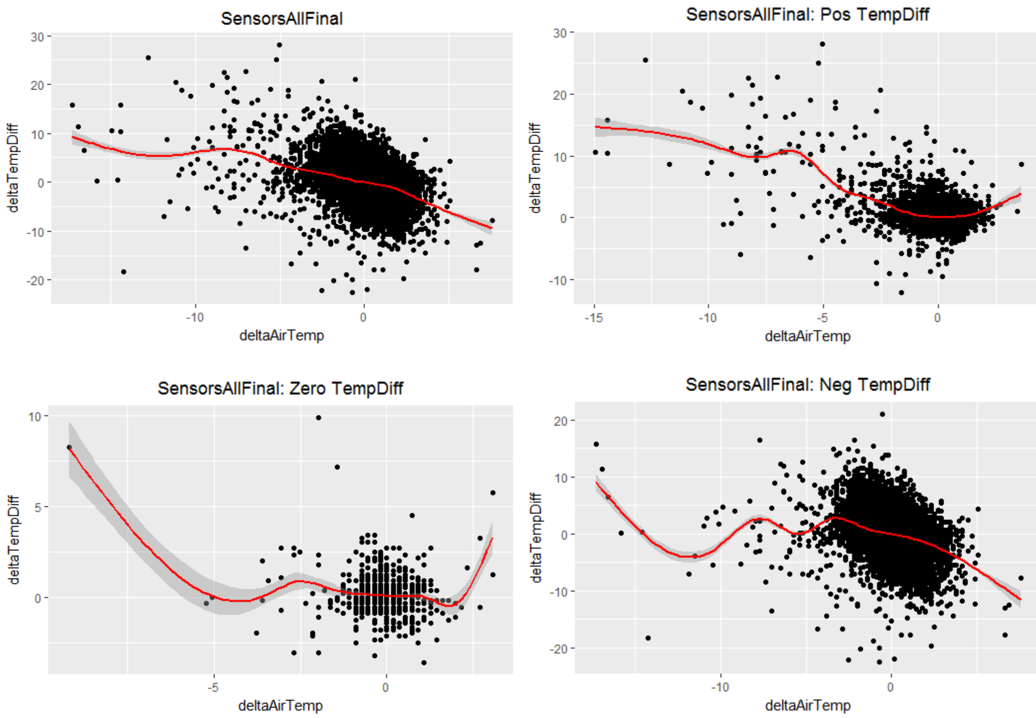

Figure 11: Graphs of change in air temperature by change in Temperature Difference filtered by the value of the Temperature Difference

Figure 11 shows a graph of the unfiltered relationship in which a somewhat linear form running from quadrant 1 to quadrant 3 represents the negative correlation. Positive Temperature Difference values result in a much larger range of values for deltaTempDiff and deltaAirTemp, while, Zero Temperature Difference has the smallest range of change values. Of particular note is the much higher number of observations taken when

Temperature Difference was negative. Because so much variation exists across each of the three domains listed for Temperature Difference values, correlation test were run for each set similar to relationships including the rainLength variable.

When using the Precipitation variable as a filter, a general divide was created between positive and negative Temperature Difference values while correlations for observations with a Temperature Difference of 0 were generally weak. For negative Temperature Difference (i.e. road surface is hotter than air), dry conditions slightly strengthen the correlation (-0.32). Contrastingly for positive Temperature Difference values (i.e. road surface is cooler than air), the correlation between deltaAirTemp and deltaTempDiff was more than doubled in strength (-0.65) when only considering observations taken in precipitation. The effect was amplified by filtering for the beginning of rain events (-0.76).

To simply these results, when the road surface is warmer than the air, a lack of precipitation will contribute to a more rapidly expanding gap between the air temperature and the road temperature as air temperatures rise. Meanwhile, when the air is warmer than the road surface, precipitation increases the likeliness that a disparity between road temperature and air temperature will increase as air temperatures falls. This second result is especially true at the beginning of a precipitation event. Effectively, precipitation cools the road surface faster than it cools the air.

The time of day varies in how it affects correlation dependent on the sign of the Temperature Difference. For positive Temperature Differences, correlation was much stronger at Night (-0.67). Correlation for this domain ranged from -0.17 to -0.27 for Morning, Day, and Evening. Observations with negative Temperature Difference values did not significantly vary in correlation strength by time of day. However, Day and Night tied for the highest correlation coefficient (-0.32), noted as usually being the hottest times of day for both air and road temperatures.

Seasonality of correlation strengths for this relationship was most apparent in observations with positive Temperature Differences. Spring (-0.42) and summer (-0.58) had significantly stronger correlations in this domain as compared to the baseline correlation. When Temperature Difference was negative, Summer (-0.37) still strengthened the correlation but to a lesser degree. The seasonality of this relationship will be particularly important when assessing the importance of insolation to RST determination.

The road surface state proved to be a non-negligible factor for this relationship. When roads were dry, correlation strength held around the baseline correlation at -0.3 for both positive and negative Temperature Difference values. ‘Wet’ and ‘Moist’ roads, though, create a divide between the two domains. For positive Temperature Difference values, a combination of ‘Wet’ and ‘Moist’ roads (-0.59) greatly strengthened correlation between deltaAirTemp and deltaTempDiff. Contrastingly for negative Temperature Difference values, correlation was largely weakened by ‘Wet’ and ‘Moist’ roads (-0.07).

The correlation between these two variables tended to increase with traffic. The top 25% of traffic counts slightly strengthened correlation from the baseline to -0.34. The bottom 25%, however, cut the correlation coefficient in half (-0.15). These correlation strengthens remain proportional between the two domains of traffic counts when filtering for positive and negative Temperature Difference values.

4.1.9 TempDiff/RoadTemp

The correlation between Temperature Difference and road temperature is predictably strong due to Temperature Difference being calculated from the Road Temperature variable. However, there are two important things to note from the base correlation results. First, the magnitude of this correlation is much higher than that of Temperature Difference and air temperature – which is the other variable used in calculating the Temperature Difference variable. The second observation is shown in the graph of these two variables (Figure 12). The increasing range of Temperature Difference values as road temperature rises means road temperature changed more quickly than air temperature. This will be key to the analysis of road temperature and air temperature in the Discussion section.

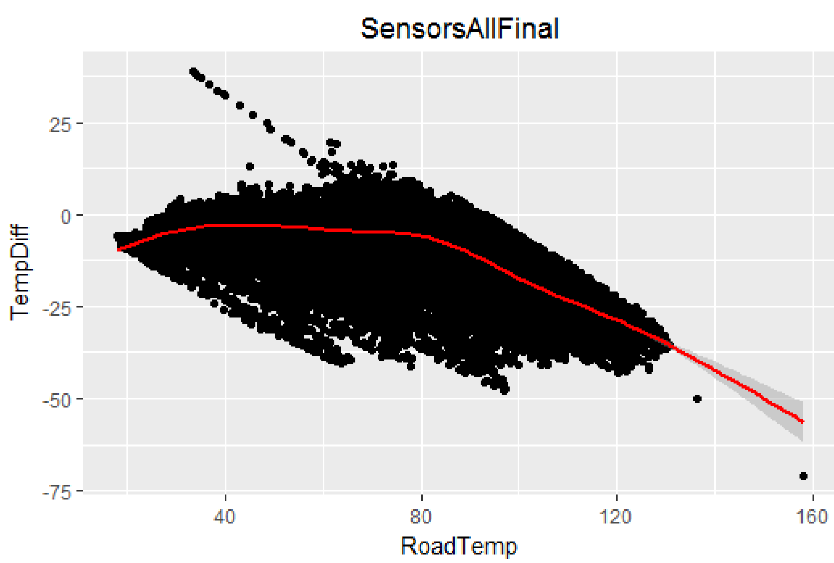

Figure 12: Graph of road temperature by the temperature difference

When considering precipitation, correlation was weakened for all observation subgroups except ‘No Precipitation’ (-0.58). Precipitation (-0.11) greatly weakened the correlation and fell between ‘Precip Start’ (0.05) and ‘Precip Stop’ (-0.2). No precipitation variable filters significantly strengthened this relationship, though the increase seen amongst ‘No Precipitation’ observations would make insolation an important consideration. This increase could may have been greater if it had been possible to filter for clear days.

Using the Time of Day variable to filter this relationship had similar effects as previous variable pairs. Evening (-0.66) was the only time when the correlation was stronger than the baseline. Though Day (-0.51) and Night (-0.4) were weaker than the baseline, they still retained moderately strong correlation coefficients. Filtering for Morning (-0.14), however, resulted in a negligible correlation.

The seasonality of this relationship was also similar to previous variable pairs with correlation strengthening from winter to summer. Winter (-0.4) was the only coefficient whose magnitude was lower than the baseline. Spring (-0.78) had a notably stronger correlation than the baseline, but summer (-0.89) was near perfect. This increase in correlation from winter to summer runs contrary to the original graph showing larger variation in Temperature Difference at higher road temperatures. Summer also had higher number of ‘Precipitation’ observations than winter or spring which should have weakened its correlation. The change in Air Temperature’s diurnal range could bear culpability for this unexpected trend and will be discussed further in the Analysis section.

Filtering for road surface state resulted in a similar trend as precipitation. Again moisture reduced the correlation strength. A ‘Dry’ (-0.58) road surface increased the correlation from the baseline for the variable pair. 'Wet' (-0.05) roads resulted in a much weaker correlation, and 'Moist' (0.05) roads produced a positive but negligible coefficient.

Traffic, unsurprisingly, greatly affected correlation values. The observations with the top 25% of traffic counts resulted in a significantly stronger correlation (-0.69) than the variable pair's baseline. Filtering for observations with the bottom 25% of traffic counts showed a full trend with a much weaker correlation (-0.28) than the baseline.

4.1.10 deltaRoadTemp/deltaTempDiff

The last and most negatively correlated variable pair falls in the rate of change category. The baseline correlation (-0.93) between the rate of change in Road Temperature and the rate of change in Temperature Difference was nearly perfect. The only stronger correlation was that between air temperature and road temperature. The relationship between air temperature, road temperature, and temperature difference will be discussed further in the Analysis section.

Considering the strength of the baseline correlation for this variable pair, time of day produced a considerable effect. Day (-0.93) and Night (-0.91) were the negligible times, but the transitional periods were more important. Correlation was slightly strengthened in Evening (-0.95). As was true for the majority of variable pairs, Morning (-0.86) resulted in the weakest correlation, though still having a high coefficient.

The seasonal trend was also familiar as correlation strengthened from winter (-0.81) to summer (-0.96). The increase was fairly uniform as spring (-0.92) fell right around the baseline correlation. Seasonality did have less effect on correlations for this pair than it did on deltaAirTemp/deltaTempDiff. This once again pointed to a difference in stability between road temperature and air temperature.

The slight trend in correlation strength found when filtering for traffic volumes paralleled that seen in the Road Temperature/Temperature Difference correlation analysis. High traffic volumes (-0.94) - the top 25% of traffic counts - essentially held the baseline correlation, while low traffic volumes (-0.88) – the bottom 25% of traffic counts – weakened the correlation. In other words lower traffic volumes made it less likely that an increase in road temperature would increase the temperature difference.

4.2 ANOVA

The following five ANOVA analyses were performed to examine how road temperature varied by season, time of day, location, precipitation condition, and road surface state. Road temperature was examined from both an absolute perspective (i.e. using the Road Temperature variable) and from a relative perspective in relation to the air temperature (i.e. using the Temperature Difference variable). Rate of change for both Road Temperature and Temperature Difference was considered in each of the four analyses - though, it was mostly found to be insignificant. All records from all five RWIS stations were considered simultaneously for each analysis.

4.2.1 Seasonal Analysis

For the seasonal analysis, comparisons were made of winter, spring, and summer averages of road temperature, temperature difference, and their respective rates of change. The rates of change did not have a statistically significant difference between their averages for each season. By virtue of orders of magnitude in time, volatile variables such as rates of change calculated every 10 minutes would be negligible compared to changes in a variable such as seasonality which has a long timescale.

