Validation of WUI-NITY compared to real-world data

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Abstract
This thesis compares the wildfire evacuation simulation programme, WUI-NITY, against real-world data by analysing and comparing three wildfire events of the past. The wildfire events were all limited to be within the state of California and was further analysed based on the available quality of data derived of the chosen database. The goal with this thesis was to setup simulations based on the evidence found from the wildfire events with the aim of establishing benchmark values and to address further improvement recommendations towards simulating real-world events. This was performed by doing a total of 24 simulations, eight for each case whereof there was a total of two varying factors, route choice and response curve, meaning there was four route choices and four derived response curves for each wildfire case. The four route choices available was fastest, shortest, random, and route depending on evacuation group. For each route choice it was simulated a default response curve which was compared against a derived response curve. Each simulation was compared to the equivalent real-world case to establish the wanted benchmark values and to address further improvement recommendations. For all simulations, no matter which case was studied, it was found that it must always be derived a response curve when replicating a real-world event. Another finding was that even with a proper response curve it may still not mirror the real event in the sense that the population and the number of vehicles used may not match the one of the real-world. This effects the traffic flow and therefore also the time of traffic events to happen (e.g congestions). As future improvement recommendations it is of interest to implement devices to measure critical outputs such as traffic flow, congestions, and number of vehicles.

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I.Summary

WUI-NITY is a wildfire simulator using the three models, fire, pedestrian, and traffic, to simulate evacuations. WUI-NITY has not yet been validated towards real-world data and is therefore not yet confirmed how well the programme performs, replicating, a real-world event. For this thesis the focus has been to simulate a replicate of a real-world wildfire to compare against the result derived of findings from the chosen wildfire. The aim of the comparison has been to establish benchmark values when replicating a real-world event and to address recommendations for improvement for future WUI-NITY updates. This was done in the following nine high-level steps:

- Literature study
- Choosing representative wildfires
- Find key factors of evacuation
- Choose traffic database
- Extract data using database
- Setup simulations in WUI-NITY
- Run simulations in WUI-NITY
- Compare WUI-NITY results against the real-world data of the chosen database.
- Establish benchmark values and address future recommendations

Literature study was performed to find relevant sources to learn about evacuations, wildfires, wildland urban interface, traffic databases and WUI-NITY. From those sources it was chosen three representative wildfires that could be further studied by the chosen traffic database and other findings. The chosen traffic database is limited to the traffic of California meaning the representative wildfires are all within California and other findings include key factors of evacuation. The step after determining the traffic database was to extract and derive data to use as both comparison against the WUI-NITY simulations but also as benchmark values to the setup of the simulations. Once necessary data had been gathered, the setup of each simulation was performed. It was three wildfires studied and for each case eight simulations were setup varying both response curve and route choice making it a total of 24 run simulations. The last step was to compare the results of the simulations against the data gathered from the traffic database in regards of the varied factors and key findings of evacuation. After the comparison it was concluded the use of WUI-NITY as of today and it was addressed recommendations for further implementations needed for comparison with real-world data.

II.Acknowledgments

This thesis is performed in the course of VBRM01 in the fire and protection engineering discipline of Lunds Technological University. This course is the last step before graduation and was performed in the winter of 21/22. This thesis was made mostly from own studying and research but with a lot of guidance from the supervisor and the programmer of WUI-NITY. Weekly meetings and updates were sent to the supervisor and any concerns regarding WUI-NITY was quickly answered from the programmer of WUI-NITY.

As an introduction to this thesis, the author would especially want to thank following people for guidance, help and valuable insights that made this thesis possible. Without the support from these people, it would be impossible to finish the thesis and much less draw any representative conclusions towards the improvement of WUI-NITY. The interest for this subject was greatly increased with the support and guidance of the following people.

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	Supervisor for this thesis which committed with great enthusiasm and a lot of good input throughout the working process. Weekly meetings that became one of many things to look forward to each time with every new insight given.
Enrico Ronchi	Senior lecturer
	Spider in the web of this thesis which committed by being, connecting the author to important contacts and was the person who brought the authors attention towards the subject of this thesis.
Jonathan Wahlqvist	Researcher
	Programmer of WUI-NITY. Every problem in regards of WUI-NITY was quickly addressed and solved, no matter the time of the day. If there was any issue greater than what could be solved by the user, Jonathan made sure to update WUI-NITY accordingly.
Friends and family	Always supportive no matter how the work is going. Always there to cheer one up when it is tough and always there to continue the support when in good progress.

III.Terminology

VHD	Vehicle hours of delay
VDS	Vehicle detector station
WUI	Wildland urban interface
VKT	Vehicle kilometre travelled
PeMS	Performance Measurement System
Caltrans	California department of transportation

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1. Introduction

1.1. Background

The world-wide wildfire situation has historically worsened, especially in the US, Australia, and Southern Europe. Factors affecting the severity of wildfires include increased fire activity, warmer and drier summers, stronger winds, and population growth near or in the wildland urban interface (WUI) (Ronchi, et al., 2020). In California alone the losses from WUI fires are fundamental, averaging 177 million USD per year. Over a twenty-year timespan has the size of WUI increased by 33 % and the number of homes increased by 41 % (U.S Fire Administration, April 2021).

The expanding of the WUI in combination with the warmer and drier climate is a contribution to more severe and higher losses due to wildfires. In regards of future WUI fires it can be expected that community evacuations will pose a severe safety challenge. The safety challenge includes factors such as short- and long-term damage to infrastructure, social disruption, evacuee, and even responder fatalities or injuries (Ronchi, et al., 2020). A community evacuation may also face fast growing and rapidly spreading fires in an unpredictable way which further exhausts a safe evacuation (Ronchi, et al., 2021).

Due to this evolved situation with harsher wildfires threatening communities along with its population it becomes more important by day to understand, learn, and even predict future disasters.

As of now there are limited resources to evaluate previous and ongoing fires but even fewer resources available to quantify the vulnerability of communities for future designs. Tools are appearing (e.g. WUI-NITY). WUI-NITY is a platform made to assess the evacuation performance of residents while implementing three model platforms, pedestrian movement, fire development and traffic simulation. These evacuation scenarios enable us not only to evaluate the past and present, but also to assess future scenarios. Without such tools, design assessments would only be qualitative limiting the types of comparisons that can be made and the insights that might be drawn (e.g. whether one community design or evacuation plan is more effective than others that might be used given the scenarios faced) (Ronchi, et al., 2020). This type of tool aims at achieving safety of the inhabitants of threatened areas as they are being affected by the larger and more severe wildfires occurring (Hoover & Hanson, October 4 2021).

To make the tool more representative and to increase confidence and capabilities in real life applications it must be tested against credible and representative data-sets, meaning not only drills but also to real-world data. This thesis will identify such real-world data and compare the performance of the WUI-NITY model against it.

1.2. Purpose and goals

The purpose of this thesis is to extract and analyse real-world data of wildland urban interface fires and compare these against WUI-NITY with the goal of making it more trustworthy to use but also to increase confidence and capabilities in real life applications.

1.3. Boundaries and limitations

This thesis will compare WUI-NITY against traffic conditions derived from a third-party resource over which the collected data is controlled. Any data used will be partial and likely exclude key factors that might impact the analysis conducted, for example cars point of origin and end destination. The limited time available for the thesis makes it necessary to narrow down and focus on the most vital key factors of community evacuation traffic flow to validate WUI-NITY. The specifics of this focus will be outlined during this thesis.

1.4. Method

The first step will be to conduct background reading of the selected wildfire evacuation material to get a general understanding of the factors that might be present, the responses likely and the conditions that might be faced (i.e. evacuation scenarios). This includes background reading of other evacuation tools available to be able to place WUI-NITY capabilities into context.

The second part of the thesis is to perform a review of existing databases that may be used for validation of WUI-NITY (e.g. traffic databases such as PeMS). Data is extracted and derived from the chosen traffic database with focus of the evacuation factors found from the first step. The gathered data is analysed to be used as benchmark values and to be compared against WUI-NITY.

The third step is to get familiarized with the WUI-NITY platform being used for this project. Simulation scenarios are created by using benchmark values from the second step. The benchmark values used for the setup of the simulations are to define the response curve, background density, car accidents, lane reversals among others.

The fourth step is to compare the result of WUI-NITY against the chosen traffic database. From the comparison, conclusions regarding the use of WUI-NITY as of today can be drawn and recommendations for future WUI-NITY updates can be presented.

2. Key factors of community evacuation

A community evacuation is complex, involving multiple series of events and multiple interacting elements. It involves not only the individual evacuee but also the surrounding environment in regards of available escape routes, eventual loss of routes due to progressing fires (and exposure to fire conditions), potential congestion experienced along the available routes or even accidents along the way.

Throughout a community evacuation the existence and impact of background traffic should be considered. In addition, the preference of people to remain rather than evacuate might affect the number and timing of evacuation. Just as any other action, there is also a certain response time of the individual before the actual evacuation begin (Ronchi, et al., 2020). In the paper by Sandra et al. (2021), the complexity of wildfire evacuation is established pointing to the need to consider various factors. These factors include available routes, time to reach shelters and response time of the population when determining the survivability and the appropriateness of staying over leaving. Key factors of community evacuation are concluded to be response time and traffic flow. Traffic flow includes events like congestions, vehicle speed, lane reversals and even car accidents.

3. Earlier wildland urban interface fire events

The fire events below are a summary of some case studies from Case studies of large outdoor fires involving evacuations (Ronchi, et al., 2021). These cases will be of use when using the traffic flow data source to find information regarding traffic flow but also to set up the simulations of WUI-NITY to compare data with.

3.1. Camp fire

Camp fire occurred in November 2018, California USA. The fire was a fast-moving and had an impact of several living areas but especially the town of Paradise, California. Paradise was ordered an evacuation but had trouble executing it because of traffic congestion and the fast-moving fire. This caused people to be trapped in their cars forcing them to either continue on foot or stay in their car. The problem was even greater for the elderly people or individuals with disabilities who may not have had the opportunity to choose the option by continuing by foot. Despite Paradise having a well-prepared plan of evacuation the setbacks occurred as the speed and magnitude of the fire progressed faster than what the inhabitants and officials could respond to. Ultimately the consequence of Camp fire turned to be the deadliest wildfire in United States history, taking 85 lives in the process. In total about 52 000 people were ordered to evacuate and was on top of that proven to be of great cost primarily financially but it also caused plenty of burned down buildings leading to, among other things, a housing crisis (Ronchi, et al., 2021).

3.2. Carr fire

Carr fire occurred in July through August 2018, Northern California USA. The fire was destructive and had a major impact on Shasta and Trinity Countries in Northern California. Weather of high temperatures and low humidity contributed to a fast-moving fire in combination with dry vegetation. In consequence to this and the direction of which the fire headed toward lead to several communities to evacuate. The evacuation progressed slowly and with problems as the roads were heavily congested especially for a lot of evacuees attempted to escape through one area. Another reason for the poor evacuation was because of inconsistent messaging and wide variations in distribution times which lead to some evacuees having little to no time evacuating. The officials also had a problem being one step ahead of the fire in regards of the erratic behaviour it had. The weather was so extreme the fire created its own local weather systems, worsen the spread and prediction of future spread even more.

Carr fire took 8 lives and had a total of about 39 000 people ordered to evacuate. Around 1 600 structures were destroyed causing damages for over $1.5 billion. (Ronchi, et al., 2021)

3.3. Atlas fire

Atlas fire occurred in October 2017, Northern California USA. The atlas fire was one of many wildfires in that area at that time. The mountain terrain at which the Atlas fire took place at caused rapid spread through the elevated, dry, landscape surrounding the city of Napa. The weather also contributed with high winds. Evacuations were ordered hours after ignition across the rural area at which the fire threatened to spread. Evacuation was not easy to carry out due to the hilly terrain and was therefore assisted by helicopters. Further evacuations were ordered out before the fire became under control.

Atlas fire did not take any lives but caused about 20 000 people to be evacuated. In addition, 120 structures were destroyed and another 783 damaged. Together with the other wildfires occurring in the area at that time an estimation of 100 000 people was ordered to evacuate (Ronchi, et al., 2021).

3.4. Woolsey fire

Woolsey fire occurred in November 2018, California USA. This was a fast-moving wildfire that had an impact on several communities and in particular the town of Malibu. The fire was fuelled by dry vegetation, low humidity and high winds making it spreading fast and unpredictable. By the time at which town Malibu and many nearby societies was ordered to be evacuated was several of the connecting routes to safety blocked by the fire resulting in major congestions at the one still available. Contraflow was implemented at the highway in attempt to increase the traffic flow.

Woolsey fire took 3 lives in the process and resulted in about 300 000 people to be evacuated. The fire proved to destroy over 1 600 structures leading to damages of approximately $6 billion (Ronchi, et al., 2021).

3.5. Hill fire

Hill fire occurred in November 2018, California USA. Hill fire coincided with the Woolsey fire and Camp fire but was the first one to threaten a large number of people and structures which lead to early orders of evacuation and a lot of firefighting resources was put in. Hill fire spread fast and towards Highway 101. Within only 15 minutes from the start, it had reached the highway which in return caused massive congestion, especially after the closure of Highway 101. The closure of Highway 101 caused congestion both for regular traffic but also for the evacuees.

Hill fire took no lives but lead to 17 000 people ordered an evacuation. This fire destroyed 4 residences (Ronchi, et al., 2021).

3.6. Fort McMurray fire

Fort McMurray fire occurred in May 2016, Alberta Canada. Fort McMurray fire started deep in the forest in an area of which consisted of both urban and rural societies. At first the weather conditions favoured the fire, fuelling it by heavy winds. As a result, warnings for eventual evacuations were ordered for vulnerable societies. Evacuation centres was opened, and a local state of emergency was declared. Eventually there were orders of evacuation of Fort McMurray leading to 12 neighbourhoods and tens of thousands of people to evacuate, there were even some evacuation centres that had to relocate because of the fire. At this point more than 60 000 people had evacuated and 2 people died. The evacuation did put the highways under great pressure.

The following days 1 600 structures had been destroyed and a provincial state of emergency was declared with 80 000 people instructed to evacuate. Another 4 000 people had to be airlifted from north of Fort McMurray. At last, there was 8 000 people evacuated from oil sites as the fire spread north.

Most people who evacuated did not have short-term contingency plans in order other than getting out of immediate danger.

Fort McMurray caused two lives to be taken (car accident when evacuating) and resulted in over 88 0000 people to evacuate. The fire destroyed over 2400 structures and leading to damages of approximately $7.6 billion (Ronchi, et al., 2021).

3.7. Victoria fire

Victoria fire occurred in February 2009, Victoria Australia. Victoria fire, also known as Black Saturday fire, started out as several smaller fires where of which most was because of natural causes. Due to extreme weather conditions with temperatures reaching around 45 degrees Celsius, low humidity and extreme winds the fires grew in size and took seven days to put out. Throughout the Victorian fire the ‘stay or go’ policy was implemented but as it spread closer to societies more people began to evacuate, especially when it was within a visible distance. Because of this late reaction of evacuation, it was not considered for the evacuation to be done until one day or a few minutes before the fire reached the society.

During the Victoria fire there was around 7 562 people who had evacuated. There was also 414 injuries and a total of 173 deaths. Over 3 500 structures were destroyed. The cost of this fire was estimated to be around $2.8 billion USD (Ronchi, et al., 2021).

3.8. Chosen fire events

From the listed fire events above, it is clear that harsh weather conditions such as high temperatures, low humidity and strong winds in combination with unpredictable fire progression can lead to dangerous wildfires in a relatively short time. These wildfires have proven to be a danger, especially for those living in wildland urban communities, but also larger towns as well including both structures and inhabitants lives. Due to the unpredictable spread of these dangerous wildfires, it has also been shown that it is not always obvious and easy to, beforehand, execute evacuation orders to ensure a safe evacuation nor the effectiveness or impact of such. Out of the listed events above they all have in common that late evacuations occurred which may have had an impact on the final result of injuries or even deaths (by compacting people’s evacuation into delayed and narrower period). In most evacuations from the cases above there was evidence of heavy traffic congestion and route clogging which may also have been a result of the late evacuation executions, perhaps an earlier evacuation may have had a positive result as more people could have evacuated for a longer period of time without the fire being a risk.

However, out of the listed events above, only the events of California will be further analysed in this thesis. This is because the chosen traffic data source, PeMS), is restricted to the Californian traffic database (see discussion in, Gather data for WUI-NITY comparisons). To make a comparison with the WUI-NITY simulation and the PeMS data only events which compile with both can be used, that is events happened in California alone.

4. Californian fires

This section covers a deeper analysis of the Californian fires. The information from this section is used as input data for the WUI-NITY simulation. The information will also be used to know where and when to look for archive data in the PeMS traffic database. A timeline for the analysed fire has been derived, Figure 1. All data gathered, are in a reduced form from the tables of each chosen fire from the reference, (Ronchi, et al., 2021). Key factors of each fire in regards of evacuation for input data for WUI-NITY and historical data for PeMS investigation are summarised below from, (Ronchi, et al., 2021).

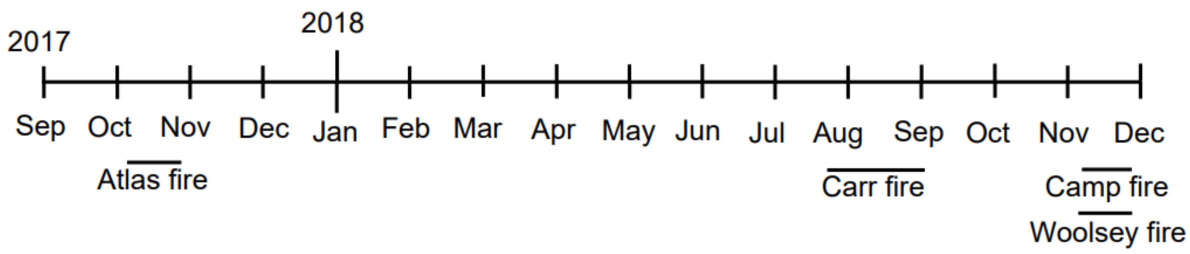


Figure 1 Timeline over the time periods of the analysed fires, Atlas fire, Carr fire, Camp fire and Woolsey fire.

4.1. Camp fire

The fire occurred from the 11th to the 25th of November 2018 within the county of Butte. During this time 153 335 acres burned and caused evacuations for Pulga, Paradise and Magalia to be ordered. The evacuation of Pulga at 8th of November 7:23 am, part of Paradise at 8th of November 8:00 am was expanded and included all of Paradise at 2:00 pm, and Magalia at 8th of November around 2:30 pm. Containment was reached at 25th of November and the evacuation orders was lifted the 5th of December.

4.2. Carr fire

The fire occurred from the 23rd of July to the 30th of August 2018 within the two counties of Shasta and Trinity. A total of 229,651 acres burned and caused orders of evacuations of both rural but also larger towns including French Gulch, Whiskeytown, Lewiston and parts of Redding. On the 23rd of July a mandatory evacuation of French Gulch was ordered. Highway 299 was closed and Whiskeytown became under mandatory evacuation on the 24th of July 9:00 am. Communities of Old Shasta, Keswick, areas around Swasey, Lower springs and Victoria Dr, including all roads coming off Rock Creek Rd and Iron Mountain Rd had a mandatory evacuation on the 26th of July at 4:03 am. On the 26th of July 7:00 am westbound traffic was closed starting at Buenaventura in Redding. On the 26th of July the fire reached the city limits of Redding forcing mandatory evacuation of urban neighbourhoods, the primary evacuation centre located at Shasta High School was evacuated to Shasta College. Parts of Redding were under mandatory evacuation stretching from west of downtown up north to Shasta Dam and down south to Happy Valley. On the 28th of July is Lewiston ordered mandatory evacuation followed up the day after to extend evacuations west.

4.3. Atlas fire

Atlas fire occurred from the 8th of October to the 28th of October 2017 within the two counties of Solano and Napa. A total of 51,624 acres burned and resulted in mandatory and advised evacuations throughout the county of Solano and Napa. On October the 8th at 11:45 pm, evacuation orders are executed around Napas county. On October the 9th at 2:00 am, evacuation orders were issued around Napa, and evacuation centres filled by 4:00 am. Throughout the night helicopters rescued 42 people from Atlas Peak. During October 9th 2:20 pm, new advisory evacuations begin around Solano County. October 9th 7:53 pm, mandatory evacuation orders are executed for the rural areas in Solano County. October 9th at 8:30 pm, further evacuations in large sections of Napa. During the day of October, the 10th evacuation orders continue to be issued in Napa County because of multiple fires in the area. On October 11th, advisory evacuation orders continue to expand across Napa County and Solano County. The information is summarised from.

4.4. Woolsey fire

Woolsey fire occurred from the 8th of November to the 21st of November 2018 within the two Counties of Ventura and Los Angeles. A total of 96,949 acres burned and affected several communities, especially Malibu. The fire started at the Santa Susana Field Laboratory and from there spread mostly South. The first mandatory evacuation order was executed on the 8th of November approximately 5:40 pm for Bell Canyon straight south of fire origin. On the 9th of November at 12:00 am, Oak Park, southwest of Bell Canyon, was subject to a mandatory evacuation order followed by Kevington just 2 hours and 20 minutes later. Around that time the fire spread quickly south and jumped highway 101 at 5:15 am resulting in mandatory evacuations for multiple communities south of Highway 101. At 10:00 am Malibu was ordered to evacuate. Around 12:00 pm fire reached heavily populated parts of Malibu and spread over the next few days all the way to the Pacific Ocean.

4.5. Hill fire

Hill fire occurred from the 8th of November to the 16th of November 2018 within the County of Ventura. A total of 4351 acres burned and had both Highway 101 closed and had multiple societies south of Newbury Park evacuated. The fire started near eastern Camarillo/Newbury Park on the 8th of November 2:00 pm. 15 minutes later the fire reaches Highway 101. At 2:27 pm evacuation orders for the local water treatment plant and hiking trails in the area are issued. At 2:44 pm Camarillo Springs is under mandatory evacuation. At 3:03 pm Highway 101 is closed in both directions and mandatory evacuation expands to include Vicieto Trailer Park, Dos Vientos and California State University Channel Islands. At 7:49 pm Areas in the South Coast are issued mandatory evacuation. Over the next following days is the fire being under control and on the 16th of November is it 100 % contained.

5. Gather data for WUI-NITY comparisons

The practitioner can gather data on real-world incidents and associated evacuations. Several platforms exist representing these data-sets. This data might be used to gain insights into historic events and to project future conditions. Evacuation models exist that can estimate evacuation performance. The effectiveness of these projections will be reliant on the model's functionality and the data available. In this chapter data platforms and evacuation models are examined. The intention is to identify data platforms that enable insights into real-world performance during incidents and enable evacuation models to be configured to make retrospective projections. In essence, the data (suitably segmented) will be used to configure the model and provide a benchmark against which the model's output can be compared.

5.1. Traffic modelling source

Traffic modelling is made up of beforehand analysed data of which the user chooses. That data can be used for the tool to calculate an event to predict a possible outcome. To perform a traffic model, input data must be inserted for the modelling tool to function. This input data is either gathered from quantitative methods, which is based on statistical data, or qualitative methods, which is based on visual examination or expert knowledge. With the chosen input data, the modelling tool predicts what would happen in that given scenario and can be used in many ways, for example to increase the road safety of an accident-prone road (Moutari, et al., 2012).

5.2. Traffic data source

Traffic data source consists of archived events in the past or even happenings occurring in the present. The data is gathered from example vehicle detectors logging events such as vehicle speeds. The logged information is sent to an archive base for later use. The data can be compared to other data-sets to create more complex analysis tools (e.g charts over traffic congestions over time). One of the tools available to gather traffic data is PeMS which is a Californian based traffic software tool (California department of transportation, 2020).

5.3. Modelling or data source?

For this thesis it is of interest to compare WUI-NITY to data gathered from earlier real-world events. The chosen data to work with should not have been tempered with but should rather be taken straight from the specific event. Therefore, there it is of no interest for this thesis to use any data from traffic modelling but instead have it from a first-hand data source. WUI-NITY must be compared to non-user-modified data because it must be analysed and made more trustworthy. It does not become trustworthy if the chosen data to work with comes from a modelling tool since the entire model is user defined. The chosen dataset of this thesis after comparison of the two alternatives ends up being traffic data source.

5.4. Different data sources

There are plenty of data sources available as of today. Therefore, it is necessary to find and compare a few alternatives against each other to determine the best suitable data source for this project.

One alternative is to choose a commercial data source. There are plenty of commercial options available (e.g CARTO (CARTO, Accessed January 2022)). A commercial data source may be good because the companies' goal is to keep the costumers pleased and therefore aims to be the best on the market to provide good quality of data for easy access. The downside with a commercial data source is that it is not free of charge.

A second alternative is to use a data source free of charge. There are several different options in this category of traffic data sources as well. One data source available is to use, Google Maps traffic, which tracks traffic in real-time and can give an estimate of traffic data (Google, Accessed January 2022). A data source such as Google is user friendly and is also easy to access. Google is also world-wide covering meaning fire all over the world may be studied. The downside of using a database like Google is that the traffic data registered is in real-time and therefore not of use for the fires of interest stretching back in time. Google does not measure specific traffic data (key factors of evacuation) but rather a general traffic flow of chosen time.

The third alternative which is also free of charge is to use a data source with archived data. This archived data would be of interest to find traffic data for a specific time period (e.g fire events). One data source that meets this criterion is, performed measurement system (PeMS) (California department of transportation, 2020). PeMS both tracks data in real-time but also archives historical data for later use, which is of convenience for this project. PeMS registers and archives data including key factors of evacuation which is also of interest. The downside of PeMS is that it is limited to register traffic within the state of California, USA.

5.5. Chosen source

The chosen data source tool from the mentioned above is, PeMS. PeMS is chosen because it is the only found data source free of charge which archives historical data and includes data of key factors for evacuation. PeMS is a software tool developed for California department of transportations (Caltrans). The tool tracks real-time traffic data throughout California state highways or provided by a consolidated database both of which is gathered from Caltrans or any other partner agency. The data is stored and can be accessed at any time from any standard browser. The gathered traffic data can be accessed both for current and archived, historical, events. Some variables that may be analysed are volumes, speeds, delays, and travel time (California department of transportation, 2020).

PeMS is chosen therefore it meets all requirements asked for this thesis. The data from PeMS is first-hand data gathered from detectors, among other sources, and thereafter archived in the PeMS database. This enables data from the past (e.g earlier fire events) to be extracted, studied, and ultimately compared to data from WUI-NITY. The most vital reason for choosing PeMS is because the data includes the key factors of a community evacuation to be compared to the data of WUI-NITY.

6. WUI-NITY – what it is and why the tool was chosen

WUI-NITY modelling platform is an evacuation tool of wildland urban interface wildfires. The platform includes several modelling layers (fire, pedestrian, and traffic) and merge them into one single modelling environment. The aim of this platform is to quantify the result of these three modelling layers to be able to compare the models together, usually in a timeline (Ronchi, et al., 2020). This platform is new (released 2019) and has therefore not yet been validated to real-world data. For broader use and a more trustworthy result, WUI-NITY, must be compared to and validated for real-world data of earlier fire events.

The latter is the reason why WUI-NITY was chosen for this thesis. To make WUI-NITY more trustworthy and thereby making it accessible for broader use with validated data. WUI-NITY may not be the only tool to simulate community evacuations, but the reason WUI-NITY was chosen over any other evacuation tool, besides what is already mentioned, is that the programmer behind WUI-NITY is based at Lund University. This makes it convenient and easier for any concerns or even future solutions for the tool to be directly addressed to the programmer and implemented into the WUI-NITY tool.

6.1. Important information to run WUI-NITY

WUI-NITY requires the user do download, Framework .NET 3.5, before any simulation can be run (Microsoft, Accessed January 2022). This is because WUI-NITY is run using the necessary tools gathered from Framework .NET 3.5. It is still possible to open WUI-NITY and to look at the menus, but it will not be possible to load and run a simulation without the user having Framework .NET 3.5 on the computer. Once that is added WUI-NITY will function.

7. Analysis of PeMS Data-Sets

Data for each chosen fire event in California are studied and extracted from PeMS database, see (Table 1). The extracted data are collected and analysed below in a sub-section for each fire event. Data is extracted and analysed for comparison with the data collected from the results of the WUI-NITY simulation for the scenarios based on input data from each fire event. The data is also used as benchmark for configuring the simulations in WUI-NITY.

Table 1 The analysed data of PeMS

Analysed data	Comment
Data quality	All data gathered for this thesis must be of good quality. The registered data of the PeMS VDS's is either observed (good quality data) or input (bad quality data) where only the good quality data is used, meaning any input data will be excluded. This is analysed in the sub-chapter Data quality.
Traffic flow	Traffic flow changes over time. It is of interest to find and conclude these changes, especially to see the difference varying between day and night-time. The gathered traffic flow data is also used to establish a benchmark of the traffic flow over each fire event which is later used to derive the redefined response curves.
Vehicle speed	Vehicle speed is one factor that is dependent on the ongoing traffic flow. If the roads flow capacity is high the vehicle speed decreases. These changes are of interest to compare against WUI-NITY.
Car incident	Car incidents are analysed because it is one factor which can be turned either on or off from the setup of WUI-NITY. If evidence from PeMS of car incidents can be derived it is assumed this factor true over the fire event.
Background density	In a real-world event there are always some levels of background traffic going on, on top of the evacuating population. This is also a factor that can be defined in the setup of each simulation and is therefore of interest to derive and define for each simulation.

7.1. Data quality

To consider the data analysed from PeMS reliable, it must be assessed. This is done by analysing the detector health; i.e. that the expected sources of data being gather on traffic movement were functioning as expected. This is achieved from an aggregate level (district and County) down to a detailed level of any chosen vehicle detection station (VDS). The detector health from an aggregate level is an overall indication of how good the data is for that specific area, with a higher percentage of detector health meaning better quality of data. Low detector health indicates that registered data is either missing or incorrect. To compensate for that PeMS develops estimated or input data to replace the holes of bad data. For this thesis it is of no interest to use developed data and therefore only data consisting of 100 % good detector health is used and all other data excluded. The analysis of the data is performed to ensure that whatever data is used as benchmark towards WUI-NITY and for comparison against the simulations of WUI-NITY is of high quality and therefore should reflect the reality better (California department of transportation, 2020).

Aggregate detector health is found from either a district or County of interest and from the PeMS menu choosing, DATA QUALITY, DETECTOR HEALTH AND SUMMARY. The detailed level analysis is studied for the data quality of each chosen detector which is found using the inventory map. From the VDS menu address DATA QUALITY, DETECTOR HEALTH AND TIME SERIES. It is not only the quality of data that must be verified but also the fidelity of data. The fidelity is a percentage of observed data in relation to imputed data by PeMS. When a VDS registers low observations, bad data, PeMS develops estimated or input values to fill holes and replace the bad data. A good working detector registers high percentage observed data. (California department of transportation, 2020).

The data for VDS of further investigations must be of good quality. That is a good working detector with 100 % observed data. Any timespan of data that is not 100 % observed is considered non-trustworthy and that timespan will be excluded for comparison with WUI-NITY.

The sub-sections are divided to first analyse the data quality of the area around each fire. Beginning from an aggregate level to work it down to a detailed level. This is to find and verify good working detectors with reliable set of data to further address traffic flow and factors effecting traffic flow. The detectors when first mentioned are marked with SOUTH, WEST, NORTH OR EAST. This mark indicates in which direction the traffic is coming from. For example: Detector 409482 (west) indicates it is registering traffic coming from west traveling east.

7.1.1. Carr fire

District data – District 2: Northeast

Carr fire occurred within borders of District 2: Northeast (California Department of Transportation, Accessed January 2022). District 2: Northeast, has no detectors at all, regardless of time period. There cannot be any data extracted from the Carr fire because there are 0 detectors in the district to analyse. Carr fire is therefore excluded from any further analysis.

7.1.2. Camp fire

District data – District 3: North Central

Camp fire occurred within borders of district 3: North Central. The data extracted shows a total of 2676 detectors with an overall mean value detector health of 73.5 %. The best percentage detector health reached 74.8 % at the 14th and the lowest percentage detector health reached 71.0 % on the 23rd of November, Figure 2.

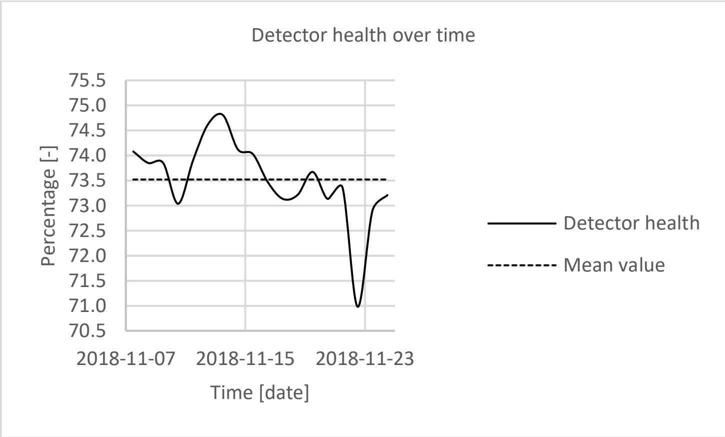


Figure 2 Detector health for District 3: North Central over the time period of which Camp Fire occurred

County data – Butte County

The fire was within borders of Butte County. The data extracted shows a total of 7 detectors with an overall detector health of 100 %.

VDS data – Butte County

Of the 7 detectors only 1 set was running at the time of the fire, Figure 3. The detector to the top left southern direction is named, 318510 (south), and the northern direction named, 318509 (north).

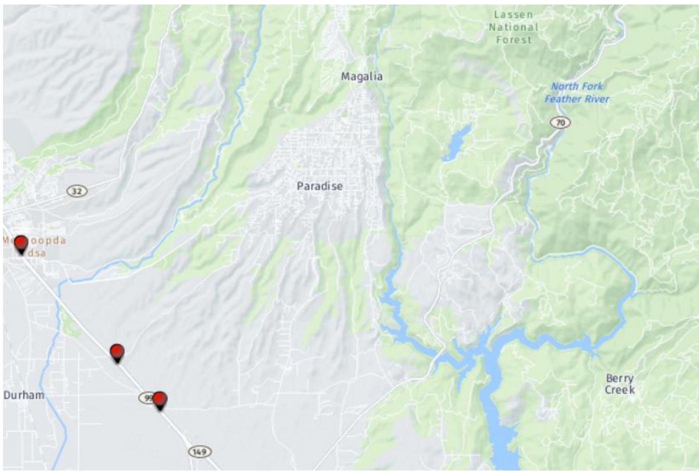


Figure 3 Map showing VDS around the towns of Paradise and Magalia. Only the top left detector was working at the time. Picture taken from the inventory map of PeMS (PeMS, Accessed January 2022).

The overall data quality for detectors 318510 and 318509 are shown in, Table 23 in Appendix A. The result show only good values throughout this time period.

The fidelity analysis, Figure 4, shows that both detector 318509 and detector 318510 got imputed data over the time period (see Table 2). For further use for comparison and use of benchmark values against WUI-NITY, the input values must be excluded as shown in, Table 2.

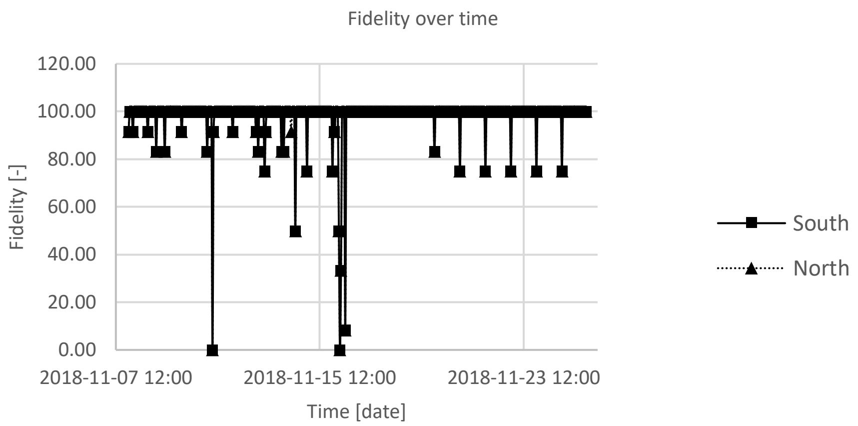


Figure 4 Fidelity over time for detector 318509 and 318510 west of Paradise.

Table 2 Times over bad data for detectors 318509 and 318510.

Date	Time of estimated or imputed data
2018-11-08	00:00
2018-11-08	04:00
2018-11-08	18:00
2018-11-09	02:00
2018-11-09	10:00
2018-11-10	02:00
2018-11-11	02:00
2018-11-11	07:00 – 08:00
2018-11-12	02:00
2018-11-13	00:00
2018-11-13	02:00
2018-11-13	08:00 – 09:00
2018-11-14	00:00
2018-11-14	02:00
2018-11-14	13:00
2018-11-15	00:00
2018-11-16	00:00
2018-11-16	02:00
2018-11-16	06:00 – 07:00
2018-11-16	12:00
2018-11-20	00:00
2018.11.21	00:00
2018-11-22	00:00
2018-11-23	00:00
2018-11-24	00:00
2018-11-25	00:00

Summary

Both detectors suffer from bad data within the time period of the Camp fire. These findings will be used when analysing the other factors of PeMS (e.g traffic flow) and the time of the estimated and imputed data will be excluded. This is to make the best quality of data possible with the means used.

7.1.3. Atlas fire

District Data – District 4: Bay Area

Atlas fire occurred within borders of District 4: Bay Area. The data extracted shows a total of 11 071 detectors with an overall mean value detector health of 67.2 %. The best percentage detector health reached 68.4 % at the 13th and the lowest percentage detector health reach 65.4 % on the 9th of October, Figure 5.

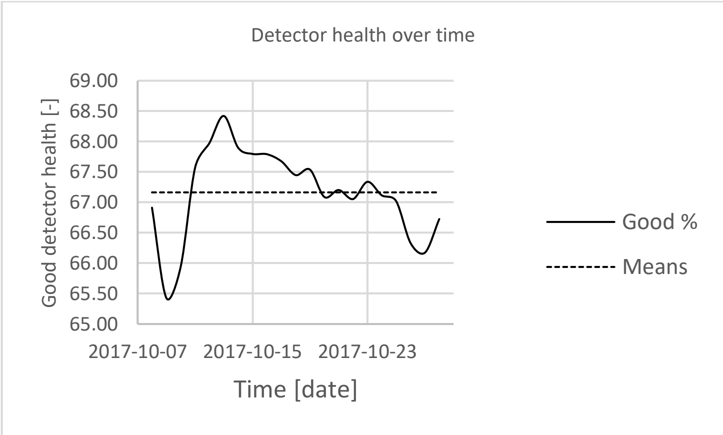


Figure 5 Detector health for District 4: Bay Area over the time period of which Atlas fire occurred.

County data – Solano and Napa County

The fire was within borders of Solano and Napa County. The data extracted shows a total of 918 detectors in Solano and 49 detectors in Napa. Detector health in Solano County shows a mean value of 63.9 % and peaks at 65.6 % the 21st of October, Figure 6. Detector health in Napa County shows a mean value of 69.8 % and peaks at 73.5 % the 21st of October, Figure 6.

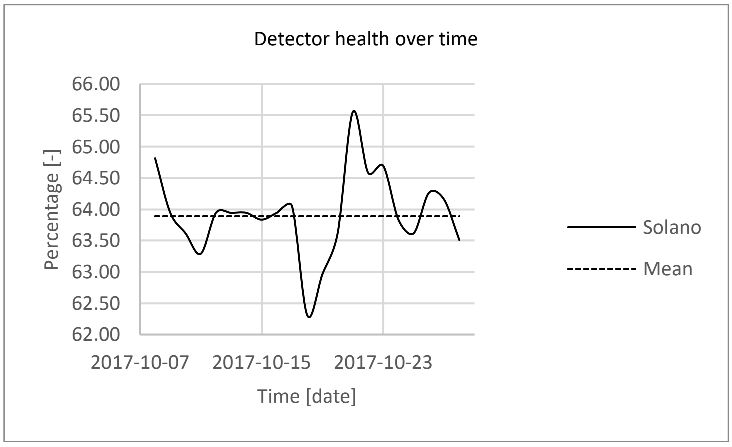


Figure 6 Detector health for County of Solano over the time period of which Atlas Fire occurred.

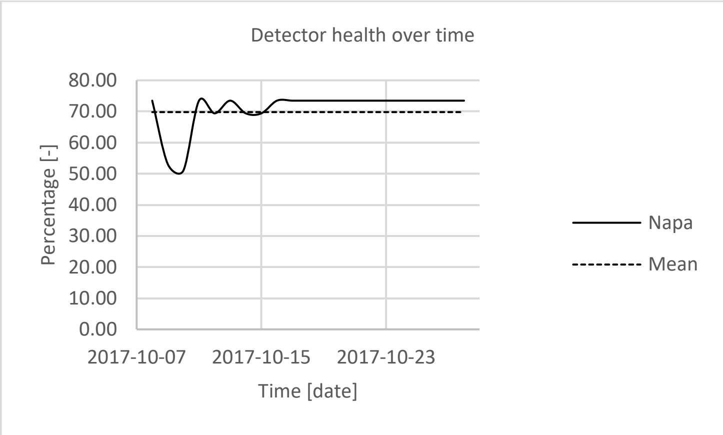


Figure 7 Detector health for County of Napa over the time period of which Atlas Fire occurred.

VDS data – Solano and Napa County

Of the total 967 detectors, only a handful were running at the time of the fire and 7 of them screened because of their geographical location. The seven chosen detectors are 409482 (west), 410790 (west), 410756 (east), 402270 (east), 402269 (west), 413373 (east) and 410817 (west), Figure 8, Figure 9.

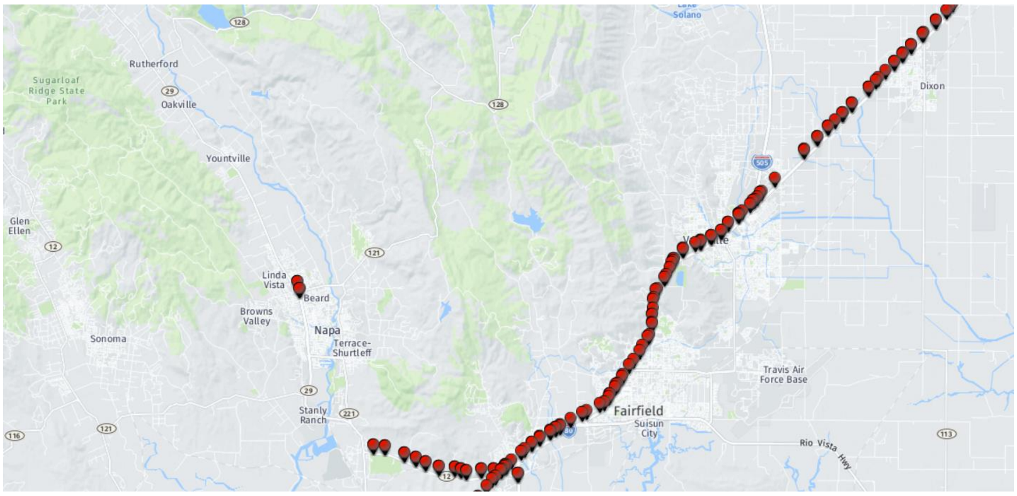
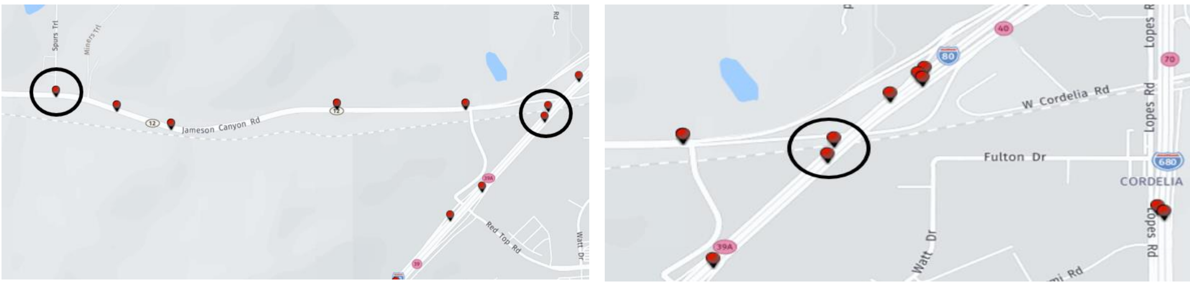


Figure 8 Map over the affected area for the Atlas fire including VDS. Map taken from PeMS inventory map.



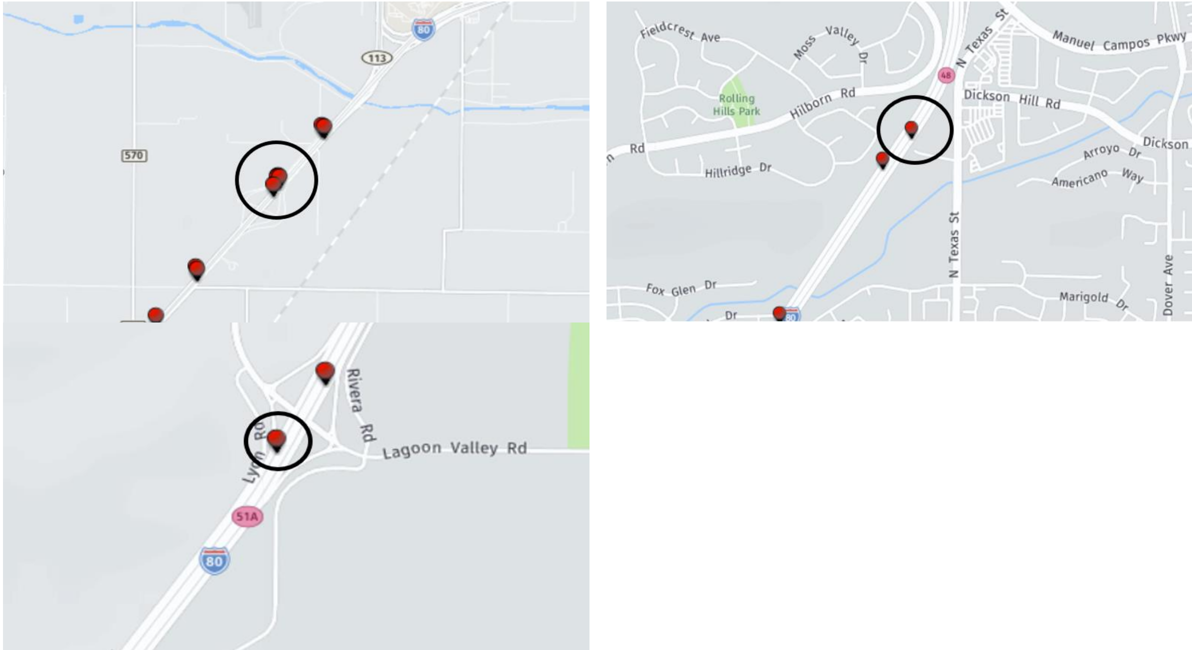


Figure 9 Map showing the VDS 409482 (upper left), 410790 and 410756 (upper right), 402270 and 402269 (middle left), 413373 (middle right) and 410817 (lower left) for further analysis. Map taken from PeMS inventory map.

The overall data quality for detector 409482 are shown in,

Table 24 in Appendix A. The result show only good values throughout this time period.

The data for fidelity of detector 409482 was analysed and extracted. It shows an overall trustworthy detector with only a few minor timespans of imputed data from PeMS, Figure 10. For further use for WUI-NITY benchmark values and comparison the imputed values must be excluded as shown in, Table 3.

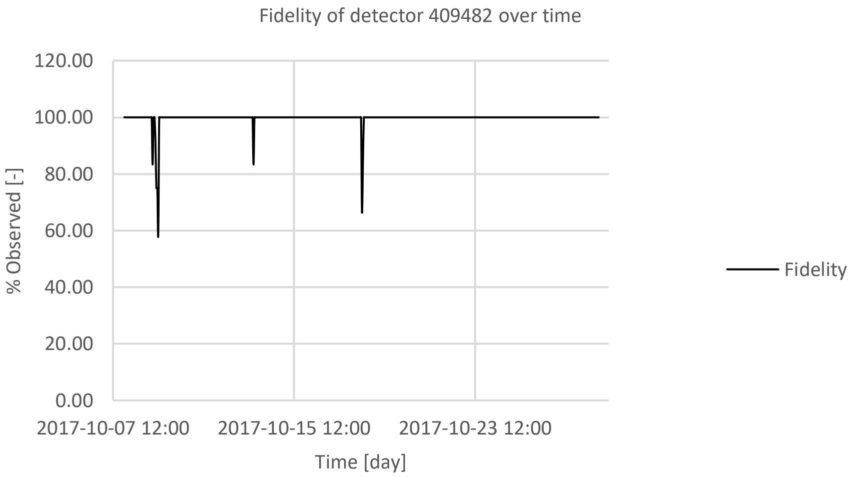


Figure 10 Fidelity for detector 409482 over time period of Atlas fire.

Table 3 Times over bad data for detector 409482.

Date	Time of estimated or imputed data
2018-10-09	06:00
2018-10-09	09:00
2018-10-09	10:00 – 11:00

2018-10-09	12:00
2017-10-13	17:00
2017-10-18	12:00
2017-10-18	13:00

The overall data for the set of detectors 410790 (Western) and 410756 (Southern) shows that both are bad detectors with faults,

Table 25 in Appendix A.

This is confirmed by analysing the fidelity of 410790 and 410756. The fidelity of both detectors shows only imputed data, Figure 11. That means all data for these two detectors are considered non-trustworthy and should therefore be excluded.

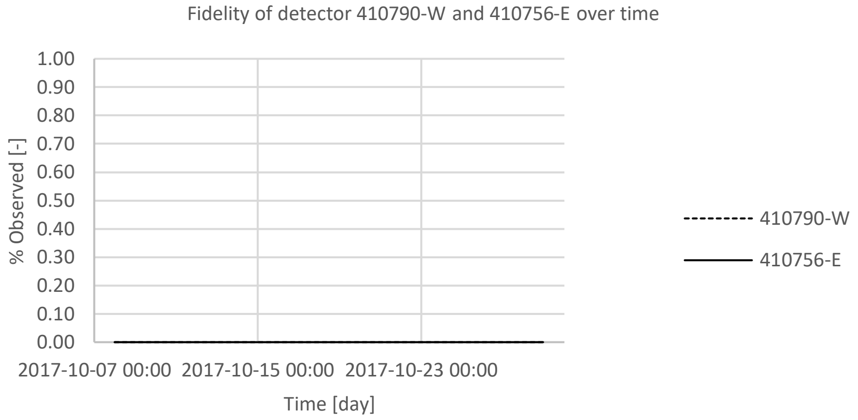


Figure 11 Fidelity for the two detectors 410790 and 410756 over time period of Atlas fire

The overall data for 402269 and 402270 is like the set of detectors 410790 and 410756 and shows it is also at fault, see Table 26 in Appendix A.

This is also confirmed by the fidelity of the two detectors which is 100 % imputed data and therefore considered non-trustworthy and excluded for further use (see Figure 12).

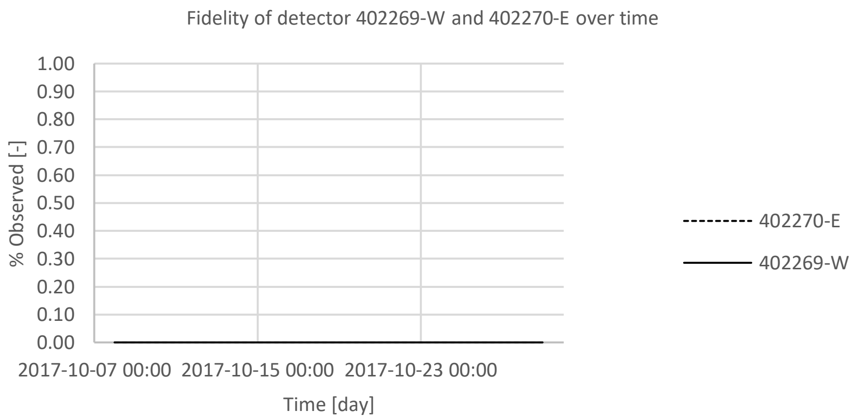


Figure 12 Fidelity for the two detectors 402270 and 402269 over time period of Atlas fire.

The overall data quality for detector 413373 are shown in, Table 27 in Appendix A. The result show only good values throughout this time period.

The fidelity of detector 413373 was analysed and extracted. It shows an overall trustworthy detector with only a few minor timespans of imputed data from PeMS, Figure 13. For further use for WUI-NITY benchmark values and comparison the imputed values must be excluded as shown in, Table 4.

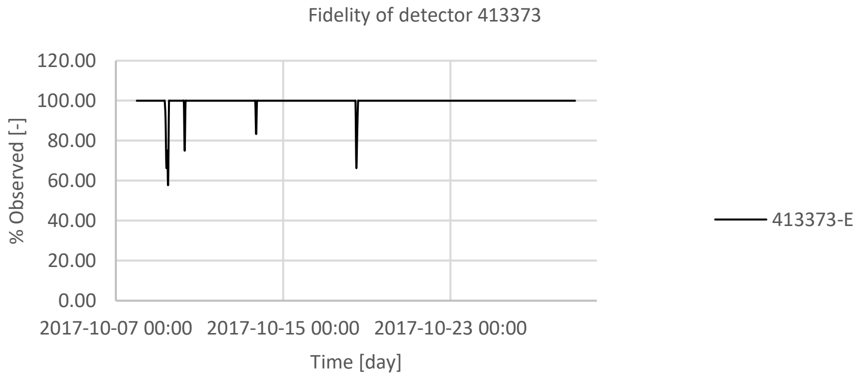


Figure 13 Fidelity for the detector 413373 over time period of Atlas fire.

Table 4 Times over bad data for detector 413373.

Date	Time of estimated or imputed data
2017-10-09	09:00 – 12:00
2017-10-10	07:00
2017-10-13	17:00
2017-10-18	12:00 – 13:00

The overall data quality for detector 410817 are shown in Table 28 in Appendix A. The result shows only good values throughout this time period.

The fidelity of detector 410817 was analysed and extracted. It shows an overall trustworthy detector with only a few minor timespans of imputed data from PeMS, Figure 14. Times of which the detector is considered non-trustworthy and therefore exclude that data over that time period is shown in, Table 5.

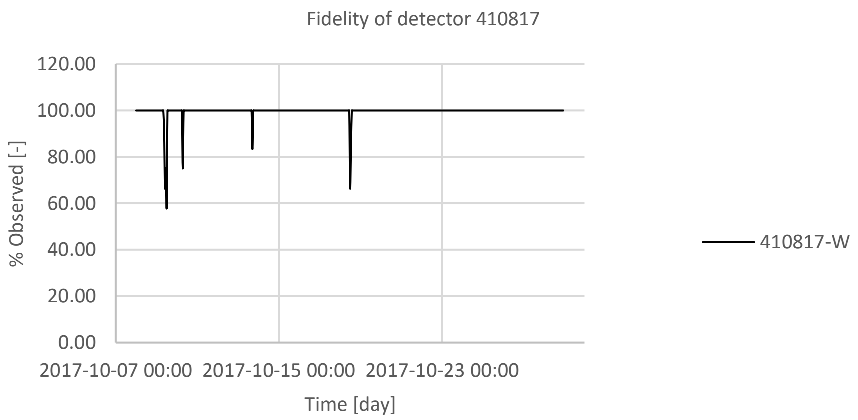


Figure 14 Fidelity for the detector 410817 over time period of Atlas fire.

Table 5 Times over bad data for detector 410817.

Date	Time of estimated or imputed data
2017-10-09	09:00 – 12:00
2017-10-10	07:00
2017-10-13	17:00
2017-10-18	12:00 – 13:00

Summary

Of the seven detectors that where screened, there are three detectors, 409482, 413373, and 410817, registering sufficient data to further derive the other factors of PeMS (e.g traffic flow). Some data within this time period is however of bad quality and will be excluded when deriving the other factors. This is to make the best quality of data possible with the means used.

7.1.4. Hill fire and Woolsey fire

District Data – District 7: LA/Ventura

Hill fire and Woolsey fire occurred within borders of District 7: LA/Ventura. The data extracted shows a total of 11 104 detectors with an overall mean value detector health of 76.0 %, Figure 15.

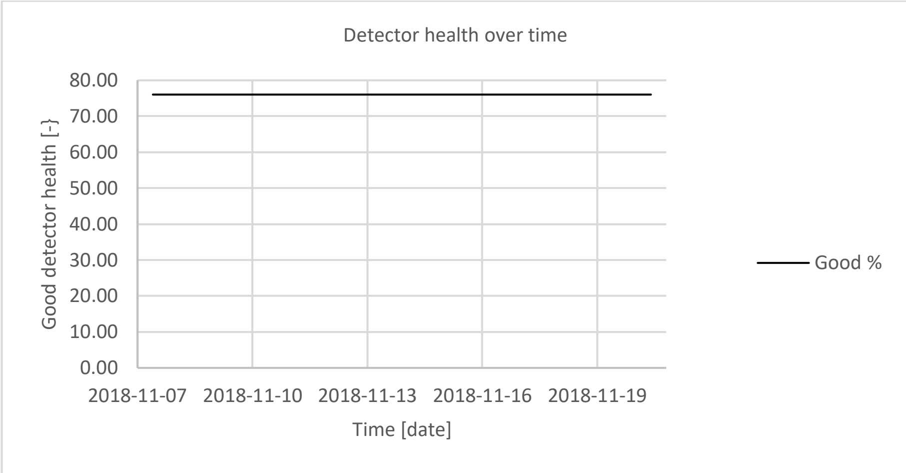


Figure 15 Detector health for District 7: LA/Ventura over the time period of which Hill fire and Woolsey fire occurred.

County data – LA and Ventura County

The fire was within borders of LA and Ventura County. The data extracted shows a total of 10 499 detectors in LA and 605 detectors in Ventura. Detector health in LA County shows a mean value of 61.1 % and peaks at 62.5 % the 8th of November, Figure 16. Detector health in Ventura County shows a mean value of 89.0 % and peaks at 93.7 % the 19th of October, Figure 17.

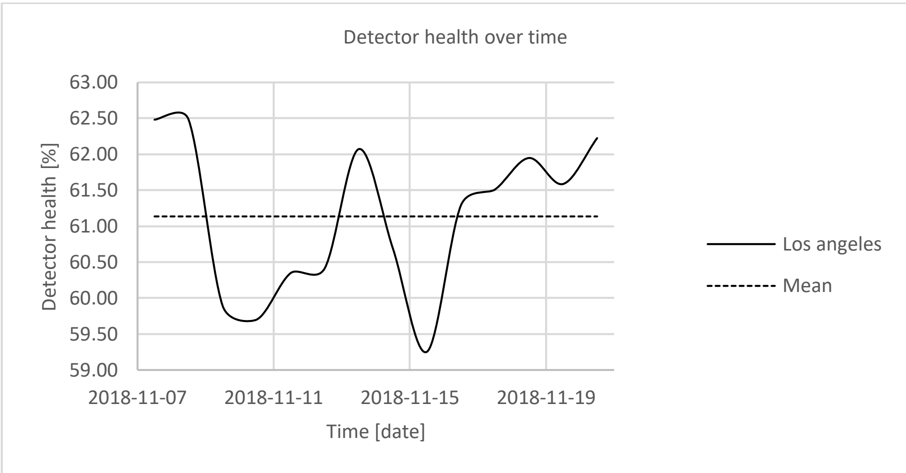


Figure 16 Detector health for County of LA over the time period of which Hill fire and Woolsey Fire occurred.

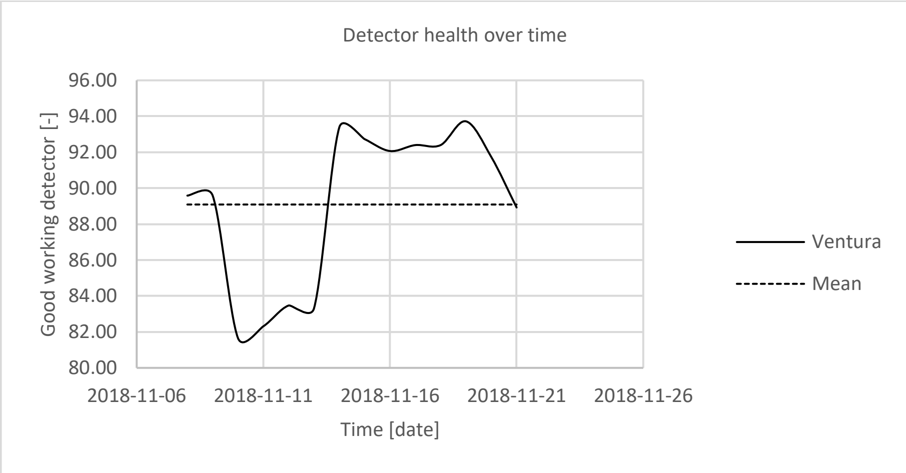


Figure 17 Detector health for County of Ventura over the time period of which Hill fire and Woolsey Fire occurred.

VDS data – LA and Ventura County

Of the in total 11 104 detectors only a handful was running at the time of the fire and 10 of them chosen because of their geographical location based on, 4.4. The 10 chosen detectors are 764781 (south), 717816 (south), 717814 (north), 717813 (south), 765171 (south), 767812 (north), 737258 (west), 737257 (east), 717814 (north) and 764130 (east) which is shown in, Figure 18, Figure 19.

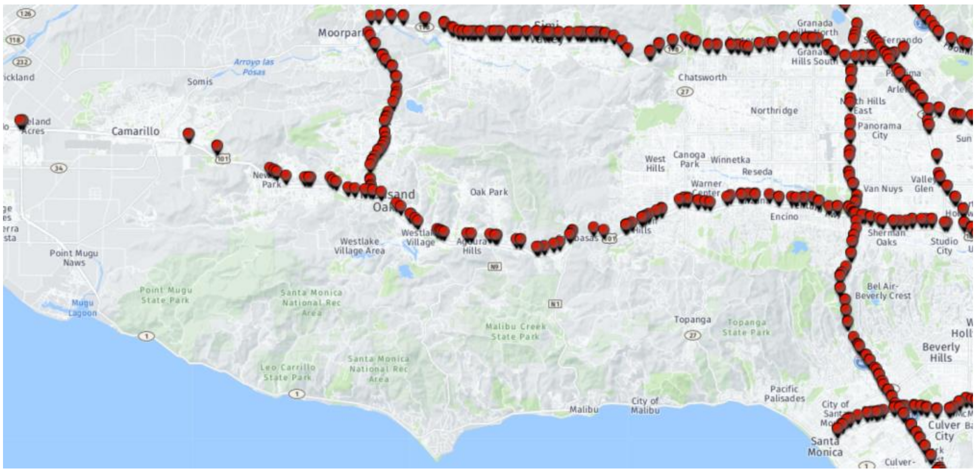


Figure 18 Map over the affected area for the Woolsey fire including VDS.

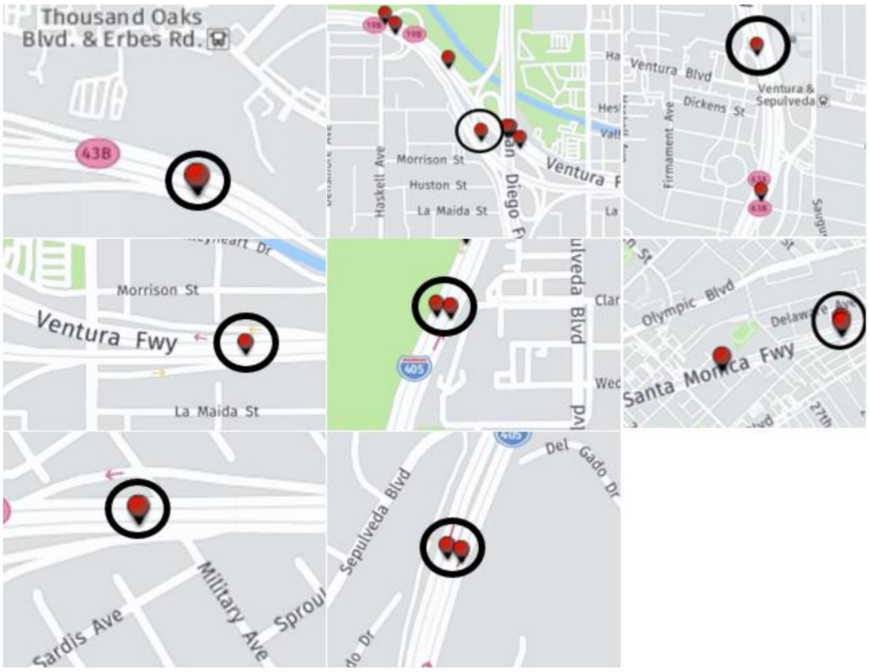


Figure 19 Map showing the VDS 764834 (upper left), 764781 (upper middle), 717816 (upper right), 717813 (center left), 765171 and 767812 (center middle), 737258 and 737257 (center right), 764130 (lower left) and 775225 for further analysis

The overall data quality for detector 764834 are shown in, Table 29 in Appendix A. The result show mostly good values excluding dates of 10th through 13th and for lane 1 the 20th of November this time period.

The fidelity of detector 764834 was analysed and extracted. It shows a varied trustworthy detector with major timespans of imputed data from PeMS, Figure 20. Times of which the detector is considered non-trustworthy and therefore exclude that data over that time period is shown in, Table 6.

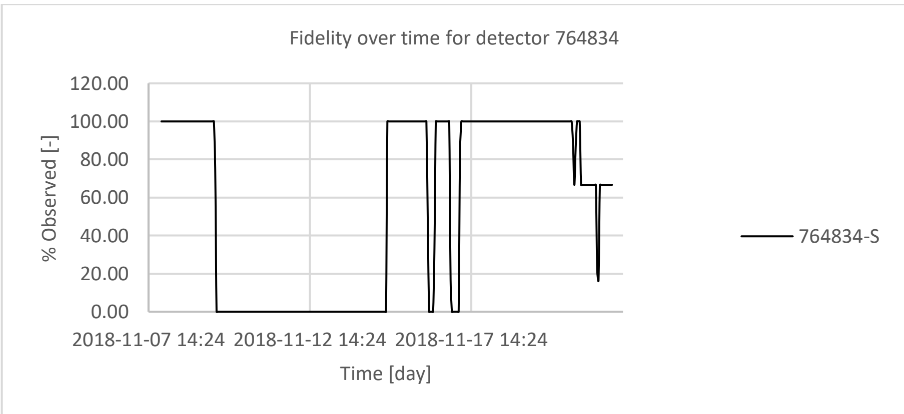


Figure 20 Fidelity for the detector 764834 over time period of Woolsey fire.

Table 6 Times over bad data for detector 764834.

Date	Time of estimated or imputed data
2018-11-09	16:00 – 23:00
2018-11-10	00:00 – 23:00

2018-11-11	00:00 – 23:00
2018-11-12	00:00 – 23:00
2018-11-13	00:00 – 23:00
2018-11-14	00:00 – 23:00
2018-11-16	06:00 – 11:00
2018-11-16	23:00
2018-11-17	00:00 – 06:00
2018-11-20	18:00 – 20:00
2018-11-21	00:00 – 23:00

The overall data quality for detector 764781 are shown in, Table 30 in Appendix A. The result show only good values of this time period.

The fidelity of detector 764781 was analysed and extracted. It shows in general a trustworthy detector with minor timespans of imputed data from PeMS, Figure 21. Times of which the detector is considered non-trustworthy and therefore exclude that data over that time period is shown in, Figure 14.

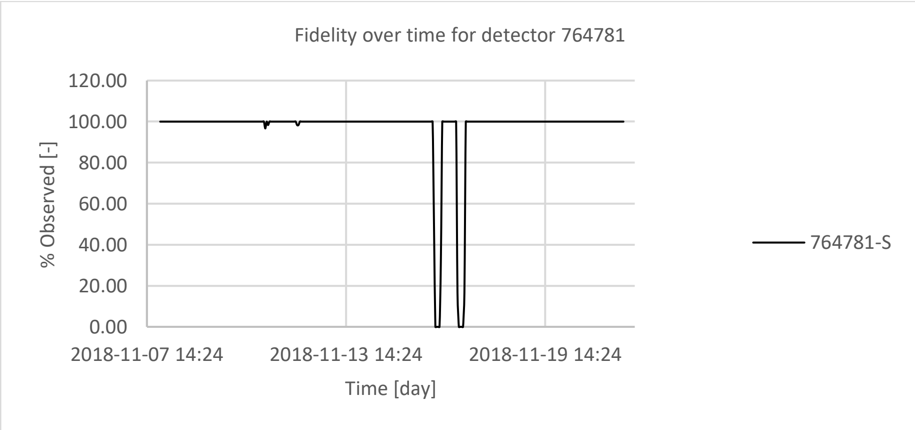


Figure 21 Fidelity for the detector 764781 over time period of Woolsey fire.

Table 7 Times over bad data for detector 764834.

Date	Time of estimated or imputed data
2018-11-11	04:00
2018-11-11	06:00
2018-11-11	03:00 – 04:00
2018-11-16	06:00 – 11:00
2018-11-16	23:00
2018-11-17	00:00 – 04:00

The overall data quality for detector 717816 are shown in, Table 31 in Appendix A. The result show only good values of this time period.

The fidelity of detector 717816 was analysed and extracted. It shows in general a trustworthy detector with minor timespans of imputed data from PeMS, Figure 22. Times of which the detector is considered non-trustworthy and therefore exclude that data over that time period is shown in Figure 14.

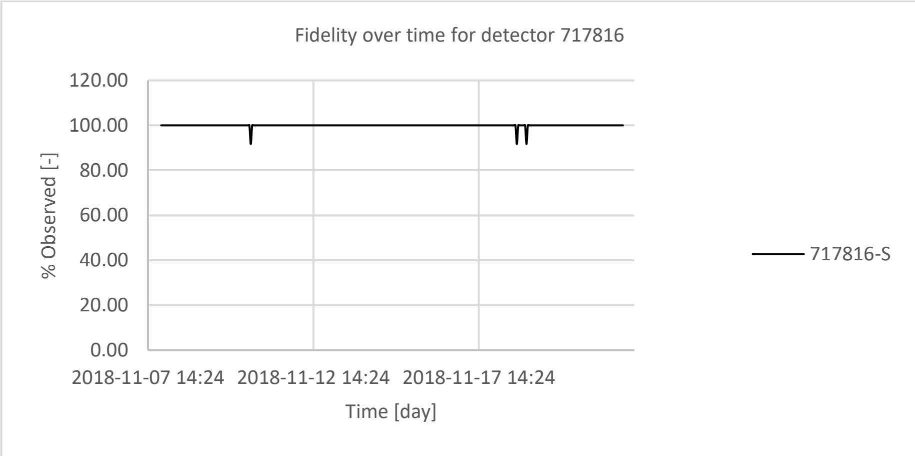


Figure 22 Fidelity for the detector 717816 over time period of Woolsey fire.

Table 8 Times over bad data for detector 717816.

Date	Time of estimated or imputed data
2018-11-10	17:00
2018-11-18	18:00
2018-11-19	01:00

The overall data quality for detector 775225 are shown in, Table 32 in Appendix A. The result shows only good values of this time period.

The fidelity of detector 775225 was analysed and extracted. It shows a general trustworthy detector with three minor timespans of imputed data from PeMS, Figure 23. Times of which the detector is considered non-trustworthy and therefore exclude that data over that time period is shown in, Figure 14

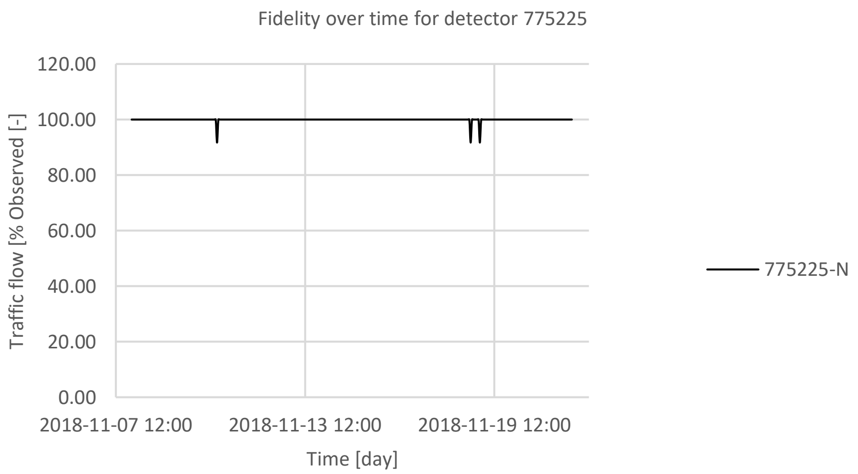


Figure 23 Fidelity for the detector 775225 over time period of Woolsey fire.

Table 9 Times over bad data for detector 775225.

Date	Time of estimated or imputed data
20018-11-10	17:00

2018-11-18	18:00
2018-11-19	01:00

The overall data quality for detector 760024 are shown in, Table 33 in Appendix A. The result show mostly good values of this time period excluding lane 1 on the 10th.

The fidelity of detector 760024 was analysed and extracted. It shows a general trustworthy detector with two major drops with timespans of imputed data from PeMS (see Figure 24). Times of which the detector is considered non-trustworthy and therefore exclude that data over that time period is shown in Table 10.

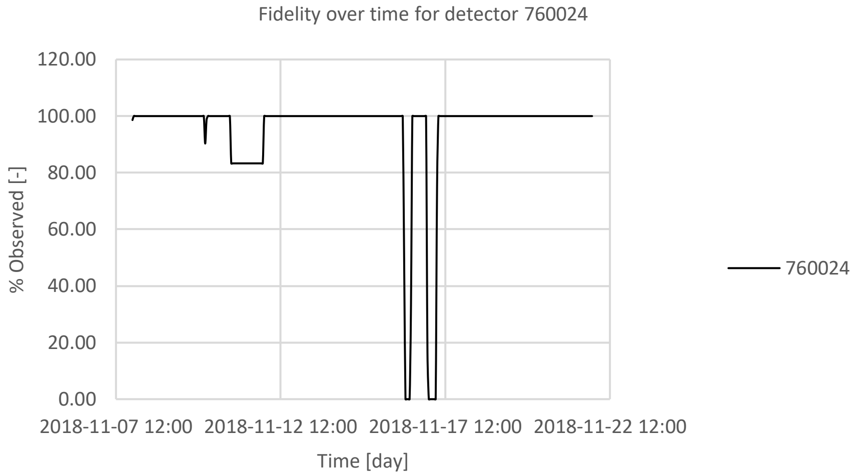


Figure 24 Fidelity for the detector 760024 over time period of Woolsey fire.

Table 10 Times over bad data for detector 760024.

Date	Time of estimated or imputed data
2018-11-08	00:00
2018-11-10	05:00 – 06:00
2018-11-11	00:00 – 23:00
2018-11-16	06:00 – 11:00
2018-11-16	23:00
2018-11-17	00:00 – 06:00

The overall data quality for the detector-set, 765171 and 767812, are shown in, Table 34 in Appendix A. The result shows that both detectors where at fault at the time.

The fidelity of detectors, 765171 and 767812, was analysed and extracted. It shows a non-trustworthy detector with only imputed data from PeMS, Figure 25. The complete period of time throughout Hill and Woolsey fire consisted of pure imputed data. Therefore, is this set of detectors no further analysed.

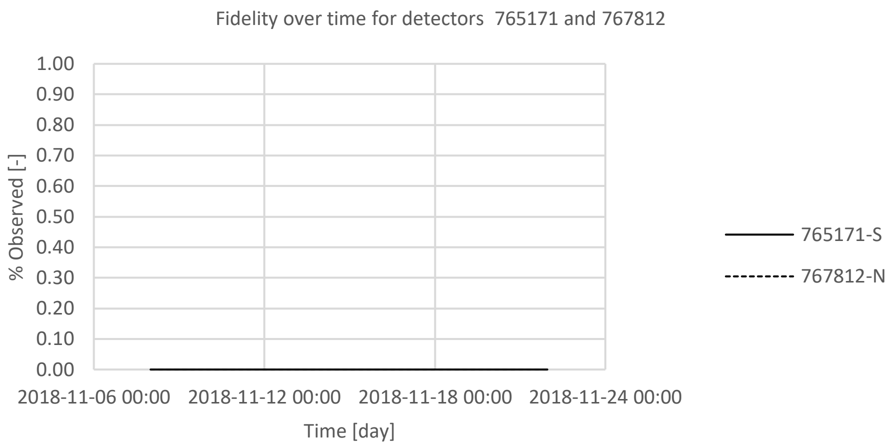


Figure 25 Fidelity for the detectors 765171 and 767812 over time period of Woolsey fire

The overall data quality for the detector-set, 737258 and 737257, are shown in, Table 35 in Appendix A. The result shows both detectors gave good data at the time.

The fidelity of detectors, 737258 and 737257, was analysed and extracted. It shows a general trustworthy with only three minor drops of imputed data from PeMS, Figure 26. Times of which the detector is considered non-trustworthy and therefore exclude that data over that time period is shown in Table 11

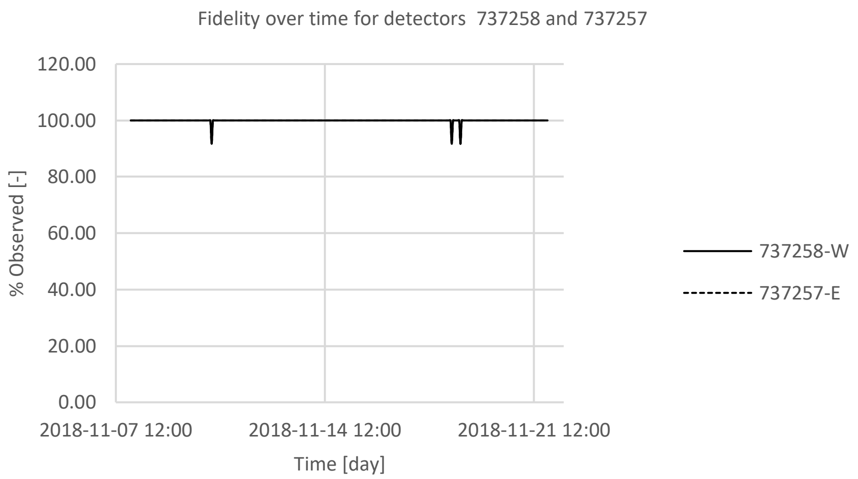


Figure 26 Fidelity for the detectors 737258 and 737257 over time period of Woolsey fire.

Table 11 Times over bad data for detectors 737258 and 737257.

Date	Time of estimated or imputed data
2018-11-10	17:00
2018-11-18	18:00
2018-11-19	01:00

Summary

Of the ten detectors screened, there are five detectors, 764834, 764781, 717816, 775225 and 760024, registering sufficient data to further derive the other factors of PeMS (e.g traffic flow). Some data within this time period is however of bad quality and will be excluded when deriving the other factors. This is to make the best quality of data possible with the means used.

7.1.5. Conclusion

The fire events and detectors to be used for further analysis in the following sub-chapters are listed in table, Table 12. All detectors included estimated and imputed data but did for most part register good, observed data. For the time of which it did register estimated or imputed data it will be excluded to make a more trustworthy result. For the Carr fire case no detectors were found for that time period which is why that case is further excluded for analysis. The found detectors of good working quality will be used when deriving the data of the other factors from PeMS (e.g traffic flow).

Table 12 The chosen fire events with the detectors analysed for each case.

Fire event	Detector
Camp fire	318510 and 318509
Atlas fire	409482, 413373 and 410817
Hill and Woolsey fire	764834, 764781, 717816, 775225 and 760024

7.2. Traffic Flow

Traffic flow is a measured quantity of PeMS. Traffic flow is measured by vehicle detectors (VDS) which is registered as the number of passing vehicles per time period. Traffic flow data is found at any VDS in PeMS from the performance menu and selecting aggregates. There are four types of aggregates, TIME OF THE DAY, DAY OF WEEK, TIME SERIES AND QUANTITY RELATIONSHIPS. Time of day shows the average traffic flow for each hour of the chosen day, day of week show the difference between the days of the week for the selected quantity, time series show traffic flow for a specific detector over time and quantity relationships show two quantities and plot them against each other. More information can be found in PeMS user guide, chapter 4 – Basic performance applications, (California department of transportation, 2020).

7.2.1. Camp fire

Traffic flow of VDS 318510 and 318509 shows a distinct change of flow comparing night and day. This is interesting because the change of flow over the day is not a factor included in the setup of the simulation and is therefore going to differ from the flow of the simulation. The detector 318510 registers a general higher flow throughout this time period, especially daytime. For both detectors traffic flow increases from the 9th, with just 459 (318510) and 623 (318509) passing vehicles per hour, to the 16th of November, with 1419 (318510) and 1854 (318509) passing vehicles per hour, where of it after that for the 17th and 18th makes a halt and decreases slightly to reach a maximum of 971 (318510) and 1336 (318510) passing vehicles per hour, Figure 27.

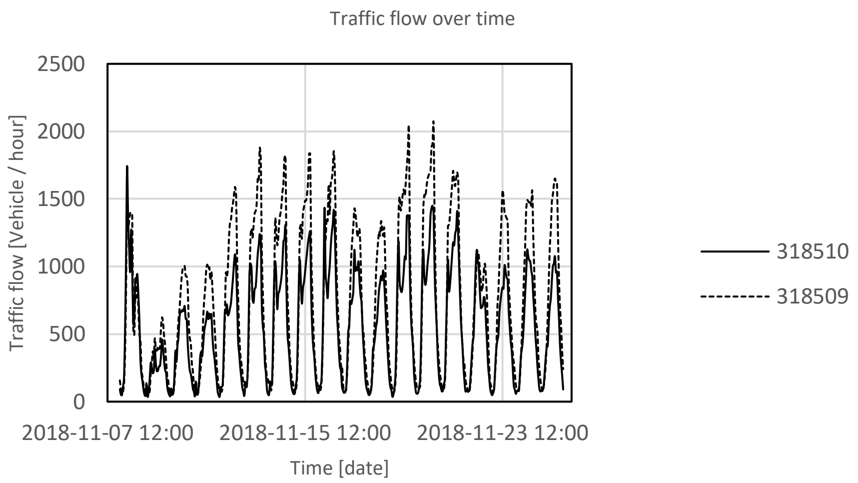


Figure 27 Traffic flow over time for detector 318509 and 318510 west of Paradise.

7.2.2. Atlas fire

Detector 409482 that maximum flow occurred at the 23rd and reached 3109 passing vehicles per hour and the lowest measured flow, during daytime, occurred at the 14th and only registered 1039 passing vehicles per day, Figure 28.

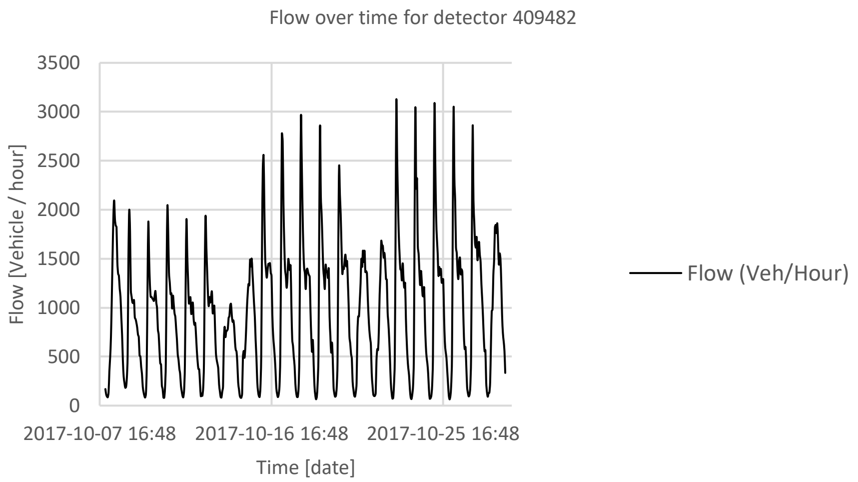


Figure 28 Traffic flow over time for detector 409482.

Detector 413373 shows a maximum flow of 7287 passing vehicles per hour at the 17th and lowest flow during daytime of 5942 passing vehicles per hour at the 15th, Figure 29.

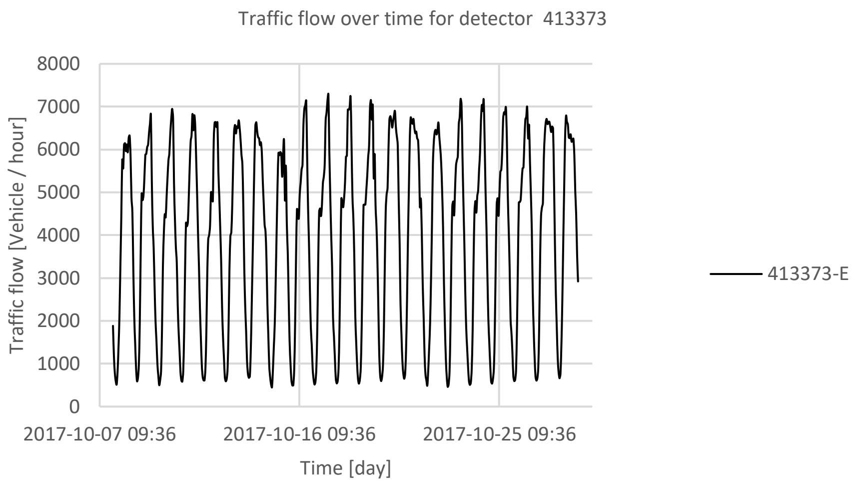


Figure 29 Traffic flow over time for the detector 413373.

Detector 410817 shows a maximum flow of 6819 passing vehicles per hour at the 22nd and lowest flow during daytime of 7110 passing vehicles per hour at the 13th, Figure 30.

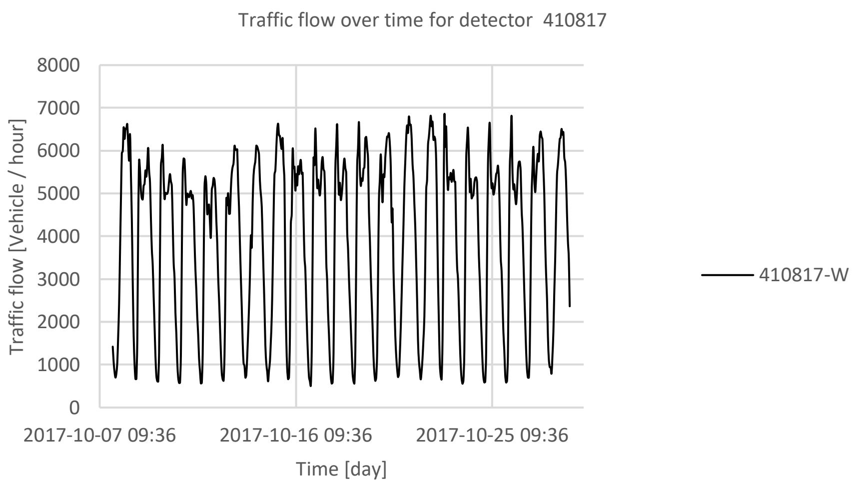


Figure 30 Traffic flow over time for the detector 410817.

7.2.3. Hill and Woolsey fire

Detector 764834 shows a maximum flow of 4800 passing vehicles per hour at the 13th and lowest flow during daytime of 2880 passing vehicles per hour at the 9th, Figure 31.

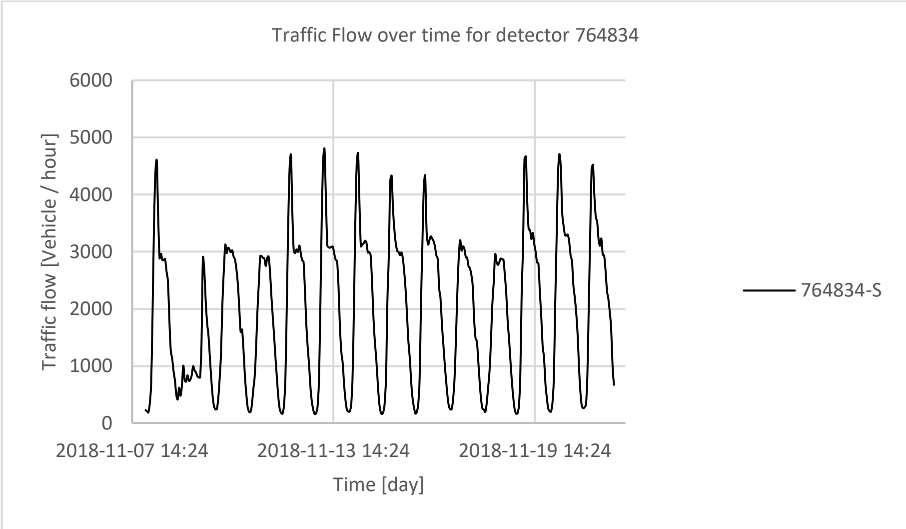


Figure 31 Traffic flow over time for the detector 764834.

Detector 764781 shows a maximum flow of 7577 passing vehicles per hour at the 16th and lowest flow during daytime of 5438 passing vehicles per hour at the 11th, Figure 32.

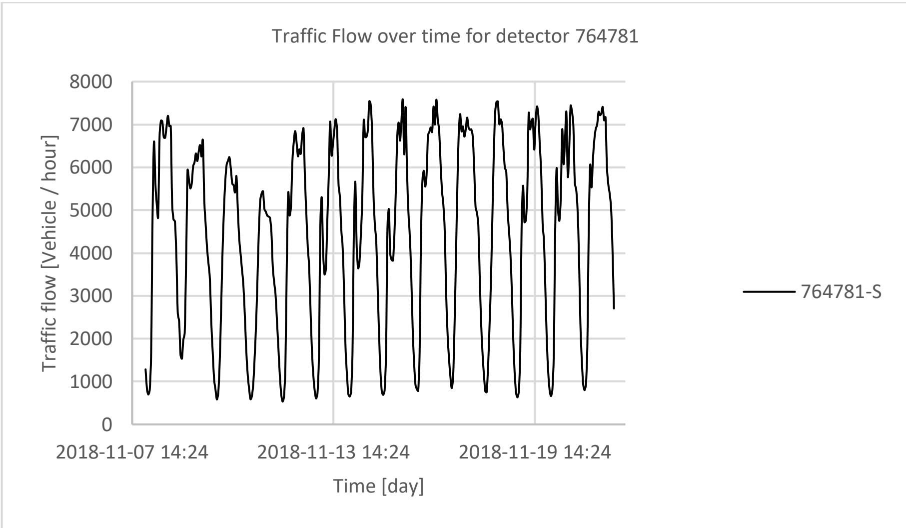


Figure 32 Traffic flow over time for the detector 764781.

Detector 717816 shows a maximum flow of 7994 passing vehicles per hour at the 18th and lowest flow during daytime of 7241 passing vehicles per hour at the 14th, Figure 33.

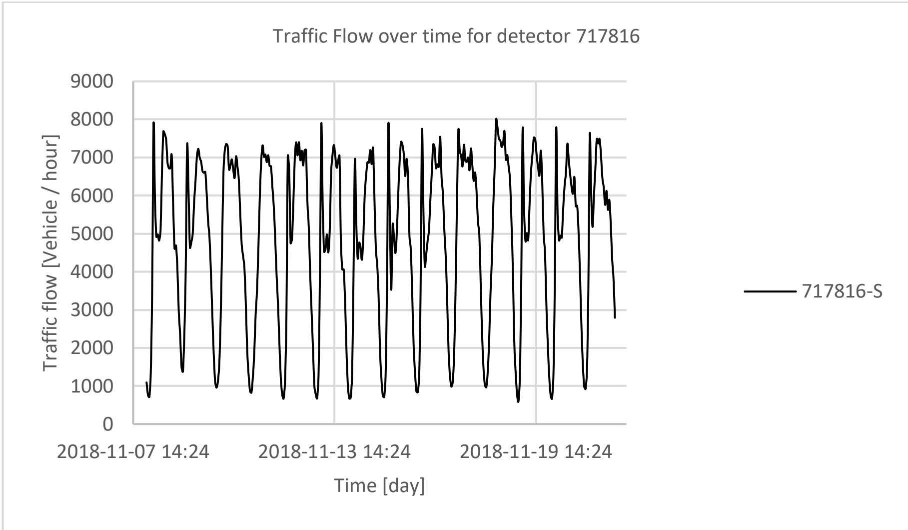


Figure 33 Traffic flow over time for the detector 717816.

Detector 775225 shows a maximum flow of 9355 passing vehicles per hour at the 19th and lowest flow during daytime of 8409 passing vehicles per hour at the 10th, Figure 34.