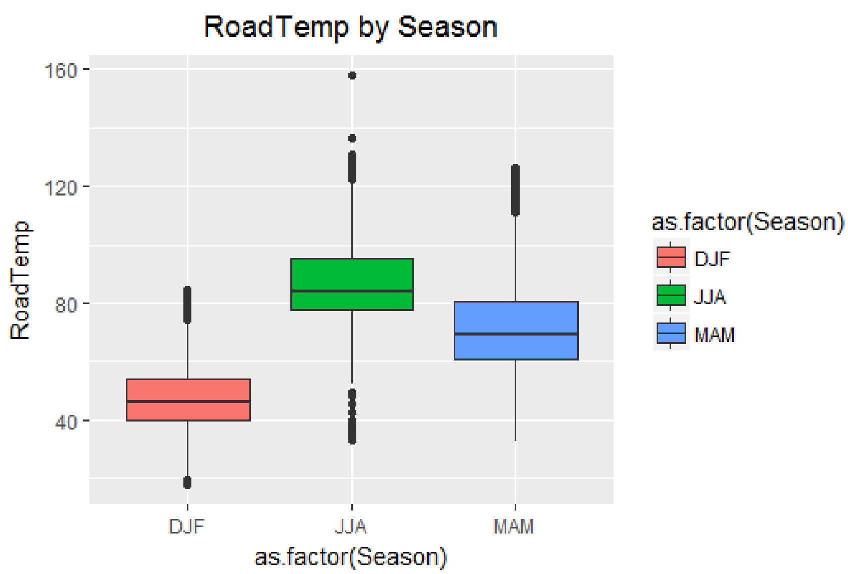

Figure 13: Boxplot of road temperature by season - Winter (DJF), Spring (MAM), and Summer (JJA)

Measuring differences in road temperature proved rather predictable. The ANOVA test showed a rising average temperature each season from winter to summer with a 40° F change in average temperature overall. A larger difference was found between winter and spring (24.44° F) than between spring and summer (15.77° F). This rise in temperature from season to season could easily be attributed to the angle of the sun increasing along with the road temperature. To further explore the impact insolation had on this result, the dataset was filtered by time of day to assess when average temperature differences were largest. The four boxplots in Figure 14, below, show this ANOVA analysis separated by time of day.

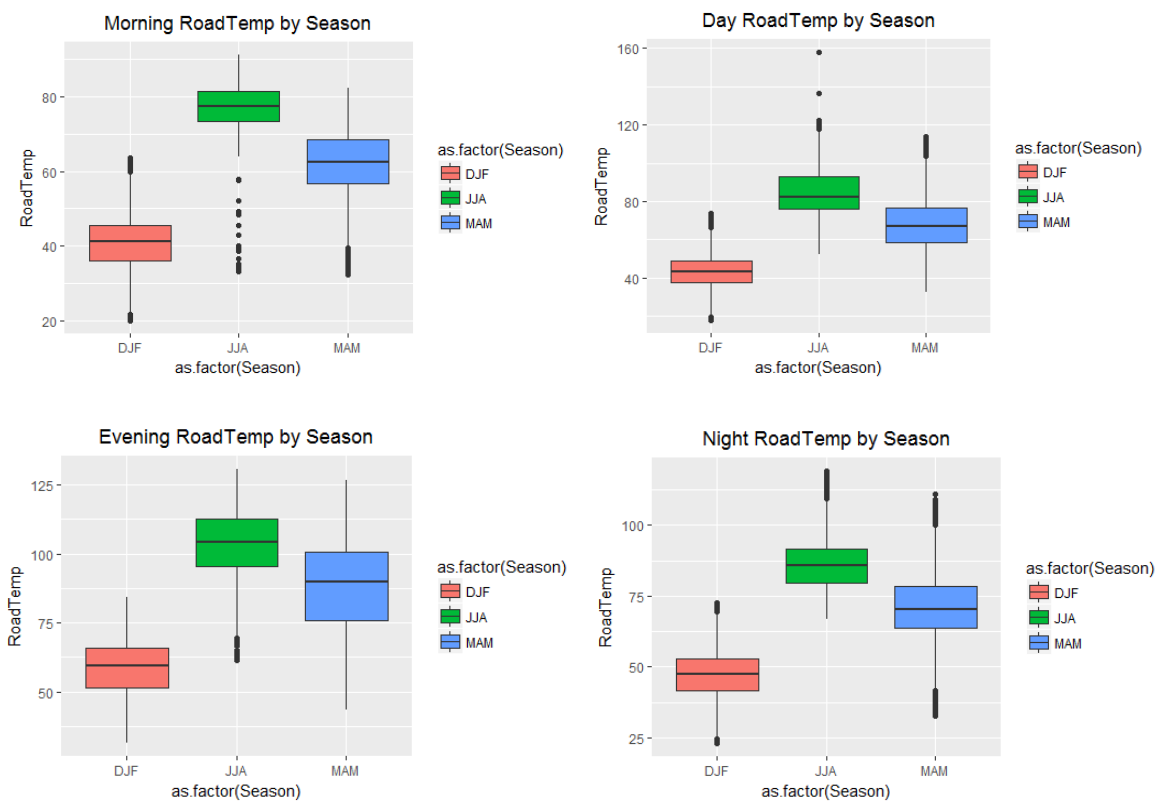

Figure 14: Boxplots showing variation in road temperature amongst seasons by time of day

Based on change in average road temperature between winter and summer, Evening (44.34° F) and Day (41.62° F) produced the greatest differences, while, Night (38.° F) and Morning (36.° F) produced slightly smaller changes. Changes between all seasons for all times of day were statistically significant. From these ANOVA it is clear that not only do average road temperatures increase from winter to spring and into summer, but that such an increase is greater or smaller in reference to specific times of day. Additionally, for each time of day, there is a larger increase in road temperatures between winter and spring than between spring and summer, though neither increase is negligible.

While understanding how road temperatures change from season to season is important, the results are certainly not unexpected considering air temperature and road temperature are strongly correlated. A more dynamic question would ask how road temperatures change from season to season in comparison to air temperature. This question was answered by performing another ANOVA test on the seasonality of the Temperature Difference variable. The results are visualized as a boxplot in Figure 15 below.

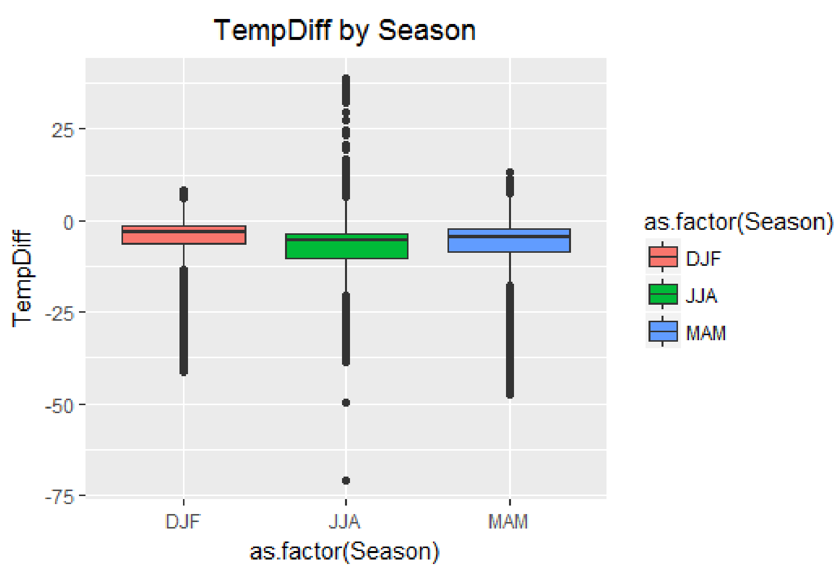

Figure 15: Boxplot of the Temperature Difference variable by season - Winter (DJF), Spring (MAM), and Summer (JJA)

The range of temperature difference values in the dataset is smaller than that of road temperature, so, the differences between seasons are not as distinguished. However, each difference between seasons as well as the overall difference between winter and summer was statistically significant above the 99th percentile. Again a linear trend from winter to summer was evident with temperature differences smallest in winter and largest in summer. An important secondary note, in all three seasons considered, on average the road surface was warmer than the air. However, spring and summer have larger variation below their average, meaning road temperature was more likely to be warmer than air temperature in those seasons. This result was similar to the ANOVA of road temperature in that spring and summer were more similar than spring and winter.

ANOVA was run again filtering for time of day in order to compare results with the road temperature ANOVAs. The boxplots in Figure 16 below visualize the results of each ANOVA by time of day. Overall variation from winter to summer again was greatest in Evening and Day while smallest in the Morning. All differences between each season for each time of day were statistically significant. The increases in average temperature difference between winter and spring for ‘Day’ and ‘Evening’ were approximately four times larger than the change in average temperature difference between spring and summer at those same times of day. Changes by season were more evenly dispersed at night and in the morning.

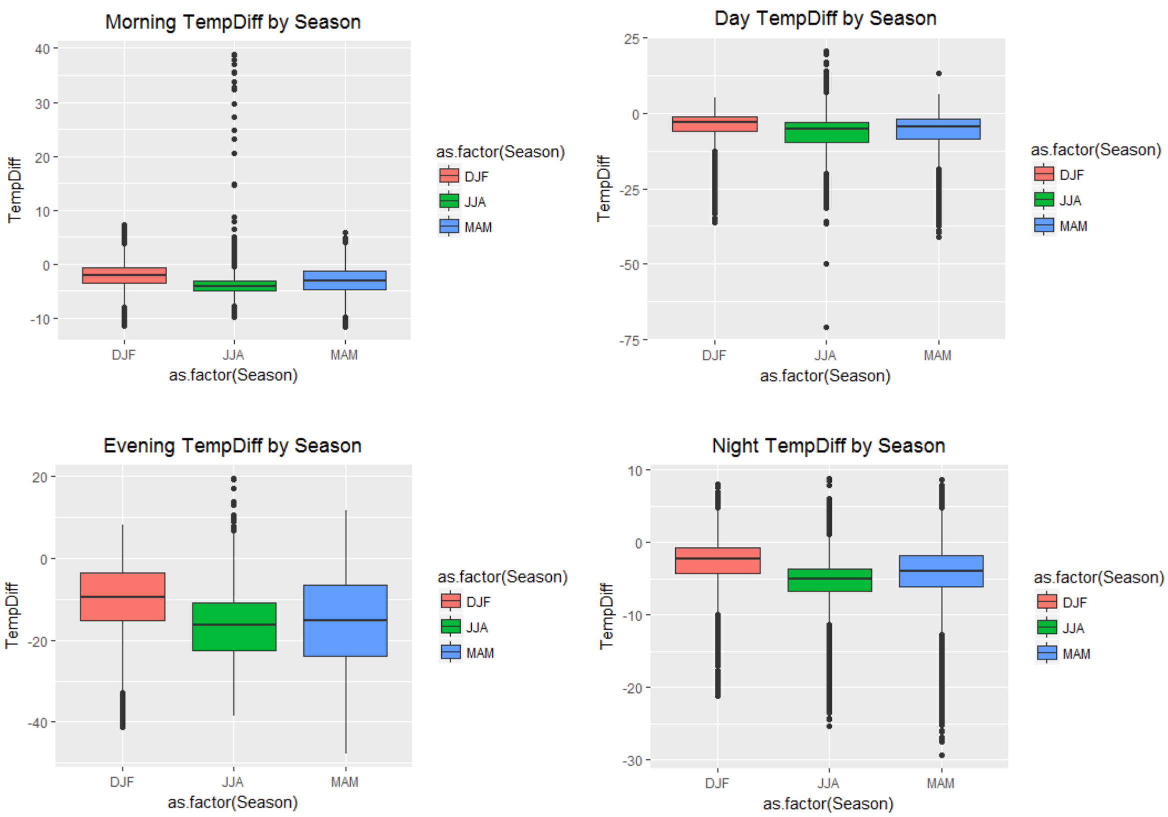

Figure 16: Boxplots showing variation in the Temperature Difference variable amongst seasons by time of day

Another measure of difference between air temperature and road temperature can be recorded by noting the number of observations in which Temperature Difference equals 0. For this dataset, there was a disproportionately high number of observations with zero temperature difference in winter and a disproportionately low number of such observations in summer. This simple assessment helps corroborate the ANOVA analysis showing road and air temperatures increasingly diverging from winter to summer.

4.2.2 Time of Day Analysis

The second ANOVA series compared morning, day, evening, and night by averages of road temperature, temperature difference, and their respective rates of change. Analyzing road temperature by time of day serves a similar purpose as the seasonal analysis. As Figure 17 shows, over the course of the year, the length of days increase and decrease. These changes in the length of the day are accompanied by changes in the angle of incidence between incoming sunlight and the earth. Furthermore, analysis of RST by time of day helps demonstrate to what degree these increased solar angles impact the amount of incoming energy throughout the year.

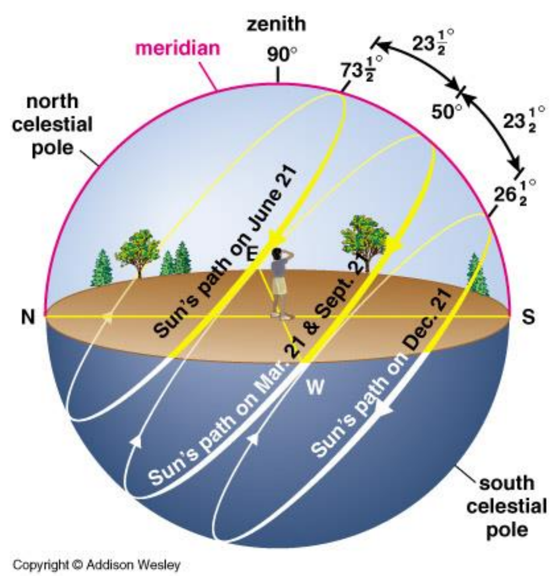

Figure 17: Diagram of the sun's longer time in the sky and higher angle of incidence during summer vs. its shorter time in the sky and lower angle of incidence in the winter. (Source: Pearson Education 2007)

Again for time of day, variations in rate of change in road temperature and in temperature difference was not statistically significant at the 95th percentile. The four different periods of the day still did not match the order of magnitude of time for average rates of change to be unequal.

The seasonal analysis gave a preview of the results for the time of day analysis. Evening produced the highest average road temperature easily explained by the amount of sunlight collected over the course of the day. Morning produced the lowest average road temperature again explained by a lack of insolation and adequate time to release heat back into the atmosphere. Day and night were most similar having average road temperatures within 2.36° F of each other. This points to a symmetrical pattern with evening being the high extreme, day and night forming the midpoints, and morning producing the low extreme. Figure 18 shows a boxplot visualizing the differences (in deg F) in average road temperature for each part of the day shown below the graph.

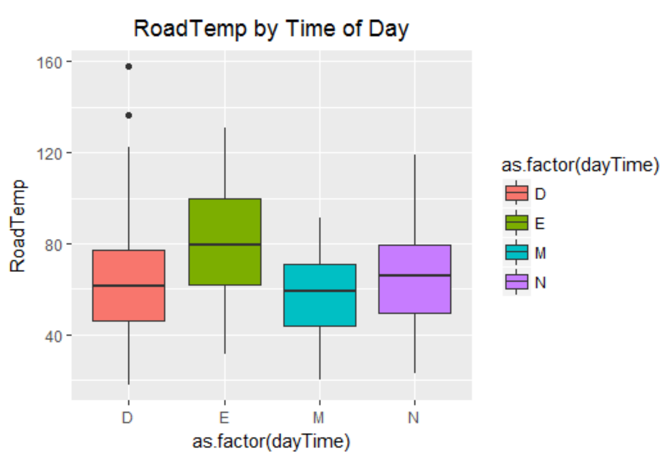

Figure 18: Boxplot of road temperature by time of day
(Top) Boxplot graphically showing variation in road temperature
(Bottom) Actual differences in deg F between average road temperatures

Table 10: Differences in road temperature (deg F) between times of day

Times of Day	Difference
Evening - Day	17.572
Morning - Day	-5.162
Night - Day	2.364
Morning - Evening	-22.734
Night - Evening	-15.209
Night - Morning	7.526

The second ANOVA in the time of day analysis considers changes in road temperature with respect to air temperature. To make this assessment, changes in average Temperature Difference between times of day were compared. The boxplot in Figure 19 represents the results of this ANOVA, while the chart below that shows the exact differences between average Temperature Difference values.

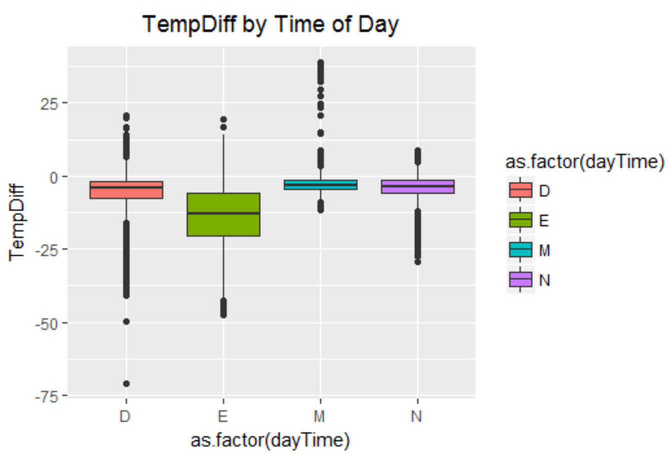

Figure 19: Boxplot showing variation in the Temperature Difference variable by time of day

Table 11: Actual differences in deg F between average Temperature Differences

Time of Day	Difference
Evening - Day	-8.171
Morning - Day	2.789
Night - Day	1.719
Morning - Evening	10.960
Night - Evening	9.890
Night - Morning	-1.070

Variations in Temperature Difference by time of day results in a 3-1 divide. Evening has a much lower (larger magnitude of negative values) average temperature difference than morning, day, or night. Evening also has the largest range in temperature difference values which is fairly evenly dispersed around its average value according to the boxplot. Using the precipitation variable as a filter, the importance of sunlight in creating the noted disparity was further investigated.

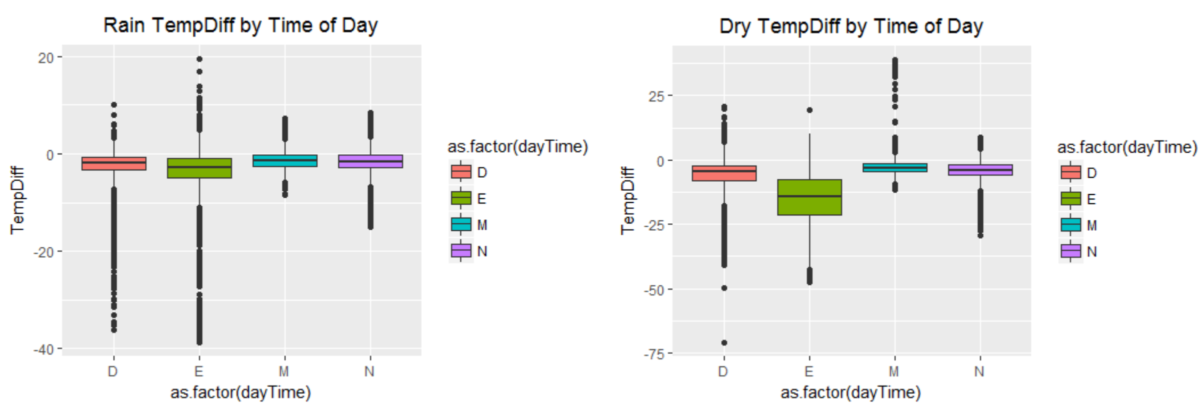

Figure 20: Boxplots showing in variation in the Temperature Difference variable amongst times of day by whether or not precipitation was falling when an observation was recorded

Comparing the two boxplots in Figure 20 above with each other and with the unfiltered boxplot, it was clear that precipitation/cloud cover almost completely resolved the disparity between evening and the other times of day. Per the ANOVA and ad-hoc tests, evening and its most similar time of day, ‘Day’, had a difference in average Temperature Difference of 8.84^{o} F when only considering observations without precipitation. Changing the filter to only consider observations taken during precipitation events reduced that disparity to 1.54^{o} F.

Traffic volumes had the largest effect on average Temperature Difference values and in a rather unexpected way. The difference between Night and Morning was the only statistically significant difference between average Temperature Differences when filtering for low traffic. No difference exceeded 1^{o} F, and all average Temperature Differences were between 0 and -5 with Night having the only large range of values.

Conversely, high traffic volumes created a strong divide with two times of day on either side. Day and Morning had average temperature differences with a much smaller magnitude than that of Evening and Night. The difference between averages for Evening and Night was the only non-statistically significant difference with a p-value close to 0.5. High traffic volumes also created the largest range of average Temperature Differences. Additionally, the range of values for each individual time of day increased for all times except Morning. However, the average Temperature Difference for Day and for Morning was practically the same for both high and low traffic volumes.

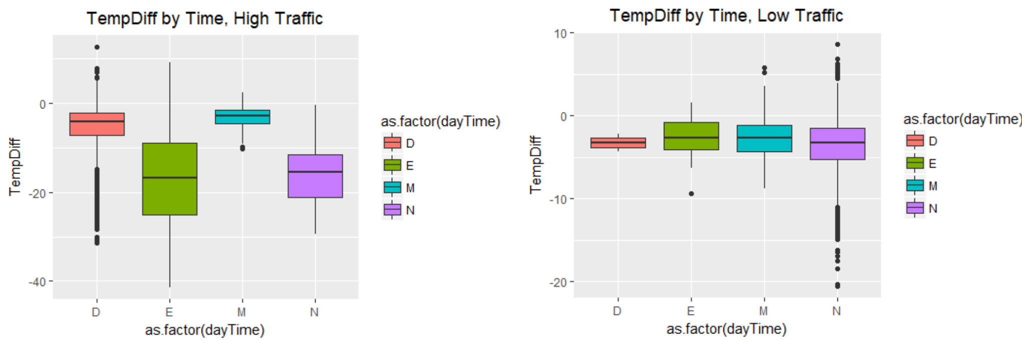

Figure 21: Boxplots showing in variation in the Temperature Difference variable amongst times of day differentiating for high and low traffic volumes

Precipitation's effect on average temperature difference was thoroughly explored through correlation tests in the previous section. Most directly noted, Temperature Difference had a positive correlation coefficient of 0.21 with the rainLength variable. As precipitation continued - the less 'dry' time there was - the Temperature Difference value increased. Noting that average temperature difference is negative, this could mean precipitation - or at least cloudy conditions – reduce the magnitude of the Temperature Difference variable; a result which is corroborated and contextualized by the comparison of these ANOVA tests.

4.2.3 Spatial Analysis

There are many spatial characteristics that can affect both ambient temperature and the temperature of specific objects. In this study, spatial characteristics refer to the distance from the urban core. This was measured by both listing stations 1 through 5 from north to south along the I-85 corridor and by grouping them into Urban Classes by their distance from the city center. As shown in Figure 22 below, slight differences in road temperature were found between both stations and urban classes. These differences were all considered statistically significant above the 99th percentile besides Station 1 – Station 4 and Station 4 – Station 5.

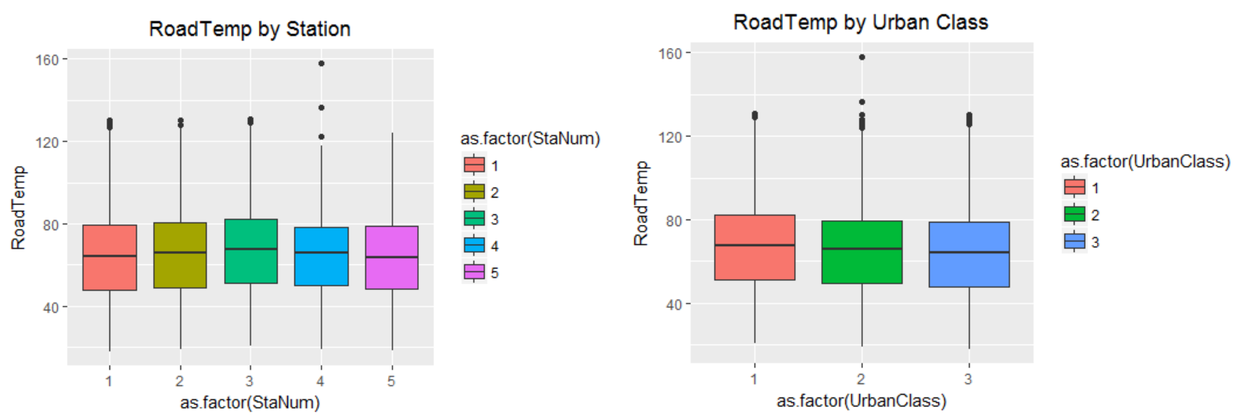

Figure 22: Boxplots showing spatial differences in road temperature
(Left) Graphical representation of road temperature by RWIS station
(Right) Graphical Representation of road temperature by Urban Class

From the two boxplots in Figure 22 it is clear that the most urban locations (Station 3 and Urban Class 1) have slightly higher road temperatures. While the majority are statistically significant differences, the largest difference between locations was only 3° F. This trend over urban locations being warmer than suburban locations continues without regard for precipitation or time of day. Figure 23 - Left below shows the breakdown of average road temperatures by station and urban class according to whether precipitation was falling or not. Figure 23 - Right shows similar data, but differentiates by time of day rather than presence of precipitation.