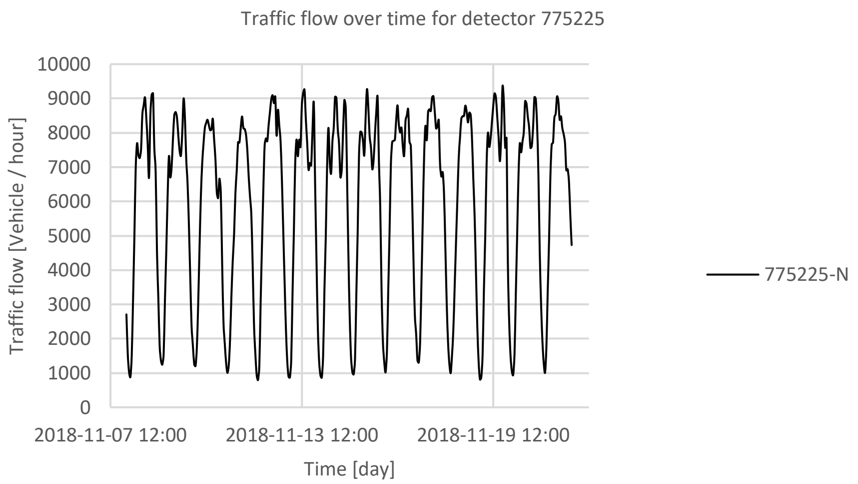


Figure 34 Traffic flow over time for the detector 775225.

Detector 760024 shows a maximum flow of 9 125 passing vehicles per hour at the 18th and lowest flow during daytime of 7 486 passing vehicles per hour at the 11th, Figure 35.

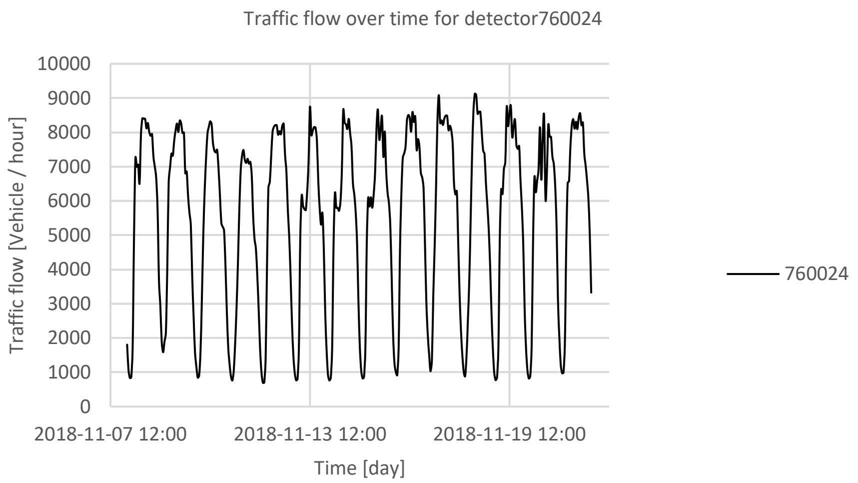


Figure 35 Traffic flow over time for the detector 760024

Detectors 737258 and 737257 is a set of detectors which shows a general higher flow in the western direction reaching a maximum flow of 6360 passing vehicles per hour the 8th. The lowest flow during daytime was in the eastern direction of 3853 passing vehicles per hour at the 11th, Figure 36.

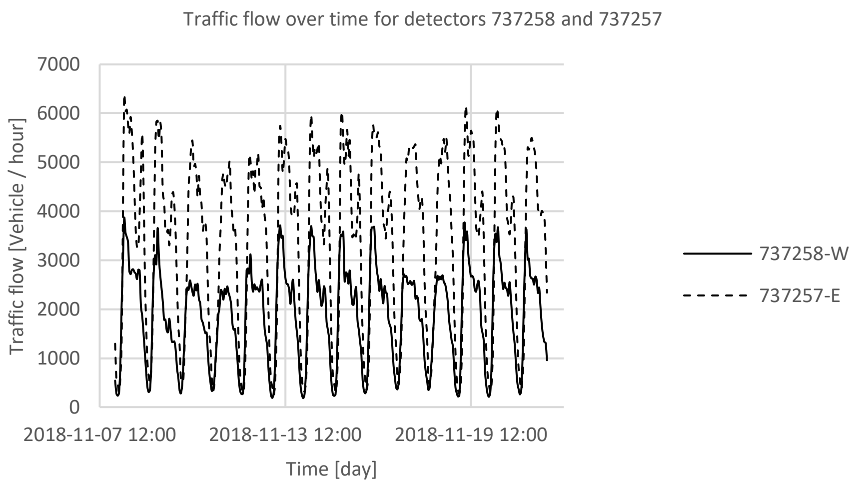


Figure 36 Traffic flow over time for the detectors 737258-W and 737257-E.

7.3. Vehicle speed

Registered vehicle speed is found from the same menu as described in, 7.2, but instead of quantity flow, choose quantity speed.

7.3.1. Camp fire

Detectors 318509 and 318510 shows that detector 318509 has six major events of decreasing speed as compared to 318510. Besides those six events both detectors vehicle speed occurs in between 60 – 70 mph, Figure 37.

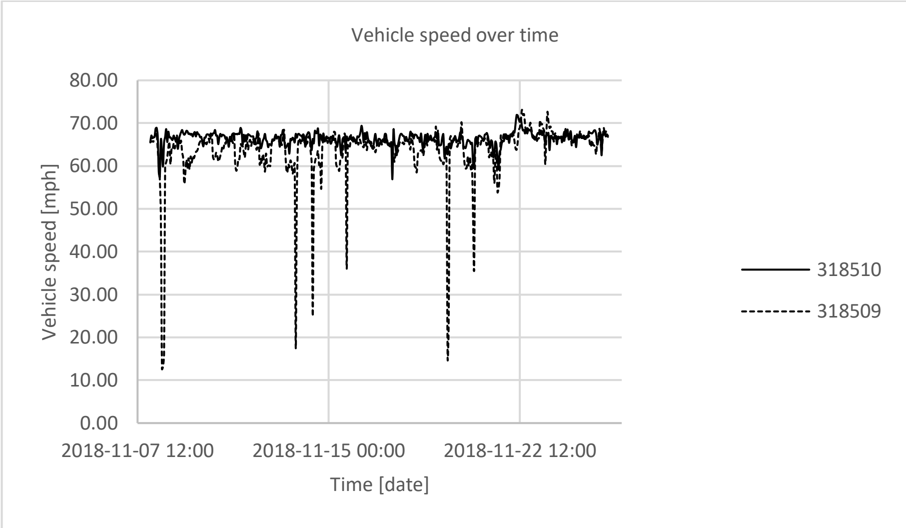


Figure 37 Vehicle speed over time for detector 318509 and 318510 west of Paradise.

7.3.2. Atlas fire

Detector 409482 shows that most traffic occurs at around 60 – 70 mph at a mean value of 64 mph with 6 major drops in speed over the course of the fire, Figure 38.

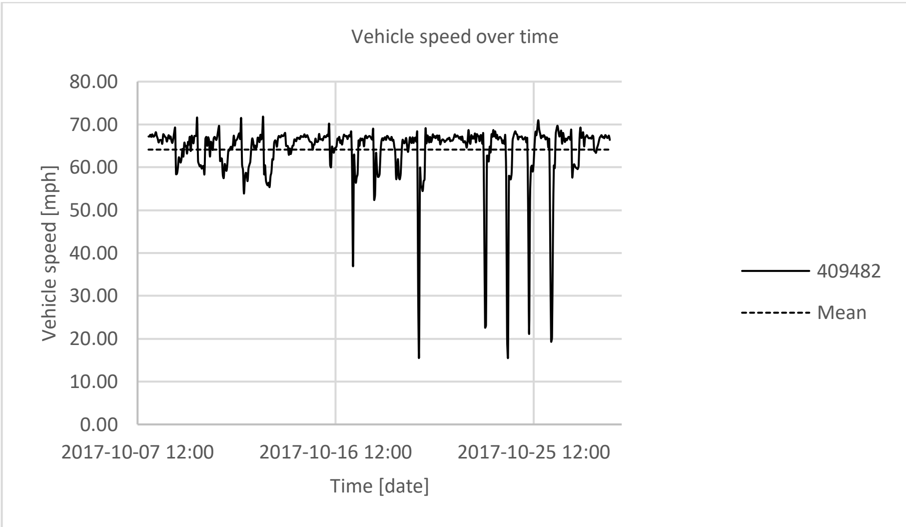


Figure 38 Vehicle speed over time for detector 409482.

Detector 413373 shows that most traffic occurs at around 40 – 70 mph at a mean value of 62 mph, Figure 39.

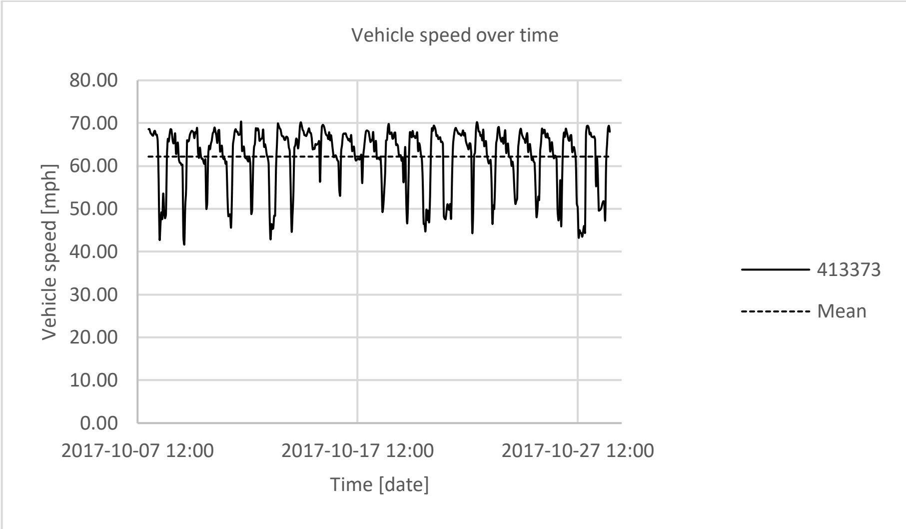


Figure 39 Vehicle speed over time for detector 413373.

Detector 413373 shows that most traffic occurs at around 50 – 70 mph at a mean value of 62 mph. However, there are five occasions of which the speed decreases further below 50, Figure 40.

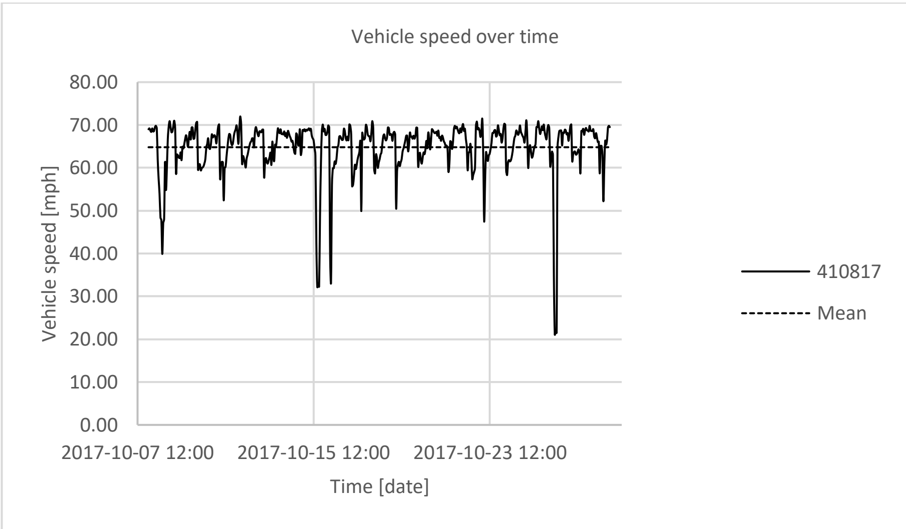


Figure 40 Vehicle speed over time for detector 410817.

7.3.3. Hill and Woolsey fire

Detector 764834 shows that most traffic occurs at around 60 – 80 mph at a mean value of 69 mph. However, there are four occasions of which the speed decreases further below 60, Figure 41.

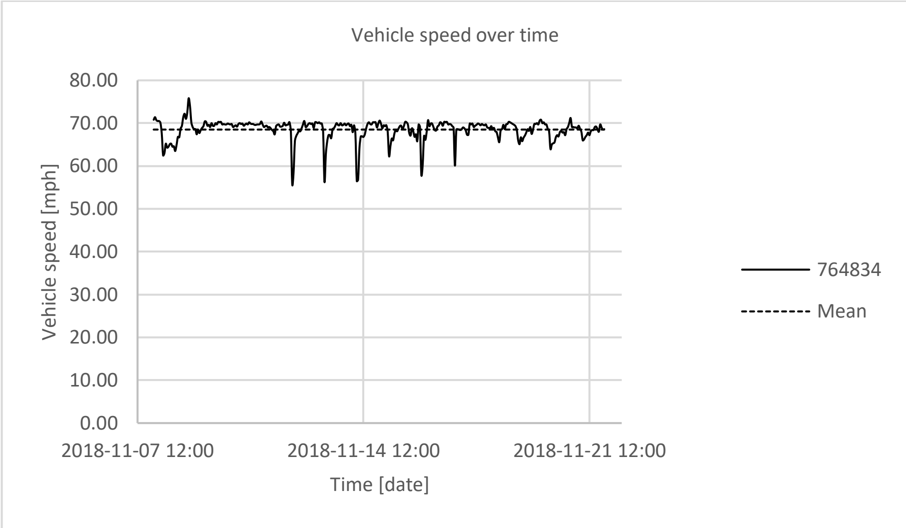


Figure 41 Vehicle speed over time for detector 764834.

Detector 764781 shows that most traffic occurs at around 50 – 70 mph at a mean value of 65 mph. However, there are ten occasions of which the speed arises above 70 mph and sic occasions decreases below 60, Figure 42.

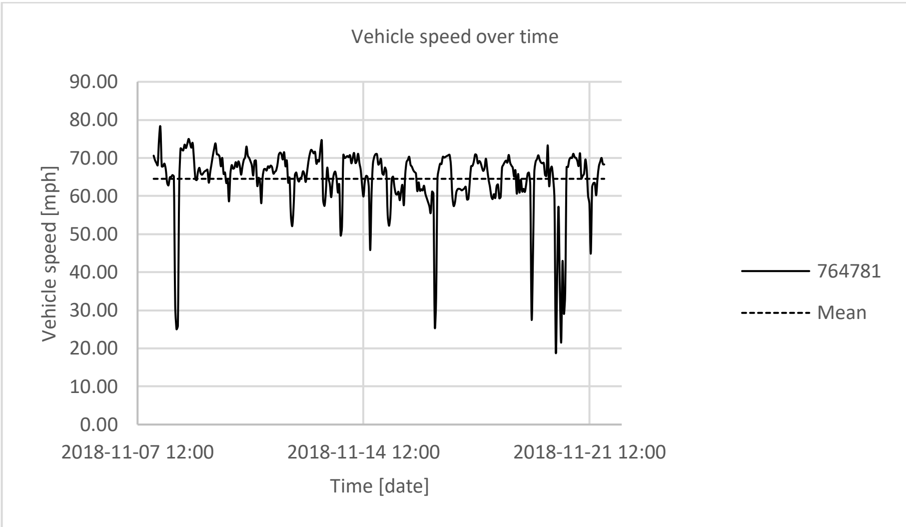


Figure 42 Vehicle speed over time for detector 764834.

Detector 717816 shows a varied vehicle speed ranging from 10 mph to just above 70 mph with a mean value of 55 mph, Figure 43.

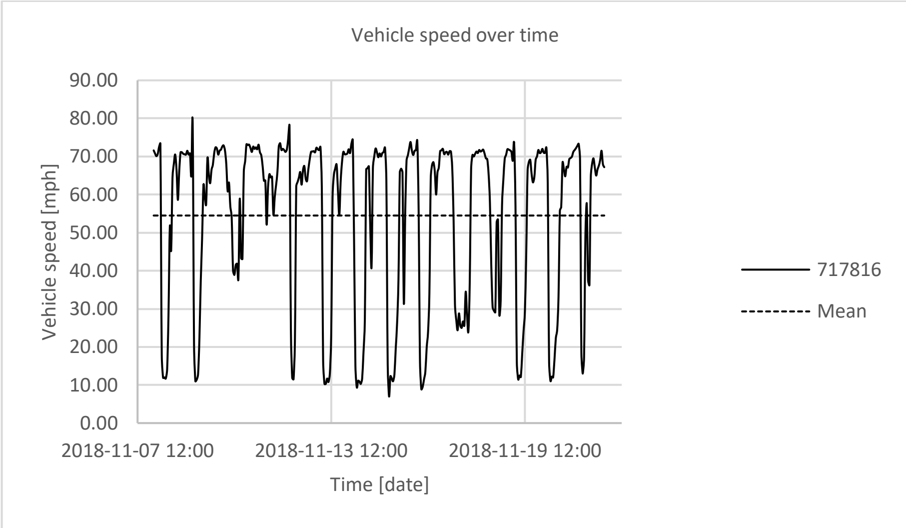


Figure 43 Vehicle speed over time for detector 717816.

Detector 775225 shows a varied vehicle speed ranging from around 20 mph to just above 70 mph with a mean value of 55 mph, Figure 44.

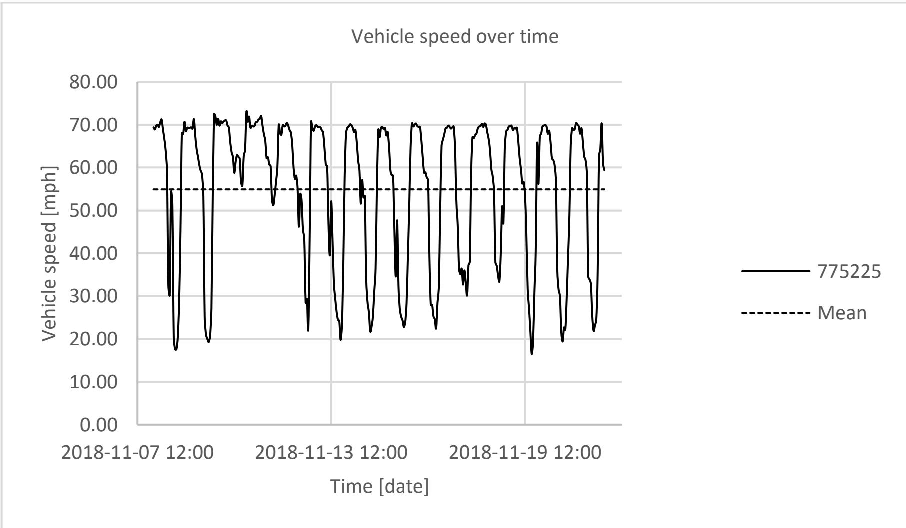


Figure 44 Vehicle speed over time for detector 775225.

Detector 760024 shows that most traffic occurs at around 60 – 70 mph at a mean value of 63 mph. However, there are ten occasions of which the speed decreases below 60, Figure 45.

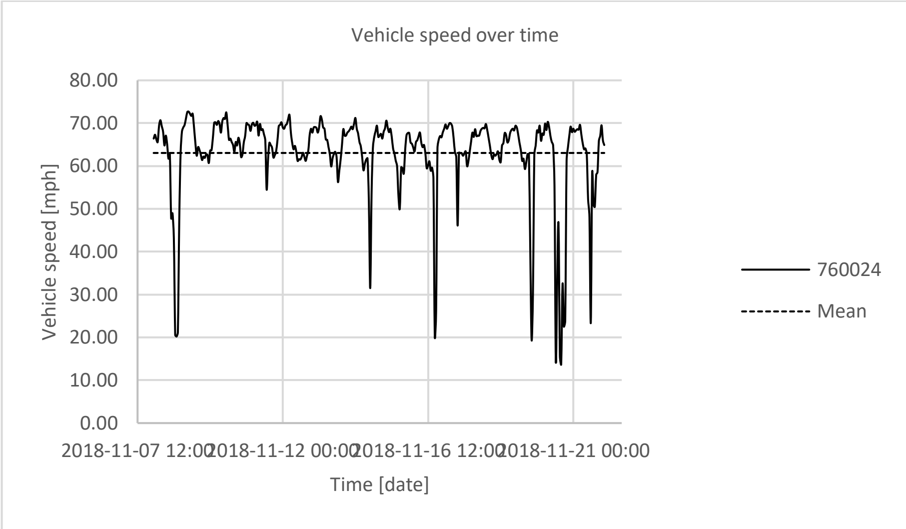


Figure 45 Vehicle speed over time for detector 760024.

Detectors 737257 and 737258 shows a general higher vehicle speed registered at 737258 with a mean value of 65 mph compared to detector 737257 at a mean value of 59 mph. Both detectors register a drop in speed at several occasions, Figure 46.

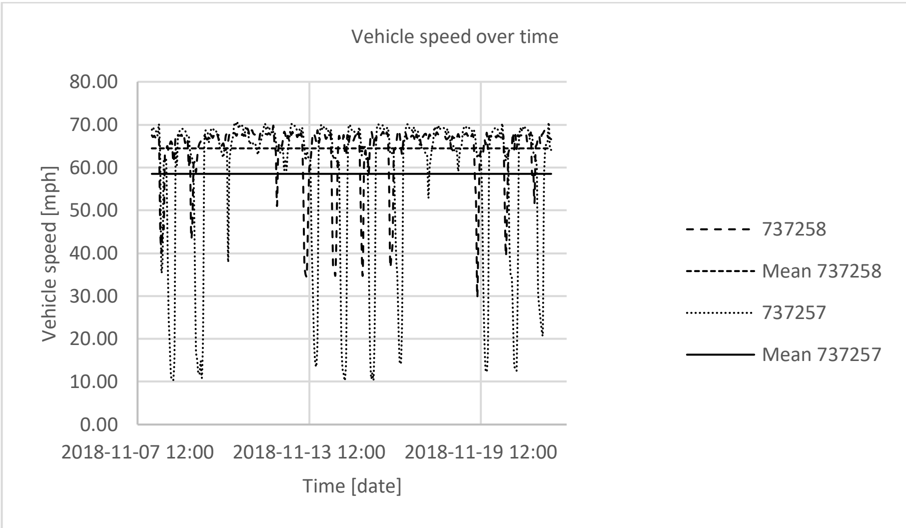


Figure 46 Vehicle speed over time for detectors 737257 and 737258.

7.4. Car incident

A car incident includes non-injury, injury, and fatal events. This is analysed to use as an input factor of the WUI-NITY simulations to define the factor, trafficAccidents. In regards of WUI-NITY it is of only interest to know if any congestion occurs, which is partly controlled if accidents happen. Therefore, it will be analysed if there are any incidents and if so, the factor will set to true for the entire simulation.

WUI-NITY does not include the number, locations, nor the direction of the incidents so therefore is the data from PeMS only concluding if there are incidents within the simulated area, but not in more detail than that (e.g where on the road the incident occurred). This affects the model because in a real-world scenario there might be a car incident lasting for a shorter time but also a longer time meaning that any specific road will be congested and blocked for a time being. If this data is not inserted into the model it will not be able to replicate that specific road congestion. Depending on the size of the road congestion it might also affect the route choice of the population which is critical in an evacuation scenario.

7.4.1. Camp fire

Freeway SR99, south and north, over the segment of Butte County shows a total of 25 incidents over the time period of Camp fire, Figure 47. Traffic accidents for Camp fire are set to true because these are the only two detectors analysed over this area.

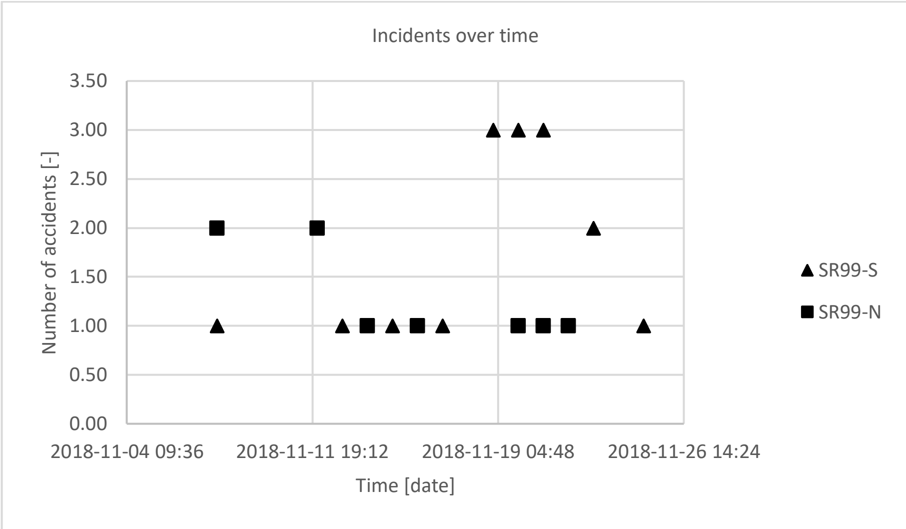


Figure 47 Incidents over time for Freeway SR99-S and SR99-N.

7.4.2. Atlas fire

Freeway SR12, west and east, over the segment of Napa County shows a total of 8 incidents over the time period of Hill and Woolsey fire, Figure 48.

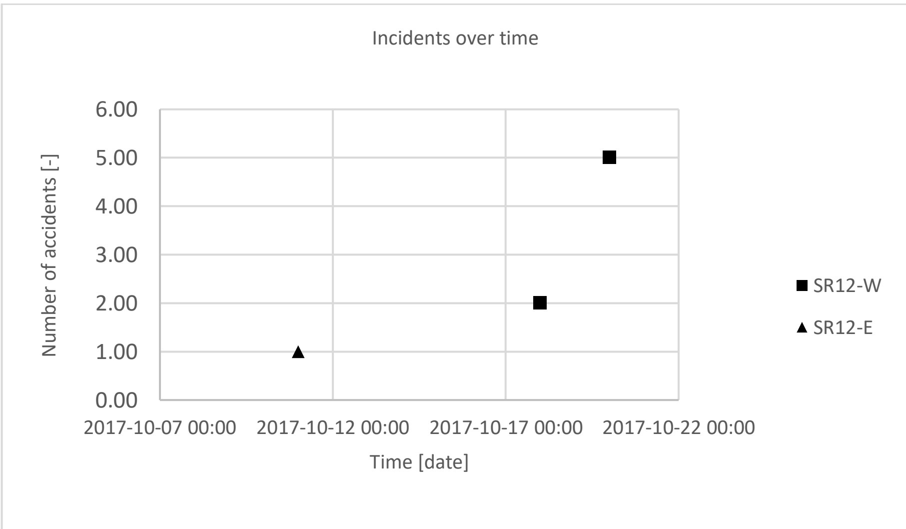


Figure 48 Incidents over time for Freeway SR12-E and SR12-W.

Freeway I80, west and east, over the segment of Solano County shows a total of 170 incidents over the time period of Hill and Woolsey fire, Figure 49.

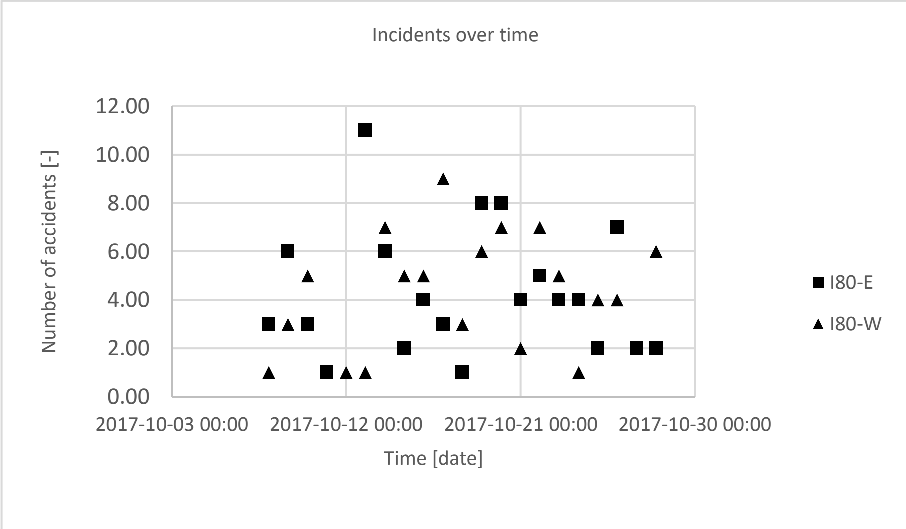


Figure 49 Incidents over time for Freeway I80-E and I80-W.

Traffic accidents is set to true because both analysed freeways shows that accidents occurred during the time of Atlas fire.

7.4.3. Hill and Woolsey fire

Freeway US101, south and north, over the segment of Los Angeles County shows a total of 155 incidents over the time period of Hill and Woolsey fire, Figure 50.

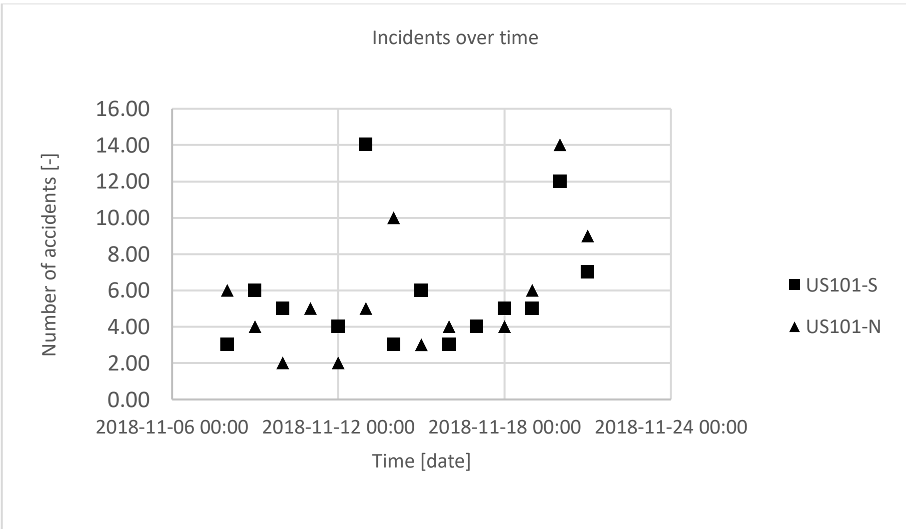


Figure 50 Incidents over time for Freeway US101-S and US101-N.

Freeway I405, south and north, over the segment of Los Angeles County shows a total of 489 incidents over the time period of Hill and Woolsey fire, Figure 51.

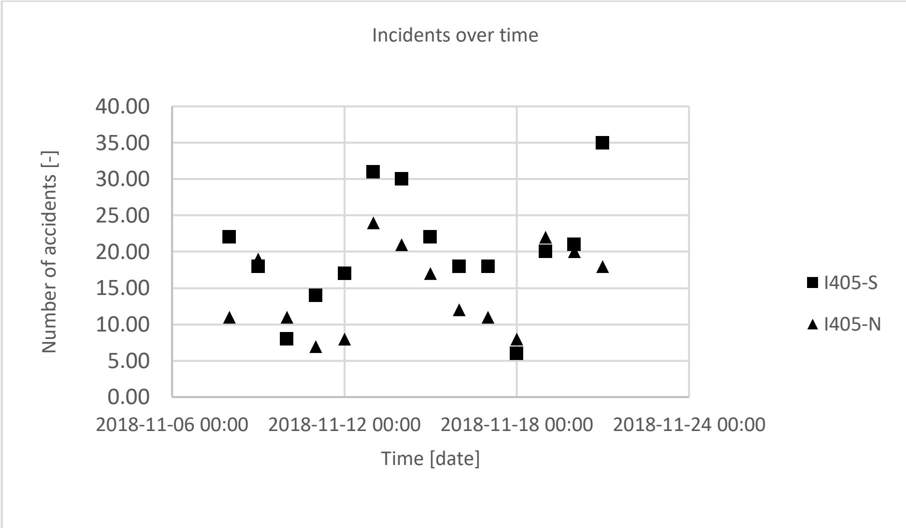


Figure 51 Incidents over time for Freeway I405-S and I405-N.

Traffic accidents is set to true because both analysed freeways shows that accidents occurred during the time of Hill and Woolsey fire.

7.5. Background density

The background traffic density must be decided for the best representation of the real-world events. This is necessary to identify the uplift in traffic demand due to the emergency itself. This is done by extracting traffic density over a three-month period period the event (maximum time range of PeMS). A minimum and maximum traffic density is extracted from the extracted data and put in the code for each of the events. In WUI-NITY it is not possible to decide the density in different direction (west, north, east, or south). Because of that an average density of all the detectors for each event is calculated.

7.5.1. Camp fire

The overall density over the three months September, October and November for detectors 318509 and 318510, are showing a maximum density of 18,483 vehicle kilometre travelled, VKT, (northern detector) and a minimum density of 281 VKT (southern detector), Figure 52. A maximum average density of the two directions combined, 17300 VKT, and a minimum average density of, 322 VKT.

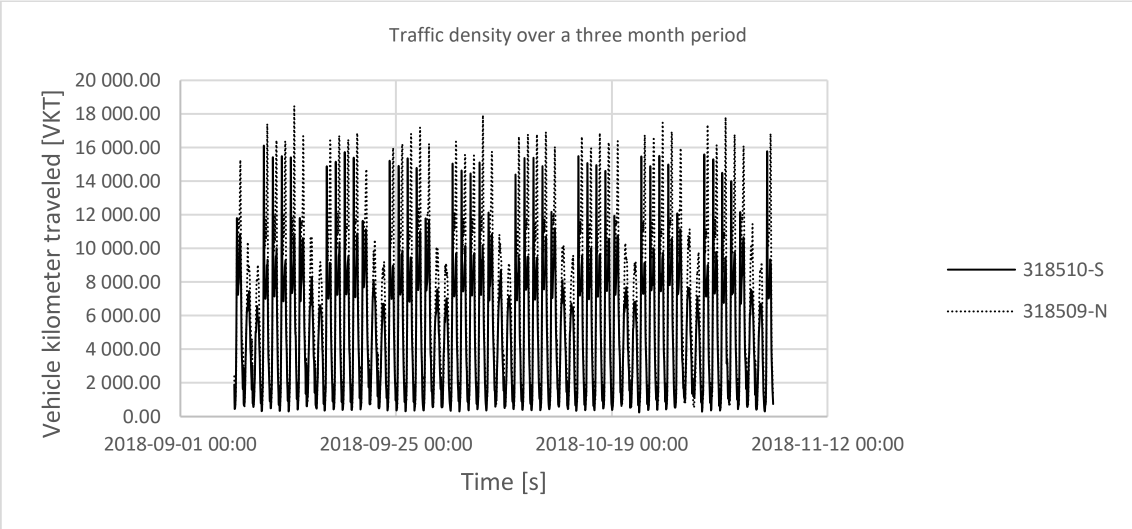


Figure 52 Density over time for detectors, 318510 and 318509.

7.5.2. Atlas fire

The overall density over the three months august, September and October for detector 409482, are showing a maximum density of 4,783 VKT, and a minimum density of 92 VKT, Figure 53.

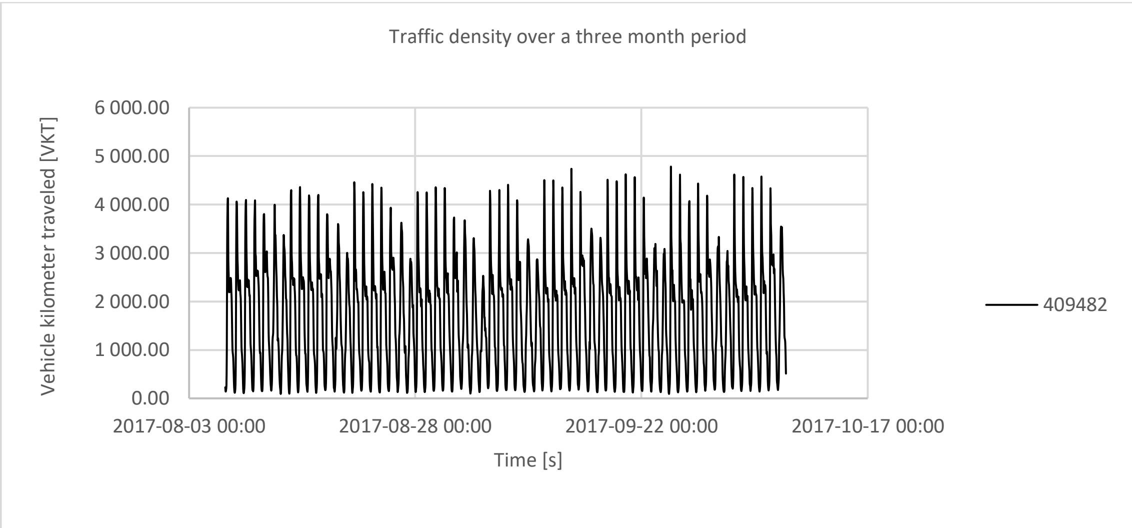


Figure 53 Density over time for detector, 409482.

The overall density over the three months august, September and October for detector 413373, are showing a maximum density of 5,002 VKT, and a minimum density of 274 VKT, Figure 54.

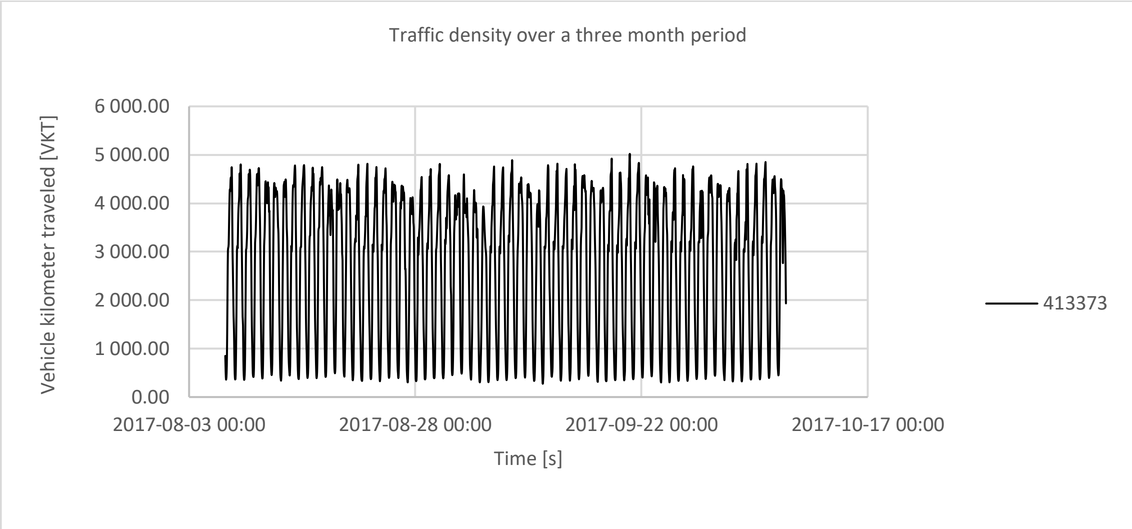


Figure 54 Density over time for detector, 413373.

The overall density over the three months august, September and October for detector 410817, are showing a maximum density of 5,483 VKT, and a minimum density of 382 VKT, Figure 55.

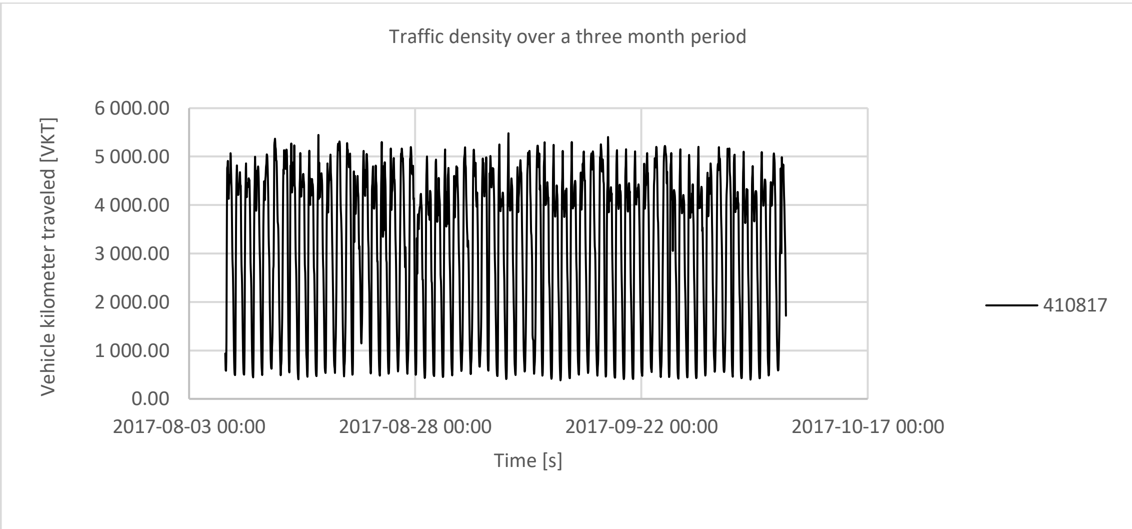


Figure 55 Density over time for detector, 410817.

An overall average maximum density for all the analysed detectors of the Atlas fire is 5090 VKT and the minimum density 250 VKT.

7.5.3. Hill and Woolsey fire

The overall density over the three months September, October, and November for detector 764834, are showing a maximum density of 6,393 VKT, and a minimum density of 170 VKT, Figure 56.

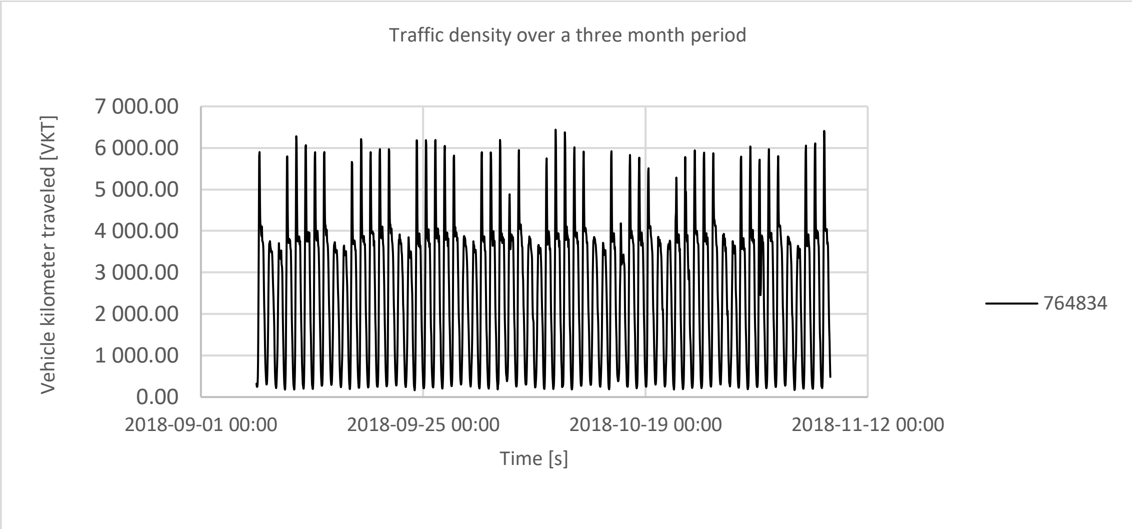


Figure 56 Density over time for detector, 764834.

The overall density over the three months September, October, and November for detector 764781, are showing a maximum density of 5,704 VKT, and a minimum density of 399 VKT, Figure 57.

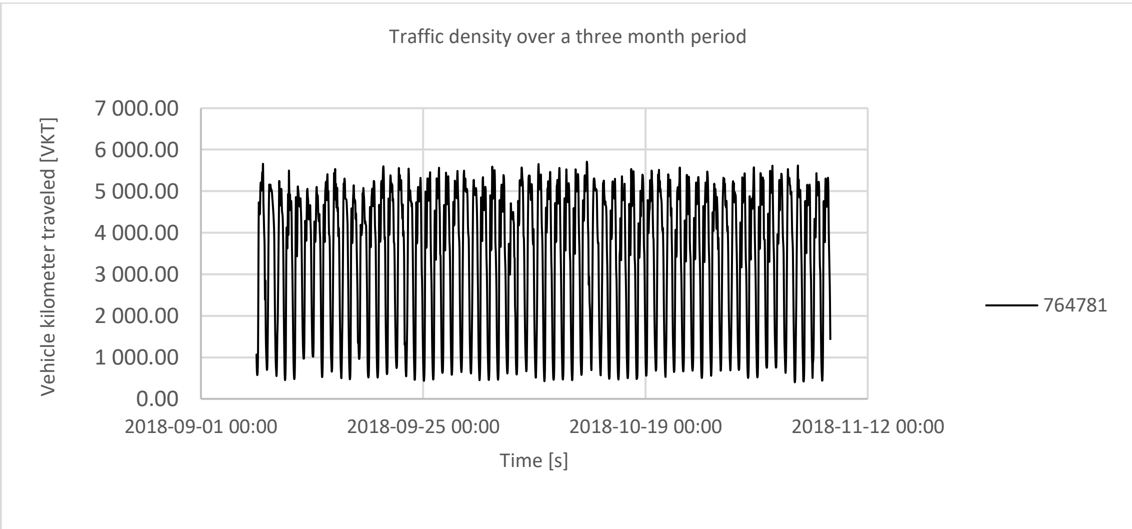


Figure 57 Density over time for detector, 764781.

The overall density over the three months September, October, and November for detector 717816, are showing a maximum density of 10,730 VKT, and a minimum density of 717 VKT, Figure 58.

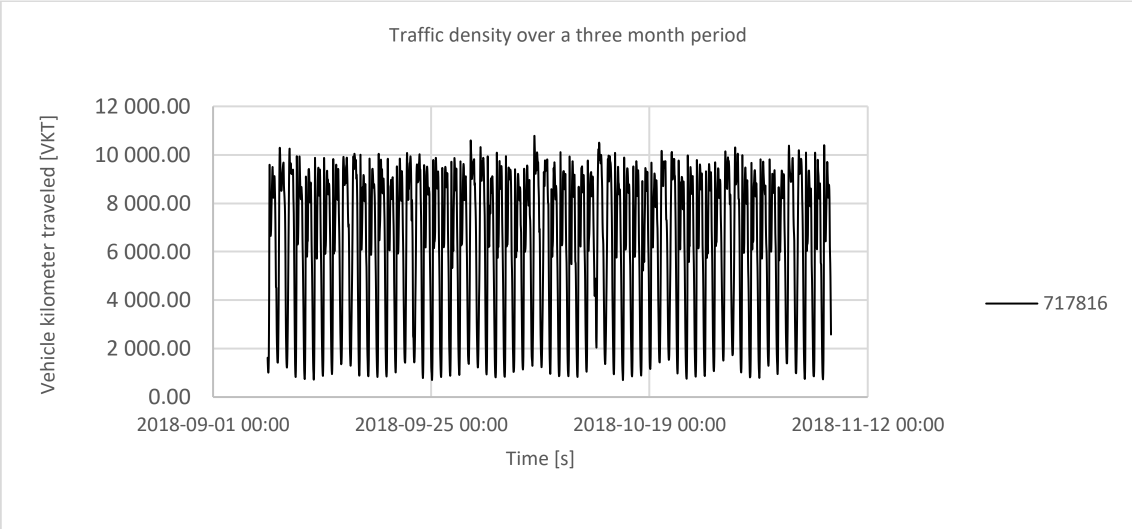


Figure 58 Density over time for detector, 717816.