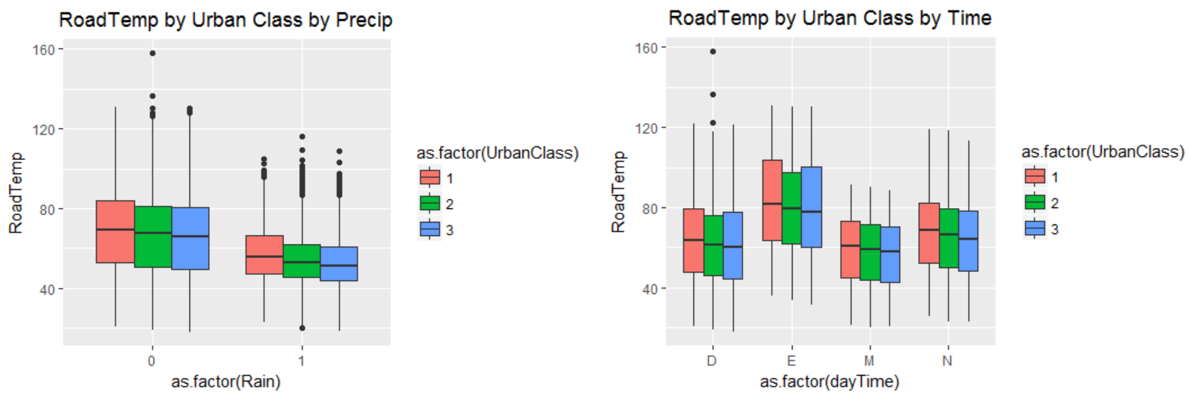

Figure 23: Boxplots showing variation in road temperature by Urban Class
(Left) Broken down by observations taken in dry conditions (0) and taken during precipitation (1)
(Right) Broken down by time of day of the observation

Though other factors could not enhance or mitigate the variation in road temperature from urban to rural locations, the fact that road temperatures are higher in the urban core remained true, if only slightly. Furthermore, the two variable pairs that were statistically insignificant corroborate a split between urban core and surrounding areas. Station 4 was essentially the same as stations 1 and 5 according to the ANOVA ad-hoc test (Figure 24). Because the southside stations (stations 1 and 2) were closer to the city center than the northside stations, station 1 could be as similar to 4 as it is to 5 (stations 1 and 5 were grouped in the same urban class because they were farthest from the city center).

Table 12: Post-hoc results of ANOVA analysis showing actual difference in average road temperature (in deg F) between RWIS stations

Station	Difference	P-Value
2-1	1.136	0.000
3-1	2.932	0.000
4-1	-0.344	0.272
5-1	-0.634	0.002
3-2	1.796	0.000
4-2	-1.480	0.000
5-2	-1.770	0.000
4-3	-3.275	0.000
5-3	-3.565	0.000
5-4	-0.290	0.452

A lack of spatial trend in the Road Temperature variable was somewhat unexpected due to the size of the study area. The spatial scope of this thesis incorporated just under a 40 mile radius around the city which should have been large enough to measure changes in precipitation or ambient temperature changes that would alter the RST. Giving context to the road temperature through normalization by air temperature reduced the chance for significant variation between locations.

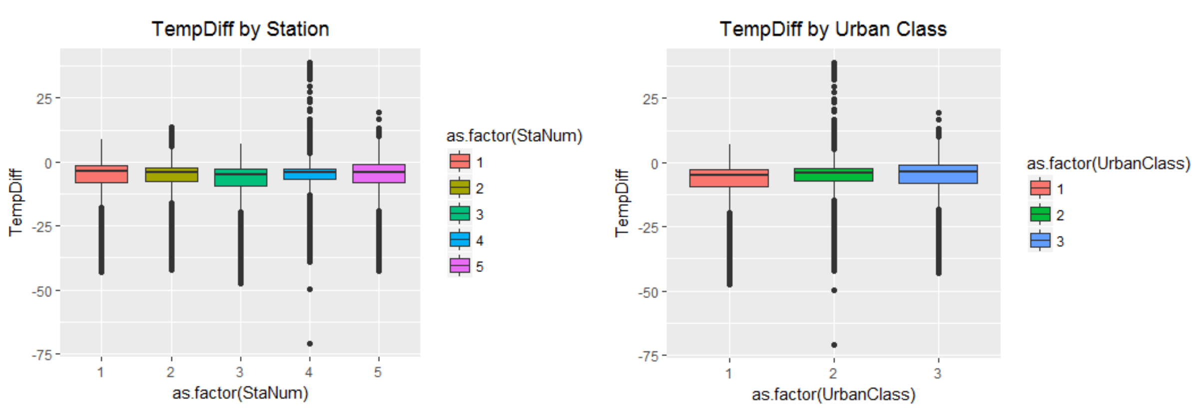

Figure 24: Boxplots showing spatial difference in the average of the Temperature Difference variable
(Left) Variation in the Temperature Difference variable by RWIS station
(Right) Variation in the Temperature Difference variable by Urban Class

As seen on the left side of Figure 25, average temperature difference is almost identical between all 5 stations. No variation in temperature difference exceeded 1.56° F between any two stations. The differences between Stations 1 – 2 and Stations 4 – 5 were not statistically significant at the 95th percentile. The right side of Figure 25 shows a similar problem amongst Urban Class with no difference between two urban classes exceeding 1.32° F. The difference between classes 2 and 3 was not statistically significant at the 95th percentile. In summary, no spatial relationship was noted amongst neither the urban classes nor the individual station locations in regards to average temperature difference values.

4.2.4 Impacts of Rain Analysis

Through various correlation analyses and other ANOVA tests, precipitation proved to have a strong effect on road temperatures. The fact that precipitation acts as a cooling or tempering agent for air in meteorological and climatological processes is explained and accounted for in concepts such as wet-bulb temperature. However the magnitude and rate of cooling or temperament on the road surface, especially in relation to the air, has not been as well researched.

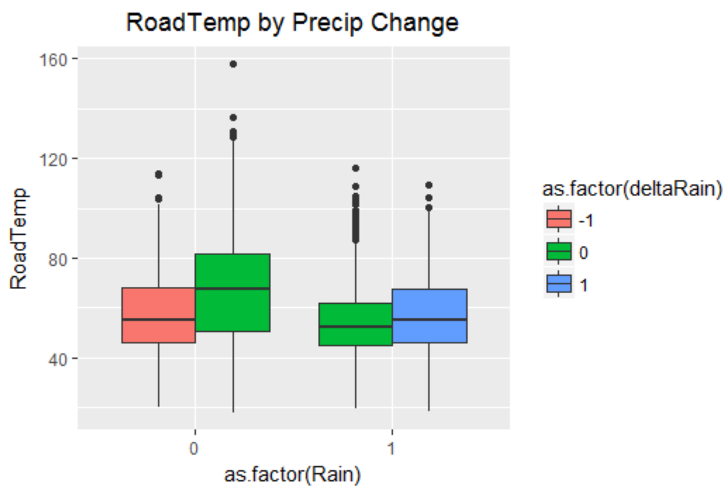

Figure 25: Boxplot showing variation in road temperatures by whether conditions were dry or precipitation was falling as well as changes in precipitation - (Pink) End of precipitation, (Green) Sustained precip or dry, (Blue) Start of precipitation

Figure 26 shows the variation in average road temperature amongst observations without precipitation (0 on the x-axis) and with precipitation (1 on the x-axis). Green coloring indicates either sustained precipitation or sustained lack of precipitation. Pink coloring indicates observations taken just after the end of a precipitation event, and blue coloring denotes observations taken just after the start of a precipitation event.

Observations taken without precipitation unsurprisingly have the highest average road temperature. Specifically, the average of these observations was 13.5^{o} F warmer than the average road temperature of observations taken in precipitation. The stop and start of precipitation did not have a strong effect on road temperatures, though statistical significance remained above the 99th percentile for all differences.

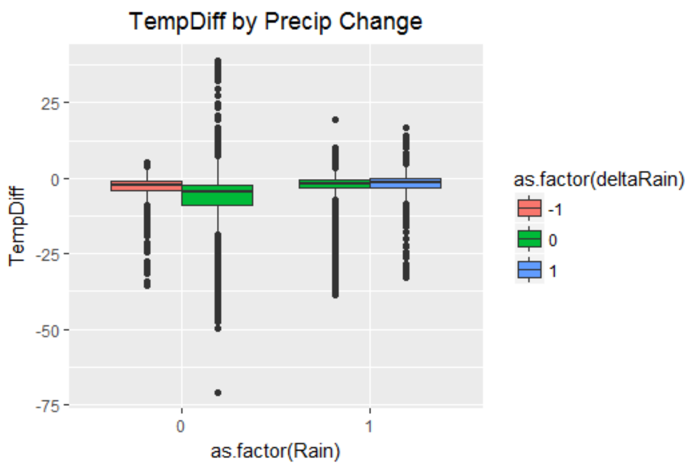

Figure 26: Boxplot showing variation in the Temperature Difference variable by whether conditions were dry (0 on the x-axis) or precipitation was falling (1 on the x-axis) as well as changes in precipitation - (Pink) End of precipitation, (Green) Sustained precip or dry, (Blue) Start of precipitation

Temperature Difference had even less variation than Road Temperature. The main divide shown in Figure 27 was still caused by precipitation vs no precipitation. However, the beginning of precipitation was more similar to sustained precipitation than the end of precipitation was to sustained no-precipitation. This may be caused by remaining water on the road surface which will be explored further in the next subsection on surface state.

Though neither of the precipitation variables notably affected the rate of change in Temperature Difference, the actual average rates of change did provide one takeaway. Figure 28 - Left shows averages and variation in the rate of change in Temperature Difference. Sustained precipitation, sustained no precipitation, and the end of precipitation all had averages approximately equal to zero. The one exception was the beginning of precipitation events which has a positive average rate of change; in other words, the beginning of rain events are likely to make road temperatures drop faster than air temperatures. Referring back to correlation analyses, a graph of the 'rainLength' variable versus the 'deltaTempDiff' (Figure 28 - Right) presents a short, dramatic broadening of the range of 'deltaTempDiff' values for the smallest positive 'rainLength' values. This equates to a faster change in Temperature difference at the beginning of precipitation events before the rate of change slows down again helping explain why the change in Temperature Difference was not zero for precipitation start in the boxplot.

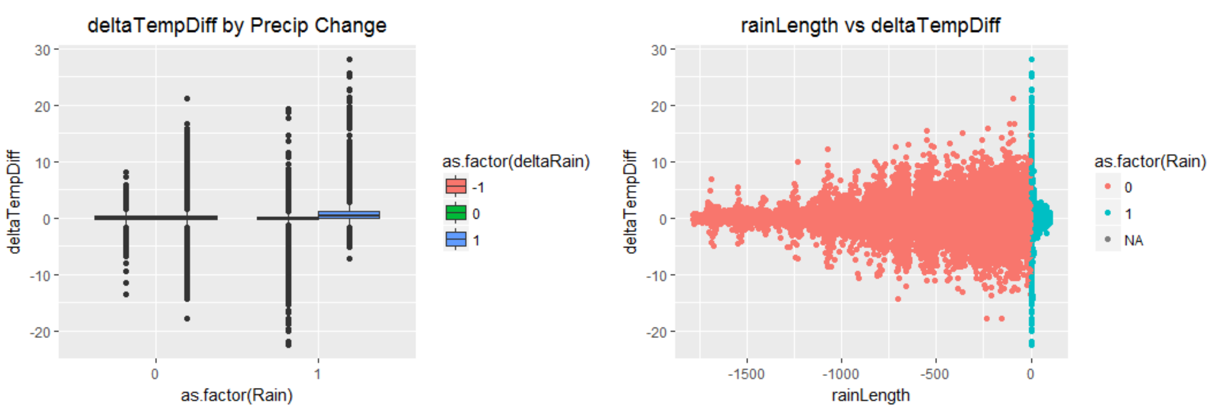

Figure 27: Change in the Temperature Difference variable by length of precipitation
(Left) Change in the Temperature Difference by whether observations were taken in dry conditions (0 on the x-axis) or precipitation (1 on the x-axis) timing of conditions (Pink) End of precip, (Green) Sustained, and (Blue) Start of precip
(Right) Graph of the change in Temperature Difference by rainLength

4.2.5 Impacts of Surface State

As countless statistical tests in this study have shown, water and moisture are important considerations when assessing heat flow. Considering the intent of this thesis is to investigate the freezing of water on roadways, it would be irresponsible to overlook the effects of water or a lack of water on RST changes. Unfortunately, only one sensor collected any observations including either snow or slush on the road surface. This accounted for a total of 7 observations which is much too low of a number to use in any statistical examination of road surface state. However, three values were included in this ANOVA: Dry, Moist, and Wet.

An initial ANOVA shows significant differences between road temperatures according to each state of the road surface. ‘Dry’ road had the highest average temperature, while ‘Moist’ roads had the lowest. ‘Wet’ roads had an average temperature between the other two values but only had a 3 degree difference with ‘Moist’ roads; which was much lower than the 11 degree difference they had with ‘Dry’ roads.

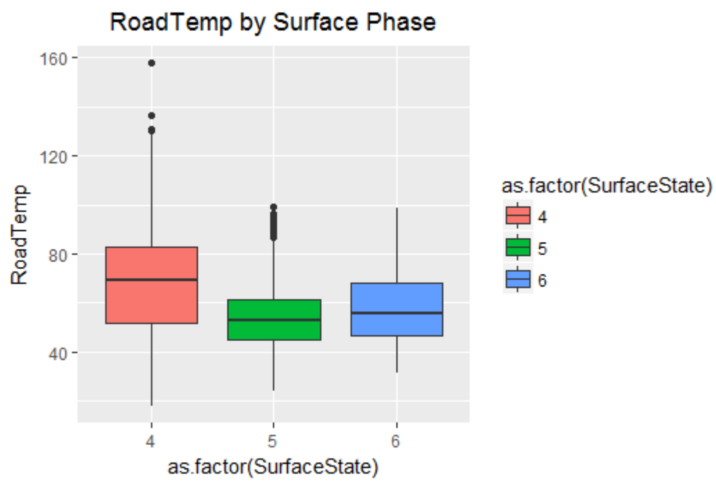

Figure 28: Boxplot showing variation in road temperature by the phase of moisture on the road surface
(Pink) Dry road surface, (Green) Moist road surface, (Blue) Wet road surface

Filtering the dataset using traffic counts changed the order of the variables values. The average RST increases by 10-20^{o} F for each of the three surface states. Additionally, the average RST for ‘Moist’ roads is higher than that of ‘Dry’ roads for observations with the top 25% of traffic counts (Figure 30).

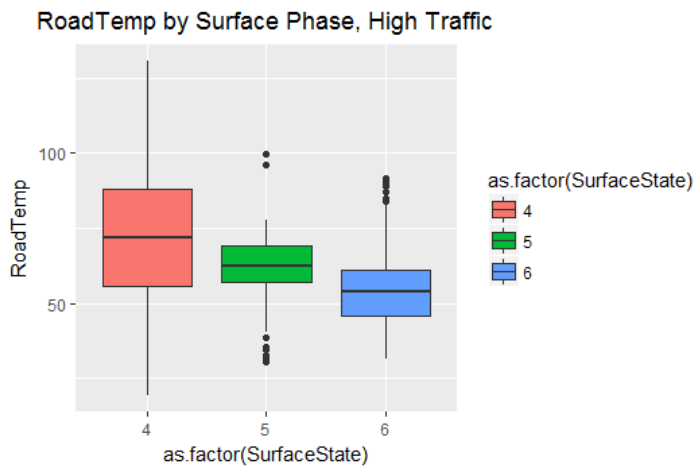

Figure 29: Boxplot showing variation in road temperature by phase of moisture on the road surface in high traffic
(Pink) Dry road surface, (Green) Moist road surface, (Blue) Wet road surface

Based on the correlation analyses, the ANOVA of temperature difference by surface state produced expected results. All average temperature differences were negative and the differences between all three averages were statistically significant. The average temperature difference for 'Dry' roads had the largest magnitude and the largest variation in values. 'Moist' roads and 'Wet' roads were much more muted. This was in-line with other results which showed water having a dampening effect on temperature difference. High Traffic volumes did not have the same effect on Temperature difference that they did on Road Temperature. However, the difference between 'Moist' and 'Wet' roads were no longer statistically significant.

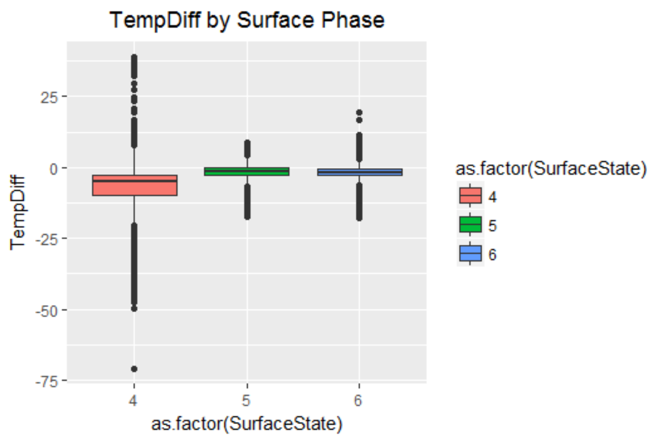

Figure 30: Boxplot showing variation in the Temperature Difference variable by phase of moisture on the road surface
(Pink) Dry road surface, (Green) Moist road surface, (Blue) Wet road surface

4.3 Multiple Regression

Multiple Regression analysis was performed to provide a secondary, multi-variate analysis of road temperature and temperature difference dependencies. The tables below show the results for each dependent variable, road temperature in section 4.1.3.1 and temperature difference in section 4.1.3.2. Each table is sorted first by the number of variables considered and then by the adjusted R^2 values highlighted in green.

4.3.1 Road Temperature

All of the Road Temperature regression models included air temperature as an independent variable because of how strong the correlation (0.94) was between the two variables. The significance of dewpoint in predicting the road temperature provided corroboration for the early results placing importance on water. This was again noted by the significance rainLength tended to play.

Visibility and the spatial variable 'DistToCtr' – meaning the distance from the station to the center of the city modelled by station 3 – were weak performers. However, both did perform well when used alone in addition to air temperature. So, though they may not be the strongest predictors, visibility and the distance from the city center may still be important due to their quick and easy access at any data point. Traffic volumes were also somewhat disappointing. While they were included in many of the stronger models, they were not as integral to a high R^2 value as originally expected.

Air Temp	Sub-Surfac	Dewpoint	Visible	Rain Length	DistToCtr	Traffic Count	Adj. R^2	# Vars
1.439	0.078	-0.432		0.003		0.0004	0.9308	5
1.42	0.054	-0.399				0.0003	0.9295	4
1.487		-0.412		0.003		0.0003	0.9294	4
1.458		-0.39				0.0003	0.9284	3
1.421	0.048	-0.391					0.9267	3
1.474		-0.397		0.002			0.9261	3
1.453		-0.381			-0.012		0.9258	3
1.454		-0.382					0.9257	2
1.218	-0.135			-0.005			0.8957	3
1.222	-0.125		6.045				0.8932	3
1.222	-0.124				-0.032		0.8929	3
1.221	-0.108					0.0003	0.8926	3
1.221	-0.121						0.8925	2
1.101				-0.004			0.8915	2
1.113			5.168				0.8894	2
1.114					-0.028		0.889	2
1.127						-0.0003	0.8888	2
1.114							0.8887	1

4.3.2 Temperature Difference

Air Temperature was also used for most of the Temperature Difference regression models. However, some models made use of variables without air temperature since, overall, R^2 values were lower for Temperature Difference models. Road temperature was also considered as an independent variable for comparison with others. It was not used in any of the models since the point of the analysis is to study road temperature rather than use it as a predictor.

Dewpoint was again a strong predictor further underlining the importance of moisture content for this entire thesis. Visibility also performed well, but not in conjunction with other variables. As stated with road temperature, the ease of accessing visibility data makes it an important variable to consider in context of this thesis' argument and later-stated conclusions.

Air Temp	Road Temp	SubSurface	Dewpoint	Visibility	Rain Length	DistToCtr	Traffic Count	Month	Adj. R^2	Var Coun
-0.4035			0.4316		-0.00471	-0.00898	-0.000347	-1.165	0.4571	6
-0.435			0.4316			-0.00898	0.0003471	-1.165	0.4571	5
-0.4025			0.4315				-0.000342	-1.173	0.4569	4
-0.4025			0.4315				-0.000342	-1.173	0.4569	4
-0.4872			0.4121		-0.00282		-0.000347		0.4462	4
-0.4581			0.39				-0.000339		0.44	3
-0.4009			0.422007			0.1197		-1.0517	0.3969	4
-0.4737			0.03969		-0.00187				0.386	3
-0.4591			0.384371						0.3766	2
	-0.2026								0.3401	1
-0.1268							-0.000292		0.13	2
-0.1011					0.004259				0.0984	2
-0.2206		0.120856							0.0979	2
-0.1125				-5.16768					0.0808	2
-0.1138						0.02796			0.0802	2
-0.1106									0.0777	1
-0.1518								0.48502	0.0745	2
							-0.000295		0.0426	1
					0.005839				0.0405	1

CHAPTER 5: DISCUSSION

Across all of the results listed in Section 4, several themes emerge that will be analyzed and discussed in this section. The introduction to this thesis highlighted the importance of understanding heat transfer in looking for ways to improve bus transit during winter weather. Intrinsic to that concept are road and air temperatures along with water, sunlight, anthropogenic heat, land cover, and rates of change. The impacts these components have will be framed using the results of correlation, ANOVA, and multiple regression analyses to assemble an understanding of heat transfer mechanisms on Metro Atlanta's roadways.

5.1 Relationships among Temperatures

The introduction to the correlation results notes that there is a strong correlation between road temperature and air temperature, a confirmation rather than a novel result. This relationship is important as it justifies the use of air temperature as a main variable in this study used to approximate road temperature. Because air temperature and changes in air temperature are generally well understood, the dynamic of this study, after seeing this correlation result, changes from "What affects road temperature?" to "When and why does road temperature differ from air temperature?"

Comparing road, subsurface, and air temperatures was an important first step in answering the new question raised in the last paragraph. Using that analysis, it is possible to asses which of the three is most stable. Stability is important for this thesis in identifying the main source of heat control for the road surface. Because road temperature and air temperature have a closer relationship, it can be theorized that air temperature has a larger effect on road temperature than subsurface temperature does.

As previously explained, the Temperature Difference variable was created to measure variation between road and air temperatures. The results of correlation analyses show a stronger correlation between road temperature and the Temperature Difference than air temperature and the Temperature Difference. In the most simple of terms, this means that changes in the Temperature Difference are most likely a result in changes to the road temperature rather than the air temperature, thus proving the relative stability of the air temperature in comparison to the road temperature.

This is further corroborated by the coefficients and R^2 values associated with air temperature in the regression models for both Temperature Difference and road temperature. The models for the former show higher coefficients and R^2 values when using road temperature than when using air temperature alone. This signifies that road temperature is a better predictor of the Temperature Difference than air temperature. However, air temperature is a stronger predictor of road temperature by R^2 values than road temperature is of the Temperature Difference. In other words, air temperature in large part sets the temperature of the road, and variations between the two are driven by outside heat sources and sinks acting on the road surface.