The overall density over the three months September, October, and November for detector 775225, are showing a maximum density of 14,533 VKT, and a minimum density of 1,057 VKT, Figure 59.

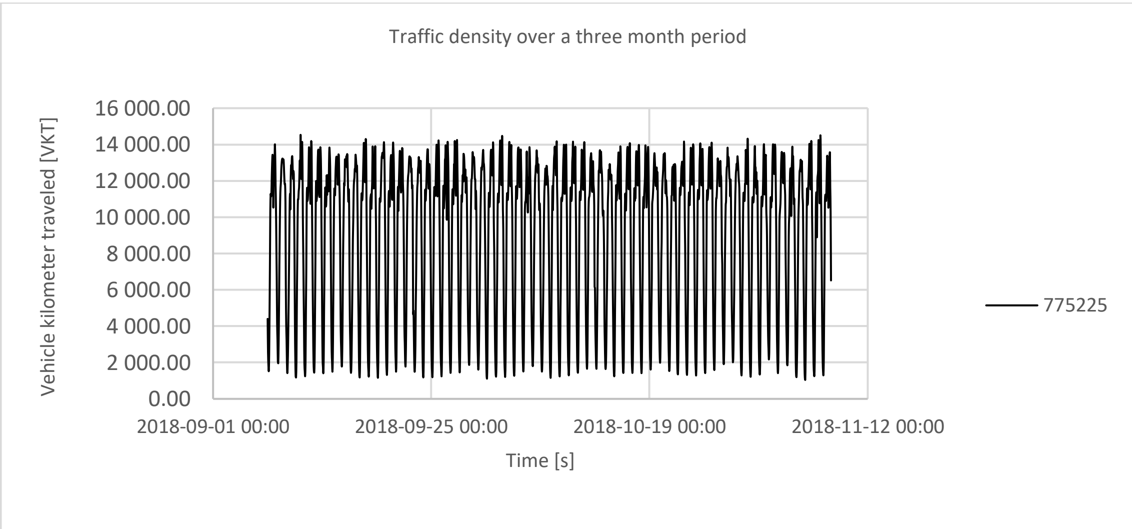


Figure 59 Density over time for detector, 775225.

The overall density over the three months September, October, and November for detector 760024, are showing a maximum density of 6,439 VKT, and a minimum density of 462 VKT, Figure 60.

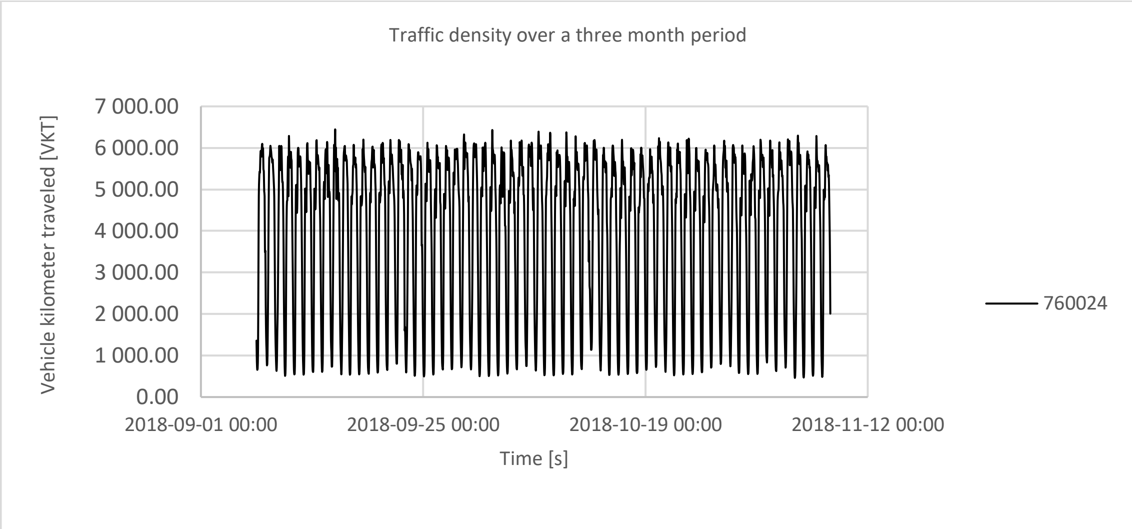


Figure 60 Density over time for detector, 760024.

An overall average maximum density for all the analysed detectors of the Hill and Woolsey fire are 8,030 VKT and the minimum density 406 VKT.

7.6. Summary

Given the working detectors with good quality data only the three fire events, Camp fire, Atlas fire and Hill and Woolsey fire, will be analysed, simulated, and compared. For all fires there was evidence of an increased traffic flow over daytime and decreased flow over night-time. The average flow occurred around 60 mph with a few detectors registering higher and a few lower. For all events it occurred car incidents over the time period of the fires. The background density varied between day and night-time whereof the highest density was found at daytime and the lowest at night-time for all detectors.

8. Analysis of WUI-NITY

In this chapter key findings of WUI-NITY will be discussed and analysed. Result of the WUI-NITY simulations run will also be presented given the assumptions and code described in, Appendix C. The key findings are analysed to further understand (a) the user decisions taken in making the input files but above all to (b) identify flaws and limitations that might be improved in future WUI-NITY updates. The latter in regards of better user experience but also to add missing functionality and output generation.

The fire events examined to simulate are based Camp fire, Atlas fire and Hill and Woolsey fire. Sufficient data is provided for those three fires whereas for the other mentioned fires not enough data could be provided and is therefore excluded.

For each event (e.g Camp fire) there will be eight scenarios run. These scenarios differ according to route selection and redefined response curve. The route selection includes evacuees taking the fastest, closest, or random routes, and also based on evacuation goal distribution. In the setup of WUI-NITY it is possible to define a specific area which has a unique distribution to some or all evacuation goals, this setup is the fourth route selection. The four route selections will first be simulated using a default response curve and secondly simulated using a redefined response curve using evidence derived off PeMS. Those two variations, default and redefined response curve for each route selection, will be compared against each other and also against PeMS derived data to find which route choice and response curve reflects the reality best. The redefined response curve is described in, Appendix B.

8.1. Key findings of WUI-NITY

Some interesting key findings with regard to simulating real-world events was found while simulating the scenarios using the data derived from the events examined. This includes both model settings and model output in regards of limitations on how the data may be used and what data that were able to be provided. The key findings are interesting because the level of data when performing simulations of real-world events compared to controlled evacuation drills (as the only comparison done in WUI-NITY before this thesis) varies. Key findings of interesting output data were also found. Both of which is further discussed below.

8.1.1. Initial Conditions - Total population

Total population of the simulation is one factor that may be defined in the input file. It is also possible to override the defined population and instead use the number of the total population from the used GPW-file. The GPW-file is gridded population data of the world which is extracted for the geographical area of which the simulation is run, see (SEDAC, Accessed January 2022). When simulating an evacuation-drill, this data is given and is controlled which means the outcome in WUI-NITY will be closer to the outcome of the drill. However, when replicating and simulate a real-world event, this data is not controlled, and an exact number of the total population may not be found. Even if the number of evacuees or citizens are found in a specific community it must also be in consideration that rural areas may not be included in the found population data. Therefore, it is recommended when simulating real-world events, including both communities and rural areas, to use data of the GPW-file. Even though the GPW-file may be a better choice of real-world simulations, it must also be taken into account that the GPW-file data is gathered from a specific time period (2000, 2005, 2010, 2015 or 2020) and it should therefore be decided which year to choose. **For this thesis it is chosen the GPW-data-set prior the incident for all cases, 2015.**

8.1.2. Initial Conditions - Household and car usage

It is possible to modify the size of the simulated households and how many cars each household may use in the simulation. This will affect the number of vehicles entering the system given a known number of residencies. This is often unknown in a real-world and must be assumed or estimated using population data. Increasing or decreasing the number of household size will have an impact of pedestrian flow and whether the household using single or multiple cars will also impact the traffic flow. In a drill it could be decided that a maximum number of cars per household may be used but in a real-world event such numbers will remain unknown and therefore for this thesis discussed. Some households may choose to evacuate together and might even invite an evacuee on foot and some household may use multiple cars. Since no data was found for this, for the sake of this thesis, **the use of multiple cars was chosen to be disabled and the size of the household left at default, one to five people**.

8.1.3. Initial Conditions – Background Density

The background density is another factor the user can define. However, when simulating an event lasting several days it is not only of interest to know the maximum and minimum density but also to define key time of when the density changes (e.g day or night). The traffic density over several days when only defining maximum and minimum density for the whole period will not replicate important events (e.g probability of bottlenecks day compared to night-time). **For the simulations in this thesis it is derived a background density using the data of PeMS.**

8.1.4. Resident Performance- Response curve

The response of the population is an input defined by the user that represents the initial delay of residents to initiate movement to a place of safety. When in a controlled environment (e.g evacuation drill) this factor can be found using data from the drill, meaning it is known at what times each evacuee responded. When in an uncontrolled environment (e.g real-world event) this data cannot be found using any data but rather must be calculated using assumptions and estimations from existing data (e.g PeMS). An inaccurate response curve may not represent the wanted outcome and is therefore important to analyse closely.

Because no data is given as to when the population responded and because the response time may vary depending on if there is a rural community or a larger town (within the same simulation), one way of finding a response curve is to analyse the flow of the detectors in PeMS – between normal and emergency incidents – to establish the uplift due to the emergency response. To do this it must be assumed one normal traffic flow and one emergency flow. This assumption is based on an average time period before the fire event as to be the normal flow and the time period of the fire to be the emergency flow. The average time period prior the incidents must be equivalent to the time of the fire and that is done by taking the time period of the fire, or as close to the time period of the fire possible, but for years before to be averaged. To use another time of the year would not represent that specific scenario (e.g more vacation during summer that may affect the flow). That averaged flow is assumed to be the normal traffic flow over that location and is compared against the emergency flow to identify a difference.

The difference between these two flows should in theory be the actual flow of the evacuation.

Once that flow is found it can be reverse engineered to find the response time. Given gaps in our understanding, it is assumed that resident movement from their home to the road is neglible in comparison to their actual delays to initiate movement). However, this approach is not flawless because it is not known if there are any congestions or other obstacles that may have increased the time it took traveling from the origin point to the detector (experienced before they reached a detector) and may therefore give an inaccurate response curve. It is also not known from where the registered vehicle of the detector comes from, whether it is from the closest community or from further afar. The response curve is because of the reasoning above, considered to be crucial for the output data, but impossible to define precisely due to the limitation of input data.

In the simulations this knowledge is used to derive a redefined response curve to be run for each route selection to be compared against the same route selection but with a default response curve.

In regards of the simulations for this thesis it will be compared for each case the difference between the default response curve and a calculated estimated response curve.

8.1.5. Resident Performance - Route selection

For an evacuation drill it might be known fairly precisely where the subjects evacuate from and to where they should finish. However, in a real-world event, the scenario might change due to the fire progression, road accidents or similar – and such detailed understanding might not be available for use in the modelling process. Any change of the conditions during the evacuation event may have a different outcome of where the evacuees decide to redirect and select a new evacuation destination. Perhaps a road was closed, or a lane reversal occurred, which forces the evacuee to deviate the known evacuation plan. If this change is significant, it can affect the general evacuation.

In WUI-NITY there is an option to control blocked goals (end destination of evacuation) but only as for when the blockage will start. This would equal a real-world event as for when a shelter capacity is full, and no more evacuees is welcome. In a real-world event that might be of interest not only to manage access to shelters but also to simulate the closing and re-opening of roads and its impact on evacuation performance. The evacuation goal might be accessible during the complete time of the simulation but the path of getting to that goal may change and therefore have an impact of how the evacuees behave while traveling. A road may open or close due to road accidents, fire progression or similar.

8.1.6. Model Representation of Traffic, Pedestrian, and Fire Conditions

The user must decide whether to use every available model or using a specific one when setting up the simulation in WUI-NITY. For some cases it might not be of interest to simulate all three aspects of the evacuation scenario available, traffic, pedestrian, and fire, even though it is an asset worth having. Therefore, it should be of interest to make it easier for the user to enable or disable any or more models instead of having to go through the entire input code. **In this thesis both pedestrian and traffic are used.**

The fire model would not have had any impact of the evacuation so it would not have been used regardless but it should also be noticed that the fire model as of now is under construction and can therefore not be used in any of the cases run for this thesis anyways.

8.1.7. Output values

The data output given from WUI-NITY is based on the result over time from the entire simulation, that is the entire distance of the evacuation paths. However, the data (PeMS) found to compare against WUI-NITY is based on a certain location (detector) rather than the entire distance – for instance, it likely excludes the journey from the residence to the detector. Because of these two different approaches it might not be possible to compare the result directly as desirable. For a future WUI-NITY update it should therefore be of interest to look over a few different approaches for the output data. For instance, to allow times to be extracted from user-selected locations, rather than starting positions.

Due to this limitation, it was only possible to compare the traffic flow in a proper way but even so by averaging the flow over the domain for both PeMS and WUI-NITY. Congestions, vehicle speed, lane reversals and car accidents where factors that was not possible to compare with the reason being the lack of data over a specific location. Hence why it is so important to implement devices for future updates.

8.1.8. Simulation limitations

WUI-NITY is applied at a scale not previously examined. It was found to be limited to a maximum simulated population/area size. This limited the size of the map and therefore the methods to replicate the full scale of a real-world event. The data size of the simulation differs from different locations because some areas have more population and a broader road network which leads to more computational power compared to locations of less population and fewer roads. Therefore, the higher population and road density there is, the smaller the map size it must be. These limitations are not strictly caused by WUI-NITY but also the computational power of which the computer the simulation is run on.

The computational power also limits the size of data which can be stored on the computer (output data). This is strictly caused by the choice of time step factor in the simulation. The default value is 1 time step per second which, in extreme time periods, creates lots of data. To manage the output data size this had to be adjusted. The bigger the time step, the less accurate the model will be and therefore the chosen number is a compromise of lost accuracy of the model data against manageable size of data for the computer to handle. The chosen time step for each simulation is 60 seconds.

The above statements regarding, simulation size and time step, was performed to allow for the simulations to conduct.

8.2. Scenarios

In this chapter it is reviewed the 24 simulations that were conducted for this thesis. In regards of computational power and time to this thesis the simulations were single runs, not multiple runs, which further is a limitation towards convergence for each simulated outcome. The result from these scenarios are produced in following chapters. Each fire event, Camp fire, Atlas fire, and Hill and Woolsey fire, are divided into eight scenarios each. Four scenarios using the default response curve and four scenarios with a redefined response curve derived from the PeMS database. Both response curves is run for each route selection, see (Table 13).

Table 13 The 24 simulations run for this thesis. Eight scenarios for each fire event of Camp fire, Atlas fire and Hill and Woolsey fire.

Scenario	Incident	Response Curve	Route Selection
Default_0_CF	Camp fire	Default	0 – fastest
Default_1_CF			1 – closest
Default_2_CF			2 – random
Default_3_CF			3 – based on evacuation groups
PeMs_0_CF		PeMs derived	0 – fastest
PeMs _1_CF			1 – closest
PeMs _2_CF			2 – random
PeMs _3_CF			3 – based on evacuation groups
Default_0_AT	Atlas fire	Default	0 – fastest
Default_1_AT			1 – closest
Default_2_AT			2 – random
Default_3_AT			3 – based on evacuation groups
PeMs_0_AT		PeMs derived	0 – fastest
PeMs _1_AT			1 – closest
PeMs _2_AT			2 – random
PeMs _3_AT			3 – based on evacuation groups
Default_0_HW	Hill and Woolsey fire combined	Default	0 – fastest
Default_1_HW			1 – closest
Default_2_HW			2 – random
Default_3_HW			3 – based on evacuation groups
PeMs_0_HW		PeMs derived	0 – fastest
PeMs _1_HW			1 – closest
PeMs _2_HW			2 – random
PeMs _3_HW			3 – based on evacuation groups

8.3. Results: Camp fire

The simulations of Camp fire are divided into two sets and named the following, one set of simulations with default response curve (Scenario Default_X_CF) and one set with the derived response curve (Scenario PeMS_X_CF). The assumptions used and the changes of the default code for the Camp fire simulations are explained in, Table 14, and is based on the derived data of Appendix C. The X in this text is replaced with 0, 1, 2, and 3 respectively reflecting the route selection method employed.

Table 14 Assumptions made for the default case of Camp fire.

Code	Value	Comment
TotalEvacTime	1,531,800 sec	The total evacuation time was derived by analysing the fire scenario in (Ronchi, et al., 2021). The value used is the input setting of the maximum allowed evacuation time for the simulation.
Start of origin	(39.701669, -121.805414)	Based on the evacuated area including vehicle detectors and the fire progression.
Size	20,000 x 11,000 (X,Y)	The approximate maximum manageable size before WUI-NITY crashes. This may vary depending on population and road density.
Model used	Pedestrian and traffic	Fire model is in progress and non-functional.
EvacuationOrderStart	Camp fire: 3,180 sec	The input setting for the time of which the first evacuation was ordered from the time of which the fire originated.
Response curve	**Scenario Default_X_CF** Time: -3,180 – 0 sec Prob: 14 % Time: o – 9,086 sec Prob: 81 % Time: 9,086 – 27,258 sec Prob: 94.9 % **Scenario PeMS_X_CF** Time: -3,180 – 40,020 sec Prob: 6,7 % Time: 40,020 – 346,020 Prob: 7,2 % Time: 346,020 – 860,820 sec Prob: 45 % Time: 860,820 – 925,620 sec Prob: 45,3 % Time: 925,620 – 1,530,000 sec Prob: 100 %	The response curve used as input setting for both the default and the derived simulations.
Blocked goals	No blocked goals	
Evacuation goals	Two in the city of Chico, one in the direction of Butte Meadows and three in direction of Oroville	The exact location of Oroville and Butte Meadows could not be determined. Instead, it was chosen three goals in the direction of Oroville and one in the direction of Butte Meadows.

Route choice	0, 1, 2 and 3	This is the model approach to define the route selection of the population. 0 – Fastest available route 1 – Closest available route 2 – Random route 3 – Based on the defined evacuation groups.
Reverse lanes	False	No evidence of reversed lanes.
Traffic accidents	True	Evidence of traffic accidents was found.

Each of the simulations with default response curve, regardless of route selection, produced a total result of 43,464 population. Depending on the route selection it varied the number of people that decided to stay. For Default_0_CF 2,212 people stayed, making it a total 41,252 evacuees. For Default_CF_1, 2,230 people stayed, making it a total 41,234 evacuees. For route Default_2_CF, 2,129 people stayed, making it a total 41,335 evacuees. For Default_3_CF, 2,281 people stayed, making it a total 41,183 evacuees. For the scenario Default_2_CF the greatest number of cars was used, 14,623 and for the scenario Default_1_CF the least number of cars was used, 14,537. The most visited evacuation goal was Butte Meadows involving 41 % of the evacuated people and occurred during Default_1_CF (fastest route). The least visited evacuation goal was ChicoJunior which remained unvisited for all cases. None of the default cases reached the maximum allowed simulation time, the longest evacuation occurred for route choice 3, 160,920 seconds while the fastest evacuation occurred for route selection 0, 102,720 seconds, see (Figure 61, Table 15).

The differences of result for the scenarios depend on the route selection of each scenario. Each scenario uses a different approach of evacuee route selection in the simulation and will therefore effect the different factors in the model (e.g congestions) and ultimately the total evacuation time.

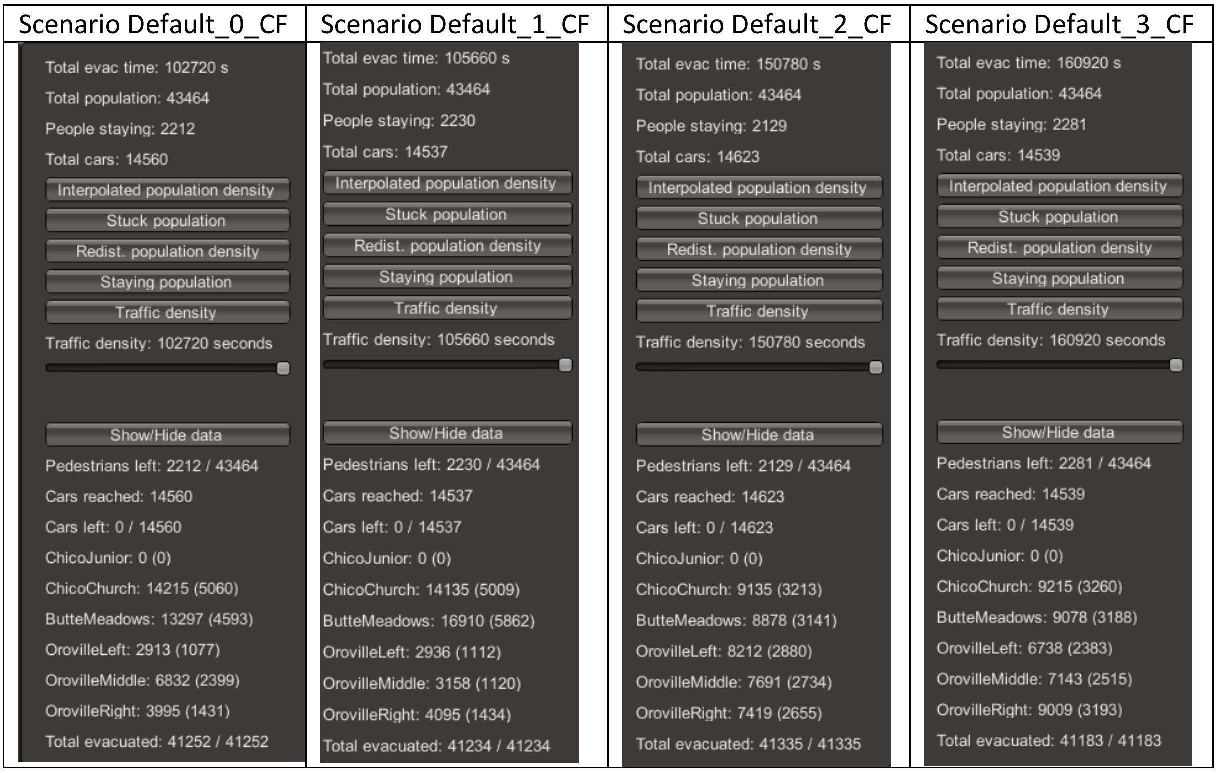


Figure 61 Output slice file from WUI-NITY for the Camp fire simulations with the used default response curve.

Table 15 The distribution of the evacuating vehicles over the evacuation goals for the four default cases (Scenario Default_0_CF – Scenario Default_3_CF).

	Percentage [-]					
	ChicoJunior	ChicoChurch	ButteMeadows	OrovilleLeft	OrovilleMiddle	OrovilleRight
Default_0_CF	0	34.46	32.23	7.06	16.56	9.68
Default_1_CF	0	34.28	41.01	7.12	7.66	9.93
Default_2_CF	0	22.10	21.48	19.87	18.61	17.95
Default_3_CF	0	22.38	22.04	16.36	17.34	21.88
Mean	0	28.30	29.19	12.60	15.04	14.86

The four scenarios with redefined response curve produced a total initial population of 43,464. All of the population evacuated in all scenarios. Scenario PeMS_0_CF used a total of 15,344 cars in the evacuation. Scenario PeMS_1_CF used a total of 15,407 cars in the evacuation. Scenario PeMS_2_CF used a total of 15,442 cars in the evacuation. Scenario PeMS_3_CF used a total of 15,333 cars in the evacuation. The distribution of the six evacuation goals is like the default response curve, see (Figure 62, Table 16).

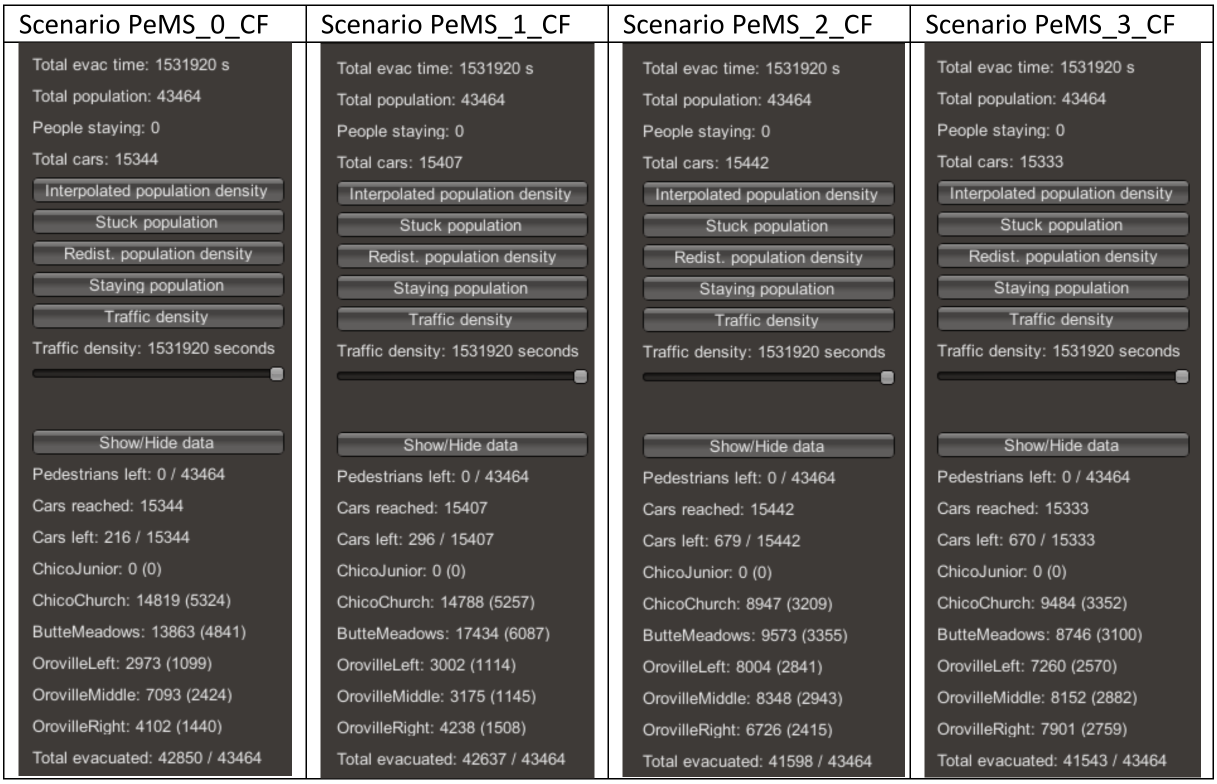


Figure 62 Output slice file from WUI-NITY for the Camp fire simulations with the used redefined response curve.

Table 16 The distribution of the evacuating vehicles over the evacuation goals for the four redefined cases.

	Percentage [-]					
	ChicoJunior	ChicoChurch	ButteMeadows	OrovilleLeft	OrovilleMiddle	OrovilleRight
PeMS_0_CF	0	34.58	32.35	6.94	16.55	9.57
PeMS _1_CF	0	34.68	40.89	7.04	7.45	9.94
PeMS _2_CF	0	21.51	23.01	19.24	20.07	16.17
PeMS _3_CF	0	22.83	21.05	17.48	19.62	19.02
Mean	0	28.40	29.33	12.67	15.92	13.68

The number of active vehicles over time for the four simulations with the default response curve produced no difference regardless of route choice, see (Figure 63).

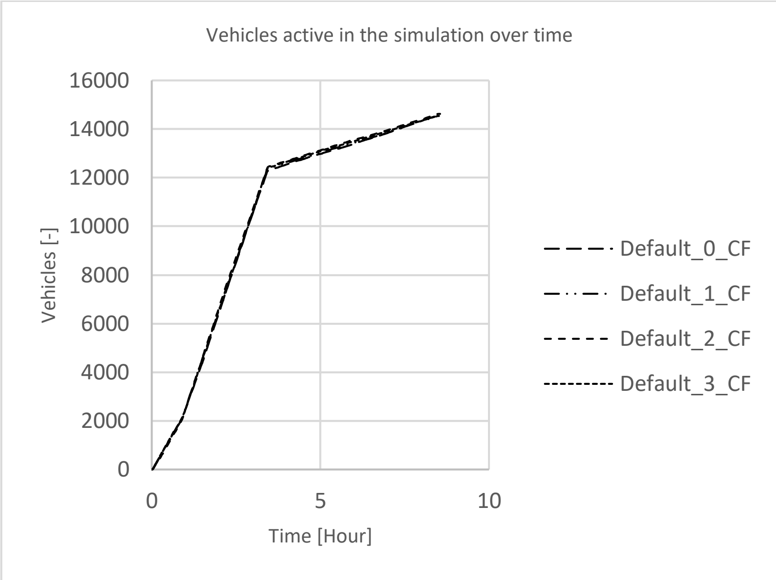


Figure 63 Active cars in the simulation for the four simulations with the default response curve.

The response curve of the four default simulations produced a similar result to the default WUI-NITY response curve, see (Figure 64).

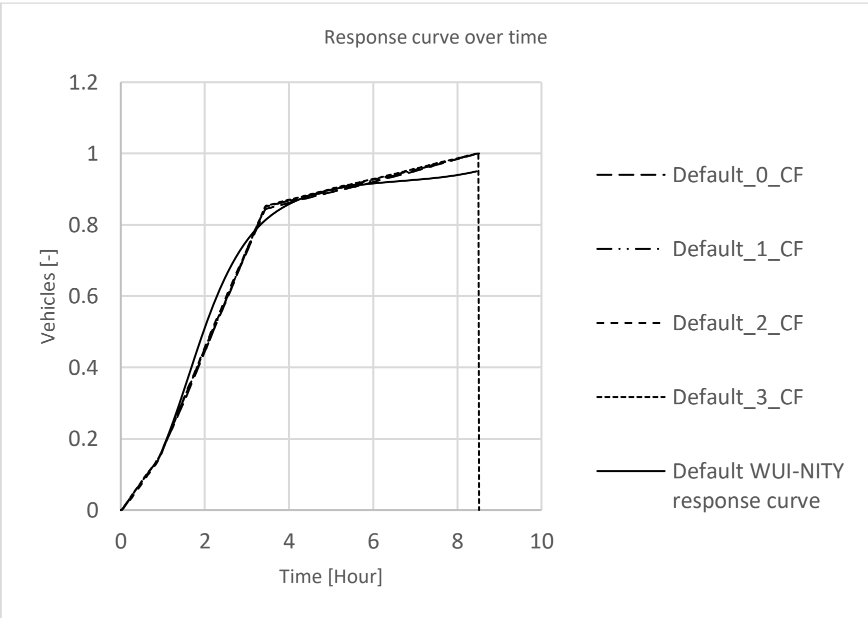


Figure 64 Response curve of the evacuating vehicles over time for the four default simulations with the default response curve.

The number of active vehicles over time for the four simulations with the redefined response curve produced no difference regardless of route choice, see (Figure 65).

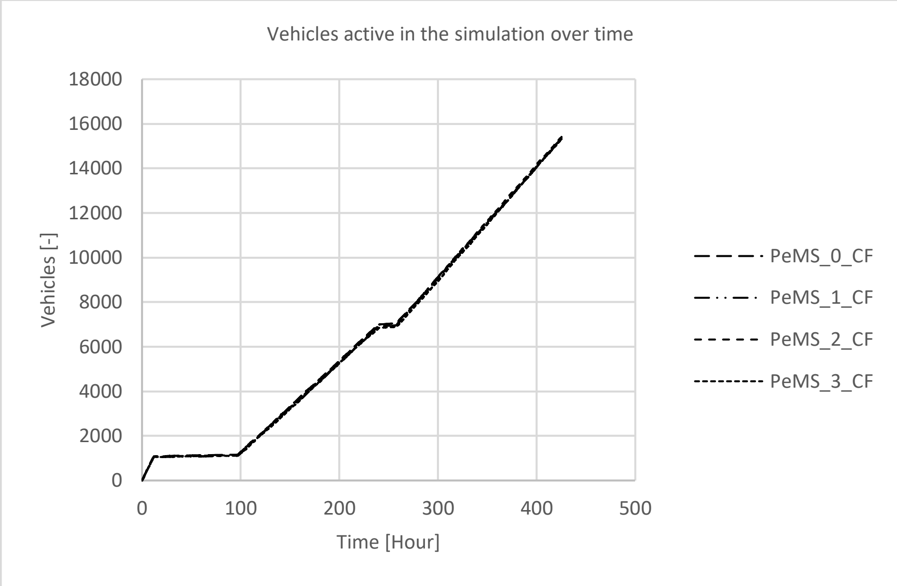


Figure 65 Active cars in the simulation for the four simulations with the derived response curve.

The response curve of the four redefined simulations produced a similar result to the PeMS response curve derived from PeMS database, see (Figure 66).

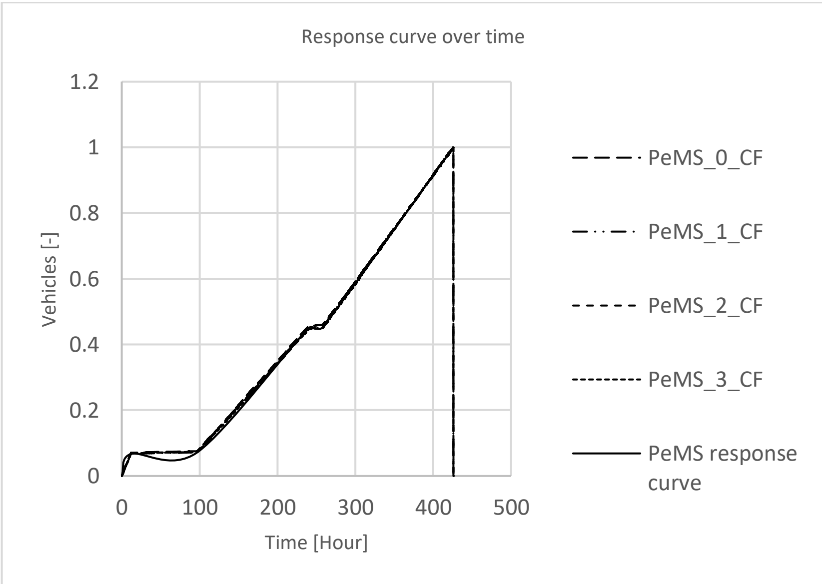


Figure 66 Response curve of the evacuating vehicles over time for the four default simulations with the derived response curve.

8.4. Result: Atlas fire

The simulations of Atlas fire are divided into two sets and named the following, one set of simulations with default response curve (Scenario Default_X_AT) and one set with the derived response curve (Scenario PeMS_X_AT). The assumptions used and the changes of the default code for the Atlas fire simulations are explained in, Table 17. The X in this text is replaced with 0, 1, 2, and 3 respectively reflecting the route selection method employed.

Table 17 Assumptions made for the simulations of the Atlas fire.

Code	Value	Comment
TotalEvacTime	1,087,680sec	The total evac time was derived by analysing the fire scenario in (Ronchi, et al., 2021).
Start of origin	(38.204514, -122.28349)	Based on the evacuated area including vehicle detectors and the fire progression.
Size	24,000 x 14,000 (X,Y)	The maximum manageable size before WUI-NITY crashes.
Model used	Pedestrian and traffic	Fire model is in progress and nonfunctional.
EvacuationOrderStart	Atlas fire: 6,700 sec	The input setting for the time of which the first evacuation was ordered from the time of which the fire originated.
Response curve	**Scenario Default_X_AT** Time: -6,700 – 0 sec Prob: 14 % Time: o – 19,143 sec Prob: 81 % Time: 19,143 – 57,249 sec Prob: 94.9 % **Scenario PeMS_X_AT** Time: -6,700 – 101,300 sec Prob: 40,1 % Time: 101,300 – 493,700 sec Prob: 40,1 % Time: 493,700 – 788,900 sec Prob: 75,7 % Time: 788,900 – 1,008,500 sec Prob: 83 % Time: 1,008,500 – 1,084,100 sec Prob: 100 %	The response curve used as input setting for both the default and the derived simulations.
Blocked goals	No blocked goals	
Evacuation goals	Solano community college and Allan Witt Park	The exact location of Oroville could not be determined. Instead it was chosen three goals in the direction of Oroville.
Route choice	0, 1, 2 and 3	This is the model approach to define the route selection of the population. 0 – Fastest available route 1 – Closest available route 2 – Random route 3 – Based on the defined evacuation groups.

Reverse lanes	False	No evidence of reversed lanes.
Traffic accidents	True	Evidence of traffic accidents was found.

Each of the simulations with default response curve, regardless of route selection, produced a total result of 124,858 population. Depending on the route selection it varied the number of people that decided to stay. For Default_0_AT, 6,017 people stayed, making it a total 118,841 evacuees. For Default_1_AT, 6,327 people stayed, making it a total 118,531 evacuees. For Default_2_AT, 5,981 people stayed, making it a total 118,877 evacuees. For Default_3_AT, 6,323 people stayed, making it a total 118,535 evacuees. For the scenario Default_2_AT the greatest number of cars was used, 40,809 and for the scenario Default_0_AT the least number of cars was used, 40,654. The most visited evacuation goal was AllanWittPark of 74 % of the evacuated people and was similar in both AtlasFire_0 (fastest route) and AtlasFire_1 (closest route), see (Figure 68, Table 18).

The differences of result for the scenarios depend on the route selection of each scenario. Each scenario uses a different approach of evacuee route selection in the simulation and will therefore effect the different factors in the model (e.g congestions) and ultimately the total evacuation time.

Scenario Default_0_AT	Scenario Default_1_AT	Scenario Default_2_AT	Scenario Default_3_AT

Figure 67 Output slice file from WUI-NITY for the Atlas fire simulations with the used default response curve.

Table 18 The distribution of the evacuating vehicles over the evacuation goals for the four default cases.

	Percentage [-]	
	SolanoCommunityCollege	AllanWittPark
Default_0_AT	26.2	73.8
Default_1_AT	26.2	73.8
Default_2_AT	48.7	51.3
Default_3_AT	63.0	37.0
Mean	41.0	59.0

The four scenarios with redefined response curve produced a total initial population of 124,858. All of the population evacuated in all scenarios. Scenario PeMS_0_AT used a total of 43,109 cars in the evacuation. Scenario PeMS_1_AT used a total of 43,030 cars in the evacuation. Scenario PeMS_2_AT used a total of 42,850 cars in the evacuation. Scenario PeMS_3_AT used a total of 42,719 cars in the evacuation. AllanWittPark was the higher percentage out of the route choices, 0, 1 and 2, but for route choice 3 it was an even distribution, see (Figure 68, Table 19).

Scenario PeMS_0_AT	Scenario PeMS_1_AT	Scenario PeMS_2_AT	Scenario PeMS_3_AT

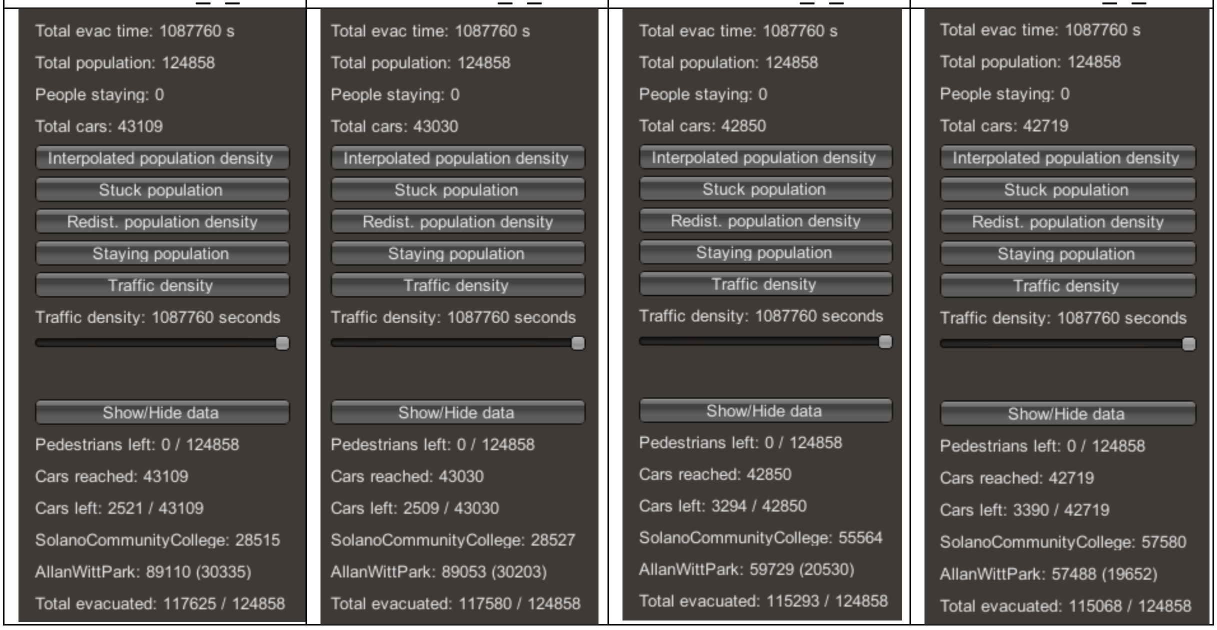


Figure 68 Output slice file from WUI-NITY for the Atlas fire simulations with the used redefined response curve.

Table 19 The distribution of the evacuating vehicles over the evacuation goals for the four redefined cases.

	Percentage [-]	
	SolanoCommunityCollege	AllanWittPark
PeMS_0_AT	24.2	75.8
PeMS _1_AT	24.3	75.7
PeMS _2_AT	48.2	51.8
PeMS _3_AT	50.0	50.0
Mean	36.7	63.3

The number of active vehicles over time for the four simulations with the default response curve produced similar result for route choice 0, 1, and 3, see (Figure 69).

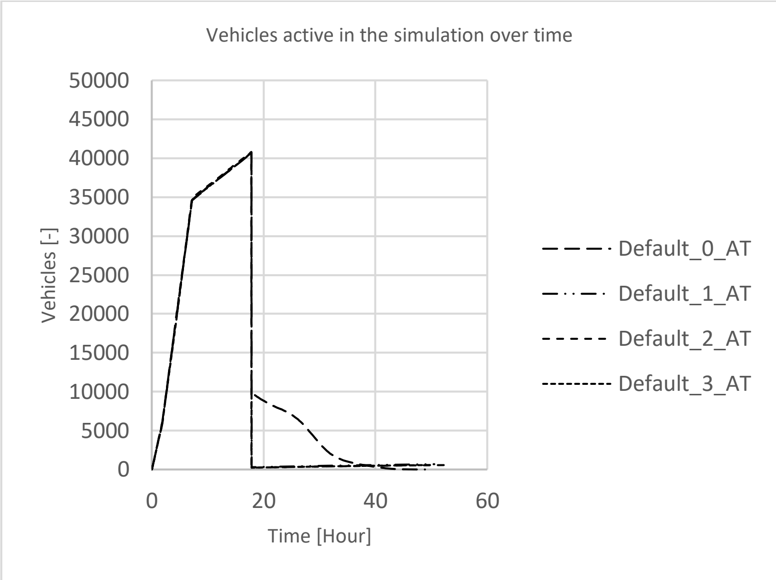


Figure 69 Active cars in the simulation for the four simulations with the default response curve.

The response curve of the four default simulations produced a similar result to the Default WUI-NITY response curve, see (Figure 70)

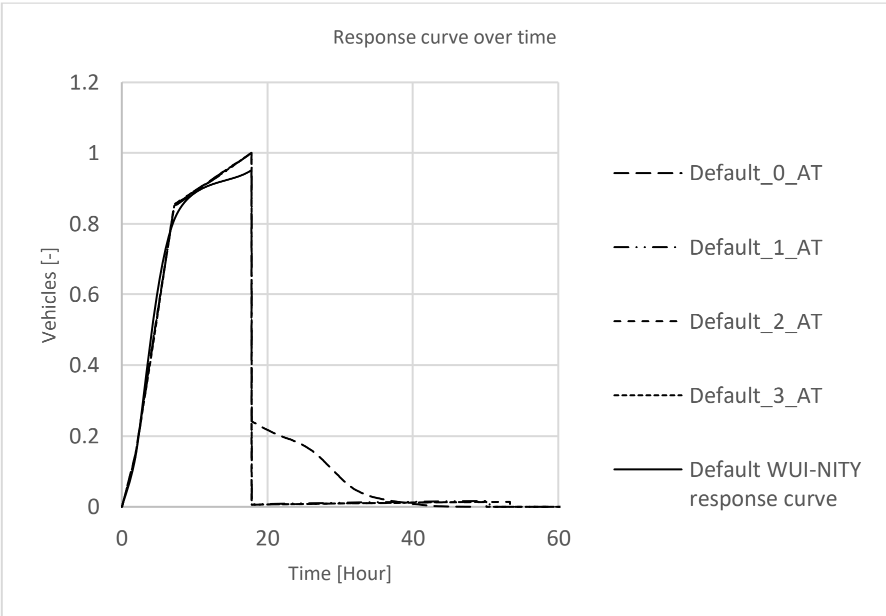


Figure 70 Response curve over time for the four default simulations with the default response curve.

The number of active vehicles over time for the four simulations with the redefined response curve produced no difference regardless of route choice, see (Figure 71).

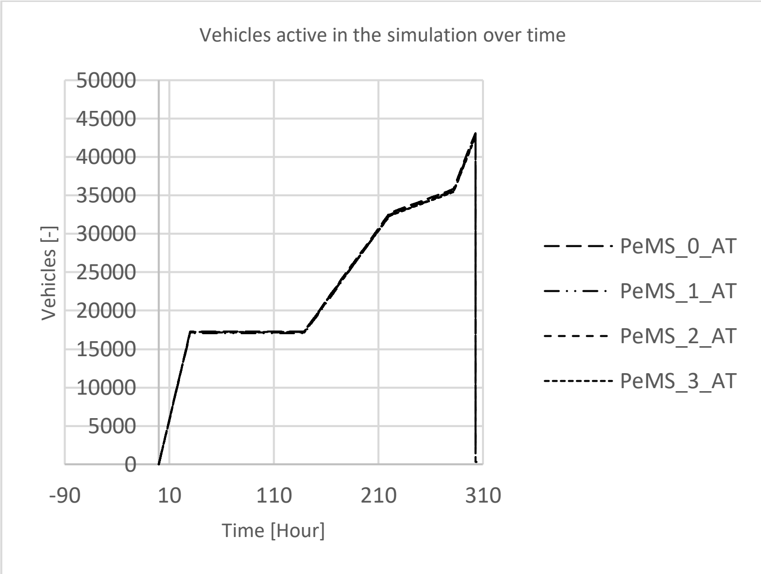


Figure 71 Active cars in the simulation for the four simulations with the derived response curve.

The response curve of the four redefined simulations produced a similar result to the PeMS response curve derived from PeMS database, see (Figure 72 Response curve over time for the four default simulations with the derived response curve.).

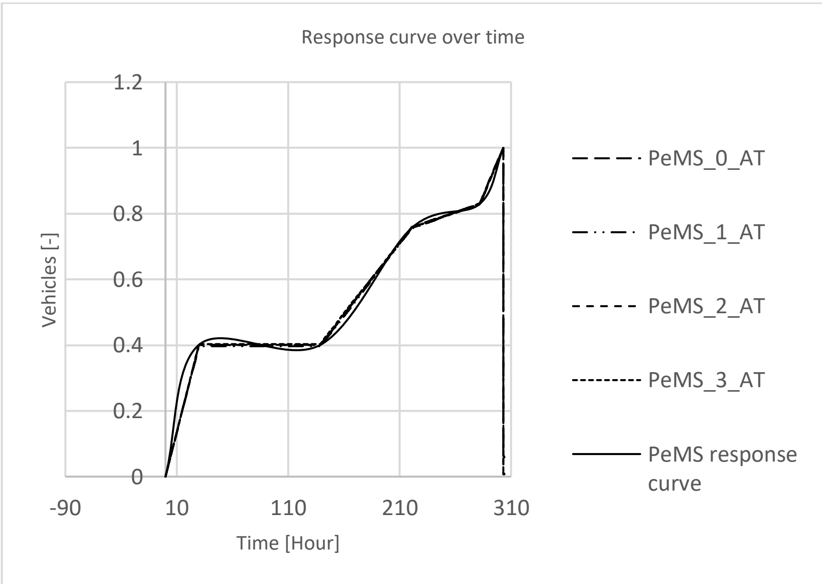


Figure 72 Response curve over time for the four default simulations with the derived response curve.

8.5. Result: Hill and Woolsey fire

The simulations of Camp fire are divided into two sets and named the following, one set of simulations with default response curve (Scenario Default_X_HW) and one set with the derived response curve (Scenario PeMS_X_HW). The assumptions used and the changes of the default code for the Hill and Woolsey fire simulations are explained in, Table 20. The X in this text is replaced with 0, 1, 2, and 3 respectively reflecting the route selection method employed.

Table 20 Assumptions made for the simulations of Hill and Woolsey fire.

Code	**Value**	**Comment**
TotalEvacTime	1,157,400 sec	The total evac time was derived by analysing the fire scenario in (Ronchi, et al., 2021).
Start of origin	(34.079023, -118.840713)	Based on the evacuated area including vehicle detectors and the fire progression.
Size	24,000 x 11,000 (X,Y)	The maximum manageable size before WUI-NITY crashes.
Model used	Pedestrian and traffic	Fire model is in progress and nonfunctional.
EvacuationOrderStart	Hill and Woolsey fire: 11,400 sec	The input setting for the time of which the first evacuation was ordered from the time of which the fire originated.
Response curve	**Scenario Default_X_HW** Time: -11,400 – 0 sec Prob: 14 % Time: o – 32,571 sec Prob: 81 % Time: 32,571 – 97,714 sec Prob: 94.9 % **Scenario PeMS_X_HW** Time: -11,400 – 17,400 sec Prob: 11,1 % Time: 17,400 – 75,000 sec Prob: 11,9 % Time: 75,000 – 103,800 sec Prob: 24,0 % Time: 103,800 – 593,400 sec Prob: 67,5 % Time: 593,400 – 769,800 sec Prob: 72,3 % Time: 769,800 – 1,097,400 sec Prob: 84,1 % Time: 1,094,400 – 1,155,600 sec Prob: 100 %	The response curve used as input setting for both the default and the derived simulations.
Blocked goals	No blocked goals	
Evacuation goals	West and east	The exact location of Oroville could not be determined. Instead it was chosen three goals in the direction of Oroville.

Route choice	0, 1, 2 and 3	(Fastest route, closest route, random route and based on the evac groups)
Reverse lanes	False	No evidence of reversed lanes.
Traffic accidents	True	Evidence of traffic accidents was found.

Each of the simulations with default response curve, regardless of route selection, produced a total result of 129,957 population. Depending on the route selection it varied the number of people that decided to stay. For Default_0_HW, 6,775 people stayed, making it a total 122,482 evacuees. For Default_1_HW, 6,455 people stayed, making it a total 122,802 evacuees. For Default_2_HW, 6,581 people stayed, making it a total 122,676 evacuees. For Default_3_HW, 6,639 people stayed, making it a total 122,618 evacuees. For the scenario Default_2_HW the greatest number of cars was used, 42,310 and for the scenario Default_0_HW the least number of cars was used, 42,095. The most visited evacuation goal was West of 70 % of the evacuated people which occurred for route HillWoolseyFire_3 (EvacGroup), see (Figure 73, Table 21).

The differences of result for the scenarios depend on the route selection of each scenario. Each scenario uses a different approach of evacuee route selection in the simulation and will therefore effect the different factors in the model (e.g congestions) and ultimately the total evacuation time.

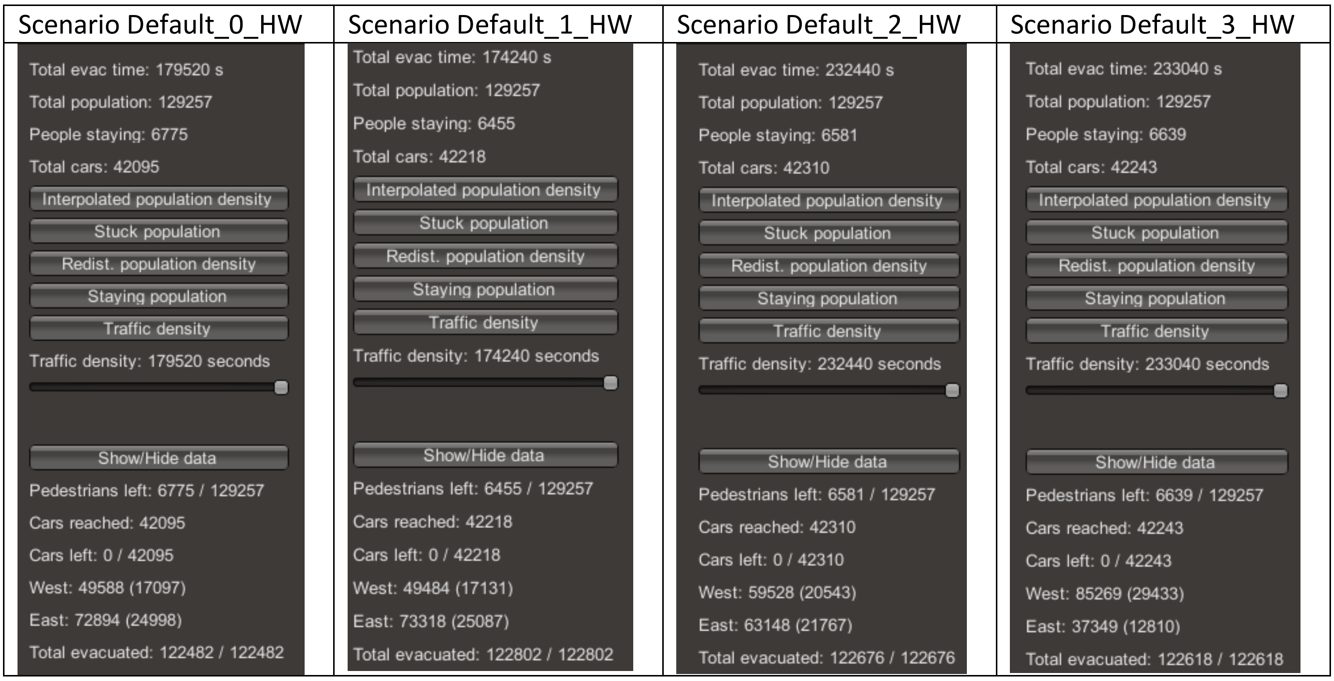


Figure 73 Output slice file from WUI-NITY for the Hill and Woolsey fire simulations with the used default response curve

Table 21 The distribution of the evacuating vehicles over the evacuation goals for the four default cases.

	Percentage [-]	
	West	East
Default_0_HW	40.49	59.51
Default_1_HW	40.30	59.70
Default_2_HW	48.52	51.48
Default_3_HW	69.54	30.46
Mean	49.71	50.29

The four scenarios with redefined response curve produced a total initial population of 129,257. All of the population evacuated in all scenarios. Scenario PeMS_0_HW used a total of 44,276 cars in the evacuation. Scenario PeMS_1_HW used a total of 44,487 cars in the evacuation. Scenario PeMS_2_HW used a total of 44,616 cars in the evacuation. Scenario PeMS_3_HW used a total of 44,587 cars in the evacuation. The distribution of evacuating vehicles over the evacuation goals is similar to the default response curve, see (Figure 74, Table 22).

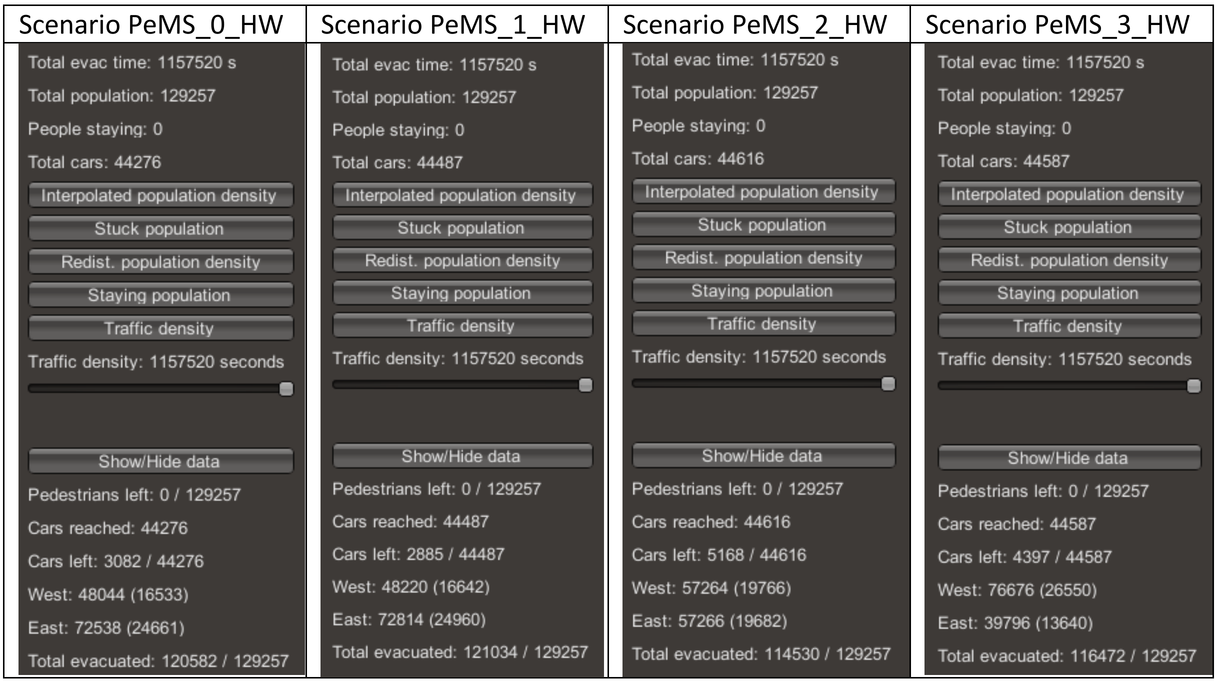


Figure 74 Output slice file from WUI-NITY for the Hill and Woolsey fire simulations with the used redefined response curve.

Table 22 The distribution of the evacuating vehicles over the evacuation goals for the four redefined cases.

	Percentage [-]	
	West	East
PeMS_0_HW	39.84	60.16
PeMS _1_HW	39.84	60.16
PeMS _2_HW	50.00	50.00
PeMS _3_HW	65.83	34.17
Mean	48.88	51.12

The number of active vehicles over time for the four simulations with the default response curve produced similar result for route choice 0, 1, 2, and 3, see (Figure 75).

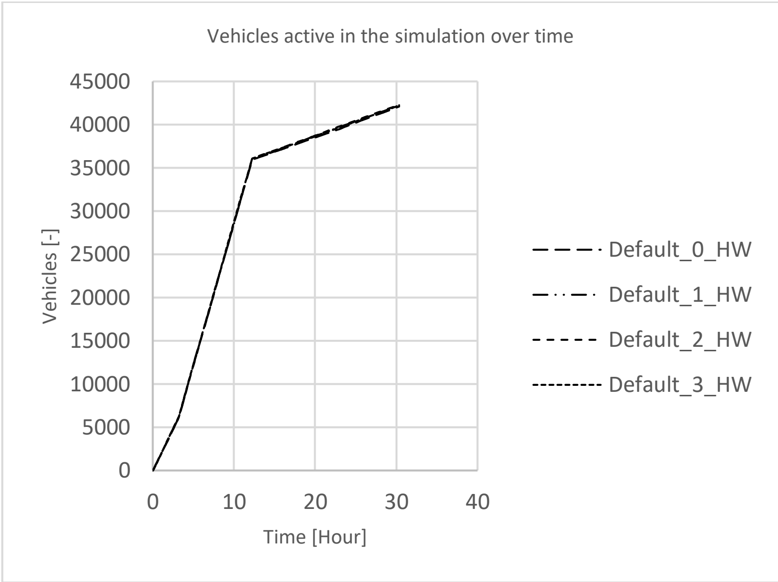


Figure 75 Active cars in the simulation for the four simulations with the default response curve.

The response curve of the four default simulations produced a similar result to the Default WUI-NITY response curve, see (Figure 76)

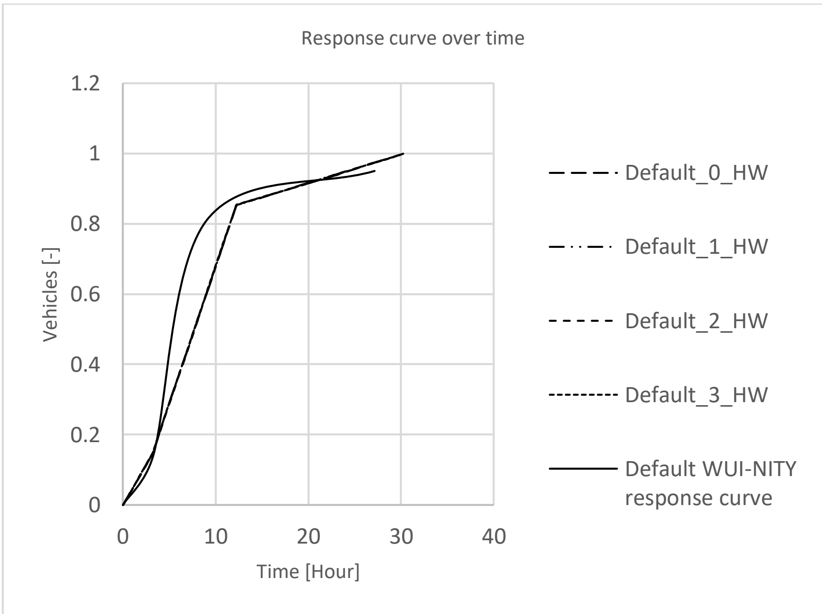


Figure 76 Response curve over time for the four default simulations with the default response curve.

The number of active vehicles over time for the four simulations with the derived response curve produced no difference regardless of route choice, see (Figure 77).

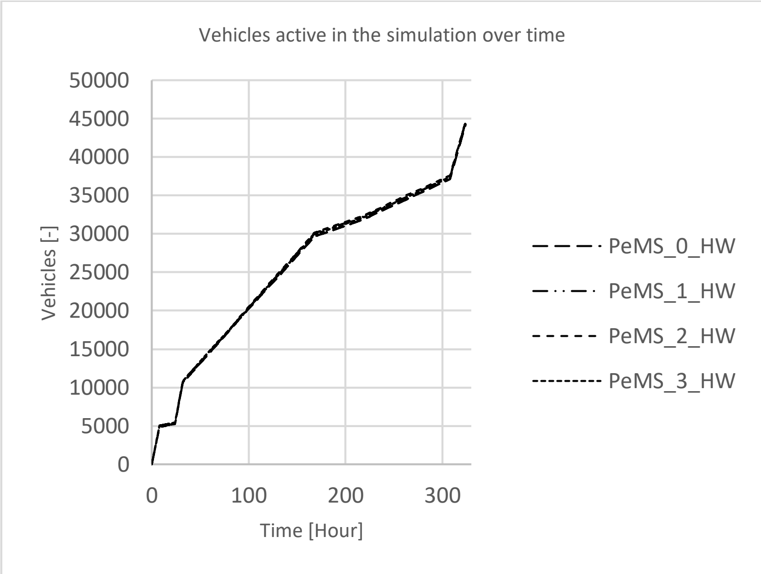


Figure 77 Active cars in the simulation for the four simulations with the derived response curve.

The response curve of the four redefined simulations produced a similar result to the PeMS response curve derived from PeMS database, see (Figure 78).

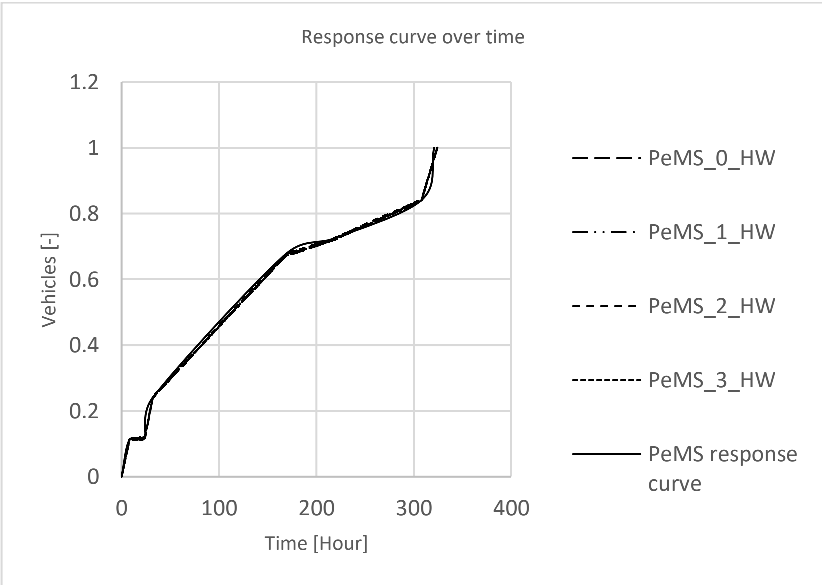


Figure 78 Response curve over time for the four default simulations with the derived response curve.

9. Comparing result of WUI-NITY against real-world data

This chapter presents the comparison of results derived from WUI-NITY against the PeMS database. This includes both the key factors of community evacuation; response time, traffic flow, congestion, vehicle speed, lane reversal and car accident and also correlation of number of vehicles and the two different response curves; default curve and a redefined curve derived from the data of PeMS. The result of the compared data will be used to define the range of use for WUI-NITY as it is today and to address issues to solve for a future WUI-NITY update.

The data from PeMS are based on specific dates and the run simulations in WUI-NITY are based on time starting at time 0 and ends at time X where X is the total number of hours from the origin of fire to the end of evacuation. All comparisons are therefore based on a timeline from the start of the fire origin to best review the compared results of the simulations and PeMS. However, this means that the comparisons is not based on the same time spectra but is rather a representation of how sensitive WUI-NITY is to changes of the defined input settings in compliance to the data derived from PeMS. The end points of the curves may therefore differ from the real-world data compared to the simulated data.

9.1. Accumulated number of vehicles

The PeMs database was used to derive the accumulated number of vehicles over time. This was generated as an output value in WUI-NITY and is therefore possible to compare. As a representation only the scenario with route selection 0 will be used for both Default and PeMS as benchmark value to be compared against the real-world data. This is because there was no difference in numbers between the different route selections.

Accumulated number of vehicles was not included in the key findings of evacuations but is at least as important to compare from a simulation perspective. This is because the number of cars influences the traffic flow and therefore effects other factors (e.g congestion). Therefore, this factor is compared with the real-world data against the simulations.

9.1.1. Camp fire

Regardless of the response curve, both types of WUI-NITY simulations *underestimate* the data derived from PeMS over the time of Camp Fire. The simulation with redefined response curve (PeMS_0_CF) replicates the data of PeMS best but is still lower than the wanted outcome, see (Figure 79).

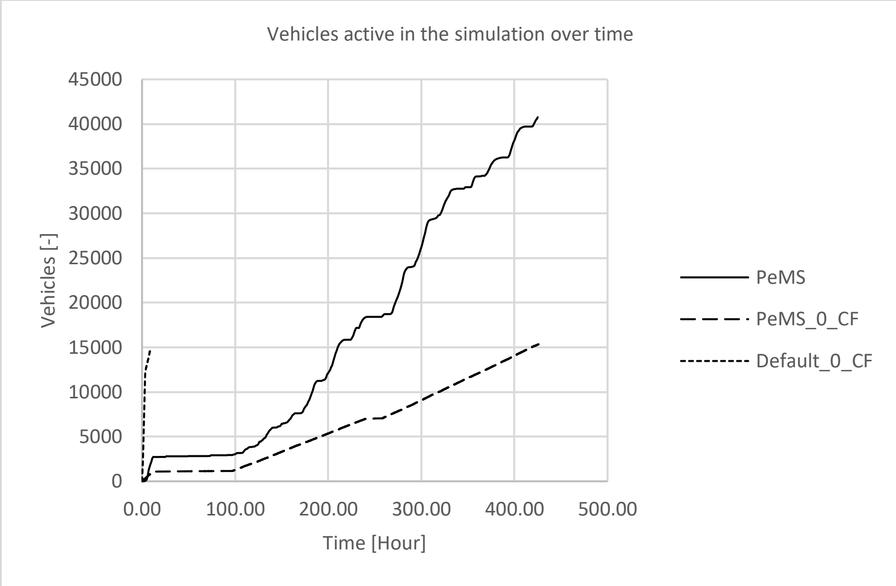


Figure 79 Accumulative number of vehicles over the time of Camp Fire shown for both PeMS and WUI-NITY.

9.1.2. Atlas fire

Regardless of the response curve, both types of WUI-NITY simulations *overestimate* the data derived from PeMS over the time of Atlas Fire. The simulation with redefined response curve (PeMS_0_AT) replicates the data of PeMS best but is still higher than the desired outcome, see (Figure 80).

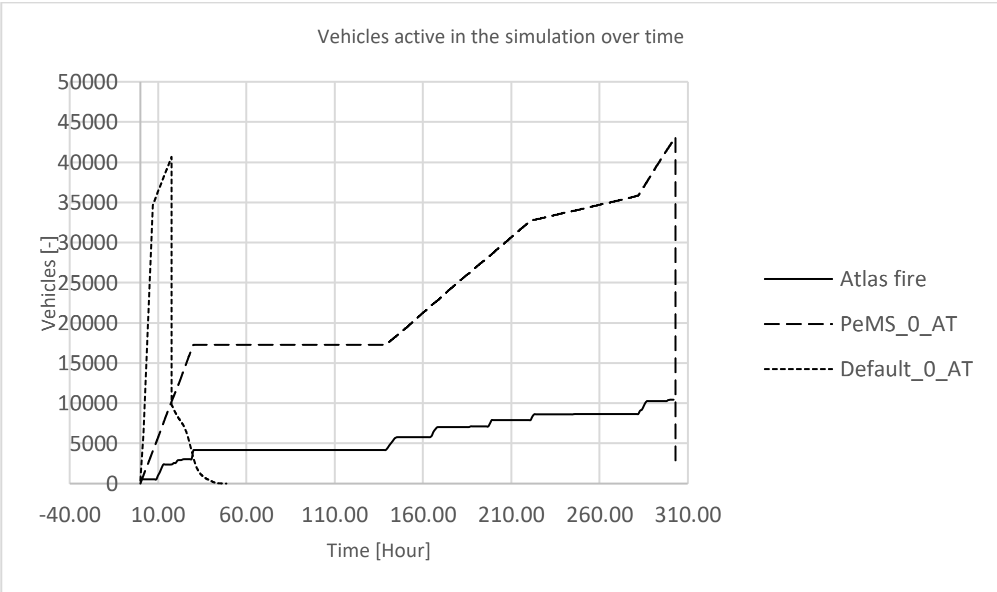


Figure 80 Accumulative number of vehicles over the time of Atlas Fire shown for both PeMS and WUI-NITY.

9.1.3. Hill and Woolsey fire

Regardless of the response curve, both types of WUI-NITY simulations underestimate the data derived from PeMS over the time of Hill and Woolsey Fire. The simulation with redefined response curve (PeMS_0_HW) replicates the data of PeMS best but is still lower than the wanted outcome, see (Figure 81).

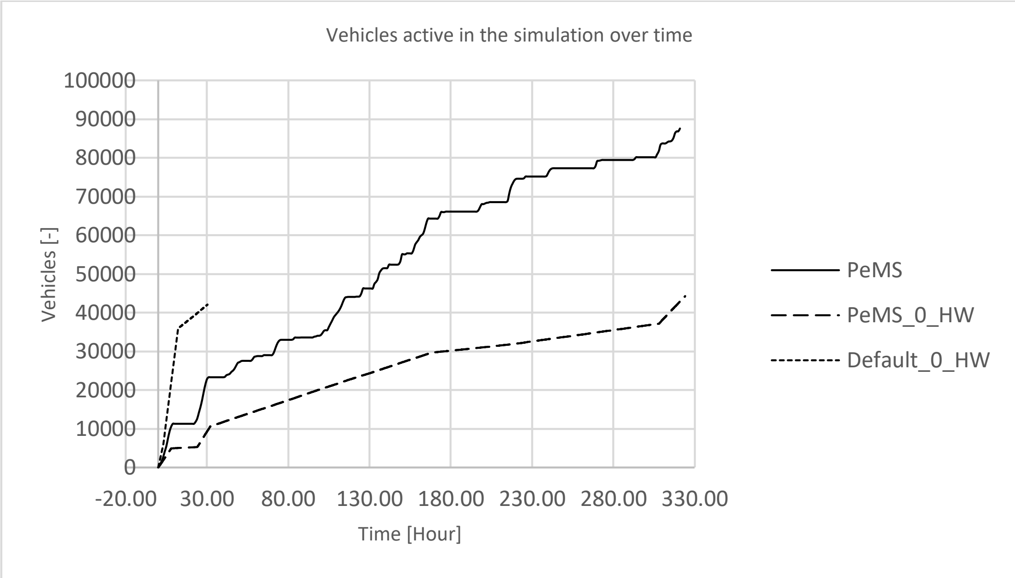


Figure 81 Accumulative number of vehicles over the time of Hill and Woolsey Fire shown for both PeMS and WUI-NITY.

9.1.4. Conclusion

For the Atlas fire the number of vehicles was overestimated while for the other two cases it was underestimated. To adjust this outcome for a better replication of the real-world data, the factor defining the number of cars per household could be changed. This would solve the problem for cases underestimating the data since the factor is restricted to one car per household. However, for Atlas fire which is overestimating the data it would need to overrule the population of the GPW-file and decrease the total population in order to match the wanted outcome of vehicles over time.

The reason why the number of vehicles does not match the derived data of PeMS may be because of the analysed populated areas. It must be remembered that the number of vehicles derived from PeMS is an average of several detectors registering cars coming from unknown origins, this includes locations outside the simulated domain. Therefore, there is an uncertainty regarding how many of those registered cars really passed from within the area of interest. If the simulated population is less than the registered population passing the vehicle detectors, it will produce less vehicles than the real-world derived data and vice versa. This due to the limitation of the scenario setup factor for vehicle per household of one car per household. It must also be taken into account that any adjustment of a chosen factor (population or car usage) may not be linear as the three different cases are different from each other. It is only noted that a change of either population or car usage could solve the problem, but it is always up to the users knowledge to adjust and find the correct value for the desired outcome of any event.

This is a factor that must be redefined after a run simulation to further adjust the numbers to become more precise to the desired outcome. This is because WUI-NITY does not provide the population of the simulation until the simulation is finished.

9.2. Response curve

Response curve was the other factor that varied in addition to the four different route selections. For each route selection approach, the default response curve and a redefined response curve derived from PeMS was run. Both scenarios with the Default and the PeMS response curve will be compared against the real-world data. As a representation only the scenario with route selection 0 will be used for both Default and PeMS as benchmark value to be compared against the real-world data. This is because there was no difference in numbers between the different route selections.

9.2.1. Camp fire

Of the two response curves from the simulation only the redefined response curve (PeMS_0_CF) replicates the data of the defined response curve derived of PeMS. The replication of the PeMS scenario is close in approximation to the real-world data, see (Figure 82).

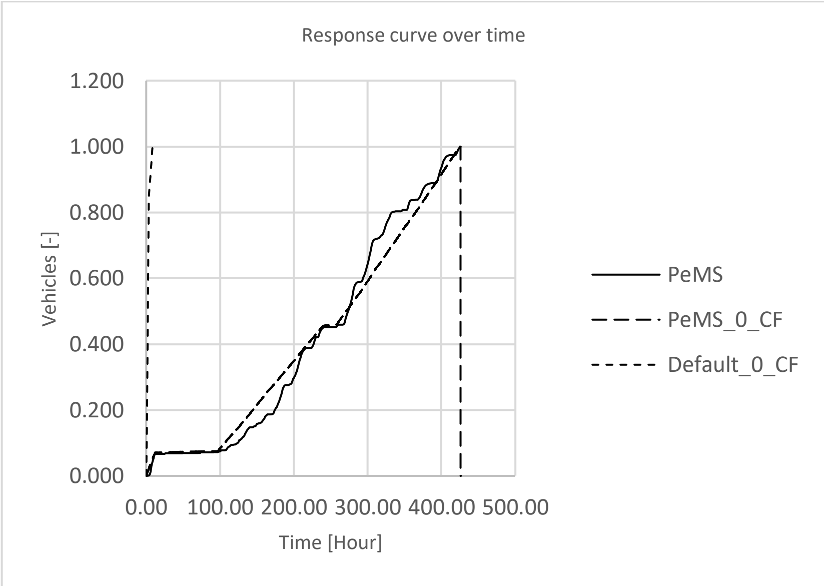


Figure 82 Response curve over the time of Camp Fire shown for both PeMS and WUI-NITY.

9.2.2. Atlas fire

Of the two response curves from the simulation only the redefined response curve (PeMS_0_AT) replicates the data of the defined response curve derived of PeMS. The replication of the PeMS scenario is close in approximation to the real-world data, see (Figure 83).

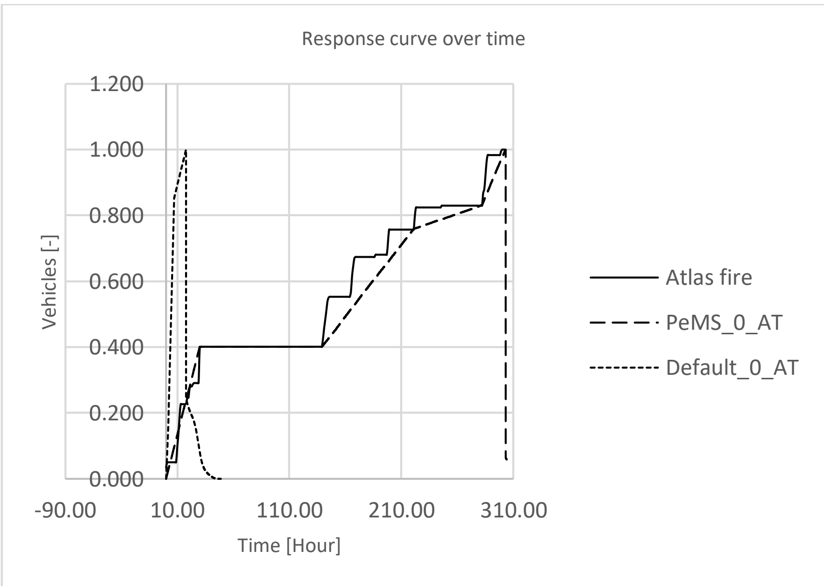


Figure 83 Response curve over the time of Atlas Fire shown for both PeMS and WUI-NITY.

9.2.3. Hill and Woolsey fire

Of the two response curves from the simulation only the redefined response curve (PeMS_0_HW) replicates the data of the defined response curve derived of PeMS. The replication of the PeMS scenario is close in approximation to the real-world data, see (Figure 83).

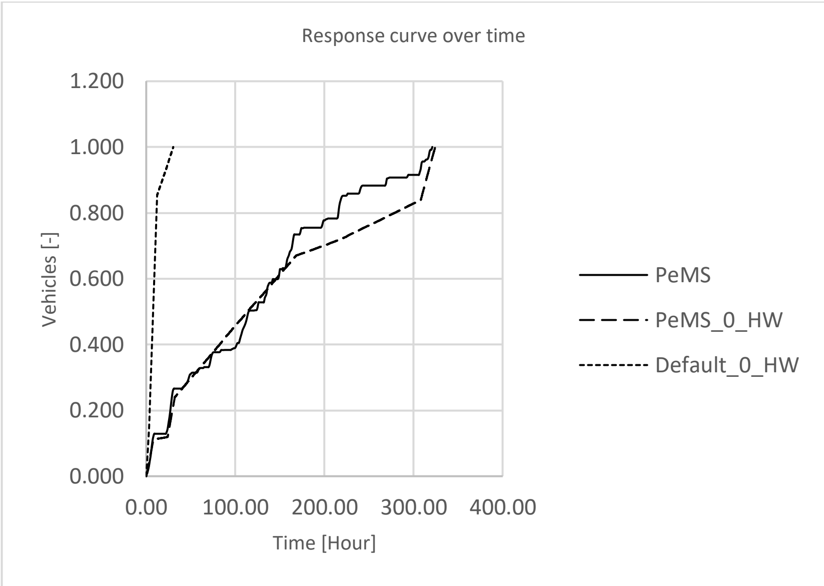


Figure 84 Response curve over the time of Hill and Woolsey Fire shown for both PeMS and WUI-NITY.

9.2.4. Conclusion

The default response curve should not be used nor trusted when replicating a real-world event. Instead, an adjusted response curve should be derived from representative wildfire event data and used to reflect the underlying conditions. This produces more representative outcomes in all cases that approximate the traffic movement extracted from the actual events. It would also be concerning if the default response curve did outperform the redefined response curve given that the redefined curve is closer in approximation of the initial response. For this thesis the adjusted response curve was derived of PeMS database. The adjusted response curve can be derived in larger or smaller time steps depending on the scenario and quality of data. The better quality of data and the smaller the time step, the better replication of the used dataset. **However, due to the extreme time periods of these events it was for this thesis chosen to be derived in larger time steps which is why the simulated response curve does not perfectly fit the one derived of PeMS.**

It must also be taken into consideration that the redefined response curve derived from PeMS, that was used in all non-default scenarios, is averaged from several detectors within the simulated area. This effects the response curve in multiple ways. Firstly, some detectors are located on busy roads with a general higher traffic flow meaning that it is likely a higher overall background traffic density there, even during the time of the fire. This is likely to effect the derived response curve in a way that makes it not as precise as the reality is because it includes a traffic flow of cars that is not participating in the evacuation. Secondly, the redefined response curve does not consider the cars origin and is therefore averaging an overall response curve for the entire domain which is not accurate either. In the real-world a response curve also includes the time of which the resident gets aware of the evacuation, time of movement to the car and time from the parked car to the registered detector. All time prior the registering of the detector is excluded. What these simplifications result in is a response curve that in some ways resembles the real-world event but not in a detailed level to adjust a unique response curve for different communities within the simulation. However, no other solution to derive the response curve using the real-world data was found and is therefore used anyways. It is the closest approximation of the real-world response curve possible.

9.3. Traffic flow

Traffic flow is influenced by several factors including congestion, vehicle speed, lane reversals and even car accidents as described in Chapter 2, Key factors of community evacuation. Traffic flow was derived from PeMS database but cannot be compared to WUI-NITY in detail. The reason why, is that WUI-NITY does not grant output flow data of a specific point source (e.g location of vehicle detectors) but rather outputs flow data of the chosen evacuation goals.

One alternative method to get output flow data of the same location as the studied VDS is to place an evacuation group at that coordinate. However, the evacuation group does not act as a measurement device. Once a pedestrian or vehicle reaches the evacuation group, they either disappear from the simulation or stack up until the evacuation group is full. This would either create loss of evacuees that would have normally travelled further, or it would congest and clog the road network as the evacuation goals fill up. This change of traffic flow is unwanted, and this method is therefore not used.

Another important finding when comparing the real-world traffic flow against the simulation input data is that the real-world traffic flow fluctuates when an event occurs over a longer period of time (e.g both day and night). The real-world traffic flow derived from the PeMS database showed a higher flowrate during daytime and a lower during night-time for all studied VDS's. In the setup of the simulation for WUI-NITY it was not possible to define the change of flow over time but for a future update it may be of interest to look over the possibility to implement a factor defining traffic flow over time.

As conclusion for the traffic flow, it is therefore recommended for a future WUI-NITY update to implement output traffic flow devices so the user can compare flow against the same geographical location as the real-world data. It is also recommended to implement a flow factor to replicate the day and night-time.

9.4. Congestion

Congestion was excluded from analyse from PeMS because it is not comparable against WUI-NITY since WUI-NITY lacks location source data. Instead, congestion was assumed to be included in the vehicle speed analysis. The reason to why congestion was included in the vehicle speed analysis was because the speed of when congestion occurred had to be defined for PeMS. No data was found to specify the speed of which congestion occurred and instead it was assumed to be included in the vehicle speed factor. That is, when the speed decreased over time it could be caused due to a congestion of unknown reason.

Also, WUI-NITY has no good way of comparing the result of the congestion against a location source. WUI-NITY estimated an average speed over the whole simulation for each time-step and the user must determine when and if that speed is considered to be an ongoing congestion or not. As of now that is not possible to determine because the compared data of PeMS is from a location source rather than an entire area.

Therefore, for a future WUI-NITY update it is recommended to implement a device measuring congestion from a location source.

9.5. Vehicle speed

Vehicle speed was studied in PeMS and was estimated for the time period over each fire event. However, the estimated vehicle speed data cannot be compared against WUI-NITY. This is because WUI-NITY estimated the vehicle speed for the entire simulation. The estimated vehicle speed of PeMS is derived from vehicles already on highways but WUI-NITY includes all traffic, even smaller roads. Therefore, is the output speed from WUI-NITY much lower than the derived from PeMS. In the setup of the simulation, it was also determined a stall speed which is the minimum speed any vehicle would travel even if the road were clogged. From the output of WUI-NITY it could be concluded that the average speed in the simulation occurred at stall speed meaning it occurred massive congestions throughout the simulated area. To be able a comparison of this factor between the simulations against PeMS it is necessary to implement a location device measuring vehicle speed. This would be a better approach comparing the speeds derived of PeMS against the simulations.

Therefore, for a future WUI-NITY update it is recommended to implement a device measuring vehicle speed from a location source.

9.6. Lane reversal

Lane reversal was activated in WUI-NITY for the entire simulation of the events when lane reversal occurred. However, from the WUI-NITY output file it lacked data of this factor and could therefore not be further compared. The evidence of lane reversal was not found using PeMS but instead it was gathered from a case study (Ronchi, et al., 2021).

In the setup of WUI-NITY it was not possible to define what road should be reversed and at which time. Lane reversal is controlled by setting a time of which lane reversals globally within the simulated domain starts and at what time it globally within the domain ends.

For a future WUI-NITY update it would therefore be recommended to implement a tool to define what local roads or areas should be affected by lane reversals and at what times. It would also be of interest to define in which direction the reversal faces (e.g a northern lane reverse to southern lane).

9.7. Car accident

From PeMS it was discovered that car accidents occurred for all events. It could not be specified the location of the accident, but it was determined that it had happened within the simulated area and in the setup of each simulated case this factor was therefore activated. However, in WUI-NITY there is no output data of registered car accidents. The factor of car accidents can therefore not be compared and concluded to as how well the simulation replicates the real-world data.

To compare this factor against real-world data it is necessary for a future WUI-NITY update to include an output file measuring car accidents.

9.8. Setup factors of the simulation scenarios

It was not always obvious to determine the factors to be used in the setup of the simulation. This was mostly due to lack of knowledge and data. Two factors that proved to be changing the output of the simulations greatly was population and number of cars used per household. Even with a correct redefined response curve the result still differed from the data of PeMS. This would be because of a difference in the actual

10. Discussion

In this chapter it is discussed any concerns that occurred during the work of this thesis. This includes everything from questioning the working method to level of data used.

10.1. Challenges – from start to finish

The author had limited experience of validation of a simulation program. In addition, the author was unfamiliar with the WUI-NITY model before starting this thesis. Therefore, the work involved a big learning curve requiring research about the key tasks to conduct this work. It included knowledge how and what validation is, research about traffic databases, learn about WUI-NITY and understand the code behind it, learn about earlier wildfires, understand, and derive key factors of community evacuations. A considerable amount of effort was required to acquire sufficient understanding of wildfires, evacuation, available data, modelling and data analysis. The application of the WUI-NITY model therefore only presented a portion of the work conducted.

Most of the work behind this thesis involved gathering information about the topics mentioned above: validation, traffic databases, data extraction and processing, wildfire evacuation models (specifically WUI-NITY), earlier wildfires, understand and derive key factors of community evacuations. To further conduct this thesis, it was necessary for the author to gain deep knowledge in all mentioned topics to be able to make qualified decisions on how to progress the work and how to branch down the data to a manageable size. It was necessary to learn WUI-NITY from the core to make decisions on how to setup the code best way possible to best represent the real-world event. It was necessary to learn the traffic database, PeMS, from the core to make qualified decisions to provide good quality data to support the claims made in this thesis with the aim of making WUI-NITY more trustworthy. The remaining part of the work, to derive the data of PeMS, setting up the WUI-NITY simulations and to compare the result of these was just a fraction of the work but is described in a deeper context below.

Once the basic concept of the work method was outlined other challenges occurred throughout the project. One of the biggest challenges, other than learning about the above-mentioned topics, has been deriving relevant and good quality data from the PeMS database. PeMS contains large amounts of data, requiring considerable time to navigate and use the functions within the PeMs database. Once understood, the data had to be interrogated to determine the data-sets to be compared against WUI-NITY. Therefore, most data were derived alongside the learning of WUI-NITY. The data selected had to be checked to ensure it was sufficiently reliable for this work.

The work identified the limitations of the WUI-NITY model prompting model development. It was realised (in conjunction with a WUI-NITY developer) that it was necessary to install Framework .NET 3.5 (a system component that execute programmes written for .Net Framework) for the simulation program to function. This had been a problem in the past as well but is now addressed for users in the future.

The setup of WUI-NITY consisted of lots of trial-and-error configuration to find the model limitations and sensitivities – given user inexperience and challenges with the model application. Two major limitations that especially had to be finetuned was the size of the scenario domain (occasionally causing the model to crash), and the simulation time step (given the large simulated timespans). Left unconstrained, the output produced large output files of data. That data was too big for the computer to manage when dealing with 24 different scenarios and therefore had to be reduced. The bigger the time span, the less accurate the simulation became. Therefore, it was desired to have as small of a time span as possible but still big enough for the compute to cope. This required trial-and-error until a compromise was found. The increased time step also shortened to simulation time as well and took in total for the 24 simulations about 20 hours to complete.

It was also hard to compare the derived data of PeMS against the output data from the simulations. Most data from the simulation (averaged over the domain) was not comparable to a location source (vehicle detector). This suggested additional model functionality for future development.

10.2. Work method

The work method employed in this thesis managed to complete a comparison of real-world data with WUI-NITY which was the goal with the thesis. **However, if a similar work is to be performed in the future it is recommended to focus on one fire event rather than several**. The reason for that is that it is difficult (and time consuming) to find the detailed level of data that could be found by focusing on one fire instead. There was insufficient time to gather the necessary levels of detailed data from each fire event when studying multiple fires. The reason to why multiple fires were studied for this thesis was because it was not known in advance which fires had sufficient data to conduct detailed modelling – it could not be ascertained quickly and required time-consuming data extraction and analysis. Therefore, it was necessary to research of multiple fires to branch it down to fewer as the work progressed. In the end three fires was considered to include sufficient data whereof all fires were analysed completely.

This thesis has produced a number of interesting insights regarding model benchmarking, third party data selectin/extraction, model configuration, model testing, computer resource management, results comparison.

The limitations of the WUI-NITY model might be equally applicable to other large-scale incidents – especially where real-world data is available. Therefore, many of the lessons learned here might be more generally applicable.

10.3. Strength of data

The data used for this thesis is mainly derived from the database of PeMS with a few exceptions when referred sources was used instead (e.g case studies (Ronchi, et al., 2021)). All data used from PeMS was analysed for every detector associated with an incident. All data that was not 100 % registered was assumed to generate unreliable (and therefore unusable) data. Adopting this approach strengthens the quality of data used and therefore the probability of having a benchmark against which to compare the model results across the scenarios examined.

Even with the data used, there were some issues. There was some lack of clarity regarding the location and number of shelters/targets/evacuee objectives for every fire event. Instead, media reports (e.g. local newspapers) were used to help identify where and how many shelters there was, this is referred to and described in detail in, Appendix C. A newspaper should not be the first choice of source used in this kind of work, but it was the only available source other than assuming the location of the shelters out of the blue and was therefore used regardless.

10.4. Accuracy of result

When comparing the results produced from WUI-NITY against the derived data from PeMS it was hard to determine the method to be used. Initially, a statistical correlation was preferred concluding the validity of each factor leading to the overall validity of WUI-NITY against a real-world event. However, the data available was insufficiently detailed to allow such rigorous comparison that might warrant statistical analysis. The method of comparison finally chosen was visually comparing graphs to establish qualitative similarities. It was also decided to rather focus on what could be improved and what was missing from WUI-NITY rather than to determine a statistical result – to focus on the modelling process, rather than simply on the model output.

10.5. Evacuation times

From the studied wildfire cases it was found that the time periods of larger wildfires often stretched over several days and the evacuations were made partially as the fire progressed. This makes the evacuation complex and hard to replicate in a simulation. Given the scale and complexity of a wildfire evacuation, it is difficult to make local comparisons between real-world and simulated evacuations. This is because it requires a detailed level of data over a vast area regarding when evacuations were ordered out as the fire progressed and also to derive unique response curves of these areas by using data that has been averaged from several detectors within the analysed domain. This is because these detectors registers, not only the evacuating vehicles but also the background traffic of which the user must define and take into account. This complicates the derivation of the response curve in two steps. First it must be defined a general traffic flow of data so that it can be differenced from the traffic flow of the time over the fire which assumes the evacuation flow that further can be derived to a response curve. But even with that assumption there is a second problem. Second the step is that with that assumed traffic flow it is not known from where the vehicles come from and therefore it is not possible to derive a more detailed response curve than that. That means, it is not possible to define a detailed response curve of communities but rather an averaged for the whole simulation domain.