Lastly, the stability of the air temperature variable was seen in the strength of its relationship with subsurface temperature across all variables. The subsurface temperature - or ground temperature – being insulated from other heat sources and sinks is a fairly stable element still largely driven by ambient air temperature. Noting that correlations were strong between the air and subsurface across all variables shows that exterior influences such as rain, traffic, or - to a certain extent – sunlight did not have a disproportionately higher influence on air temperature than they did on ground temperature. This is again a justification for using air temperature to study variations in road temperature.

5.1.1 Air Temperature vs. Road Temperature

While it has been shown that air temperature can be used as a viable proxy for road temperature and that road and air temperatures are very strongly correlated, it is important to note which conditions weaken the relationship. Seasonality and time of day are the only variables that notably affected the correlation between air and road temperatures. Evening is the only time of day which decreases the correlation, however, morning is when the correlation is strengthened. A potential explanation may come from excess heat accrued during the afternoon hours reaching a peak in the evening driving road temperatures higher than air. Heavy traffic from commuters may also have an impact, though, lower traffic volumes tend to be more supportive of the road/air temperature relationship.

The seasonality of the relationship creates a caveat complicating conclusions reached in the previous paragraph. If insolation creates a weakened relationship in evening hours then, summer should have a weaker relationship as insolation is greatest in summer. In fact, the relationship is stronger in summer and weaker in winter. The mentioned caveat is centered on the inclusion of water and precipitation in the equation. As will be discussed later in this section, water is a significant heat sink and has a large effect on this primary relationship. It is possible that larger amounts of precipitation in the summer cancels out the increased direct sunlight that would otherwise be collected in that season.

The fact that the filter variables had little impact on this relationship again justified the need for a Temperature Difference variable. It allowed for a more concise analysis describing the conditions under which the air temperature proxy might vary from the road temperature while specifying the amplitude of that variation. In turn, this increases the reliability of the proxy by determining when it is less similar to road temperature and to what degree.

5.2 Importance of Water

Water was shown to be an important heat sink and overall factor in the heat transfer to and from the road surface. This was most easily summarized across all statistical tests by the dewpoint variable. After air temperature, the dewpoint was the most significant and influential variable in the regression analysis using each road temperature and the temperature difference as the dependent variables.

The dewpoint also had a strong correlation with road temperature and temperature difference. The importance of water was corroborated by similarly strong and statistically significant correlations and ANOVA results with each ‘rainLength’ and surface state used as the independent variables. Finally, water proved to be a mitigating force for rates of change in road temperature and the ‘TempDiff’ variable creating stability amongst rates of heat flux. The Introduction section of the thesis laid out two separate categories of water: precipitation and standing water. Both will be discussed with focus placed on how each form of water contributes to a better understanding of RST variations.

5.2.1 Standing Water

The effects of water concentrations on the road surface were examined using the 'rainLength' and surface state variables. Both variables resulted in measurable impacts on fluctuations in road temperature both objectively and with respect to air (measured through 'TempDiff). ANOVA, correlations, and regressions using these variables reinforced the concept of water as a strong heat sink. In correlation analyses, higher, positive 'rainLength' values (meaning longer periods of precipitation implying larger stocks of precipitation on the ground) decreased the road temperature, and conversely, higher magnitudes of negative 'rainLength' values (longer periods without precipitation and implicitly drier air and roadway) increased the road temperature.

ANOVA analysis of Surface State and road temperatures showed strong decreases in average road temperature when the surface was wet or moist. However, there were caveats in this relationship as increases in the amount of water did not always linearly increase effects on the roadway. For instance, moist roads were found to produce the coolest average road temperatures, while dry roads resulted in the warmest average temperature. This suggests that higher specific heat and an increased potential for storing energy are not the sole physical vehicles by which water reduces and stabilizes road temperature.

Lower RST of moist roads may result from stored energy in the road surface inducing evaporation of pooled water on the ground. Wet roads use the stored heat as latent heat of vaporization. Such a dynamic would result in roads having higher temperatures while wet and cooler temperatures as evaporation begins and heat is used to convert water to vapor.

Moist roads also produce stronger positive correlation between the rate of change in road temperature and the rate of change in air temperature. This would show both their direction and magnitude of change to be more similar causing less change in the temperature difference. The strengthened correlation may be a result from physical processes caused by the precipitation.

5.2.2 Precipitation

Three variables were used to analyze the effects of precipitation on RST variation. These variables first provided whether an observation was taken during a precipitation event or not. Additionally, the variables were used to assess how these effects of precipitation changed as it began, was sustained, and ended creating a deeper, more multi-level analysis.

The binary variable specifying the presence of precipitation provided basic results regarding precipitation's effects on RST. As expected, road temperatures were lower for observations taken in precipitation and average 'TempDiff' values were more negative (road was warmer than air) without precipitation.

To go past the expected differences between precipitation and no-precipitation scenarios, the 'deltaRain' variable was used to assess how a change in precipitation conditions initially affected RST variation. Correlation analyses showed the positive relationship between the rate of change in each air and road temperatures strengthened significantly when precipitation first began. Additionally, ANOVA analysis showed that the beginning of precipitation resulted in a positive average change in temperature difference – this was the only value which resulted in a positive rate of change for the

‘TempDiff’ variable – reinforcing the conclusion that road temperatures fall faster than air temperatures when precipitation begins.

A second ANOVA showed an insignificant difference between average ‘TempDiff’ values when rain begins and as it is sustained – both are much higher than average ‘TempDiff’ without precipitation. This means the majority of convergence of road and air temperatures must take place within the first few minutes of precipitation beginning. Once the precipitation has been sustained, road temperatures continue to fall but at a rate more equal to that of the air.

This finding is perhaps more interesting when considering the concept of wet-bulb temperature and the cooling potential of precipitation. When precipitation begins, measured air temperature should fall due to increases in moisture content. What these ANOVA results show is that even though air temperature falls as precipitation begins, the road surface still cools faster than the air. The change in road temperature then decreases and approaches zero as an insulating layer of water builds on the road surface.

Correlation analysis of the relationship between rate of change in each road and air temperatures corroborated the previous assertions. Correlation between both rates of change was stronger when precipitation began. Interestingly, correlation was weaker when precipitation was sustained. This is most likely a result of the increasingly slower cooling of the road surface as precipitation continues.

As with standing water, not all of the effects of precipitation on RST can be explained by increased heat capacity. Most, if not all, precipitation events take place beneath cloud cover which blocks insolation. While no cloud cover variable was available for this study, precipitation variables were used as a proxy to test this theory on a general level. As previously discussed, road temperatures are hottest with respect to air in the early evening hours after accruing sunlight all day. This is when the 'TempDiff' variable has its largest, negative magnitude. ANOVA analysis of 'TempDiff' vs. time of day confirms this theory resulting in statistically significant differences between each period of the day. However, when using a subset of observations taken during precipitation events, these statistical differences disappear. Similarly, correlation between 'TempDiff' and 'rainLength' is strongest in the evening and weakest in the morning when analyzing the general population of observations. But, when using a subset of observations taken during precipitation events, correlation coefficients are virtually identical for all times of day.

5.3 Energy Inputs

This thesis attempts to explain how energy in a road surface moves and how that affects urban transportation. One of the most important elements in establishing such an understanding is showing how the object received energy in the first place. Knowing the source or sources of energy for any object or system logically helps identify when that system or object is cut-off from further energy additions.

As was discussed in section 2.1.1, the road surfaces can have many sources of energy or heat. In general, however, there is debate over how these heat sources interact in additive or inhibitive ways. Specifically looking at the two most commonly studied sources - automobile traffic and insolation from the sun - much of the research in RST behavior is focused on assessing how much vehicles contribute to energy stored in the road as it blocks radiation from the sun. Conversely, how much long wave radiation do vehicles block from leaving the road at night. These are complex concepts which are dependent on several factors. Using the wide array of variables examined in this thesis, a summary of the effects of insolation and mechanical energy with regards to this study is provided.

5.3.1 Insolation

The time of day and season variables were most important to understanding the importance of insolation on the road surfaces. Changes in the angle of the sun both from winter to summer and from morning to evening increase the intensity of the shortwave radiation received on the surface. The air temperature's noted large influence over RST makes it logical to hypothesize that road temperatures would be objectively higher in the summer than the winter and in the afternoon to evening hours than overnight through morning. Thus, the 'TempDiff' variable provides insight as to how incoming solar radiation affects the road differently than the air.

ANOVA analysis of the temperature difference by season shows a statistically significant increase in magnitude from winter to summer. By repeating the ANOVA filtering the data for each specific time of day, it was found that the increase in temperature difference from winter to summer was four times greater in day and evening than it was in morning and at night. This is a dramatic contrast showing the impact direct sunlight can have on RST and a heat source which disproportionately affects road temperatures over air temperatures. Conversely, this shows that air temperature would be a more reliable proxy for road temperatures in winter as the temperature difference is likely to be smaller.

The analysis of the temperature difference by time of day resulted in a less clear trend. Evening is the only time of day which has a statistically significant higher magnitude of temperature difference. Being that this is when the most energy has been stored in the road itself, this result also demonstrates the importance of shortwave solar radiation. However, on a daily time scale, the importance appears to be on the total energy accrued rather than the amount of instantaneous flux. In other words, the amount of energy stored is more important than the amount being received at any one moment. As discussed in section 5.2, variation in average 'TempDiff' values increases when subsetting for dry conditions. For observations during precipitation events - assuming cloud cover - all variation in 'TempDiff' values by time of day disappear. This is indicative that no other heat source is specifically driving diversions between the road and air temperatures.

The correlation between air and road temperature also shows disproportionate amounts of energy input and storage at different times of day. The correlation was stronger in the morning and nighttime hours and grew weaker into the daytime reaching its weakest point in the evening. This would support a faster rate of change in the road temperature as compared to the air temperature. When the incoming shortwave radiation ceases, the changes in the two temperatures become more equal again.

5.3.1.1 Urban Heat Islands

The results and trends discussed with respect to insolation were thought to be potentially indicative of a skin-level or canopy-level urban heat island (UHI). Because the temperature difference was shown to increase significantly in the day and evening hours, an examination of each station's average temperature difference values could reveal a UHI. The premise for studying a possible UHI in this thesis lies more on concentrations of urban surfaces demonstrating how a road's location within a metro area might affect its capacity to receive and store energy.

In general, Stations 1, 4, 5, and to a lesser degree 2 all showed similar average 'TempDiff' values and average road temperature values for each time of day. The only difference was found with Station 3 located in Midtown Atlanta. Both average road temperature and the average temperature difference were found to be slightly higher. The caveat exists that filtering the dataset for precipitation or no-precipitation observations as well as specific times of day did not increase this trend. A larger average temperature difference in the center of the city would indicate a small skin-level UHI, however, this should only exist in the day and evening hours when the sunlight is reaching the surface. The result may have to do with the inability of the study to identify unique landcovers such as an area which is specifically urban, suburban, or rural.

A second theory is derived from the higher volumes of traffic. This traffic has the possibility of providing a secondary heat source which would be greater in the city. Alternatively, as is discussed in the next section, the larger number of cars could be preventing more of the heat stored within the pavement from escaping back into the troposphere. Because winter nights have been identified as a more likely time for road temperatures to decrease and converge with air temperatures, the role of traffic in sustaining a UHI could have significant implications for urban transportation in winter.

5.3.2 Automobile Mechanical Energy Transfer

The introduction of this thesis discussed the findings of previous studies considering the impact of traffic on RST values (Chapman and Thornes, 2005; Fujimoto, Saida, and Fukuhara, 2012; Prusa et al., 2002). These studies generally made use of numeric, stochastic models to make their assessments. From their findings, it would be logical to expect higher traffic volumes to increase the RST and therefore lower the ‘TempDiff’ value. Though automobiles output a lot of heat which could be absorbed by the road, there is debate as to whether traffic is a net source or sink of heat given its inherent ability to block insolation during the day.

Regression analysis confirms the net heat additions made by traffic using raw road temperatures as the dependent variable. Though the coefficient for traffic was small in all independent variable combinations, the sign of the coefficient for traffic volume was almost always positive. Simply put, traffic added heat to the road but only in very small quantities.