This concludes to the fact that the response curve using real world data can not be more precise than the quality of data being used. For this thesis it is data gathered from both literature and the PeMS traffic database and must be assumed over the entire simulated domain.

11. Conclusion

This thesis has compared the use of WUI-NITY against real-world data from several incidents, with the goal of better understanding the modelling process, making the model more trustworthy to use but also to increase confidence and capabilities in real life applications.

This was performed by deriving data of the chosen traffic database, PeMS, with aim to replicate three real-world wildfire events. The data derived from PeMS was based on the key findings of community evacuation and WUI-NITY varied factors; route use, response time and traffic flow, whereof traffic flow includes the factors, congestion, vehicle speed, lane reversals and car accidents. Lane reversals could not be derived from the PeMS database but was found from case studies.

By looking at historical wildfires and comparing the location of those in compliance with the coverage of the chosen real-world database, PeMS, it was limited to only study wildfires from the state of California. With that criterion and the given time for this thesis, three events were chosen to be analysed further, Camp fire, Atlas fire, and Hill and Woolsey fire. The data derived from PeMS and the setup of the WUI-NITY simulations was based on the information found from the three studied wildfires.

The evacuation traffic flow was derived by assuming an average traffic flow to compare against an assumed emergency flow. The average traffic flow was based on the same time period of the analysed fire but for earlier years and the emergency flow was the traffic flow over which the fire scenario occurred. The difference between the emergency flow and the averaged flow was assumed to be the evacuation flow which the thesis is built on.

Before WUI-NITY could be used, a programme had to be downloaded, Framework .NET 3.5, for WUI-NITY to function. The code to run a simulation also had to be studied before a simulation was setup. With Framework .NET 3.5 downloaded and the code studied it was designed 24 different scenarios, eight for each fire event. Four scenarios that had a default response curve but varied the route selections, fastest, closest, random, and based on evacuation groups, and the other four scenarios had a redefined response curve based on the data provided from PeMS and also ran the four different route choices. The setup of the code for each scenario was based on information found from the wildfire case studies and PeMS.

The comparison of the simulation results against the data from PeMS for the factors of accumulated number of vehicles over time and response curves was performed by looking at graphs to find correlations of data over the different fire events. The remaining key factors of community evacuations lacked a detailed level of data and could therefore not be compared neither visually in graphs nor by statistical values. Instead, the remaining key factors of community evacuation was discussed. The discussion included reasons as to why it could not be compared and also about how to solve the problems with recommended implementations for future WUI-NITY updates. These recommendations include new devices, new input factor settings, and output files.

The visual comparison of accumulated number of vehicles correlated that the number of cars was underestimated for two out of three fires while for one fire it was overestimated. This concluded to be caused by two factors, the number of registered vehicles of the vehicle detectors and due to the population of the simulated domain. The vehicle detector registers every passing vehicle, and it is unknown the cars origin. This means that any car, both within and outside the simulated domain, could pass and be registered by the vehicle detector while for the simulation the maximum number of cars is limited to the population within the simulated domain.

The graph comparison of the response curves indicated that the use of real-world response data (i.e. from an incident) more closely approximates the evacuation output from the real incident. This is because the redefined response curve (a) has a big effect on the evacuation dynamics and (b) is based on the data of the real-world event meaning that this big impact more closely approximates the initial response from the original incident. However, the redefined response curve does not include the response time prior the registering of the vehicle detector; response time from deciding to act upon being given the information of the evacuation, time to travel from the origin location to a vehicle and the time to drive from the parked location to which the detector registers the car and is not to be assumed completely accurate compared to the real-world event. Even here there was a limitation in the data extracted from the PeMs data-set from the original incidents.

The devices recommended to implement into future WUI-NITY updates needs to measure a specific location source (e.g a specific coordinate) to be able a comparison of real-world data. The devices that are recommended are to measure, traffic flow, congestion, and vehicle speed. This is because as of now WUI-NITY averages the entire simulated domain which does not match the specific location of a vehicle detector from PeMS. This makes it impossible to do a comparison of the simulation and PeMS result of traffic flow, congestion and vehicle speed.

The input setting factors recommended to implement into future WUI-NITY updates is to get a more detailed replication of the real-world event. The input setting factors include a traffic flow factor to adjust flow over time (e.g different flow of day and night) and a factor to define a local road or areas that should be lane reversed and at what time and also to define in which direction it is reversed. These factors are both to be able a comparison of WUI-NITY and PeMS but also to simulate the real-world event in a more detailed level. These factors was identified when deriving data from PeMS and found to be of importance for a detailed simulation of the real-world event.

The output data that is recommended to be implemented is a file registering car accident. As of now it does not specify where and how many accidents occur in the simulation. It is possible to activate car accidents from the input settings of the simulations, but it is not possible to analyse if it occurred any. Therefore, it is not a possibility to compare this against the real-world data of PeMS.

By implementing the recommended devices, input setting factors, and output data, it will be possible to compare all the found key factors of community evacuation of WUI-NITY against the real-world database, PeMS, and it will also be possible to adjust the simulation in greater detail and will therefore make WUI-NITY more trustworthy to use. By making WUI-NITY more trustworthy to use it will also increase its confidence and in real life applications because a more detailed setting of the simulation can be adjusted to more precise replicate a real-world event than is possible of today.

12. Future implications

Several lessons have been learned for future applications and what steps might be taken to ensure more representative and detailed insights:

- Focus on single incidents if it is possible to allow a deeper analysis
- Ensure that the time step applied is sufficient to afford credible insights given the computational power available
- Conducted sensitivity analysis
- Apply response curve derived from incident data
- Update WUI-NITY to include:
  - User-defined data capture points to measure vehicle arrival / departure
  - User-defined data capture points to measure locations of congestion at locations of interest
  - User-defined data capture points to measure vehicle speeds at locations of interest
  - User-defined data capture points to measure traffic flow at locations of interest
  - More refined user control over time changes of traffic flow (day / night)
  - More refined user control over lane reversal locations and timing
  - Documented occurrence of vehicle incidents in output file

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13. Appendix

13.1. Appendix A

A summarised appendix producing all detector quality derived data from PeMS.

Table 23 Quality of data for detector 318510 and 318509.

318510			318509		
Day	**Lane1**	**Lane2**	**Day**	**Lane1**	**Lane2**
2018-11-08	Good	Good	2018-11-08	Good	Good
2018-11-09	Good	Good	2018-11-09	Good	Good
2018-11-10	Good	Good	2018-11-10	Good	Good
2018-11-11	Good	Good	2018-11-11	Good	Good
2018-11-12	Good	Good	2018-11-12	Good	Good
2018-11-13	Good	Good	2018-11-13	Good	Good
2018-11-14	Good	Good	2018-11-14	Good	Good
2018-11-15	Good	Good	2018-11-15	Good	Good
2018-11-16	Good	Good	2018-11-16	Good	Good
2018-11-17	Good	Good	2018-11-17	Good	Good
2018-11-18	Good	Good	2018-11-18	Good	Good
2018-11-19	Good	Good	2018-11-19	Good	Good
2018-11-20	Good	Good	2018-11-20	Good	Good
2018-11-21	Good	Good	2018-11-21	Good	Good
2018-11-22	Good	Good	2018-11-22	Good	Good
2018-11-23	Good	Good	2018-11-23	Good	Good
2018-11-24	Good	Good	2018-11-24	Good	Good
2018-11-25	Good	Good	2018-11-25	Good	Good

Table 24 Quality of data for detector 318510 and 318509.

Day	Lane1	Lane2
2017-10-08	Good	Good
2017-10-09	Good	Good
2017-10-10	Good	Good
2017-10-11	Good	Good
2017-10-12	Good	Good
2017-10-13	Good	Good
2017-10-14	Good	Good
2017-10-15	Good	Good
2017-10-16	Good	Good
2017-10-17	Good	Good
2017-10-18	Good	Good
2017-10-19	Good	Good
2017-10-20	Good	Good
2017-10-21	Good	Good
2017-10-22	Good	Good
2017-10-23	Good	Good
2017-10-24	Good	Good
2017-10-25	Good	Good
2017-10-26	Good	Good
2017-10-27	Good	Good
2017-10-28	Good	Good
2017-10-29	Good	Good

2017-10-30	Good	Good
2017-10-31	Good	Good
2017-11-01	Good	Good
2017-11-02	Good	Good
2017-11-03	Good	Good
2017-11-04	Good	Good
2017-11-05	Good	Good
2017-11-06	Good	Good
2017-11-07	Good	Good
2017-11-08	Good	Good
2017-11-09	Good	Good
2017-11-10	Good	Good
2017-11-11	Good	Good
2017-11-12	Good	Good
2017-11-13	Good	Good
2017-11-14	Good	Good
2017-11-15	Good	Good
2017-11-16	Good	Good
2017-11-17	Good	Good
2017-11-18	Good	Good
2017-11-19	Good	Good
2017-11-20	Good	Good
2017-11-21	Good	Good
2017-11-22	Good	Good
2017-11-23	Good	Good
2017-11-24	Good	Good
2017-11-25	Good	Good
2017-11-26	Good	Good
2017-11-27	Good	Good
2017-11-28	Good	Good

Table 25 Quality of data for detector 410790 and 410756.

Day	Lane1	Lane2	Lane3	Lane4	Lane5
2017-10-08	Card Off	Card Off	Card Off	Card Off	Card Off
2017-10-09	Card Off	Card Off	Card Off	Card Off	Card Off
2017-10-10	Card Off	Card Off	Card Off	Card Off	Card Off
2017-10-11	Card Off	Card Off	Card Off	Card Off	Card Off
2017-10-12	Card Off	Card Off	Card Off	Card Off	Card Off
2017-10-13	Card Off	Card Off	Card Off	Card Off	Card Off
2017-10-14	Card Off	Card Off	Card Off	Card Off	Card Off
2017-10-15	Card Off	Card Off	Card Off	Card Off	Card Off
2017-10-16	Card Off	Card Off	Card Off	Card Off	Card Off
2017-10-17	Card Off	Card Off	Card Off	Card Off	Card Off
2017-10-18	Card Off	Card Off	Card Off	Card Off	Card Off
2017-10-19	Card Off	Card Off	Card Off	Card Off	Card Off
2017-10-20	Card Off	Card Off	Card Off	Card Off	Card Off
2017-10-21	Card Off	Card Off	Card Off	Card Off	Card Off
2017-10-22	Card Off	Card Off	Card Off	Card Off	Card Off
2017-10-23	Card Off	Card Off	Card Off	Card Off	Card Off
2017-10-24	Card Off	Card Off	Card Off	Card Off	Card Off
2017-10-25	Card Off	Card Off	Card Off	Card Off	Card Off

2017-10-26	Card Off	Card Off	Card Off	Card Off	Card Off
2017-10-27	Card Off	Card Off	Card Off	Card Off	Card Off
2017-10-28	Card Off	Card Off	Card Off	Card Off	Card Off
2017-10-29	Card Off	Card Off	Card Off	Card Off	Card Off
2017-10-30	Card Off	Card Off	Card Off	Card Off	Card Off
2017-10-31	Card Off	Card Off	Card Off	Card Off	Card Off
2017-11-01	Card Off	Card Off	Card Off	Card Off	Card Off
2017-11-02	Card Off	Card Off	Card Off	Card Off	Card Off
2017-11-03	Card Off	Card Off	Card Off	Card Off	Card Off
2017-11-04	Card Off	Card Off	Card Off	Card Off	Card Off
2017-11-05	Feed Unstable	Feed Unstable	Feed Unstable	Feed Unstable	Feed Unstable
2017-11-06	Feed Unstable	Feed Unstable	Feed Unstable	Feed Unstable	Feed Unstable
2017-11-07	Feed Unstable	Feed Unstable	Feed Unstable	Feed Unstable	Feed Unstable
2017-11-08	Card Off	Card Off	Card Off	Card Off	Card Off
2017-11-09	Card Off	Card Off	Card Off	Card Off	Card Off
2017-11-10	Card Off	Card Off	Card Off	Card Off	Card Off
2017-11-11	Card Off	Card Off	Card Off	Card Off	Card Off
2017-11-12	Card Off	Card Off	Card Off	Card Off	Card Off
2017-11-13	Card Off	Card Off	Card Off	Card Off	Card Off
2017-11-14	Card Off	Card Off	Card Off	Card Off	Card Off
2017-11-15	Card Off	Card Off	Card Off	Card Off	Card Off
2017-11-16	Card Off	Card Off	Card Off	Card Off	Card Off
2017-11-17	Card Off	Card Off	Card Off	Card Off	Card Off
2017-11-18	Card Off	Card Off	Card Off	Card Off	Card Off
2017-11-19	Card Off	Card Off	Card Off	Card Off	Card Off
2017-11-20	Card Off	Card Off	Card Off	Card Off	Card Off
2017-11-21	Card Off	Card Off	Card Off	Card Off	Card Off
2017-11-22	Card Off	Card Off	Card Off	Card Off	Card Off
2017-11-23	Card Off	Card Off	Card Off	Card Off	Card Off
2017-11-24	Card Off	Card Off	Card Off	Card Off	Card Off
2017-11-25	Card Off	Card Off	Card Off	Card Off	Card Off
2017-11-26	Card Off	Card Off	Card Off	Card Off	Card Off
2017-11-27	Card Off	Card Off	Card Off	Card Off	Card Off
2017-11-28	Card Off	Card Off	Card Off	Card Off	Card Off

Table 26 Quality of data for detector 402269 and 402270.

Day	Lane1	Lane2	Lane3	Lane4
2017-10-08	Card Off	Card Off	Card Off	Card Off
2017-10-09	Card Off	Card Off	Card Off	Card Off
2017-10-10	Card Off	Card Off	Card Off	Card Off
2017-10-11	Card Off	Card Off	Card Off	Card Off
2017-10-12	Card Off	Card Off	Card Off	Card Off
2017-10-13	Card Off	Card Off	Card Off	Card Off
2017-10-14	Card Off	Card Off	Card Off	Card Off

2017-10-15	Card Off	Card Off	Card Off	Card Off
2017-10-16	Card Off	Card Off	Card Off	Card Off
2017-10-17	Card Off	Card Off	Card Off	Card Off
2017-10-18	Card Off	Card Off	Card Off	Card Off
2017-10-19	Card Off	Card Off	Card Off	Card Off
2017-10-20	Card Off	Card Off	Card Off	Card Off
2017-10-21	Card Off	Card Off	Card Off	Card Off
2017-10-22	Card Off	Card Off	Card Off	Card Off
2017-10-23	Card Off	Card Off	Card Off	Card Off
2017-10-24	Card Off	Card Off	Card Off	Card Off
2017-10-25	Card Off	Card Off	Card Off	Card Off
2017-10-26	Card Off	Card Off	Card Off	Card Off
2017-10-27	Card Off	Card Off	Card Off	Card Off
2017-10-28	Card Off	Card Off	Card Off	Card Off
2017-10-29	Card Off	Card Off	Card Off	Card Off
2017-10-30	Card Off	Card Off	Card Off	Card Off
2017-10-31	Card Off	Card Off	Card Off	Card Off
2017-11-01	Card Off	Card Off	Card Off	Card Off
2017-11-02	Card Off	Card Off	Card Off	Card Off
2017-11-03	Card Off	Card Off	Card Off	Card Off
2017-11-04	Card Off	Card Off	Card Off	Card Off
2017-11-05	Feed Unstable	Feed Unstable	Feed Unstable	Feed Unstable
2017-11-06	Feed Unstable	Feed Unstable	Feed Unstable	Feed Unstable
2017-11-07	Feed Unstable	Feed Unstable	Feed Unstable	Feed Unstable
2017-11-08	Card Off	Card Off	Card Off	Card Off
2017-11-09	Card Off	Card Off	Card Off	Card Off
2017-11-10	Card Off	Card Off	Card Off	Card Off
2017-11-11	Card Off	Card Off	Card Off	Card Off
2017-11-12	Card Off	Card Off	Card Off	Card Off
2017-11-13	Card Off	Card Off	Card Off	Card Off
2017-11-14	Card Off	Card Off	Card Off	Card Off
2017-11-15	Card Off	Card Off	Card Off	Card Off
2017-11-16	Card Off	Card Off	Card Off	Card Off
2017-11-17	Card Off	Card Off	Card Off	Card Off
2017-11-18	Card Off	Card Off	Card Off	Card Off
2017-11-19	Card Off	Card Off	Card Off	Card Off
2017-11-20	Card Off	Card Off	Card Off	Card Off
2017-11-21	Card Off	Card Off	Card Off	Card Off
2017-11-22	Card Off	Card Off	Card Off	Card Off
2017-11-23	Card Off	Card Off	Card Off	Card Off
2017-11-24	Card Off	Card Off	Card Off	Card Off
2017-11-25	Card Off	Card Off	Card Off	Card Off
2017-11-26	Card Off	Card Off	Card Off	Card Off
2017-11-27	Card Off	Card Off	Card Off	Card Off
2017-11-28	Card Off	Card Off	Card Off	Card Off

Table 27 Quality of data for detector 413373.

Day	Lane1	Lane2	Lane3	Lane4
2017-10-08	Good	Good	Good	Good
2017-10-09	Good	Good	Good	Good
2017-10-10	Good	Good	Good	Good
2017-10-11	Good	Good	Good	Good
2017-10-12	Good	Good	Good	Good
2017-10-13	Good	Good	Good	Good
2017-10-14	Good	Good	Good	Good
2017-10-15	Good	Good	Good	Good
2017-10-16	Good	Good	Good	Good
2017-10-17	Good	Good	Good	Good
2017-10-18	Good	Good	Good	Good
2017-10-19	Good	Good	Good	Good
2017-10-20	Good	Good	Good	Good
2017-10-21	Good	Good	Good	Good
2017-10-22	Good	Good	Good	Good
2017-10-23	Good	Good	Good	Good
2017-10-24	Good	Good	Good	Good
2017-10-25	Good	Good	Good	Good
2017-10-26	Good	Good	Good	Good
2017-10-27	Good	Good	Good	Good
2017-10-28	Good	Good	Good	Good
2017-10-29	Good	Good	Good	Good
2017-10-30	Good	Good	Good	Good
2017-10-31	Good	Good	Good	Good
2017-11-01	Good	Good	Good	Good
2017-11-02	Good	Good	Good	Good
2017-11-03	Good	Good	Good	Good
2017-11-04	Good	Good	Good	Good
2017-11-05	Good	Good	Good	Good
2017-11-06	Good	Good	Good	Good
2017-11-07	Good	Good	Good	Good
2017-11-08	Good	Good	Good	Good
2017-11-09	Good	Good	Good	Good
2017-11-10	Good	Good	Good	Good
2017-11-11	Good	Good	Good	Good
2017-11-12	Good	Good	Good	Good
2017-11-13	Good	Good	Good	Good
2017-11-14	Good	Good	Good	Good
2017-11-15	Good	Good	Good	Good
2017-11-16	Good	Good	Good	Good
2017-11-17	Good	Good	Good	Good
2017-11-18	Good	Good	Good	Good
2017-11-19	Good	Good	Good	Good
2017-11-20	Good	Good	Good	Good
2017-11-21	Good	Good	Good	Good
2017-11-22	Good	Good	Good	Good
2017-11-23	Good	Good	Good	Good
2017-11-24	Good	Good	Good	Good
2017-11-25	Good	Good	Good	Good
2017-11-26	Good	Good	Good	Good
2017-11-27	Good	Good	Good	Good
2017-11-28	Good	Good	Good	Good

Table 28 Quality of data for detector 410817.

Day	Lane1	Lane2	Lane3	Lane4
2017-10-08	Good	Good	Good	Good
2017-10-09	Good	Good	Good	Good
2017-10-10	Good	Good	Good	Good
2017-10-11	Good	Good	Good	Good
2017-10-12	Good	Good	Good	Good
2017-10-13	Good	Good	Good	Good
2017-10-14	Good	Good	Good	Good
2017-10-15	Good	Good	Good	Good
2017-10-16	Good	Good	Good	Good
2017-10-17	Good	Good	Good	Good
2017-10-18	Good	Good	Good	Good
2017-10-19	Good	Good	Good	Good
2017-10-20	Good	Good	Good	Good
2017-10-21	Good	Good	Good	Good
2017-10-22	Good	Good	Good	Good
2017-10-23	Good	Good	Good	Good
2017-10-24	Good	Good	Good	Good
2017-10-25	Good	Good	Good	Good
2017-10-26	Good	Good	Good	Good
2017-10-27	Good	Good	Good	Good
2017-10-28	Good	Good	Good	Good
2017-10-29	Good	Good	Good	Good
2017-10-30	Good	Good	Good	Good
2017-10-31	Good	Good	Good	Good
2017-11-01	Good	Good	Good	Good
2017-11-02	Good	Good	Good	Good
2017-11-03	Good	Good	Good	Good
2017-11-04	Good	Good	Good	Good
2017-11-05	Good	Good	Good	Good
2017-11-06	Good	Good	Good	Good
2017-11-07	Good	Good	Good	Good
2017-11-08	Good	Good	Good	Good
2017-11-09	Good	Good	Good	Good
2017-11-10	Good	Good	Good	Good
2017-11-11	Good	Good	Good	Good
2017-11-12	Good	Good	Good	Good
2017-11-13	Good	Good	Good	Good
2017-11-14	Good	Good	Good	Good
2017-11-15	Good	Good	Good	Good
2017-11-16	Good	Good	Good	Good
2017-11-17	Good	Good	Good	Good
2017-11-18	Good	Good	Good	Good
2017-11-19	Good	Good	Good	Good
2017-11-20	Good	Good	Good	Good
2017-11-21	Good	Good	Good	Good
2017-11-22	Good	Good	Good	Good
2017-11-23	Good	Good	Good	Good
2017-11-24	Good	Good	Good	Good
2017-11-25	Good	Good	Good	Good
2017-11-26	Good	Good	Good	Good
2017-11-27	Good	Good	Good	Good
2017-11-28	Good	Good	Good	Good

Table 29 Quality of data for detector 764834.

Day	Lane1	Lane2	Lane3
2018-11-08	Good	Good	Good
2018-11-09	Good	Good	Good
2018-11-10	Ctlr Down	Ctlr Down	Ctlr Down
2018-11-11	Ctlr Down	Ctlr Down	Ctlr Down
2018-11-12	Ctlr Down	Ctlr Down	Ctlr Down
2018-11-13	Insufficient Data	Insufficient Data	Insufficient Data
2018-11-14	Good	Good	Good
2018-11-15	Good	Good	Good
2018-11-16	Good	Good	Good
2018-11-17	Good	Good	Good
2018-11-18	Good	Good	Good
2018-11-19	Good	Good	Good
2018-11-20	Intermittent	Good	Good
2018-11-21	Good	Good	Good

Table 30 Quality of data for detector 763781.

Day	Lane1	Lane2	Lane3	Lane4	Lane5	
2018-11-08	Good	Good	Good	Good	Good	
2018-11-09	Good	Good	Good	Good	Good	
2018-11-10	Good	Good	Good	Good	Good	
2018-11-11	Good	Good	Good	Good	Good	
2018-11-12	Good	Good	Good	Good	Good	
2018-11-13	Good	Good	Good	Good	Good	
2018-11-14	Good	Good	Good	Good	Good	
2018-11-15	Good	Good	Good	Good	Good	
2018-11-16	Good	Good	Good	Good	Good	
2018-11-17	Good	Good	Good	Good	Good	
2018-11-18	Good	Good	Good	Good	Good	
2018-11-19	Good	Good	Good	Good	Good	Good
2018-11-20	Good	Good	Good	Good	Good	Good
2018-11-21	Good	Good	Good	Good	Good	Good

Table 31 Quality of data for detector 717816.

Day	Lane1	Lane2	Lane3	Lane4	Lane5
2018-11-08	Good	Good	Good	Good	Good
2018-11-09	Good	Good	Good	Good	Good
2018-11-10	Good	Good	Good	Good	Good
2018-11-11	Good	Good	Good	Good	Good
2018-11-12	Good	Good	Good	Good	Good
2018-11-13	Good	Good	Good	Good	Good
2018-11-14	Good	Good	Good	Good	Good

2018-11-15	Good	Good	Good	Good	Good
2018-11-16	Good	Good	Good	Good	Good
2018-11-17	Good	Good	Good	Good	Good
2018-11-18	Good	Good	Good	Good	Good
2018-11-19	Good	Good	Good	Good	Good
2018-11-20	Good	Good	Good	Good	Good
2018-11-21	Good	Good	Good	Good	Good

Table 32 Quality of data for detector 775225.

Day	Lane1	Lane2	Lane3	Lane4	Lane5	Lane6
2018-11-08	Good	Good	Good	Good	Good	Good
2018-11-09	Good	Good	Good	Good	Good	Good
2018-11-10	Good	Good	Good	Good	Good	Good
2018-11-11	Good	Good	Good	Good	Good	Good
2018-11-12	Good	Good	Good	Good	Good	Good
2018-11-13	Good	Good	Good	Good	Good	Good
2018-11-14	Good	Good	Good	Good	Good	Good
2018-11-15	Good	Good	Good	Good	Good	Good
2018-11-16	Good	Good	Good	Good	Good	Good
2018-11-17	Good	Good	Good	Good	Good	Good
2018-11-18	Good	Good	Good	Good	Good	Good
2018-11-19	Good	Good	Good	Good	Good	Good
2018-11-20	Good	Good	Good	Good	Good	Good
2018-11-21	Good	Good	Good	Good	Good	Good

Table 33 Quality of data for detector 760024.

Day	Lane1	Lane2	Lane3	Lane4	Lane5	Lane6
2018-11-08	Good	Good	Good	Good	Good	Good
2018-11-09	Good	Good	Good	Good	Good	Good
2018-11-10	Intermittent	Good	Good	Good	Good	Good
2018-11-11	Good	Good	Good	Good	Good	Good
2018-11-12	Good	Good	Good	Good	Good	Good
2018-11-13	Good	Good	Good	Good	Good	Good
2018-11-14	Good	Good	Good	Good	Good	Good
2018-11-15	Good	Good	Good	Good	Good	Good
2018-11-16	Good	Good	Good	Good	Good	Good
2018-11-17	Good	Good	Good	Good	Good	Good
2018-11-18	Good	Good	Good	Good	Good	Good
2018-11-19	Good	Good	Good	Good	Good	Good
2018-11-20	Good	Good	Good	Good	Good	Good
2018-11-21	Good	Good	Good	Good	Good	Good

Table 34 Quality of data for the detector-set 765171 and 767812.

Day	Lane1	Lane2	Lane3	Lane4
2018-11-08	Ctlr Down	Ctlr Down	Ctlr Down	Ctlr Down
2018-11-09	Ctlr Down	Ctlr Down	Ctlr Down	Ctlr Down
2018-11-10	Ctlr Down	Ctlr Down	Ctlr Down	Ctlr Down
2018-11-11	Ctlr Down	Ctlr Down	Ctlr Down	Ctlr Down
2018-11-12	Ctlr Down	Ctlr Down	Ctlr Down	Ctlr Down
2018-11-13	Ctlr Down	Ctlr Down	Ctlr Down	Ctlr Down
2018-11-14	Ctlr Down	Ctlr Down	Ctlr Down	Ctlr Down
2018-11-15	Ctlr Down	Ctlr Down	Ctlr Down	Ctlr Down

2018-11-16	Ctlr Down	Ctlr Down	Ctlr Down	Ctlr Down
2018-11-17	Ctlr Down	Ctlr Down	Ctlr Down	Ctlr Down
2018-11-18	Ctlr Down	Ctlr Down	Ctlr Down	Ctlr Down
2018-11-19	Ctlr Down	Ctlr Down	Ctlr Down	Ctlr Down
2018-11-20	Ctlr Down	Ctlr Down	Ctlr Down	Ctlr Down
2018-11-21	Ctlr Down	Ctlr Down	Ctlr Down	Ctlr Down

Table 35 Quality of data for detectors 737258 and 737257.

Day	Lane1	Lane2	Lane3	Lane4
2018-11-08	Good	Good	Good	Good
2018-11-09	Good	Good	Good	Good
2018-11-10	Good	Good	Good	Good
2018-11-11	Good	Good	Good	Good
2018-11-12	Good	Good	Good	Good
2018-11-13	Good	Good	Good	Good
2018-11-14	Good	Good	Good	Good
2018-11-15	Good	Good	Good	Good
2018-11-16	Good	Good	Good	Good
2018-11-17	Good	Good	Good	Good
2018-11-18	Good	Good	Good	Good
2018-11-19	Good	Good	Good	Good
2018-11-20	Good	Good	Good	Good
2018-11-21	Good	Good	Good	Good

13.2. Appendix B

A response curve is calculated for each case in this appendix. The response curve is calculated by estimating an average traffic flow prior to the fire to compare against the flow during the event – to act as a benchmark enabling the uplift in traffic flow to be established. The estimated flow is an average flow over the same time period of the fire incident but for five years prior to the incident. For example, Camp fire occurred in November 2018 meaning an estimated flow is calculated using the average data of November for the years 2013, 2014, 2015, 2016 and 2017. The average flow of the years 2013 – 2017 is then compared to the flow over the fire incident in November 2018 to see if there are any differences. The difference in flow is assumed to be the effect of the evacuations and therefore used as a benchmark for the response curve. This comparison enables several things to be established: the degree of the increase in flow, how this increase fluctuated over time, and the end point of the increase. From this the response curve can be established.

The response curve is the WUI-NITY input file attributed that defines the distribution of evacuee departures from their residences and directly affects their arrival into the traffic system. This is a key factor for the simulation and is therefore hand calculated using data from PeMS database. Ensuring comparison representative response curves of the incidents is a key means of ensuring similar initial evacuee response. If the response curve does not match the real-world response, then there will be discrepancies in the modelled evacuation dynamics and eventual outcomes – in effect, undermining the value of testing procedure.

13.2.1. Camp fire

This approach is demonstrated for the Camp Fire incident. Firstly, data for traffic flow is extracted from the PeMs database for the two detectors, 318509 and 318510. These were identified as being active during the Camp Fire (November 2018). Data is derived from these detectors at equivalent time period but during the previous years 2013 to 2017. The data from 2013 - 2017 was derived and averaged to develop a baseline of expected traffic conditions for the same period (November) during non-emergency periods. These flow conditions were averaged to provide a baseline benchmark. This benchmark was used to compare to the traffic flow of 2018 produced during the Camp fire incident – to establish the uptick in traffic flow that might then be assigned to the emergency conditions. For instance, the 2018 data produced a maximum value of 1,727 vehicles/hour, which fell to and 1,386 vehicles/hour for 2013 – 2017. Similarly, the 2018 data produced a minimum value of 39 vehicles/hour while a minimum of 50 vehicles/hour was produced for 2013 – 2017 (see Figure 85).

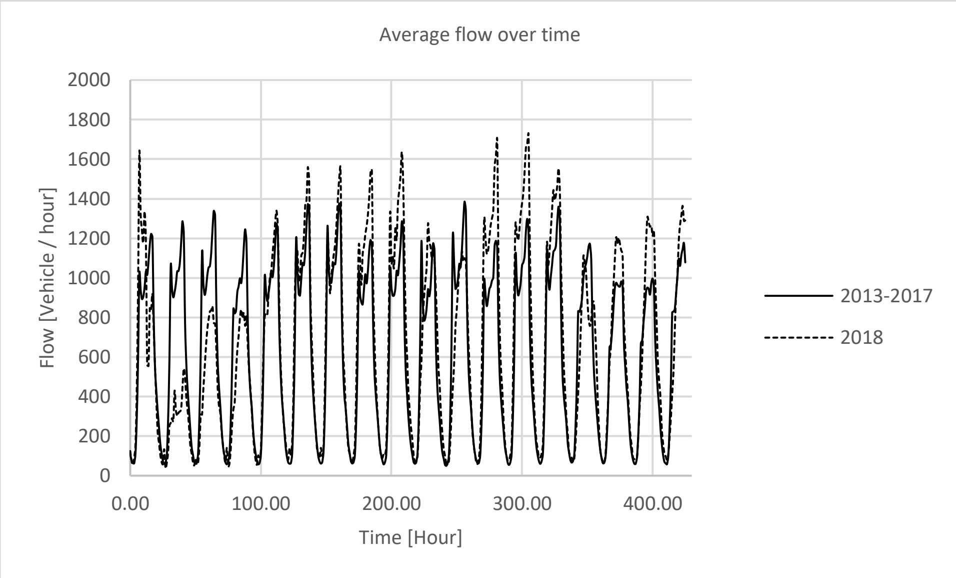

Figure 85 Average flow over time periods of 2013 to 2017 and 2018.

The difference of flow of 2018 compared to the years 2013 – 2017 shows a mean difference of increased flow by 25 vehicles per hour (see Figure 86). The positive flow is assumed to be caused by vehicles evacuating.

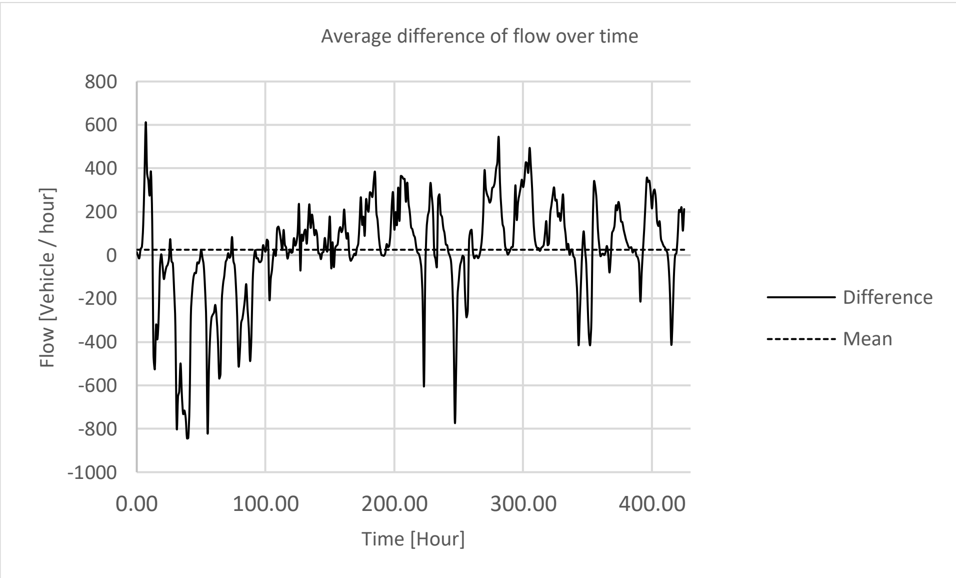

Figure 86 Average difference of flow over time periods of 2013 to 2017 and 2018.

The flow is calculated as a cumulative distribution of registered vehicles showing a total of 40,768 registered vehicles (see Figure 87).

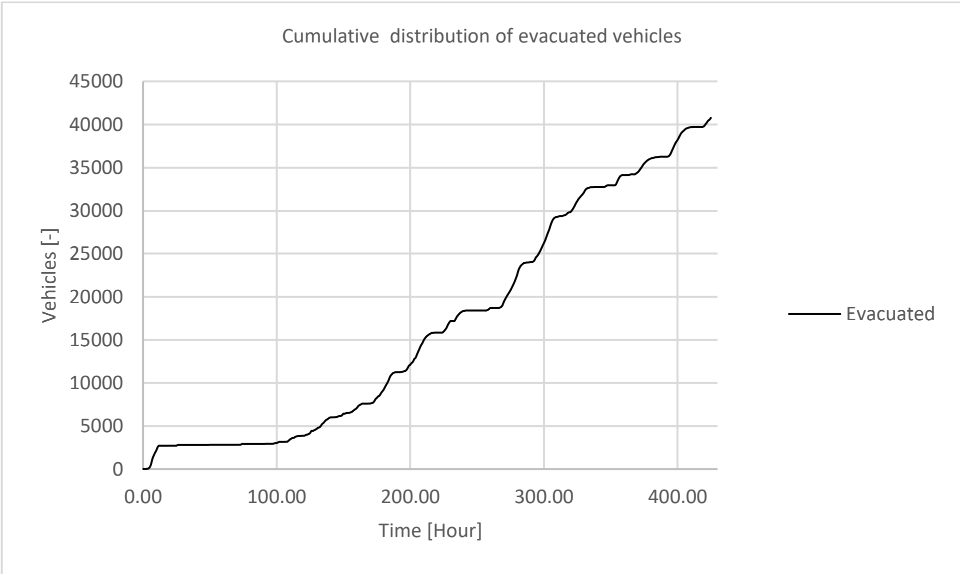

Figure 87 Cumulative distribution of assumed evacuated vehicles.

A comparison of the number calculated evacuated vehicles (40,768) against the real-world data of all evacuated people during Camp Fire (approximately 52,000 (Ronchi, et al., 2021)), shows there are 1.3 people per vehicles used in the evacuation. This is within the used criteria in WUI-NITY for household population to be randomised between 1 to 5 and therefore assumed to be data valid to calculate the response curve.

The response curve is calculated by comparing the ratio of the evacuated vehicles against the total evacuated vehicles. It is unknown from where the evacuated registered cars come from (e.g Paradise or Pulga) and therefore it is not possible to add a time delay from the origin start point to when the vehicle passes the detector. Instead, the response curve is strictly assumed to follow the registered data for the times the vehicle passes (see Figure 88); i.e. as a direct proxy for the response time curve within the model.

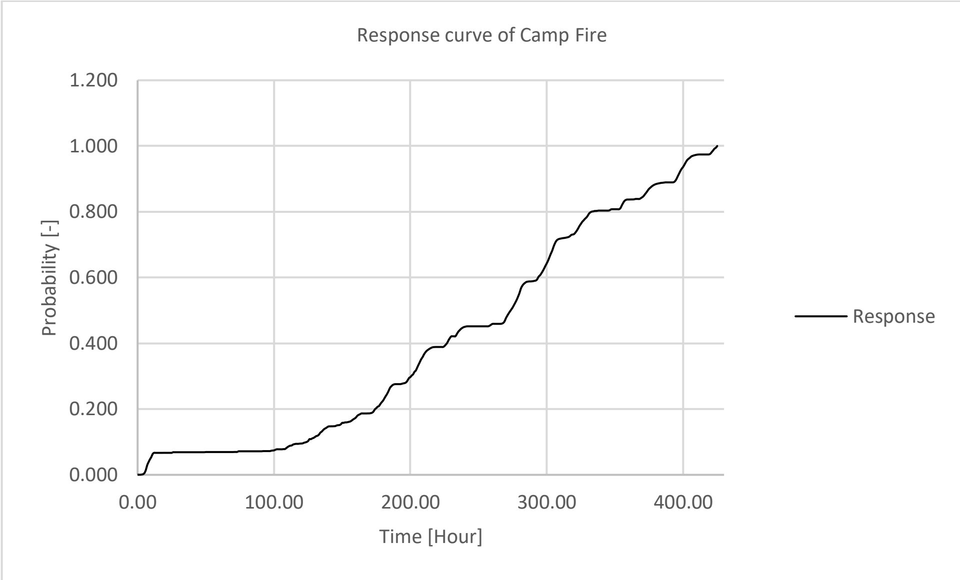

Figure 88 The response curve over Camp fire.

The response curve is divided into five parts following the plateaus of the distribution, Table 36. The table shows that 6.8 % of the population evacuated within 26 hours, 7.7 % within 198 hours, 43.9 % within 238 hours, 45.4 % within 268 hours and all within 431 hours.

Table 36 The used times for the response curve of Camp Fire.

Time [Hour]	Probability [-]
0	0
12	0.067
97	0.072
240	0.450
258	0.453
425	1

13.2.2. Atlas fire

The response curve for Atlas fire is derived doing the same method as for Camp fire (see 13.2.1). The flow data is extracted from detectors, 409482, 413373 and 410817. The detectors started operating the year 2016 which means that no data can be extracted before that. To compensate for that there will be chosen three months of 2016 (September, October, and November) and one month of 2017 (September). The data of 2016 and September 2017 will be used as average traffic flow benchmark value to compare against the traffic flow of Atlas fire in October 2017. The data prior the fire produced a maximum value of 4,794 vehicles/hour, which fell to and 4,359 vehicles/hour during the Atlas fire. Similarly, the data prior the fire produced a minimum value of 391 vehicles/hour and while a minimum of 289 vehicles/hour was produced during the fire (see Figure 89).

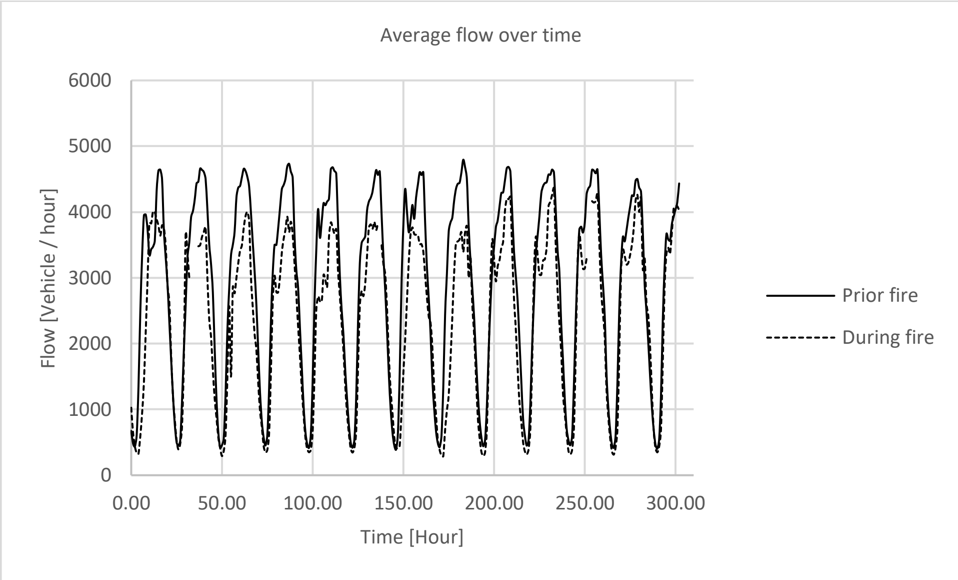

Figure 89 Average flow over time periods prior and during the Atlas fire.

The difference of flow during and prior the fire shows a mean difference of decreased flow by - 597 vehicles per hour (see Figure 90). The span of positive flow is assumed to be caused by vehicles evacuating.

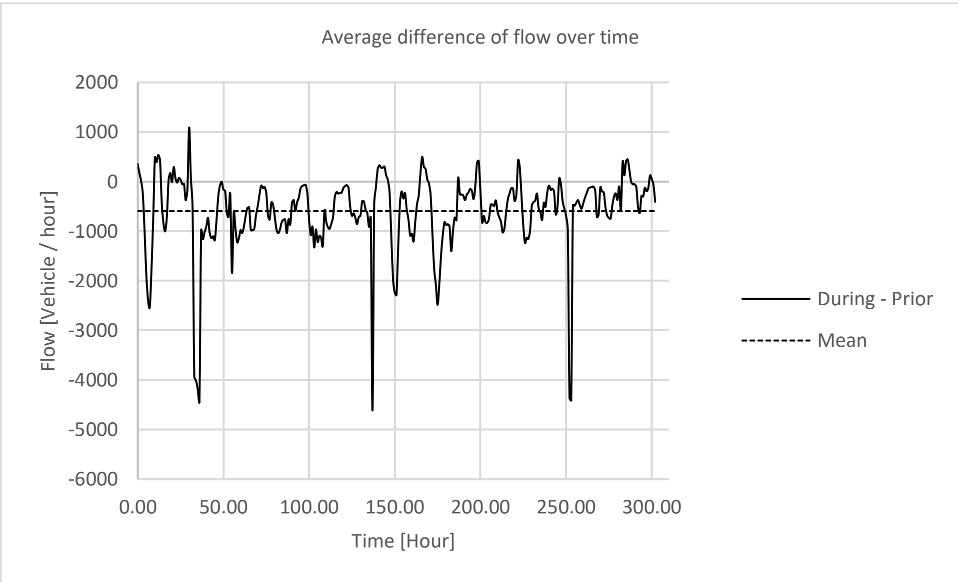

Figure 90 Average difference of flow during and prior the fire.

The flow is calculated as a cumulative distribution of registered vehicles showing a total of 10,447 registered vehicles (see Figure 91).

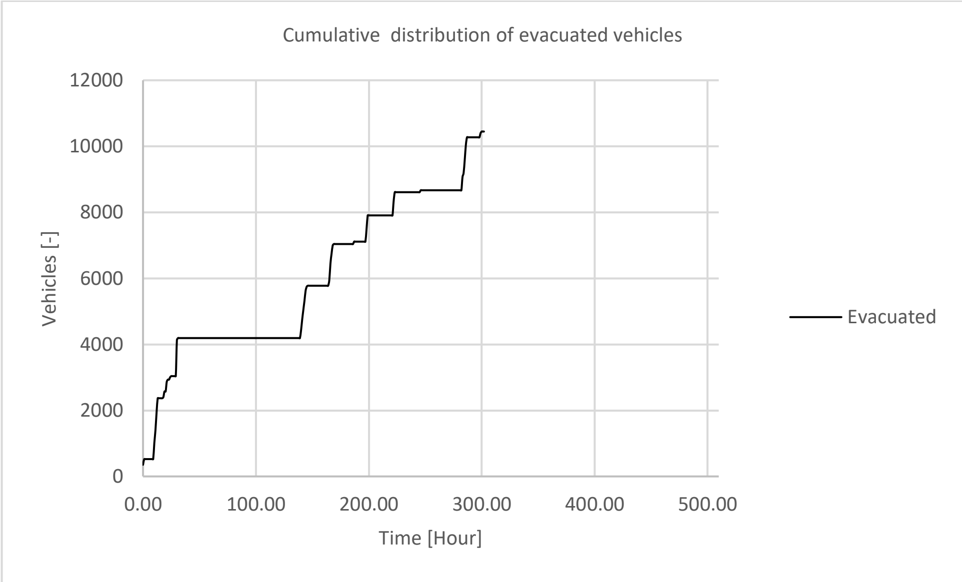

Figure 91 Cumulative distribution of assumed evacuated vehicles.

A comparison of the calculated number of evacuated vehicles (10,447) against the real-world data of all evacuated people during Atlas Fire (approximately 100,000 for all the Northern California wildfires (Ronchi, et al., 2021)), shows there are 9.6 people per vehicle used in the evacuation. This is above the used number/household ratio of 1 to 5. The estimated number of evacuated people (100,000) is for all the Northern Californian fires which may explain why the ratio of people/vehicle is so high. Atlas fire was just one of many fires so within the region of the Atlas fire it might be an appropriate number of vehicles. Therefore, the derived number of vehicles from PeMS is still used for the redefined response curve.