Using temperature difference as the dependent variable resulted in negative coefficients for traffic volumes in every model. These negative coefficients mean higher traffic volumes equated to more divergence between air and road temperatures, with road temperature increasing more than air temperature. Overall, the consensus would be that more heat exists in the road surface when traffic volumes are higher. However, the interpretation of the results from both regression analyses can be better explained through individual correlation tests and ANOVA.

An ANOVA of ‘TempDiff’ by time of day filtered for high and low traffic suggests that the overall influence traffic exerts on RST may have less to do with heat addition and more to do with heat subtraction. When traffic volumes are high, the average temperature difference increases from morning to evening and slightly drops into the night. Low traffic volumes result in much more equal average temperature differences throughout the day. Additionally, the average temperature difference does not change in morning and daytime between low and high traffic.

Thus traffic's influence was greatest at the end of the day when heat is lost from the road rather than the beginning when heat must be added to the road surface. This suggests that heat may be trapped in the road by the traffic. Furthermore, the heat input from traffic is not significant enough to offset what is lost from decreasing air temperature causing a slight drop between evening and night. The resulting conclusion is that traffic may not be contributing any measurable amounts of heat but rather slowing its release from the road surface. Thus, I propose that traffic is neither a heat source nor a heat sink but rather a type of 'heat sink-stopper', retaining heat after it is stored in the road.

These results were repeated in the correlation analysis of 'TempDiff' and traffic volume when filtering by time of day. Morning and daytime observations produced much weaker correlations between 'TempDiff' values and traffic volumes. Nighttime observations had a much stronger negative correlation. So, the more nighttime traffic, the higher the road temperature in comparison to the air temperature. In other words the amount of traffic at times when roads are absorbing insolation has little effect on the relationship between air and road temperatures. However, higher amounts of traffic keep road temperatures higher with respect to air at times when roads should be cooling by releasing long wave radiation back into the troposphere.

In previous discussions the concept of water as a major heat sink has only been applied to heat stored in the road surface, but results of regression analyses with road temperature may apply the same concept to heat output from automobiles. Moisture on the road surface or falling as precipitation negated the impact of traffic on the 'TempDiff' variable, and correlation coefficients between traffic volumes and 'TempDiff' had lower magnitudes when moisture was present in any form.

If the temperature difference – very often being negative – is seen as a measure of how much cooler the road is than the air, then a weakened negative relationship between temperature difference and traffic volumes indicates less heat is either transferred to or retained in the road.

In summation, describing traffic as a 'heat sink-stopper' refers to its capacity to create a barrier between the road and cooler tropospheric temperatures. When the sun sets and shortwave radiation becomes less direct or disappears, higher traffic volumes can prevent heat from escaping the road. In effect, higher traffic volumes help to stabilize the road temperature rather than significantly increase it or decrease it with respect to the air temperature. However, when water is present on the road surface or falling as precipitation, the insulating effect of traffic is negated.

5.4 Rates of Change

One of the main contributions of this thesis is its inclusion of rates of change calculated from road weather records. Understanding how quickly temperature may rise or fall helps officials prepare for situations that may be hard to adapt to on-the-fly. While many of the variables included in the previously discussed analyses did not have a significant impact on the rate of change in RST, some variables like precipitation yielded potentially useful insights. These impacts could be found in the rate of change of the actual road temperature as well as in how road temperatures differed from the air above them.

Several findings did less to help predict the magnitude of changes in road temperature than it did to explain dependencies of road temperature and how it is best estimated. In this way, this subsection echoes much of what was stated about the stability of air temperature in comparison to road temperature in sections 5.1. However, there are other conclusions that can be extracted from this research to move forward with the goal of assisting transit agencies in effectively creating informed winter weather policies.

5.4.1 Heat Sources

As explained in section 5.1, road temperature is less stable than air or subsurface temperatures. Thus, heat inputs such as sunlight produce large values of the 'deltaRoadTemp' variable. Correlation analysis results show that the change in temperature difference has a stronger relationship with changes in road temperature than changes in air temperature. For the most part, there was also a strong correlation between changes in road and air temperature meaning any given input produced similar results in either variable. This relationship was most likely to flip in the evening hours. This was when it was most likely for air and road temperature to diverge and the temperature difference to increase. Taken in context with trends identified in section 5.3.2, these divergences are a result of high traffic from the evening commute preventing stored heat from escaping the road surface. No other subset produced a disproportionately higher number of diverging temperature observations.

5.4.2 Heat Sinks

The concept of a heat sink and its physical implementation can both be described using rates of change in temperature. For instance, roads storing heat are much hotter than the air on a general basis. When a heat sink such as precipitation is applied, there is a negative change in road temperature. Subsequently, air and road temperatures converge as the temperature difference rises towards more positive values –air is warmer than the road.

Changes in temperature difference and road temperature are strongly correlated as has been established. However, during precipitation events, correlation between ‘deltaAirTemp’ and ‘deltaTempDiff’ strengthens and the correlation coefficient approaches the larger coefficient for ‘deltaRoadTemp’ and ‘deltaTempDiff’. This is especially true when precipitation first begins. As water makes contact with the road it absorbs heat from the road lowering the temperature. Upon changing signs, the magnitude of ‘deltaRoadTemp’ would be lower and more similar to ‘deltaAirTemp’. Thus, the strengthened correlation between ‘deltaAirTemp’ and ‘deltaTempDiff’ is actually indicative of the change in ‘deltaRoadTemp’. Furthermore, the decrease in that same correlation coefficient as precipitation is sustained shows that road temperature is more strongly affected by heat sinks than air is just as roads are more strongly affected by heat sources than air is.

The strengthened correlation between ‘deltaAirTemp’ and ‘deltaTempDiff’ is also found when the temperature difference is positive and roads are wet or moist, especially at night. The repeated result in both variables measuring water content reinforces the notion that water acts as a heat sink more than just blocking a heat source. Noting the difference between a heat sink and the absence of a heat source is important as it alludes to how RST will be affected when either the sink or the source or both the sink and the source are applied or removed.

CHAPTER 6: CONCLUSION

Winter weather provides major complications for urban transportation. Between heavy snows creating physical barriers and ice making clear paths impassable, the challenges cold weather creates vary from place to place and require creative solutions. As America continues to grapple with a large and increasing national debt, budgets do not always allow for large-scale infrastructure improvements. Additionally, continued reliance on special ballot measures and public votes to secure monies and capital costs will increasingly underfund transit infrastructure making the design of new transit systems with high capital investment requirements all but unimaginable.

Transit systems can help mitigate effects of winter weather on urban transportation networks. By designing a dynamic system that can tackle multiple challenges without major initial cost, we can improve efficiency and coordination of movement when conditions are less than ideal. Redesigning cities for future climate challenges starts with good use of existing infrastructure. This can be accomplished by implementing smart, science-based policies to improve efficacy and efficiency of the system.

6.1 Major Physical Findings

This thesis has identified that air temperature serves as a good proxy for RST in general scenarios. While direct measurements of RST are desirable, the goal of this thesis was to create ways transit agencies might better mitigate winter detriments to bus networks by understanding changes in road temperatures. Since air temperature is much more readily available on a wider spatial scale, knowing when it most accurately models road temperature allows for quick, fiscally-responsible transit improvements.

Road surface temperatures can be well modelled using air temperature and moisture content – dewpoint and precipitation amounts – as major variables. There are several key physical factors which should be noted for effective winter operating policy. In terms of heat sources, sunlight is most important to raising road temperatures above that of the air. Both the amount being absorbed at any one moment as well as previously stored amounts of energy are very important in determining RST. Pooled water on the road can block solar radiation from warming the road mitigating its importance. Similarly, times of lower solar incidence angles result in lower influence of insolation over RST because less heat reaches the road. This includes transitional times of day such as morning and evening along with the winter and late fall/early spring seasons.

Traffic could also be considered a heat source though this study shows it to act more as an RST stabilizer. In general, higher traffic volumes slightly warm roads. However, effects seem to be negligible, especially when the road surface is wet or moist. Times just after large amounts of heat are collected by the road are when traffic's impacts are most significant. The evening and nighttime hours create the best opportunity for heavy traffic to influence RST by preventing heat from escaping the road.

Precipitation acts as a heat sink causing road and air temperature to converge. It is important to understand that the beginning of precipitation events act as larger heat sinks than sustained precipitation. From an applied perspective, allowing for normal operation on road surfaces within the first 10 minutes of precipitation is not necessarily better or less hazardous than it is after an hour of precipitation. Timing, thus, becomes critical in any winter hazard prevention or mitigation plan.

As noted in the introduction, Atlanta's 'Snowpocalypse' of January 2014 began with overcast skies devolving into a mix of precipitation. According to the analysis of time variables and RST, when sunlight does not reach the road surface, the air and road temperatures are less likely to diverge. The lack of insolation in the morning and early afternoon of that day would have prevented the road temperature from lifting above that of the air. The start of precipitation would have introduced a heat sink to the road surface potentially causing its temperature to fall faster than the air temperature. Though the roads were flooded with tens of thousands of buses, trucks, and cars trying to escape the city, the addition of such anthropogenic heat sources were most likely negligible in the larger system of heat transfer to and from the road surface allowing ice to form and remain on road surfaces.

6.2 Applications to Urban Transit

Most large cities in North America have policies in place which specify operating criteria differently for each mode within their existing systems. Buses are generally at a greater disadvantage in winter weather and have lower thresholds for snow and ice accumulations before rendering a system inoperable. Policies designating when bus and rail are appropriate to use should in part be based on RST and its variations as this is the fundamental cause of winter impediments to transportation.

This thesis has placed a major emphasis on incoming solar radiation. Sunlight is a major heat source and factor in raising road temperatures. For this reason, transit operations should take note of overcast conditions. This would be particularly true in the morning through early afternoon as this is when roads accrue a majority of their heat. The less sunlight a roadway receives, the more air temperature may be used to proxy it's RST. Additionally, the importance of sunlight varies from season to season as more direct sunlight provides a roadway with more heat. This does not just apply to winter as December 21 has the lowest solar incidence angle of the year for the northern hemisphere. Days in early fall or later winter will provide much more roadway warming during a sunny day than the New Year's period.

For days when sunlight is pervasive in the morning and early afternoon, a higher frequency of vehicles can maintain higher road temperatures for longer. This is particularly useful when winter precipitation or icy conditions are expected in the evening or overnight hours. For bus routes with dedicated lanes such as Bus Rapid Transit systems, a concept similar to the Seattle 'Night Train' described in section 1.2 could keep roads warmer for several hours after sunlight is lost. However, this is not an effective method of preventing previously melted ice on wet roadways from refreezing into the evening and nighttime hours.

The 2-dimensional spatial arrangement of roads should also be taken into account. Just as signs warn drivers of bridges which freeze more quickly than other roads, there is evidence that shows road temperatures in the outlying parts of cities will fall faster than roads in the urban core. This may be an extension of the effect traffic has on roadways, but this fact holds true across all times of day. Furthermore, this demonstrates the need to monitor air and road temperatures across a large geographic footprint rather than relying on an isolated point. Space and location matter in determining RST and should be noted in operating policies.

Lastly, while precipitation is known to reduce visibility and impede transportation at all times of year, the effects of precipitation on the road surface and their changes over time should be taken into special consideration. Water is a strong heat sink meaning it can remove heat from all forms of matter including air and roads. Additionally, it can prevent the transfer of heat as it creates a barrier between the road and the heat source.

This study also notes that the effects of precipitation on RST change over time. The beginning of precipitation has a major negative impact on RST. From a policy perspective, bus operations on roadways are subject to no less hazard in the first 10 minutes of precipitation than they are after an hour of precipitation. Because precipitation causes air and road temperatures to converge, it is advisable that road temperatures be considered equal to or lower than air temperatures as soon as a precipitation event begins.

Using the above conclusions, transit agencies can better manage bus operations in inclement weather. Existing tactics for mitigating the effects of snow and ice mentioned in the introduction to this thesis can improve operations within their existing networks when applied at appropriate times and locations. Most of all, agencies must acknowledge that cities are dynamic, complex places which require adaptation and creativity to make each mode of transit operate to its highest potential.

6.3 Study Limitations and Future Recommendations

This thesis has produced a cross examination of several factors affecting changes in road surface temperatures. Several issues arose which prevented this study from going further in its findings or which may have made its findings problematic. First and most importantly, road weather sensors and traffic counters should have been better matched. Using existing datasets limits the extent to which those datasets align with each other both spatially and temporally.