The response curve is calculated by comparing the ratio of the evacuated vehicles against the total evacuated vehicles. It is unknown from where the evacuated registered cars come from (e.g Napa County) and therefore it is not possible to add a time delay from the origin start point to when the vehicle passes the detector. Instead, the response curve is strictly assumed to follow the registered data for the times the vehicle passes (see Figure 92).

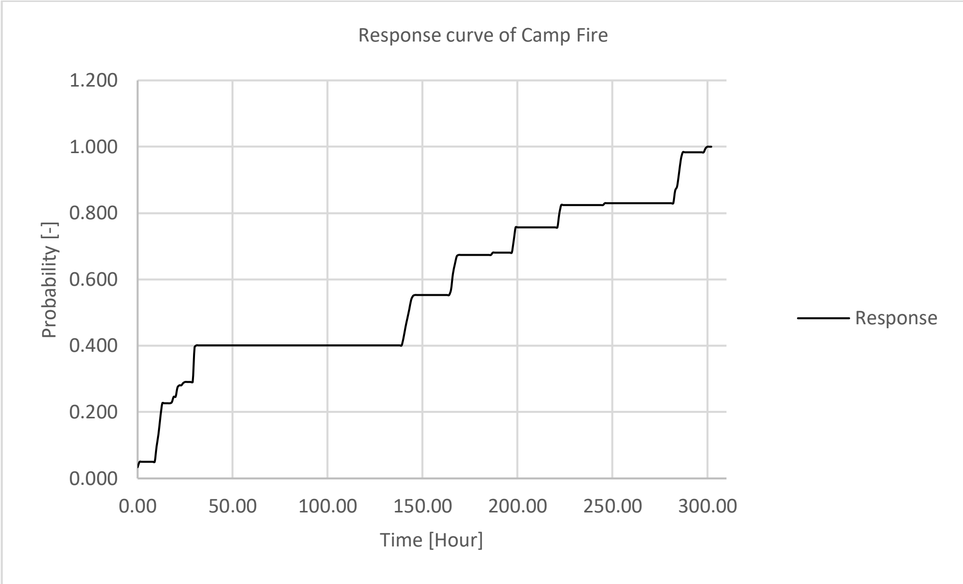

Figure 92 The response curve over Atlas fire.

The response curve is divided into six parts following the plateaus of the distribution, Table 37. The table shows that 40.1 % of the population evacuated within 31 hours, 75.7 % within 221 hours, 83.0 % within 282 hours and all within 303 hours.

Table 37 The used times for the response curve of Atlas Fire.

Time [Hour]	Probability [-]
0	0
31	0.401
139	0.401
221	0.757
282	0.830
303	1

13.2.3. Hill and Woolsey fire

The response curve for Atlas fire is derived doing the same method as for Camp fire (see 13.2.1). The flow data is extracted from detectors, 764834, 764781, 717816, 775225 and 760024, over the time period of Hill and Woolsey fire (November 2018) and for the years 2013 to 2017 (also November each year). The data of 2013 to 2017 will be used as a benchmark value for average traffic flow to compare against the traffic flow of Hill and Woolsey fire in November 2018. The data during the fire produced a maximum value of 7,710 vehicles/hour, which fell to 7,276 vehicles/hour prior the Atlas fire. Similarly, the data during the fire produced a minimum value of 453 vehicles/hour while a minimum of 723 vehicles/hour was produced prior the fire (see Figure 93).

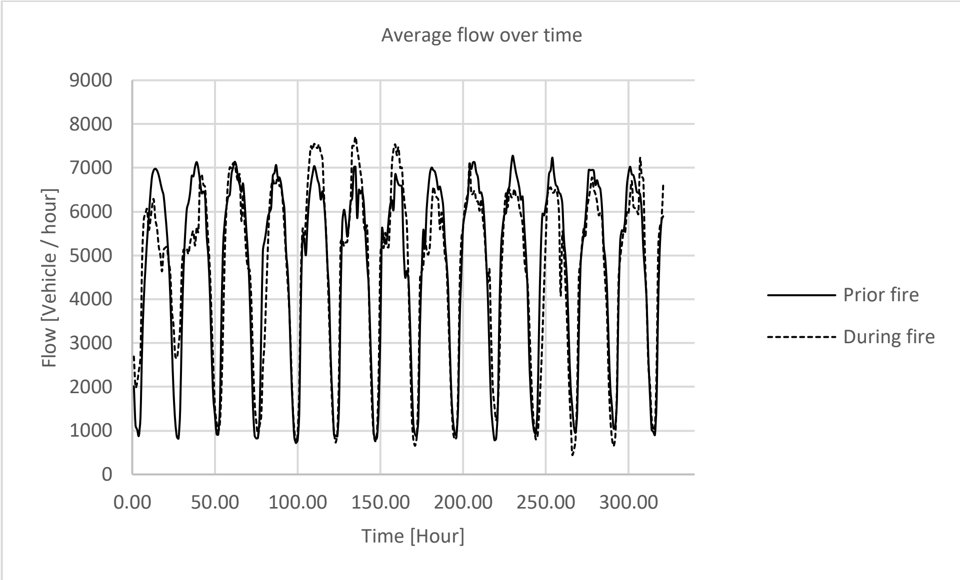

Figure 93 Average flow over time periods prior and during the Hill and Woolsey fire.

The difference of flow during and prior the fire shows a mean difference of decreased flow by - 71 vehicles per hour (see Figure 94). The span of positive flow is assumed to be caused by vehicles evacuating.

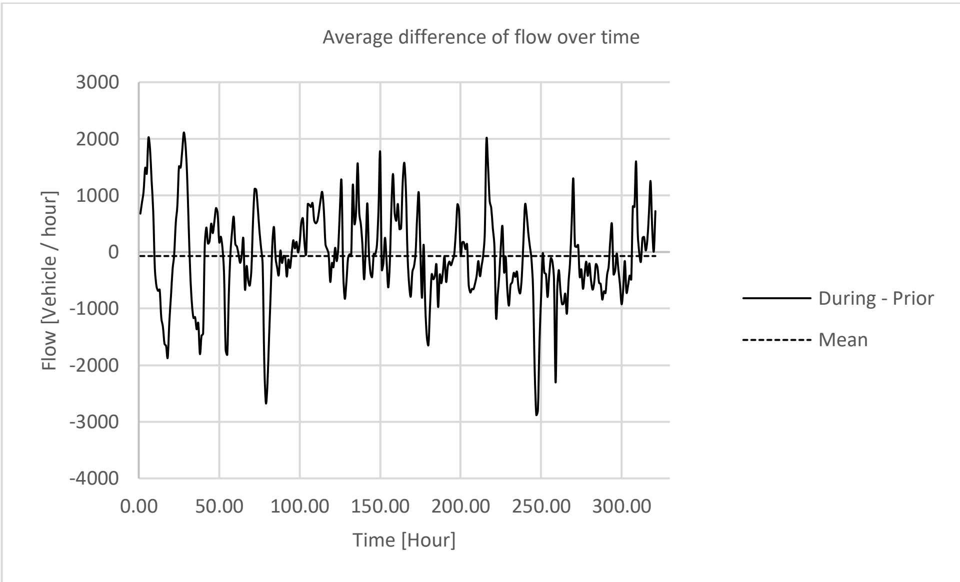

Figure 94 Average difference of flow during and prior the fire.

The flow is calculated as a cumulative distribution of registered vehicles showing a total of 87,568 registered vehicles (see Figure 95).

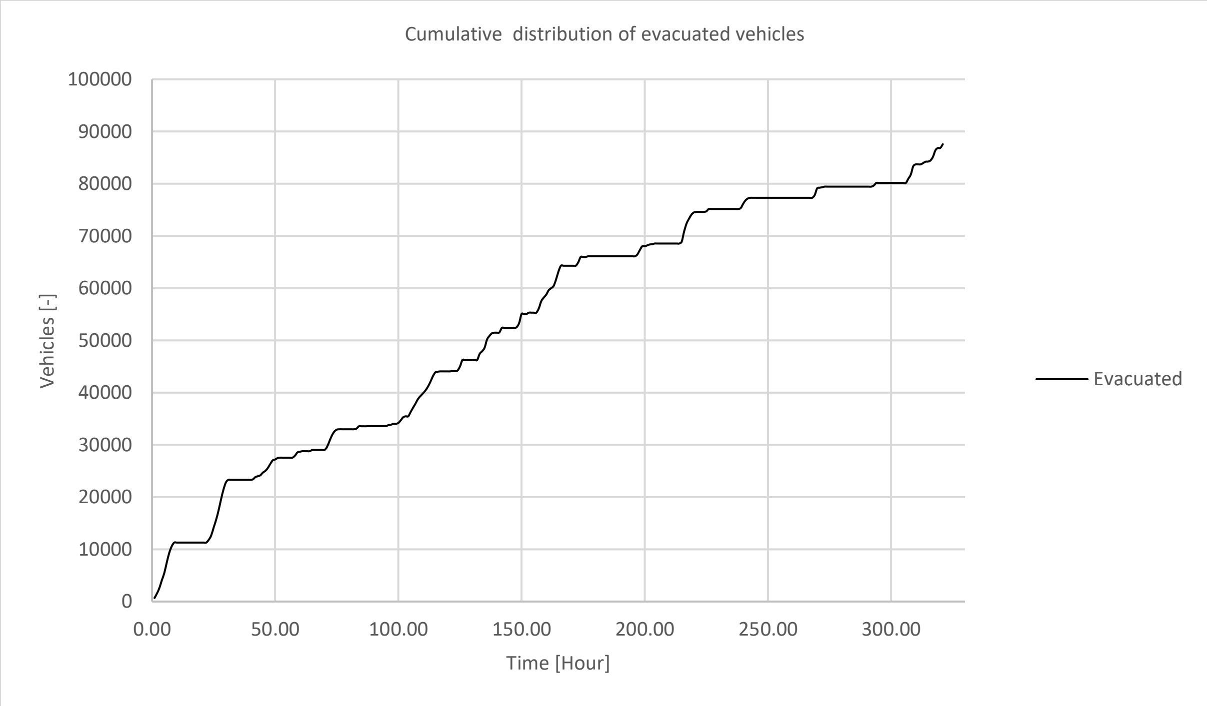

Figure 95 Cumulative distribution of assumed evacuated vehicles.

A comparison of the calculated number of evacuated vehicles (87,568) against the real-world data of all evacuated people (approximately 300,000 for Woolsey fire and 17,000 for Hill fire (Ronchi, et al., 2021)), shows there are 3.6 people per vehicle used in the evacuation. This is within the used criteria of 1 to 5 people per household used in the simulation and is therefore used to calculate the response curve.

The response curve is calculated by comparing the ratio of the evacuated vehicles against the total evacuated vehicles. It is unknown from where the evacuated registered cars come from (e.g Los Angeles County County) and therefore it is not possible to add a time delay from the origin start point to when the vehicle passes the detector. Instead, the response curve is strictly assumed to follow the registered data for the times the vehicle passes (see Figure 96).

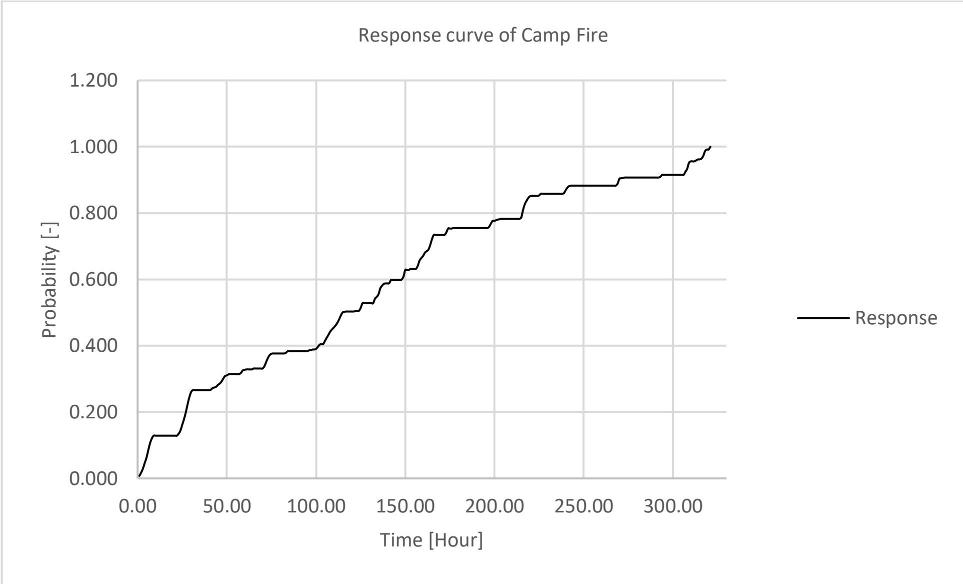

Figure 96 The response curve over Hill and Woolsey fire.

The response curve is divided into eight parts following the plateaus of the distribution, Table 38. The table shows that 11.1 % of the population evacuated within 8 hours, 24 % within 32 hours, 67.5 % within 168 hours, 72.3 % within 217 hours, 84.1 % within 308 hours and all within 321 hours.

Table 38 The used times for the response curve of Hill and Woolsey fire Fire.

Time [Hour]	Probability [-]
0	0
8	0.111
24	0.119
32	0.240
168	0.675
217	0.723
308	0.841
321	1

13.3. Appendix C

This appendix consists of data input for each of the WUI-NITY simulations and is a step-by-step guide to replicate and run the simulations used in this thesis. The data used in this appendix is found from, **Fel! Hittar inte referenskälla.**, if not referred otherwise. A simulation is run by data gathered from a WUI-file which is found from the folder, WUInity_Data ➔ Resources ➔ _input. There is a default WUI-file within the _input folder of which code is used as a benchmark. Chapter, 13.3.1, describes each step of the code and what it means followed by chapters, 13.3.2 and 13.3.3, which only describes the code used for the specific simulation.

13.3.1. Camp fire

A new folder is made and named CampFire. In that folder eight more folders are created, each representing a unique simulation. Four folders will be for the Default scenarios and four folders for the PeMS derived scenarios and will be named either Default_X_CF (X being the route selection for the simulation) for the used default response curve or PeMS_X_CF for the used redefined response curve, Figure 97. In every folder a copy of the default WUI-file is pasted and changed according to the this appendix.

Default_0_CF	2022-02-02 19:25	Filmapp
Default_1_CF	2022-02-02 19:28	Filmapp
Default_2_CF	2022-02-02 19:33	Filmapp
Default_3_CF	2022-02-02 19:40	Filmapp
PeMS_0_CF	2022-02-04 15:04	Filmapp
PeMS_1_CF	2022-02-04 15:10	Filmapp
PeMS_2_CF	2022-02-04 15:07	Filmapp
PeMS_3_CF	2022-02-04 15:12	Filmapp

Figure 97 The new folders of each CampFire simulation.

The data of the default file is found when opening either the Default_X_CF or PeMS_X_CF WUI-file. This must be changed to fit the Camp fire simulation. The simName (simulation name) is for convenience changed to CampFire_X as well. DeltaTime is changed to 60.0 because the data size of the output file is to large otherwise. MaxSimTime is the maximum simulation time which is set to be the entire fire scenario from origin of fire (6:30 on the 8th of November) to the 100 % containment of the fire (25th of November). It is no timestamp of when on the day the fire was completely contained and is therefore assumed to be the entire day. The total time of the time period is 1 531 800 seconds. StopWhenEvacuated is set to true which means that if all the population evacuates before the maxSimTime is reached, the simulation will stop. NumberOfRuns is set to 1 which means the simulation will only be run once, this can be changed in WUI-NITY later. This is shown in, Figure 98.

```
"simName": "CampFire_0",
"deltaTime": 60.0,
"maxSimTime": 1531800.0,
"stopWhenEvacuated": true,
"numberOfRuns": 1,
```

Figure 98 Code from the CampFire WUI-file showing rows 2 to 6.

Next part is to determine the location of which the simulation will be held. This is done in WUI-NITY by coordinates (longitude and latitude). The chosen coordinate is the origin. To decide the size of the simulated location it must be decided how far the map is stretched by choosing values for the x- and y-axis in meters. To decide this, it is studied how the fire progressed, Figure 99, and from there it is chosen an x- and y-axis so that all the fire area is included.

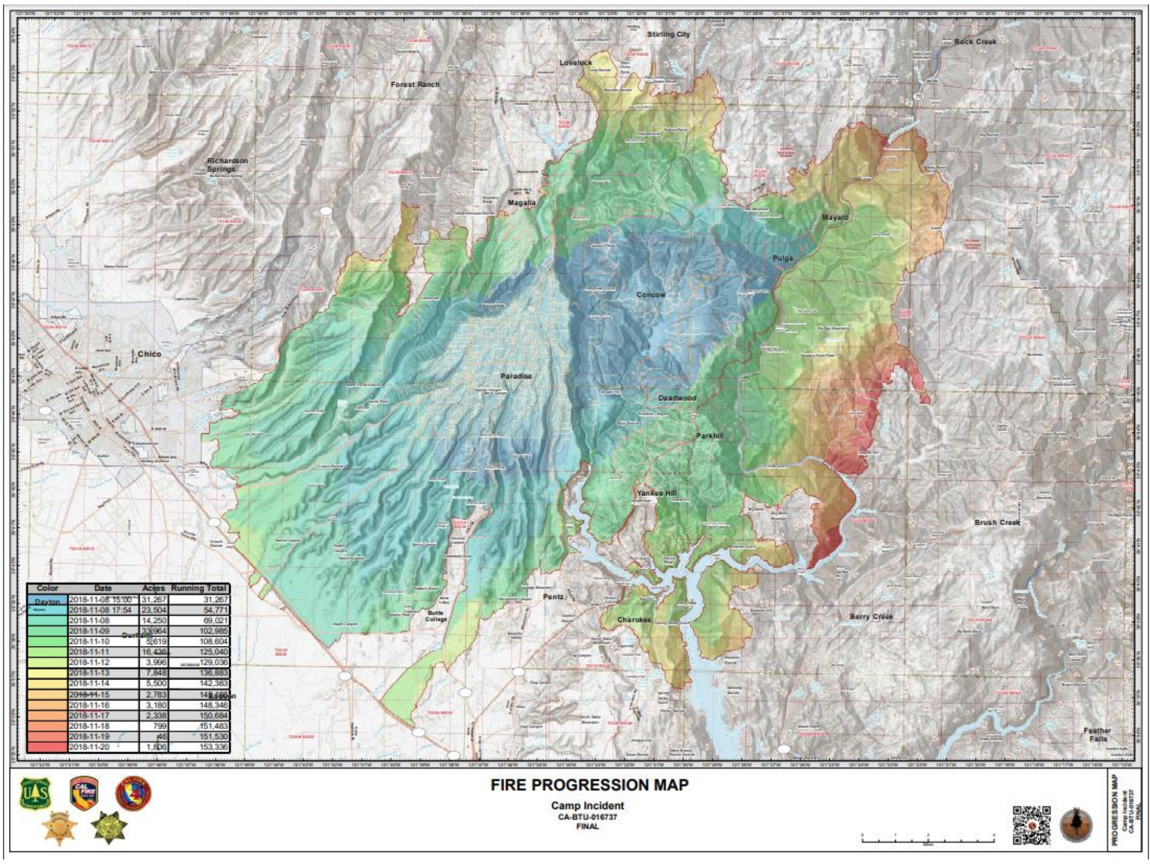

Figure 99 Fire progression map taken from CalFire (CalFire, Accessed 2022 February).

It must also be in consideration that all the areas of which was under evacuation orders is included together with the location of the analysed detectors. To fulfil the three criterias a coordinate of origin (lowerLeftLatLong) is chosen to be, 39.579304, -121.871458, which is a few kilometres west of the conjunction of Highways 149 and 99. The size of the map is determined to be 45 000 metres on the x-axis and 35 000 metres on the y-axis. A perimeter of the grid for WUI-NITY is shown in, Figure 100.

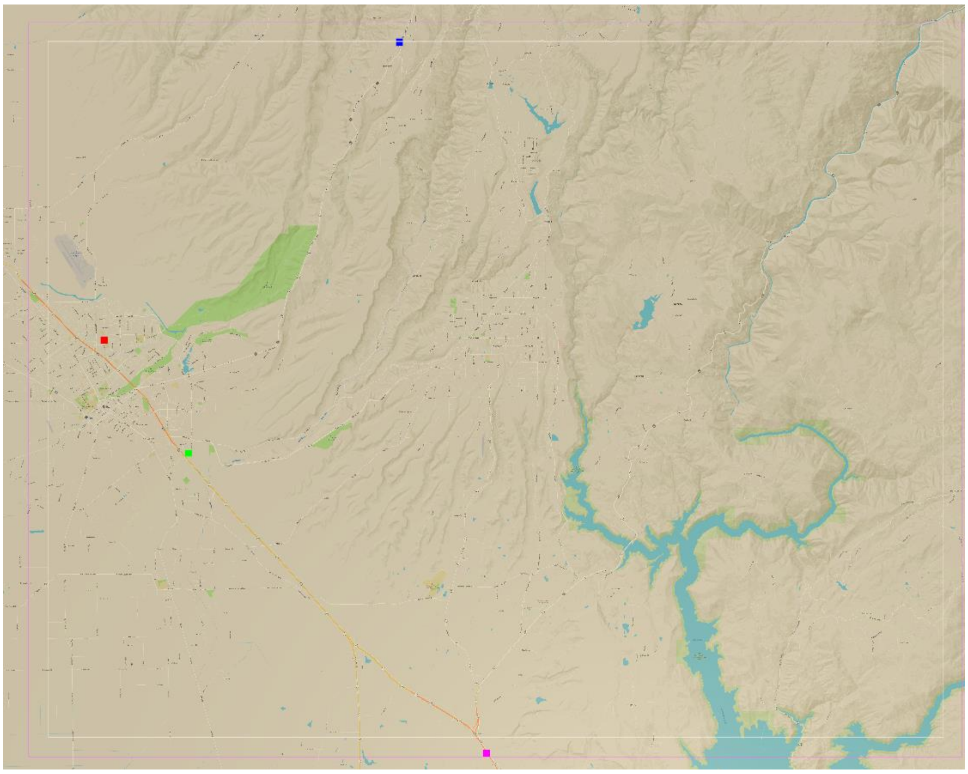

Figure 100 Map showing the perimeter used in WUI-NITY for the CampFire simulation. The four markers (red, blue, green and purple) are the used evacuation goals.

Although the desired map size is determined, it cannot be used due to the limitation of computer power and WUI-NITY. WUI-NITY crashes when simulating this much data. To make it manageable, the data must be reduced. This is done by decreasing the size of the map. To decide the new perimeter, GPW, over the area is analysed, Figure 101.

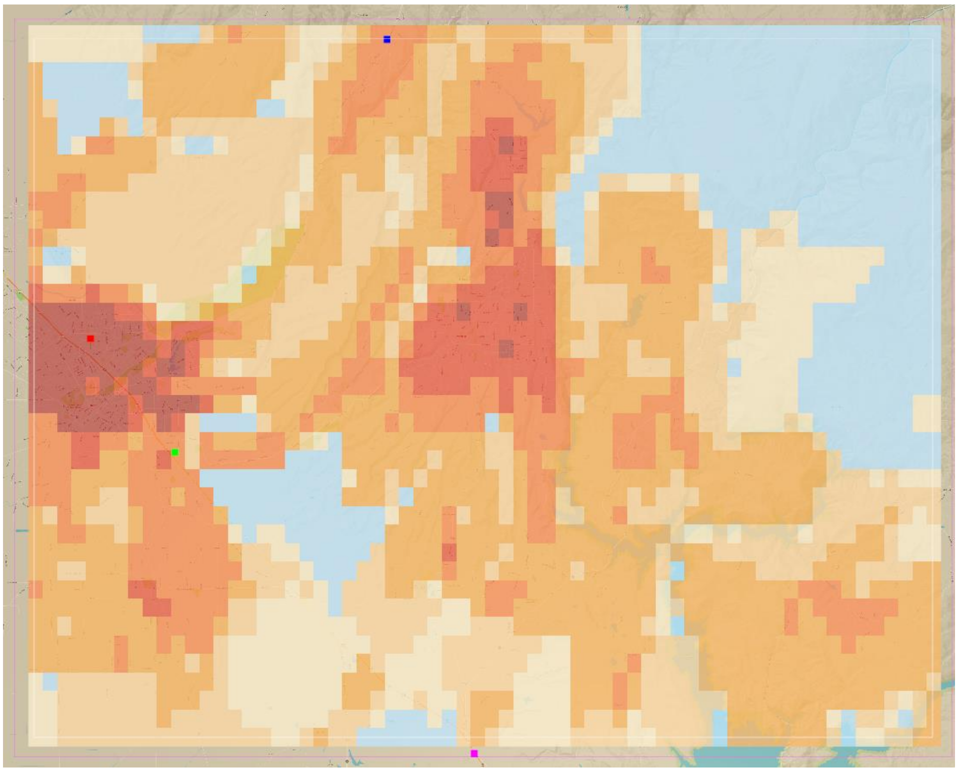

Figure 101 Loaded GPW-file of CampFire simulation. The darker the colour the higher the population.

The areas with none too little population are excluded and therefore making the map smaller. With the limitation of the computer power used it was not enough to decrease only the lesser populated areas, but a maximum of around 20,000 x 10,000 m map size was found to be the largest manageable map working. A new perimeter was chosen to include the area of the analysed detectors and the largest community around it, Paradise. The new start of origin is the coordinate, (39.701669, -121.805414) with a map size of 20,000 on the x-axis and 11,000 on the y-axis, Figure 102.

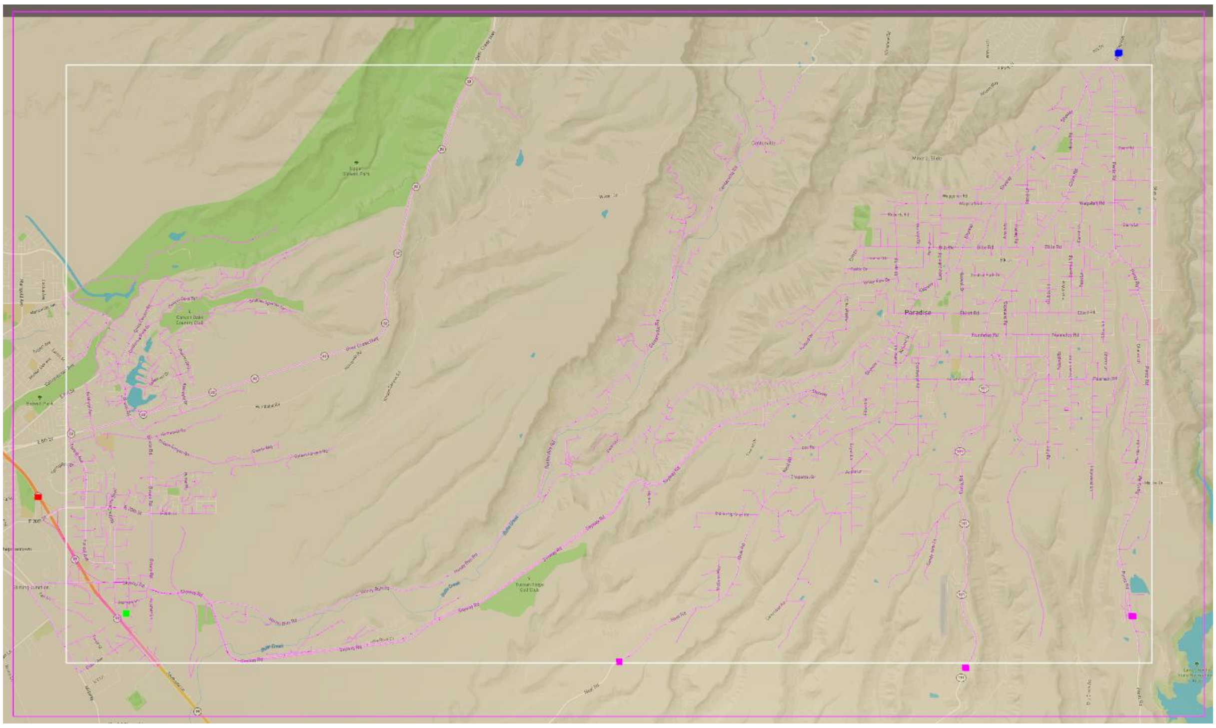

Figure 102 Map over the chosen perimeter of CampFire simulation.

ZoomLevel is left at default 13. RunInRealTime is left at default false. For the simulations of this thesis it is only of interest to run traffic and evacuation models and therefore the fire model is disabled. This is shown in, Figure 103.

```
"lowerLeftLatLong": {
    "x": 39.701669,
    "y": -121.805414
},
"size": {
    "x": 20000.0,
    "y": 11000.0
},
"zoomLevel": 13,
"runInRealTime": true,
"runEvacSim": true,
"runTrafficSim": true,
"runFireSim": false,
```

Figure 103 Code from the CampFire WUI-file showing rows 7 to 19.

The next objective after the basics is set up, is to set the evacuation scenario which is done within the rows of code included in evac. OverrideTotalPopulation is left at default false. OverrideTotalPopulation set to false means that WUI-NITY extracts data from the input GPW-file and calculates the size of population and cell size from that. Practically for the code it means that totalPopulation and routeCellSize is left at default since those values is overridden. This is shown in, Figure 104.

```
"evac": {
    "overrideTotalPopulation": false,
    "totalPopulation": 500,
    "routeCellSize": 200.0,
```

Figure 104 Code from the CampFire WUI-file showing rows 20 to 23.

AllowMoreThanOneCar is set to false. This means that every household is limited to the use of one car only. The reason to why it is set to false is because it is too little data on car usage per household. This is a parameter that will change the output data but is too detailed in these types of scenarios to vary. This disables maxCars and maxCarsChance. MinHouseholdSize and maxHouseholdSize is left at default 1 respectively 5 which limits every spawned household to be between 1 and 5 occupants. WalkingDistanceModifier is left at default value. WalkingSpeedMinMax is also left at default value. This is shown in, Figure 105.

```
    "allowMoreThanOneCar": false,
    "maxCars": 2,
    "maxCarsChance": 0.30000001192092898,
    "minHouseholdSize": 1,
    "maxHouseholdSize": 5,
    "walkingDistanceModifier": 1.0,
    "walkingSpeedMinMax": {
        "x": 0.699999988079071,
        "y": 1.0
    },
```

Figure 105 Code from the CampFire WUI-file showing rows 24 to 32.

WalkingSpeedModifier is left at default value. EvacuationOrderStart is the time of when the evacuation is ordered with a starting value from when the simulation started (in this case the origin of fire at 6:30 am on the 8th of November). The first ordered evacuation (Pulga) is ordered out at 53 minutes after the origin of fire which is the same as 3180 seconds. The code comes with a default responseCurve of which the probability is left at default, but the interval of each probability is adjusted to fit the scenario. That is the first one changed to -3180 (origin of fire), the second changed by a factor of 2.86 (ratio of default times for interval one and two) to 9086 seconds, the last changed by a factor of 3 (ratio of default times for interval two and three) to 27258 seconds. This is shown in, Figure 106.

```
"walkingSpeedModifier": 1.0,
"evacuationOrderStart": 3180.0,
"responseCurve": {
    "dataPoints": [
        {
            "probability": 0.14000000059604646,
            "timeMinMax": {
                "x": -3180.0,
                "y": 0.0
            }
        },
        {
            "probability": 0.8100000023841858,
            "timeMinMax": {
                "x": 0.0,
                "y": 9086.0
            }
        },
        {
            "probability": 0.949999988079071,
            "timeMinMax": {
                "x": 9086.0,
                "y": 27258.0
            }
        }
    ]
},
```

Figure 106 Code from the CampFire WUI-file showing rows 34 to 62.

BlockGoalEvents is left at default. The default value means that no GoalEvent is being blocked during the simulation. This is shown in, Figure 107.

```
"blockGoalEvents": [
    {
        "startTime": 3.4028234663852887e38,
        "goalIndex": 0
    }
],
```

Figure 107 Code from the CampFire WUI-file.

EvacGroups modifies evacuation groups (in this case separate communities, e.g Paradise). GoalIndices defines the number of evacuation goals of which the group has access to, in this case 5, ChicoJunior (0), ChicoChurch, (1), ButteMeadows (2), OrovilleLeft (3), OrovilleMiddle (4) and OrovilleRight (5). CumulativeWeights are left at default values. CumulativeWeights is the distribution to the different evacuation goals. Because no data was found of the distribution over the different shelters it is assumed an equal spread over the five goals. With the adjustment of the map there is only one evacuation group, Paradise. This is shown in, Figure 108.

```
"evacGroups": [
    {
        "goalIndices": [
            0,
            1,
            2,
            3,
            4,
            5
        ],
        "goalsCumulativeWeights": [
            0.16,
            0.32,
            0.48,
            0.64,
            0.8,
            1.0
        ],
        "responseCurveIndex": 0,
        "name": "Paradise",
        "color": {
            "r": 0.0,
            "g": 1.0,
            "b": 0.0,
            "a": 1.0
```

Figure 108 Code from the CampFire WUI-file showing rows 69 to 93.

Traffic and everything included in traffic concerns traffic simulation. EvacuationGoals is the location to where the evacuees will travel to. Paradise had an evacuation plan with four major evacuation routes leading to Chico, Oroville and Butte Meadows (Butte County, Accessed January 2022). Out of those three destinations only Chico remains within the simulated perimeter while Oroville and Butte Meadows location is chosen to be the end om the map in the direction of each community. The Oroville goal is split over the three roads leading in the direction of Oroville, OrovilleLeft (39.701775, -121.68643), OrovilleMiddle (39.700783, -121.611768) and OrovilleRight (39.709361, -121.575845). Oroville goals is marked as purple. Butte Meadows (39.802481, -121.578813), marked as blue. The two evacuation centres within Chico, ChicoJunior (39.729081, -121.811613) marked as red and ChicoChurch (39.709805, -121.792609) marked as green (Skropanic, Accessed January 2022). ChicoJunior had to be relocated due to the perimeter of the simulation. None of the evacuationGoals are being blocked and are therefore left at default false. MaxFlow, goalType, cumulativeWeight, maxCars and maxPeople are also left at default. By leaving this at default means that the evacuationGoal has no limit as to how many evacuees (cars or people) it can house. This is shown in, Figure 109.

```
"traffic": {
    "evacuationGoals": [
        {
            "name": "ChicoJunior",
            "latLong": {
                "x": 39.729081,
                "y": -121.811613
            },
            "color": {
                "r": 1.0,
                "g": 0.0,
                "b": 0.0,
                "a": 1.0
            },
            "blocked": false,
            "maxFlow": 0.0,
            "goalType": 0,
            "maxCars": 0,
            "maxPeople": -1
        },
        {
            "name": "ChicoChurch",
            "latLong": {
                "x": 39.709805,
                "y": -121.792609
            },
            "color": {
                "r": 0.0,
                "g": 1.0,
                "b": 0.0,
                "a": 1.0
            },
            "blocked": false,
            "maxFlow": 0.0,
            "goalType": 0,
            "maxCars": 0,
            "maxPeople": -1
        },
```

```
"name": "ButteMeadows",
"latLong": {
    "x": 39.802481,
    "y": -121.578813
},
"color": {
    "r": 0.0,
    "g": 0.0,
    "b": 1.0,
    "a": 1.0
},
"blocked": false,
"maxFlow": 0.0,
"goalType": 0,
"maxCars": 0,
"maxPeople": -1

"name": "OrovilleLeft",
"latLong": {
    "x": 39.701775,
    "y": -121.68643
},
"color": {
    "r": 1.0,
    "g": 0.0,
    "b": 1.0,
    "a": 1.0
},
"blocked": false,
"maxFlow": 0.0,
"goalType": 0,
"maxCars": 0,
"maxPeople": -1
```

```
"name": "OrovilleMiddle",
"latLong": {
    "x": 39.700783,
    "y": -121.611768
},
"color": {
    "r": 1.0,
    "g": 0.0,
    "b": 1.0,
    "a": 1.0
},
"blocked": false,
"maxFlow": 0.0,
"goalType": 0,
"maxCars": 0,
"maxPeople": -1

"name": "OrovilleRight",
"latLong": {
    "x": 39.709361,
    "y": -121.575845
},
"color": {
    "r": 1.0,
    "g": 0.0,
    "b": 1.0,
    "a": 1.0
},
"blocked": false,
"maxFlow": 0.0,
"goalType": 0,
"maxCars": 0,
"maxPeople": -1
```

Figure 109 Code from the CampFire WUI-file showing rows 98 to 206.

RouteChoice is set to 0 meaning WUI-NITY simulates the fastest route. There are 4 values (0, 1, 2, and 3) which is the fastest route, closest route, random route and evacuation groups. StallSpeed is also left at default meaning that the maximum speed when congestion occurs is limited to 1 km/h. BackGroundDensityMinMax is extracted from, 7.5.1, to be minimum 322 and maximum 17300. This is shown in, Figure 110.

```
"routeChoice": 0,
"stallSpeed": 1.0,
"backGroundDensityMinMax": {
    "x": 322.0,
    "y": 17300.0
```

Figure 110 Code from the CampFire WUI-file.

VisibilityAffectSpeed is left at default meaning there is no simulated effect of speed change due to visibility. RoadTypes is also left at default. RoadTypes is only used for the roads of which WUI-NITY is unable to extract data from for the used OSM-file. In general, road data is gathered from the OSM-file. This is shown in, Figure 111.

```
},
"visibilityAffectsSpeed": false,
"opticalDensity": 0.05000000074505806,
"roadTypes": {
    "roadData": [
        {
            "name": "motorway",
            "speedLimit": 120.0,
            "lanes": 2,
            "maxCapacity": 75.0,
            "canBeReversed": true
        },
        {
            "name": "motorway_link",
            "speedLimit": 120.0,
            "lanes": 2,
            "maxCapacity": 75.0,
            "canBeReversed": true
        },
        {
            "name": "trunk",
            "speedLimit": 90.0,
            "lanes": 2,
            "maxCapacity": 75.0,
            "canBeReversed": true
        },
        {
            "name": "trunk_link",
            "speedLimit": 90.0,
            "lanes": 2,
            "maxCapacity": 75.0,
            "canBeReversed": true
        },
        {
            "name": "primary",
            "speedLimit": 90.0,
            "lanes": 1,
            "maxCapacity": 75.0,
            "canBeReversed": true
        },
        {
            "name": "primary_link",
            "speedLimit": 90.0,
            "lanes": 1,
            "maxCapacity": 75.0,
            "canBeReversed": true
        },
        {
            "name": "secondary",
            "speedLimit": 70.0,
            "lanes": 1,
            "maxCapacity": 75.0,
            "canBeReversed": true
        },
{
    "name": "secondary_link",
    "speedLimit": 70.0,
    "lanes": 1,
    "maxCapacity": 75.0,
    "canBeReversed": true
},
{
    "name": "tertiary",
    "speedLimit": 70.0,
    "lanes": 1,
    "maxCapacity": 60.0,
    "canBeReversed": true
},
{
    "name": "tertiary_link",
    "speedLimit": 70.0,
    "lanes": 1,
    "maxCapacity": 60.0,
    "canBeReversed": true
},
{
    "name": "unclassified",
    "speedLimit": 50.0,
    "lanes": 1,
    "maxCapacity": 50.0,
    "canBeReversed": false
},
{
    "name": "residential",
    "speedLimit": 50.0,
    "lanes": 1,
    "maxCapacity": 50.0,
    "canBeReversed": false
},
{
    "name": "service",
    "speedLimit": 30.0,
    "lanes": 1,
    "maxCapacity": 50.0,
    "canBeReversed": false
},
{
    "name": "services",
    "speedLimit": 30.0,
    "lanes": 1,
    "maxCapacity": 50.0,
    "canBeReversed": false
},
```

```
{
    "name": "road",
    "speedLimit": 30.0,
    "lanes": 1,
    "maxCapacity": 50.0,
    "canBeReversed": false
},
{
    "name": "track",
    "speedLimit": 30.0,
    "lanes": 1,
    "maxCapacity": 50.0,
    "canBeReversed": false
},
{
    "name": "living_street",
    "speedLimit": 5.0,
    "lanes": 1,
    "maxCapacity": 50.0,
    "canBeReversed": false
},
{
    "name": "ferry",
    "speedLimit": 5.0,
    "lanes": 1,
    "maxCapacity": 50.0,
    "canBeReversed": false
},
{
    "name": "movable",
    "speedLimit": 5.0,
    "lanes": 1,
    "maxCapacity": 50.0,
    "canBeReversed": false
},
{
    "name": "shuttle_train",
    "speedLimit": 10.0,
    "lanes": 1,
    "maxCapacity": 50.0,
    "canBeReversed": false
},
{
    "name": "custom0",
    "speedLimit": 40.0,
    "lanes": 1,
    "maxCapacity": 50.0,
    "canBeReversed": false
},
{
    "name": "custom1",
    "speedLimit": 40.0,
    "lanes": 1,
    "maxCapacity": 50.0,
    "canBeReversed": false
},
{
    "name": "custom2",
    "speedLimit": 40.0,
    "lanes": 1,
    "maxCapacity": 50.0,
    "canBeReversed": false
},
{
    "name": "custom3",
    "speedLimit": 40.0,
    "lanes": 1,
    "maxCapacity": 50.0,
    "canBeReversed": false
},
{
    "name": "custom4",
    "speedLimit": 40.0,
    "lanes": 1,
    "maxCapacity": 50.0,
    "canBeReversed": false
},
{
    "name": "default",
    "speedLimit": 10.0,
    "lanes": 1,
    "maxCapacity": 50.0,
    "canBeReversed": false
}
]
},
```

Figure 111 Code from the CampFire WUI-file showing rows 215 to 402.

SaveInterval is left at default. It is the interval at which the simulation is saved in case it crashes. Traffic accidents occurred along Freeway 99 throughout the whole time period of Camp fire, therefore trafficAccidents is set to true from start (0 seconds) to end (1 531 800 seconds). This is shown in, Figure 112.

```
"saveInterval": 600.0,
"trafficAccidents": [
    {
        "startTime": 0,
        "endTime": 1531800,
        "isActive": true
    }
],
```

Figure 112 Code from the CampFire WUI-file showing rows 403 to 410.

ReverseLanes is left at default meaning no reversal of lanes may occur. This is shown in, Figure 113.

```
"reverseLanes": [
    {
        "startTime": 3.4028234663852887e38,
        "endTime": 3.4028234663852887e38,
        "isActive": false
    }
],
```

Figure 113 Code from the CampFire WUI-file showing rows 411 to 417.

TrafficInjections is not yet a finished system and is therefore left at default. This is shown in, Figure 114.

```
"trafficInjections": [
    {
        "cars": 1,
        "latLong": {
            "x": 0.0,
            "y": 0.0
        },
        "desiredGoal": {
            "name": "New goal",
            "latLong": {
                "x": 0.0,
                "y": 0.0
            },
            "color": {
                "r": 1.0,
                "g": 1.0,
                "b": 1.0,
                "a": 1.0
            },
            "blocked": false,
            "maxFlow": 3600.0,
            "goalType": 1,
            "cumulativeWeight": 0.0,
            "maxCars": -1,
            "maxPeople": -1
        },
        "pickGoalFromMap": false,
        "timeFlow": [
            {
                "x": 0.0,
                "y": 0.0
            },
            {
                "x": 0.0,
                "y": 0.0
            }
        ]
    }
],
```

Figure 114 Code from the CampFire WUI-file showing rows 418 to 455.

GPW is gathered data for the gridded population over the chosen map. This data is extracted from the GPW data folder, gpw-v4-population-density-rev10_2015_30_sec_asc. Once the simulations has been run once a local save of the GPW is created and therefore can be read straight from the CampFire folder. The road network and available routes are extracted from the OSM map data from the osm_itinero folder. This is shown in, Figure 115.

```
"gpw": {
    "gpwDataFolder": "gpw-v4-population-density-rev10_2015_30_sec_asc",
    "tryReadGPWFromSave": true
},
"itinero": {
    "osmFile": "C:\\Users\\Alicia_adm\\Desktop\\exjobb\\WUI-NITY.0.08\\external_data\\osm_itinero\\norcal-latest.osm.pbf",
    "osmBorderSize": 1000.0
```

Figure 115 Code from the CampFire WUI-file.

The remaining code is not changed and unused and is therefore not described in this thesis.

13.3.2. Atlas fire

The WUI-file of Atlas fire is named either Default_X_AT or PeMS_X_AT and put in the folder AtlasFire. The simulated area is defined by the progression map, Figure 116.

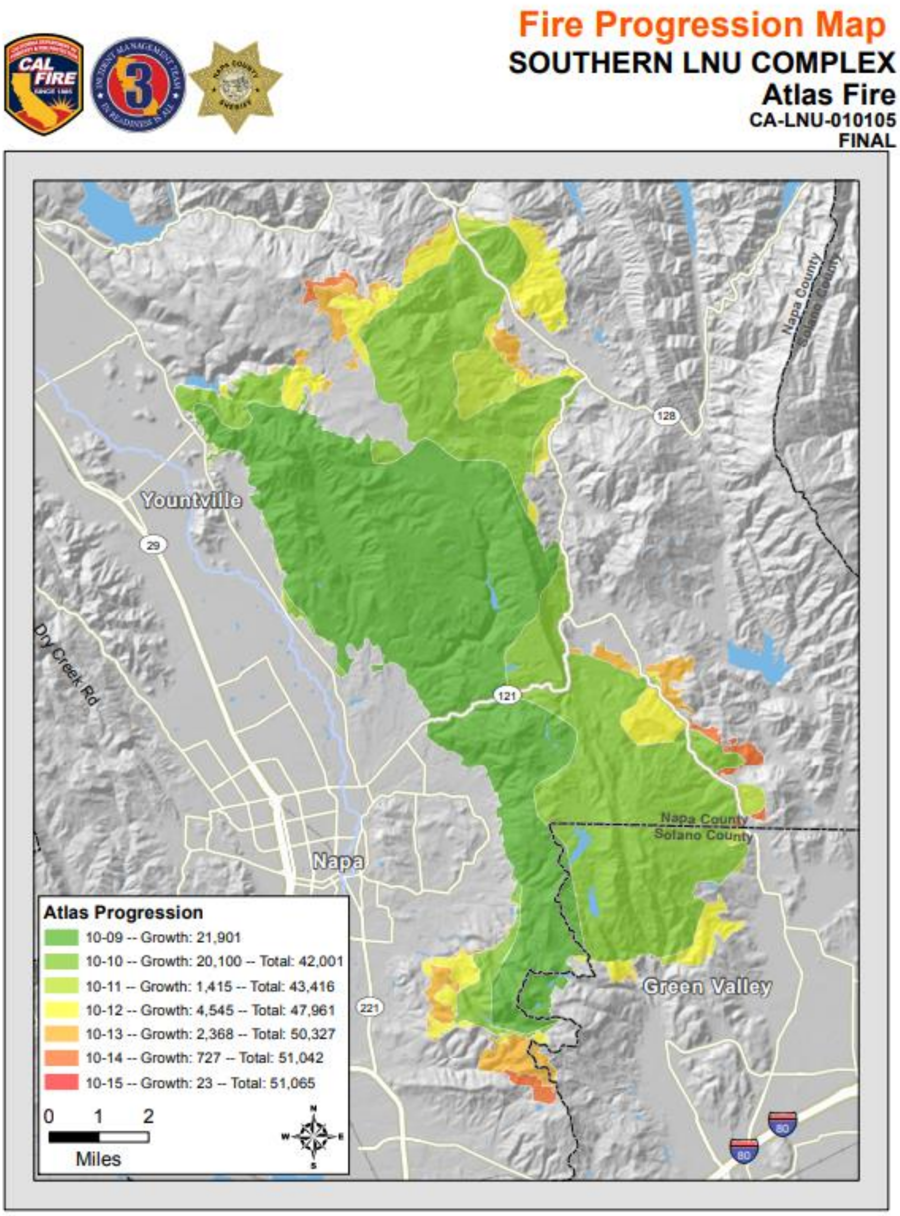

Figure 116 Progression map of Atlas fire. The map is taken from the National Interagency Fire Center, (NIFC, Accessed February 2022).