A second limiting factor existed within the range of temperatures and types of weather which were recorded by the RWIS sensors. Atlanta can experience a wide array of weather conditions within a year making it an ideal place to apply the findings of this study or a similar one. However, the collection of data here may be considered somewhat incomplete, especially in milder years. That being noted, other studies of RST in the southeastern United States are few. RST and the factors which most affect it are intrinsically regionally sensitive to some point as it is reliant on solar radiation, sun angles, population sizes, transportation network designs, and precipitation amounts and types. This makes the study of RST in every region imperative.

Finally, missing variables such as cloud cover, rainfall rates, and more detailed data would greatly benefit work on this subject. While ten minute observations create a lot of data over the course of several months, there is still a lot that can happen within a ten minute time frame, particularly in the southeastern region of the country. Similarly, while many factors are collected by the RWIS sensors and that data can be implicitly used to cover several physical factors, the noted additional variables would provide better accuracy in confirming theories and conclusions noted in this thesis.

Given the list of limitations above, there are several recommendations that can be provided for future work. A difference variable between road and subsurface might be good in future research to measure objective amounts of heat added by specific sources.

This would be helpful in comparing the effects of traffic and sunlight using a proxy different from air temperature. However, subsurface temperature may not provide the same usefulness as this work because it is less widely measured and the data is less readily available.

Future work should also make better use of winter weather observations. Variations in types of precipitation may provide slightly different conclusions. Just as snow provides more traction than ice or water, each type of precipitation might affect road temperatures to a lesser or greater degree.

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APPENDIX A

This Appendix displays tables of all results from the correlation tests performed for this thesis. General correlation coefficients for each variable pair are displayed in the first table. Subsequent tables list correlation values by filter variable. For each table, a row constitutes one variable pair and each column represents one value of the variable used to filter that variable pair.

Baseline Correlations

V_1	V_2	Sensor 1	Sensor 2	Sensor 3	Sensor 4	Sensor 5	Average
Road Temp	Air Temp	0.94	0.95	0.94	0.96	0.94	0.946
Air Temp	Subsurface Temp	0.89	0.89	0.9	0.88	0.88	0.888
Air Temp	Dewpoint	0.82	0.82	0.83	0.84	0.85	0.832
Subsurface Temp	Dewpoint	0.82	0.83	0.82	0.84	0.82	0.826
Road Temp	Subsurface Temp	0.81	0.82	0.81	0.82	0.82	0.816
Road Temp	Dewpoint	0.66	0.68	0.67	0.71	0.68	0.68
deltaRoadTemp	deltaAirTemp	0.64	0.7	0.62	0.64	0.62	0.644
Temp Diff	RainLength	0.28	0.2	0.21	0.09	0.25	0.206
Temp Diff	Dewpoint	0.02	0.03	0.07	0.27	0.05	0.088
Road Temp	Traffic Volume	0.14	0.06	0.03	0.08	0.11	0.084
Dewpoint	Traffic Volume	0.08	0.05	0.03	0.05	0.07	0.056
Air Temp	Traffic Volume	0.02	0	-0.03	0.02	0.01	0.004
Subsurface Temp	Traffic Volume	0	-0.03	-0.03	0	-0.02	-0.016
Temp Diff	Subsurface Temp	-0.23	-0.23	-0.19	0.03	-0.25	-0.174
Air Temp	RainLength	-0.34	-0.16	-0.2	-0.3	-0.11	-0.222
Temp Diff	Traffic Volume	-0.32	-0.18	-0.17	-0.21	-0.25	-0.226
Subsurface Temp	RainLength	-0.38	-0.19	-0.22	-0.3	-0.14	-0.246
Road Temp	RainLength	-0.38	-0.2	-0.24	-0.32	-0.18	-0.264
Temp Diff	Air Temp	-0.34	-0.34	-0.29	-0.06	-0.3	-0.266
deltaAirTemp	deltaTempDiff	-0.31	-0.41	-0.29	-0.21	-0.32	-0.308
Temp Diff	Road Temp	-0.64	-0.62	-0.6	-0.36	-0.61	-0.566
deltaRoadTemp	deltaTempDiff	-0.93	-0.94	-0.93	-0.89	-0.94	-0.926

Air Temp vs. Road Temp vs. Temp Diff

	AirTemp/Subsurface	AirTemp/RoadTemp	Subsurface/RoadTemp	
General	0.89	0.94	0.81	General
Top 25%	0.89	0.94	0.79	Top 25%
Bottom 25%	0.9	0.98	0.93	Bottom 25%
Dry	0.88	0.94	0.8	Dry
Moist	0.85	0.97	0.87	Moist
Wet	0.9	0.98	0.92	Wet
Not Dry	0.89	0.98	0.91	Not Dry
UC 1	0.9	0.94	0.81	UC 1
UC 2	0.89	0.95	0.82	UC 2
UC 3	0.88	0.94	0.81	UC 3
StaNum 1	0.89	0.94	0.81	StaNum 1
StaNum 2	0.89	0.95	0.82	StaNum 2
StaNum 3	0.9	0.94	0.81	StaNum 3
StaNum 4	0.88	0.96	0.82	StaNum 4
StaNum 5	0.88	0.94	0.82	StaNum 5
Winter	0.61	0.85	0.44	Winter
Spring	0.69	0.88	0.57	Spring
Summer	0.45	0.9	0.29	Summer
Morning	0.92	0.99	0.96	Morning
Day	0.91	0.95	0.86	Day
Evening	0.92	0.91	0.85	Evening
Night	0.91	0.98	0.92	Night
Sust. No Precip	0.88	0.94	0.81	Sust. No Precip
Precip Start	0.9	0.96	0.9	Precip Start
Sust. Precip	0.88	0.96	0.91	Sust. Precip
Precip Stop	0.9	0.96	0.9	Precip Stop
Precip	0.88	0.96	0.9	Precip
No Precip	0.88	0.94	0.81	No Precip

Precipitation

	Yes	No	Baseline Corr
ΔAirTemp/ΔRoadTemp	0.66	0.81	0.64
TempDiff/RainLength	0.05	0.15	0.2
AirTemp/RainLength	-0.23	-0.19	-0.22
TempDiff/Traffic Vols	-0.15	-0.21	-0.21
Subsurface/RainLength	-0.23	-0.21	-0.24
RoadTemp/RainLength	-0.25	-0.22	-0.26
TempDiff/AirTemp	0.18	-0.28	-0.28
ΔAirTemp/ΔTempDiff	-0.33	-0.31	-0.31
TempDiff/RoadTemp	-0.11	-0.58	-0.58
ΔRoadTemp/ΔTempDiff	-0.93	-0.93	-0.93

Change in Precipitation

	Sust. No Precip	Precip Start	Sust. Precip	Precip Stop	Baseline Corr
ΔAirTemp/ΔRoadTemp	0.64	0.85	0.46	0.61	0.64
TempDiff/Traffic Vols	-0.21	-0.15	-0.15	-0.11	-0.21
TempDiff/AirTemp	-0.28	0.33	0.16	0.08	-0.28
ΔAirTemp/ΔTempDiff	-0.31	-0.66	-0.04	-0.24	-0.31
TempDiff/RoadTemp	-0.58	0.05	-0.14	-0.2	-0.58
ΔRoadTemp/ΔTempDiff	-0.93	-0.96	-0.91	-0.92	-0.93

Time of Day

	Morning	Day	Evening	Night	Baseline Corr
ΔAirTemp/ΔRoadTemp	0.61	0.63	0.65	0.55	0.64
TempDiff/RainLength	0.26	0.2	0.33	0.23	0.2
AirTemp/RainLength	-0.17	-0.21	-0.29	-0.24	-0.22
TempDiff/Traffic Vols	-0.05	-0.11	-0.23	-0.5	-0.21
Subsurface/RainLength	-0.25	-0.25	-0.23	-0.23	-0.24
RoadTemp/RainLength	-0.2	-0.25	-0.37	-0.27	-0.26
TempDiff/AirTemp	-0.01	-0.23	-0.29	-0.21	-0.28
ΔAirTemp/ΔTempDiff	-0.12	-0.3	-0.36	-0.15	-0.31
TempDiff/RoadTemp	-0.17	-0.51	-0.66	-0.4	-0.58
ΔRoadTemp/ΔTempDiff	-0.86	-0.93	0.95	-0.91	-0.93

Seasonality

	Winter	Spring	Summer	Baseline Corr
ΔAirTemp/ΔRoadTemp	0.66	0.66	0.64	0.64
TempDiff/RainLength	0.12	0.22	0.21	0.2
AirTemp/RainLength	-0.08	-0.31	-0.4	-0.22
TempDiff/Traffic Vols	-0.19	-0.21	-0.21	-0.21
Subsurface/RainLength	-0.16	-0.4	-0.4	-0.24
RoadTemp/RainLength	-0.13	-0.33	-0.35	-0.26
TempDiff/AirTemp	0.14	-0.33	-0.6	-0.28
ΔAirTemp/ΔTempDiff	-0.1	-0.32	-0.4	-0.31
TempDiff/RoadTemp	-0.4	-0.74	-0.89	-0.58
ΔRoadTemp/ΔTempDiff	-0.81	-0.92	-0.96	-0.93

Surface State

	Dry (4)	Moist (5)	Wet (6)	Not Dry	Baseline Corr
ΔAirTemp/ΔRoadTemp	0.64	0.73	0.64	0.65	0.64
TempDiff/RainLength	0.1	-0.1	-0.02	-0.03	0.2
AirTemp/RainLength	-0.18	-0.05	-0.18	-0.07	-0.22
TempDiff/Traffic Vols	-0.24	-0.23	-0.15	-0.17	-0.21
Subsurface/RainLength	-0.2	-0.03	-0.17	-0.06	-0.24
RoadTemp/RainLength	-0.19	-0.01	-0.17	-0.06	-0.26
TempDiff/AirTemp	-0.27	0.28	0.13	0.16	-0.28
ΔAirTemp/ΔTempDiff	-0.32	-0.39	-0.26	-0.28	-0.31
TempDiff/RoadTemp	-0.58	0.05	-0.05	-0.04	-0.58
ΔRoadTemp/ΔTempDiff	-0.93	-0.91	-0.91	-0.91	-0.93
AirTemp/RoadTemp	0.94	0.97	0.98	0.98	0.94
Subsurface/RoadTemp	0.8	0.87	0.92	0.91	0.81
AirTemp/Subsurface	0.88	0.85	0.9	0.89	0.89

Traffic Volumes

	Top 25%	Bottom 25%	Baseline Corr
ΔAirTemp/ΔRoadTemp	0.63	0.6	0.64
TempDiff/RainLength	0.21	0.22	0.2
AirTemp/RainLength	-0.25	-0.28	-0.22
TempDiff/Traffic Vols	0.2	-0.16	-0.21
Subsurface/RainLength	-0.29	-0.28	-0.24
RoadTemp/RainLength	-0.27	-0.31	-0.26
TempDiff/AirTemp	-0.39	-0.11	-0.28
ΔAirTemp/ΔTempDiff	-0.34	-0.15	-0.31
TempDiff/RoadTemp	-0.69	-0.28	-0.58
ΔRoadTemp/ΔTempDiff	-0.94	-0.88	-0.93
AirTemp/RoadTemp	0.94	0.98	0.94
Subsurface/RoadTemp	0.79	0.93	0.81
AirTemp/Subsurface	0.89	0.9	0.89

Urban Class

	1	2	3	Baseline Corr
ΔAirTemp/ΔRoadTemp	0.62	0.67	0.63	0.64
TempDiff/RainLength	0.21	0.15	0.26	0.2
AirTemp/RainLength	-0.2	-0.23	-0.22	-0.22
TempDiff/Traffic Vols	-0.17	-0.18	-0.3	-0.21
Subsurface/RainLength	-0.22	-0.24	-0.25	-0.24
RoadTemp/RainLength	-0.24	-0.26	-0.27	-0.26
TempDiff/AirTemp	-0.29	-0.22	-0.32	-0.28
ΔAirTemp/ΔTempDiff	-0.29	-0.33	-0.32	-0.31
TempDiff/RoadTemp	-0.6	-0.51	-0.63	-0.58
ΔRoadTemp/ΔTempDiff	-0.93	-0.92	-0.94	-0.93