Including the chosen detectors the simulated area is limited to coordinate origin, 38.205219, -122.363671, with x-axis of 40 000 and y-axis of 34 000, as shown in, Figure 117.

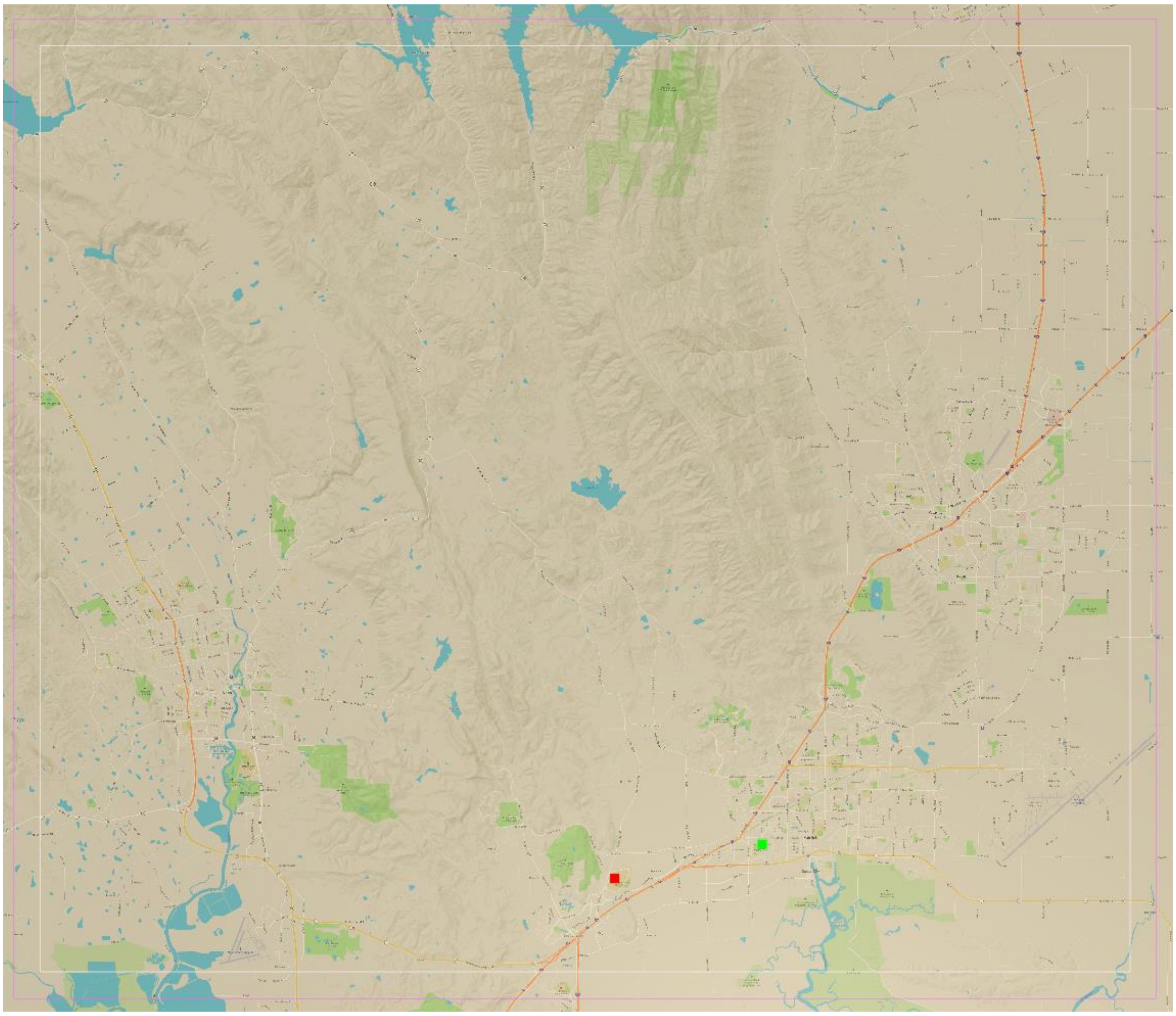

Figure 117 Perimeter of simulation illustrated in WUI-NITY. With the red (SolanoCommunityCollege) and green (AllanWittPark) being the two used evacuation goals.

The map is too large to simulate and must be reduced to approximately 10,000 x 20,000 meters. The GPW are analysed over the area to define the lesser populated areas, Figure 118.

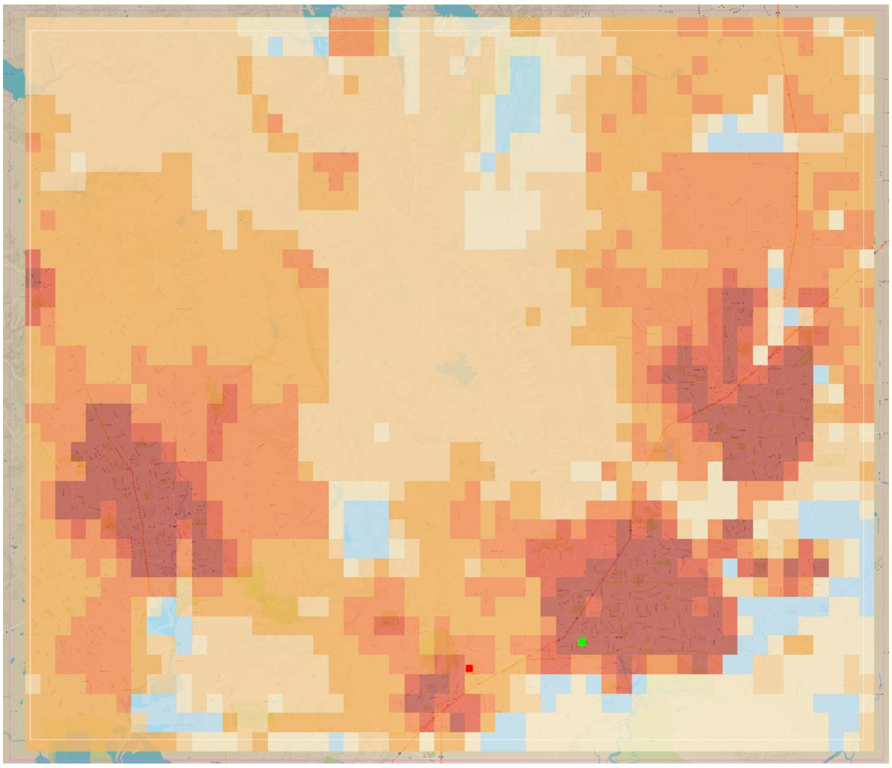

Figure 118 Map showing the GPW over the area of Atlas Fire.

Including the location of the detectors the final map is defined to be starting at the coordinate, (38.204514, -122.28349) stretching 24,000 on the x-axis and 14,000 on the y-axis, Figure 119.

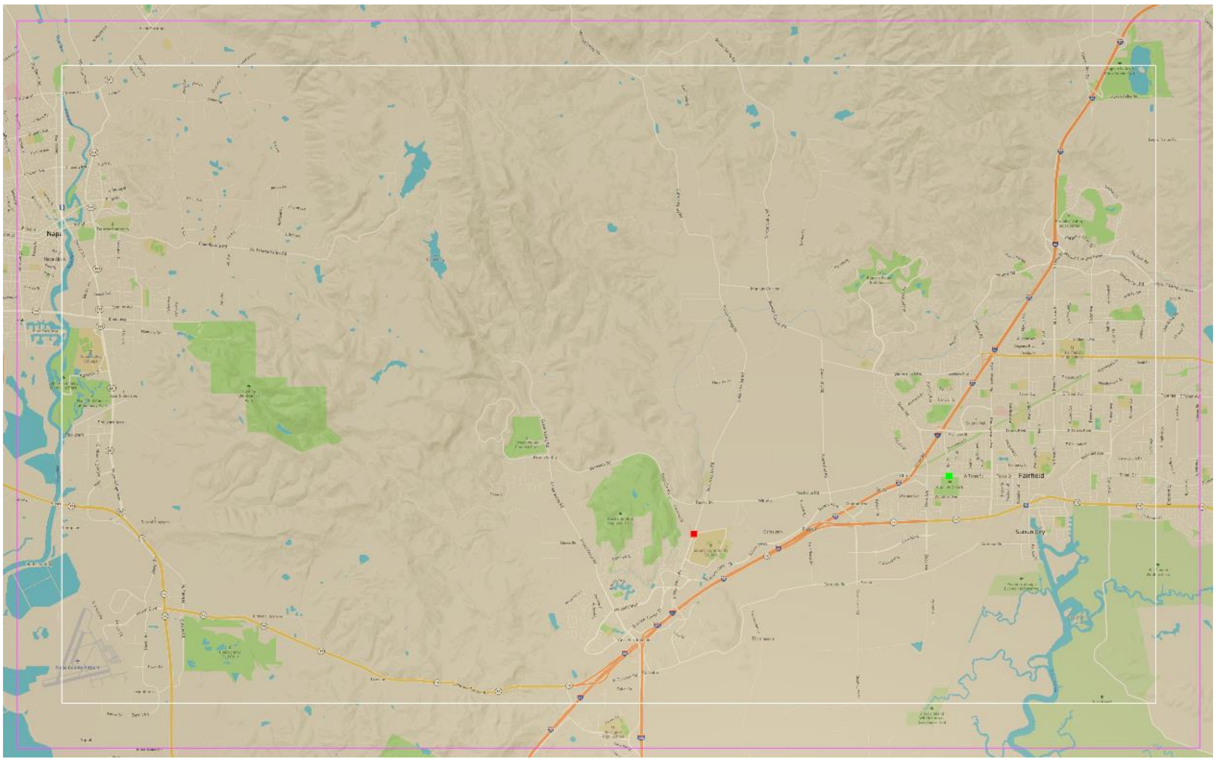

Figure 119 Map used for the simulation of AtlasFire_X illustrated in WUI-NITY.

The simulation time is from the origin of fire (8th of October) to the when mandatory evacuations are lifted (20th of October). Evacuation orders are issued 113 minutes (6700 seconds) after the origin of the fire and the responsecurve is redefined as described in 13.3.1. No evidence of blocked goal events. Evacuation groups are added to Napa, Green Valley and Yountville as three areas spread apart. The evacuation groups was chosen from the studied fire progression map of the Atlas fire and literature. 2 evacuation centres was found in Fairfield (Patch, Accessed 2022 January). The entire code is shown in, Figure 120.


```
{
    "simName": "AtlasFire_0",
    "deltaTime": 60.0,
    "maxSimTime": 1087680.0,
    "stopWhenEvacuated": true,
    "numberOfRuns": 1,
    "lowerLeftLatLong": {
        "x": 38.204514,
        "y": -122.28349
    },
    "size": {
        "x": 24000.0,
        "y": 14000.0
    },
    "zoomLevel": 13,
    "runInRealTime": false,
    "runEvacSim": true,
    "runTrafficSim": true,
    "runFireSim": false,
    "evac": {
        "overrideTotalPopulation": false,
        "totalPopulation": 500,
        "routeCellSize": 200.0,
        "allowMoreThanOneCar": false,
        "maxCars": 2,
        "maxCarsChance": 0.30000001192092898,
        "minHouseholdSize": 1,
        "maxHouseholdSize": 5,
        "walkingDistanceModifier": 1.0,
        "walkingSpeedMinMax": {
            "x": 0.699999988079071,
            "y": 1.0
        },
        "walkingSpeedModifier": 1.0,
        "evacuationOrderStart": 6700.0,
        "responseCurves": [
            {
                "dataPoints": [
                    {
                        "probability": 0.14000000059604646,
                        "timeMinMax": {
                            "x": -6700.0,
                            "y": 0.0
                        }
                    },
                    {
                        "probability": 0.8100000023841858,
                        "timeMinMax": {
                            "x": 0.0,
                            "y": 19143.0
                        }
                    },
                    {
                        "probability": 0.949999988079071,
                        "timeMinMax": {
                            "x": 19143.0,
                            "y": 57249.0
                        }
                    }
                ]
            }
        ],
        "blockGoalEvents": [
            {
                "startTime": 3.4028234663852887e38,
                "goalIndex": 0
            }
        ],
        "evacGroups": [
            {
                "goalIndices": [
                    0,
                    1
                ],
                "goalsCumulativeWeights": [
                    0.5,
                    1.0
                ],
                "responseCurveIndex": 0,
                "name": "NapaCounty",
```

```
                "color": {
                    "r": 1.0,
                    "g": 0.0,
                    "b": 0.0,
                    "a": 1.0
                }
            }
        ]
    },
    "traffic": {
        "evacuationGoals": [
            {
                "name": "SolanoCommunityCollege",
                "latLong": {
                    "x": 38.237835,
                    "y": -122.124892
                },
                "color": {
                    "r": 1.0,
                    "g": 0.0,
                    "b": 0.0,
                    "a": 1.0
                },
                "blocked": false,
                "maxFlow": 0.0,
                "goalType": 0,
                "maxCars": 0,
                "maxPeople": -1
            },
            {
                "name": "AllanWittPark",
                "latLong": {
                    "x": 38.249328,
                    "y": -122.06081
                },
                "color": {
                    "r": 0.0,
                    "g": 1.0,
                    "b": 0.0,
                    "a": 1.0
```

```
                },
                "blocked": false,
                "maxFlow": 0.0,
                "goalType": 0,
                "maxCars": 0,
                "maxPeople": -1
            }
        ],
        "routeChoice": 0,
        "stallSpeed": 1.0,
        "backGroundDensityMinMax": {
            "x": 250.0,
            "y": 5090.0
        },
        "visibilityAffectsSpeed": false,
        "opticalDensity": 0.05000000074505806,
        "roadTypes": {
            "roadData": [
                {
                    "name": "motorway",
                    "speedLimit": 120.0,
                    "lanes": 2,
                    "maxCapacity": 75.0,
                    "canBeReversed": true
                },
                {
                    "name": "motorway_link",
                    "speedLimit": 120.0,
                    "lanes": 2,
                    "maxCapacity": 75.0,
                    "canBeReversed": true
                },
                {
                    "name": "trunk",
                    "speedLimit": 90.0,
                    "lanes": 2,
                    "maxCapacity": 75.0,
                    "canBeReversed": true
                },
                {
```

```
                    "name": "trunk_link",
                    "speedLimit": 90.0,
                    "lanes": 2,
                    "maxCapacity": 75.0,
                    "canBeReversed": true
                },
                {
                    "name": "primary",
                    "speedLimit": 90.0,
                    "lanes": 1,
                    "maxCapacity": 75.0,
                    "canBeReversed": true
                },
                {
                    "name": "primary_link",
                    "speedLimit": 90.0,
                    "lanes": 1,
                    "maxCapacity": 75.0,
                    "canBeReversed": true
                },
                {
                    "name": "secondary",
                    "speedLimit": 70.0,
                    "lanes": 1,
                    "maxCapacity": 75.0,
                    "canBeReversed": true
                },
                {
                    "name": "secondary_link",
                    "speedLimit": 70.0,
                    "lanes": 1,
                    "maxCapacity": 75.0,
                    "canBeReversed": true
                },
                {
                    "name": "tertiary",
                    "speedLimit": 70.0,
                    "lanes": 1,
                    "maxCapacity": 60.0,
                    "canBeReversed": true
```

```
                },
                {
                    "name": "tertiary_link",
                    "speedLimit": 70.0,
                    "lanes": 1,
                    "maxCapacity": 60.0,
                    "canBeReversed": true
                },
                {
                    "name": "unclassified",
                    "speedLimit": 50.0,
                    "lanes": 1,
                    "maxCapacity": 50.0,
                    "canBeReversed": false
                },
                {
                    "name": "residential",
                    "speedLimit": 50.0,
                    "lanes": 1,
                    "maxCapacity": 50.0,
                    "canBeReversed": false
                },
                {
                    "name": "service",
                    "speedLimit": 30.0,
                    "lanes": 1,
                    "maxCapacity": 50.0,
                    "canBeReversed": false
                },
                {
                    "name": "services",
                    "speedLimit": 30.0,
                    "lanes": 1,
                    "maxCapacity": 50.0,
                    "canBeReversed": false
                },
                {
                    "name": "road",
                    "speedLimit": 30.0,
                    "lanes": 1,
```

```
                    "maxCapacity": 50.0,
                    "canBeReversed": false
                },
                {
                    "name": "track",
                    "speedLimit": 30.0,
                    "lanes": 1,
                    "maxCapacity": 50.0,
                    "canBeReversed": false
                },
                {
                    "name": "living_street",
                    "speedLimit": 5.0,
                    "lanes": 1,
                    "maxCapacity": 50.0,
                    "canBeReversed": false
                },
                {
                    "name": "ferry",
                    "speedLimit": 5.0,
                    "lanes": 1,
                    "maxCapacity": 50.0,
                    "canBeReversed": false
                },
                {
                    "name": "movable",
                    "speedLimit": 5.0,
                    "lanes": 1,
                    "maxCapacity": 50.0,
                    "canBeReversed": false
                },
                {
                    "name": "shuttle_train",
                    "speedLimit": 10.0,
                    "lanes": 1,
                    "maxCapacity": 50.0,
                    "canBeReversed": false
                },
                {
                    "name": "custom0",
                    "speedLimit": 40.0,
                    "lanes": 1,
                    "maxCapacity": 50.0,
                    "canBeReversed": false
                },
                {
                    "name": "custom1",
                    "speedLimit": 40.0,
                    "lanes": 1,
                    "maxCapacity": 50.0,
                    "canBeReversed": false
                },
                {
                    "name": "custom2",
                    "speedLimit": 40.0,
                    "lanes": 1,
                    "maxCapacity": 50.0,
                    "canBeReversed": false
                },
                {
                    "name": "custom3",
                    "speedLimit": 40.0,
                    "lanes": 1,
                    "maxCapacity": 50.0,
                    "canBeReversed": false
                },
                {
                    "name": "custom4",
                    "speedLimit": 40.0,
                    "lanes": 1,
                    "maxCapacity": 50.0,
                    "canBeReversed": false
                },
                {
                    "name": "default",
                    "speedLimit": 10.0,
                    "lanes": 1,
                    "maxCapacity": 50.0,
                    "canBeReversed": false
                }
            ]
        },
        "saveInterval": 10000.0,
        "trafficAccidents": [
            {
                "startTime": 0.0,
                "endTime": 1087680.0,
                "isActive": true
            }
        ],
        "reverseLanes": [
            {
                "startTime": 3.4028234663852887e38,
                "endTime": 3.4028234663852887e38,
                "isActive": false
            }
        ],
        "trafficInjections": [
            {
                "cars": 1,
                "latLong": {
                    "x": 0.0,
                    "y": 0.0
                },
                "desiredGoal": {
                    "name": "New goal",
                    "latLong": {
                        "x": 0.0,
                        "y": 0.0
                    },
                    "color": {
                        "r": 1.0,
                        "g": 1.0,
                        "b": 1.0,
                        "a": 1.0
                    },
                    "blocked": false,
                    "maxFlow": 3600.0,
                    "goalType": 1,
                    "maxCars": -1,
```

```
                    "maxPeople": -1
                },
                "pickGoalFromMap": false,
                "timeFlow": [
                    {
                        "x": 0.0,
                        "y": 0.0
                    },
                    {
                        "x": 0.0,
                        "y": 0.0
                    }
                ]
            }
        ],
        "trafficProbes": [
            {
                "nodeID": 0
            }
        ]
    },
    "gpw": {
        "gpwDataFolder": "gpw-v4-population-density-rev10_2015_30_sec_asc",
        "tryReadGPWFromSave": true
    },
    "itinero": {
        "osmFile": "D:\\UNITY\\_PROJECTS\\WUI-NITY\\wui-nity_git\\external_data\\osm_itinero\\norcal-latest.osm.pbf",
        "osmBorderSize": 1000.0
    },
    "farsite": {
        "outputPrefix": "Atlas"
    },
    "visuals": {
        "drawRoads": false
    },
    "fire": {
        "lcpFile": "D:\\UNITY\\_PROJECTS\\WUI-NITY\\wui-nity_git\\external_data\\roxborough_big.lcp",
        "ignitionPoints": [
            {
                "latLong": {
                    "x": 39.479633,
                    "y": -105.037355
                },
                "startTime": 0.0
            }
        ],
        "spreadMode": 1,
        "weather": {
            "weatherInputs": [
                {
                    "Month": 7,
                    "Day": 15,
                    "Precip": 0,
                    "Hour1": 4,
                    "Hour2": 16,
                    "Temp1": 13,
                    "Temp2": 33,
                    "Humid1": 10,
                    "Humid2": 10,
                    "Elevation": 1803
                },
                {
                    "Month": 7,
                    "Day": 16,
                    "Precip": 25,
                    "Hour1": 4,
                    "Hour2": 16,
                    "Temp1": 10,
                    "Temp2": 30,
                    "Humid1": 18,
                    "Humid2": 15,
                    "Elevation": 1803
                }
            ]
        },
        "wind": {
            "dataPoints": [
                {
                    "time": 0.0,
                    "direction": 0.0,
                    "speed": 2.0,
                    "cloudCover": 0.0
                },
                {
                    "time": 0.0,
                    "direction": 0.0,
                    "speed": 2.0,
                    "cloudCover": 0.0
                }
            ]
        },
        "initialFuelMoisture": {
            "fuelMoistures": [
                {
                    "OneHour": 6.0,
                    "TenHour": 7.0,
                    "HundredHour": 8.0,
                    "LiveHerbaceous": 60.0,
                    "LiveWoody": 90.0
                },
                {
                    "OneHour": 6.0,
                    "TenHour": 7.0,
                    "HundredHour": 8.0,
                    "LiveHerbaceous": 60.0,
                    "LiveWoody": 90.0
                },
                {
                    "OneHour": 6.0,
                    "TenHour": 7.0,
                    "HundredHour": 8.0,
                    "LiveHerbaceous": 60.0,
                    "LiveWoody": 90.0
                },
                {
                    "OneHour": 6.0,
                    "TenHour": 7.0,
                    "HundredHour": 8.0,
                    "LiveHerbaceous": 60.0,
                    "LiveWoody": 90.0
```

```
                },
                {
                    "OneHour": 6.0,
                    "TenHour": 7.0,
                    "HundredHour": 8.0,
                    "LiveHerbaceous": 60.0,
                    "LiveWoody": 90.0
                },
                {
                    "OneHour": 6.0,
                    "TenHour": 7.0,
                    "HundredHour": 8.0,
                    "LiveHerbaceous": 60.0,
                    "LiveWoody": 90.0
                },
                {
                    "OneHour": 6.0,
                    "TenHour": 7.0,
                    "HundredHour": 8.0,
                    "LiveHerbaceous": 60.0,
                    "LiveWoody": 90.0
                },
                {
                    "OneHour": 6.0,
                    "TenHour": 7.0,
                    "HundredHour": 8.0,
                    "LiveHerbaceous": 60.0,
                    "LiveWoody": 90.0
                },
                {
                    "OneHour": 6.0,
                    "TenHour": 7.0,
                    "HundredHour": 8.0,
                    "LiveHerbaceous": 60.0,
                    "LiveWoody": 90.0
                },
                {
                    "OneHour": 6.0,
                    "TenHour": 7.0,
                    "HundredHour": 8.0,
                    "LiveHerbaceous": 60.0,
                    "LiveWoody": 90.0
                },
                {
                    "OneHour": 6.0,
                    "TenHour": 7.0,
                    "HundredHour": 8.0,
                    "LiveHerbaceous": 60.0,
                    "LiveWoody": 90.0
                },
                {
                    "OneHour": 6.0,
                    "TenHour": 7.0,
                    "HundredHour": 8.0,
                    "LiveHerbaceous": 60.0,
                    "LiveWoody": 90.0
                },
                {
                    "OneHour": 6.0,
                    "TenHour": 7.0,
                    "HundredHour": 8.0,
                    "LiveHerbaceous": 60.0,
                    "LiveWoody": 90.0
                }
            ]
        },
        "windMultiplier": 1.0
    }
}
```


Figure 120 Code of AtlasFire simulation.

13.3.3. Hill and Woolsey fire

The WUI-file of Hill and Woolsey fire is named either Defualt_X_WH or PeMS_X_WH. The simulated area is defined by the progression map, Figure 121. The reason why the Hill fire progression map is excluded is because no trustworthy source of that fire could be found. The detectors used for the both fires (Hill and Woolsey) are also the same meaning there is no need to know the Hill fire progression either.

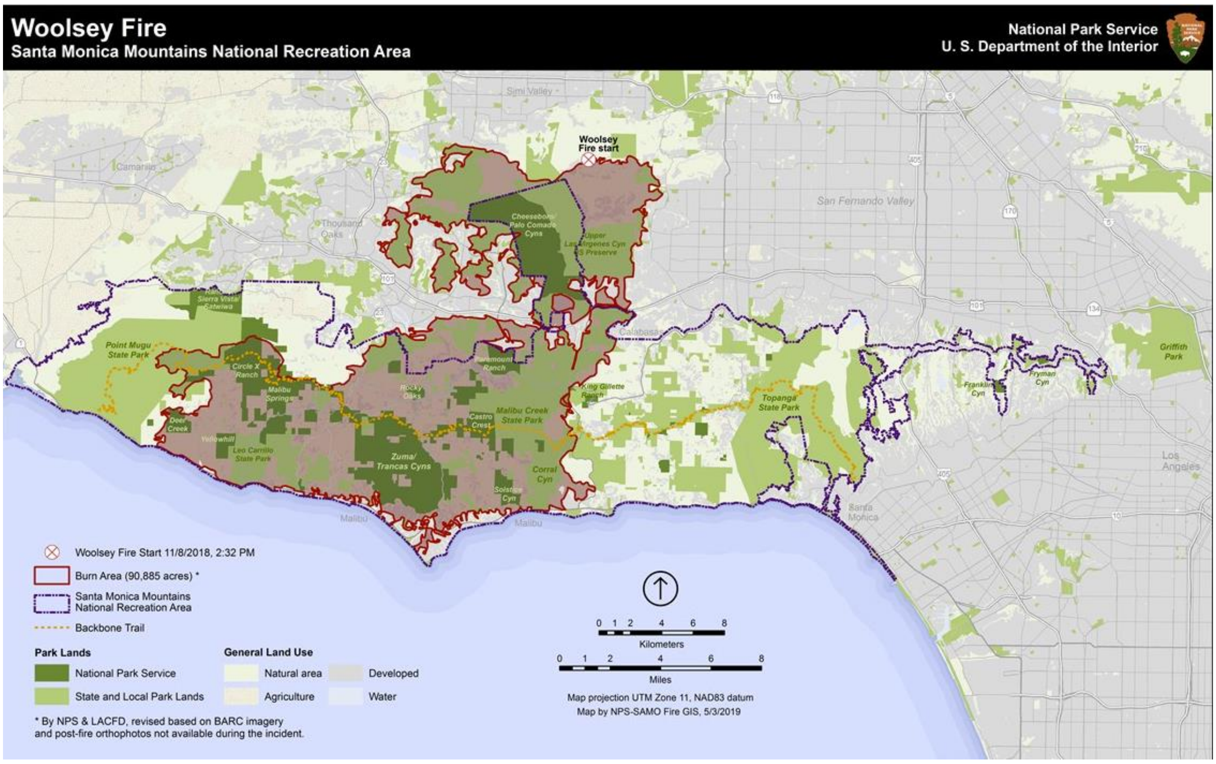

Figure 121 Progression map of the Woolsey fire. The map is taken from the National park service, (National Park Service, Accessed December 2021).

Including the location of the detectors for Hill and Woolsey fire, the simulated area is limited to coordinate origin, 34.015623, -118.895897, with x-axis of 43 000 and y-axis of 19 000, as shown in, Figure 122.

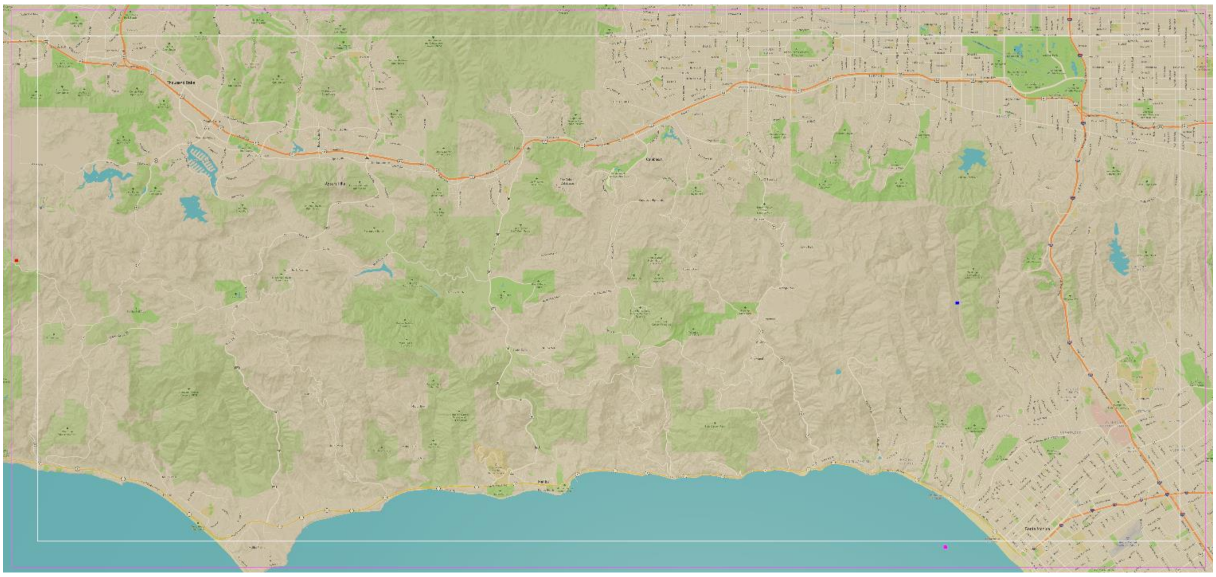

Figure 122 Perimeter of simulation illustrated WUI-NITY.

Due to the limitation of computer power and WUI-NITY data the size of the map has to be reduced. To include as much of the areas evacuated as possible together with all the detectors analysed from PeMS, the reduced manageable map size is of origin, (34.079023, -118.840713), stretching 34,000 on the x-axis and 11,000 in the y-axis. This is shown in, Figure 123.

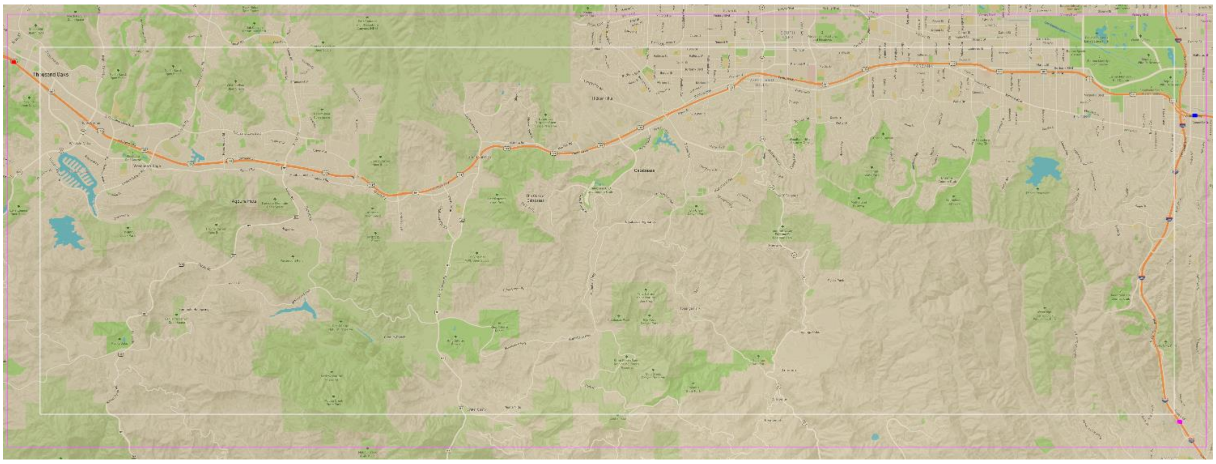

Figure 123 The reduced manageable map size used for HillWoolseyFire simulations as illustrated in WUI-NITY.

The simulation time is from the origin of fire (the 8th of November) to when the fire is 100 % contained (21st of November). Evacuation orders are issued 190 minutes (11400 seconds) after the origin of the fire and the responsecurve is redefined as described in 13.3.1. No evidence of blocked goal events. Evacuation groups are added to Oak Park, Kevington and Malibu. 4 evacuation centres were found, two west of Thousand Oaks and two North of Thousand oaks, (Ventura County Star, Accessed January 2022). The four centres will be considered to be two goals, one along Highway 101 (named West, coordinate 34.193002, -118.946346) and one along Highway 23 (named North, coordinate, 34.279547, -118.861721), since all are outside the simulated perimeter. No further evidence of evacuation centres was found but it is reasonable to assume people evacuated to the east towards Los Angeles as well. Therefore, two more evacuation goals are added, one along Highway 134 (named East, coordinate, 34.152669, -118.333934) and one along Highway 405 (named South, coordinate, 34.003130, -118.412141). The routerDatabaseName and osmDataName is set to socal-latest. The entire code is shown in, Figure 124.


```
{
    "simName": "HillWoolseyFire_0",
    "deltaTime": 60.0,
    "maxSimTime": 1157400.0,
    "stopWhenEvacuated": true,
    "numberOfRuns": 1,
    "lowerLeftLatLong": {
        "x": 34.079023,
        "y": -118.840713
    },
    "size": {
        "x": 24000.0,
        "y": 11000.0
    },
    "zoomLevel": 13,
    "runInRealTime": false,
    "runEvacSim": true,
    "runTrafficSim": true,
    "runFireSim": false,
    "evac": {
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        "totalPopulation": 500,
        "routeCellSize": 200.0,
        "allowMoreThanOneCar": false,
        "maxCars": 2,
        "maxCarsChance": 0.30000001192092898,
        "minHouseholdSize": 1,
        "maxHouseholdSize": 5,
        "walkingDistanceModifier": 1.0,
        "walkingSpeedMinMax": {
            "x": 0.699999988079071,
            "y": 1.0
        },
        "walkingSpeedModifier": 1.0,
        "evacuationOrderStart": 11400.0,
        "responseCurves": [
            {
                "dataPoints": [
                    {
                        "probability": 0.14000000059604646,
                        "timeMinMax": {
                            "x": -11400.0,
                            "y": 0.0
                        }
                    },
                    {
                        "probability": 0.8100000023841858,
                        "timeMinMax": {
                            "x": 0.0,
                            "y": 32571.0
                        }
                    },
                    {
                        "probability": 0.949999988079071,
                        "timeMinMax": {
                            "x": 32571.0,
                            "y": 97714.0
                        }
                    }
                ]
            }
        ],
        "blockGoalEvents": [
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                "goalIndex": 0
            }
        ],
        "evacGroups": [
            {
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                    1
                ],
                "goalsCumulativeWeights": [
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                    0.5
                ],
                "responseCurveIndex": 0,
                "name": "Kevington",
```

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                    "g": 0.0,
                    "b": 0.0,
                    "a": 1.0
                }
            },
            {
                "goalIndices": [
                    0,
                    1
                ],
                "goalsCumulativeWeights": [
                    0.5,
                    0.5
                ],
                "responseCurveIndex": 0,
                "name": "OakPark",
                "color": {
                    "r": 0.0,
                    "g": 1.0,
                    "b": 0.0,
                    "a": 1.0
                }
            },
            {
                "goalIndices": [
                    0,
                    1
                ],
                "goalsCumulativeWeights": [
                    0.5,
                    0.5
                ],
                "responseCurveIndex": 0,
                "name": "Malibu",
                "color": {
                    "r": 0.0,
                    "g": 0.0,
                    "b": 1.0,
                    "a": 1.0
                }
            }
        ]
    },
    "traffic": {
        "evacuationGoals": [
            {
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                "latLong": {
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                    "y": -118.849503
                },
                "color": {
                    "r": 1.0,
                    "g": 0.0,
                    "b": 0.0,
                    "a": 1.0
                },
                "blocked": false,
                "maxFlow": 0.0,
                "goalType": 0,
                "maxCars": 0,
                "maxPeople": -1
            },
            {
                "name": "East",
                "latLong": {
                    "x": 34.167729,
                    "y": -118.583990
                },
                "color": {
                    "r": 0.0,
                    "g": 0.0,
                    "b": 1.0,
                    "a": 1.0
                },
                "blocked": false,
                "maxFlow": 0.0,
                "goalType": 0,
                "maxCars": 0,
                "maxPeople": -1
            }
        ],
        "routeChoice": 0,
        "stallSpeed": 1.0,
        "backGroundDensityMinMax": {
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            "y": 7008.0
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        "visibilityAffectsSpeed": false,
        "opticalDensity": 0.05000000074505806,
        "roadTypes": {
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                    "lanes": 2,
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                    "canBeReversed": true
                },
                {
                    "name": "motorway_link",
                    "speedLimit": 120.0,
                    "lanes": 2,
                    "maxCapacity": 75.0,
                    "canBeReversed": true
                },
                {
                    "name": "trunk",
                    "speedLimit": 90.0,
                    "lanes": 2,
                    "maxCapacity": 75.0,
                    "canBeReversed": true
                },
                {
                    "name": "trunk_link",
                    "speedLimit": 90.0,
                    "lanes": 2,
                    "maxCapacity": 75.0,
                    "canBeReversed": true
                },
                {
                    "name": "primary",
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                    "lanes": 1,
                    "maxCapacity": 75.0,
                    "canBeReversed": true
                },
                {
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                    "speedLimit": 90.0,
                    "lanes": 1,
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                    "canBeReversed": true
                },
                {
                    "name": "secondary",
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                    "lanes": 1,
                    "maxCapacity": 75.0,
                    "canBeReversed": true
                },
                {
                    "name": "secondary_link",
                    "speedLimit": 70.0,
                    "lanes": 1,
                    "maxCapacity": 75.0,
                    "canBeReversed": true
                },
                {
                    "name": "tertiary",
                    "speedLimit": 70.0,
                    "lanes": 1,
                    "maxCapacity": 60.0,
                    "canBeReversed": true
                },
                {
                    "name": "tertiary_link",
                    "speedLimit": 70.0,
```

```
                "lanes": 1,
                "maxCapacity": 60.0,
                "canBeReversed": true
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            {
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                "lanes": 1,
                "maxCapacity": 50.0,
                "canBeReversed": false
            },
            {
                "name": "residential",
                "speedLimit": 50.0,
                "lanes": 1,
                "maxCapacity": 50.0,
                "canBeReversed": false
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            {
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                "speedLimit": 30.0,
                "lanes": 1,
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                "canBeReversed": false
            },
            {
                "name": "services",
                "speedLimit": 30.0,
                "lanes": 1,
                "maxCapacity": 50.0,
                "canBeReversed": false
            },
            {
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                "speedLimit": 30.0,
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                "maxCapacity": 50.0,
                "canBeReversed": false
            },
            {
                "name": "track",
                "speedLimit": 30.0,
                "lanes": 1,
                "maxCapacity": 50.0,
                "canBeReversed": false
            },
            {
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                "speedLimit": 5.0,
                "lanes": 1,
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            },
            {
                "name": "ferry",
                "speedLimit": 5.0,
                "lanes": 1,
                "maxCapacity": 50.0,
                "canBeReversed": false
            },
            {
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                "lanes": 1,
                "maxCapacity": 50.0,
                "canBeReversed": false
            },
            {
                "name": "shuttle_train",
                "speedLimit": 10.0,
                "lanes": 1,
                "maxCapacity": 50.0,
                "canBeReversed": false
            },
            {
                "name": "custom0",
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                "lanes": 1,
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                "canBeReversed": false
            },
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                "lanes": 1,
                "maxCapacity": 50.0,
                "canBeReversed": false
            },
            {
                "name": "custom2",
                "speedLimit": 40.0,
                "lanes": 1,
                "maxCapacity": 50.0,
                "canBeReversed": false
            },
            {
                "name": "custom3",
                "speedLimit": 40.0,
                "lanes": 1,
                "maxCapacity": 50.0,
                "canBeReversed": false
            },
            {
                "name": "custom4",
                "speedLimit": 40.0,
                "lanes": 1,
                "maxCapacity": 50.0,
                "canBeReversed": false
            },
            {
                "name": "default",
                "speedLimit": 10.0,
                "lanes": 1,
                "maxCapacity": 50.0,
                "canBeReversed": false
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        ]
    },
    "saveInterval": 100000.0,
    "trafficAccidents": [
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            "endTime": 1157400.0,
            "isActive": true
        }
    ],
    "reverseLanes": [
        {
            "startTime": 3.4028234663852887e38,
            "endTime": 3.4028234663852887e38,
            "isActive": false
        }
    ],
    "trafficInjections": [
        {
            "cars": 1,
            "latLong": {
                "x": 0.0,
                "y": 0.0
            },
            "desiredGoal": {
                "name": "New goal",
                "latLong": {
                    "x": 0.0,
                    "y": 0.0
                },
                "color": {
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                    "g": 1.0,
                    "b": 1.0,
                    "a": 1.0
                },
                "blocked": false,
                "maxFlow": 3600.0,
                "goalType": 1,
                "maxCars": -1,
                "maxPeople": -1
            },
            "pickGoalFromMap": false,
            "timeFlow": [
```

```
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                    "x": 0.0,
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                },
                {
                    "x": 0.0,
                    "y": 0.0
                }
            ]
        }
    ],
    "trafficProbes": [
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            "nodeID": 0
        }
    ]
},
"gpw": {
    "gpwDataFolder": "gpw-v4-population-density-rev10_2015_30_sec_asc",
    "tryReadGPWFromSave": true
},
"itinero": {
    "osmFile": "D:\\UNITY\\_PROJECTS\\WUI-NITY\\wui-nity_git\\external_data\\osm_itinero\\socal-latest.osm.pbf",
    "osmBorderSize": 1000.0
},
"farsite": {
    "outputPrefix": "HillWoolsey"
},
"visuals": {
    "drawRoads": true
},
"fire": {
    "lcpFile": "D:\\UNITY\\_PROJECTS\\WUI-NITY\\wui-nity_git\\external_data\\roxborough_big.lcp",
    "ignitionPoints": [
        {
            "latLong": {
                "x": 39.479633,
                "y": -105.037355
            },
            "startTime": 0.0
        }
    ],
    "spreadMode": 1,
    "weather": {
        "weatherInputs": [
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                "Day": 15,
                "Precip": 0,
                "Hour1": 4,
                "Hour2": 16,
                "Temp1": 13,
                "Temp2": 33,
                "Humid1": 10,
                "Humid2": 10,
                "Elevation": 1803
            },
            {
                "Month": 7,
                "Day": 16,
                "Precip": 25,
                "Hour1": 4,
                "Hour2": 16,
                "Temp1": 10,
                "Temp2": 30,
                "Humid1": 18,
                "Humid2": 15,
                "Elevation": 1803
            }
        ]
    },
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                "speed": 2.0,
                "cloudCover": 0.0
            },
            {
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                "direction": 0.0,
                "speed": 2.0,
                "cloudCover": 0.0
            }
        ]
    },
    "initialFuelMoisture": {
        "fuelMoistures": [
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                "HundredHour": 8.0,
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                "LiveWoody": 90.0
            },
            {
                "OneHour": 6.0,
                "TenHour": 7.0,
                "HundredHour": 8.0,
                "LiveHerbaceous": 60.0,
                "LiveWoody": 90.0
            },
            {
                "OneHour": 6.0,
                "TenHour": 7.0,
                "HundredHour": 8.0,
                "LiveHerbaceous": 60.0,
                "LiveWoody": 90.0
            },
            {
                "OneHour": 6.0,
                "TenHour": 7.0,
                "HundredHour": 8.0,
                "LiveHerbaceous": 60.0,
                "LiveWoody": 90.0
            },
            {
                "OneHour": 6.0,
                "TenHour": 7.0,
```

```
                    "HundredHour": 8.0,
                    "LiveHerbaceous": 60.0,
                    "LiveWoody": 90.0
                },
                {
                    "OneHour": 6.0,
                    "TenHour": 7.0,
                    "HundredHour": 8.0,
                    "LiveHerbaceous": 60.0,
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                {
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                    "TenHour": 7.0,
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                    "LiveHerbaceous": 60.0,
                    "LiveWoody": 90.0
                },
                {
                    "OneHour": 6.0,
                    "TenHour": 7.0,
                    "HundredHour": 8.0,
                    "LiveHerbaceous": 60.0,
                    "LiveWoody": 90.0
                },
                {
                    "OneHour": 6.0,
                    "TenHour": 7.0,
                    "HundredHour": 8.0,
                    "LiveHerbaceous": 60.0,
                    "LiveWoody": 90.0
                },
                {
                    "OneHour": 6.0,
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                    "HundredHour": 8.0,
                    "LiveHerbaceous": 60.0,
                    "LiveWoody": 90.0
                },
                {
                    "OneHour": 6.0,
                    "TenHour": 7.0,
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                    "LiveHerbaceous": 60.0,
                    "LiveWoody": 90.0
                },
                {
                    "OneHour": 6.0,
                    "TenHour": 7.0,
                    "HundredHour": 8.0,
                    "LiveHerbaceous": 60.0,
                    "LiveWoody": 90.0
                }
            ]
        },
        "windMultiplier": 1.0
    }
}
```

Figure 124 Code of HillWoolseyFire simulation.