WILDFIRE HAZARD PREDICTION:
A Fuzzy Model for Sensor Embedded Intelligence

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Attestation of Authorship

"I hereby declare that this submission is my own work and that, to the best of my knowledge and belief, it contains no material previously published or written by another person (except where explicitly defined in the acknowledgements), nor material which to a substantial extent has been submitted for the award of any other degree or diploma of a university or other institution of higher learning".

Lakshmi Bhargavi.K

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Last but by no means least, the final reviewers of this thesis to finally get it into existence.

Abstract-

This thesis investigates the topic of "Wildfire hazard prediction" through conducting an in-depth study on fuzzy prediction methods and geographically collected weather data. The study explores the impact of various environmental factors leading to Wildfire. These factors associated with Wildfire are extracted from analyzing the past raw weather data and using McArthur's Fire Danger Index formulations.

The indices calculated through the formula and the generated synthetic data are used to train a Fuzzy system developed in Matlab software. The trained Fuzzy system is then tested with a raw set of historical real weather data originated from National Rural Fire Authority (NRFA) and National Institute of Water and Atmospheric Research (NIWA) to analyze the accuracy of the system developed.

Finally, the predicted results of the Fuzzy system are examined and compared with that calculated using the formula, including the error percentiles between the two. Impacts of the input weather factors are also plotted in relation to the Fire Danger Indices under various conditions to understand their sensitivity towards the final prediction.

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LIST OF ABBREVATIONS

FDI	Fire Danger Index
FMC	Fuel Moisture Content
KBDI	Keetch-Byram Drought Index
D or DF	Drought Factor
RH	Relative Humidity
WS	Wind Speed
RF	Rainfall
C	Curing
DLT	Long Term Dryness
FL	Fuzzy Logic
FIS	Fuzzy Inference System
ANFIS	Adaptive Neural Fuzzy Inference System
NRFA	National Rural Fire Authority
NIWA	National Institute of Water and Atmospheric Research

CHAPTER 1: Introduction

1.1 Motivation

A wildfire is any form of unrestrained fire that erupts in the countryside or a deserted area. Also referred to as brush fire, bushfire, forest fire, grass fire, hill fire, etc., it can cause massive destruction. Known through various such names, the only difference lies in the way and the place where the phenomenon occurs.

Wildfires have proven to be a massive form of destruction for humankind for many years. These will prevail and may continue if proper prediction and suppression strategies are not used. Three main measures are essential when dealing with wildfires:

1. Prevention.
2. Prediction.
3. Suppression.

Of the three phases, the prediction phase is more significant as it eradicates the potential of huge loss. There are different means of prediction that could cause the ignition. An understanding of the actual causes is essential before working on the prediction itself.

1.2 Research scope and focus

A robust research should have all the necessary effective ingredients to attain measurable results. As such, the research study should be educational, informative, meaningful and useful.

In this research, the study focuses on prediction of wildfire before its occurrence in order to minimise the loss of property and life.

In general, this study is a comprehensive exploration of wildfire prediction modelling based on meteorological variables for two main locations acting as the case studies for the research project. Gisborne in North Island and Christchurch in South Island, both cities in New Zealand, are the locations chosen in order to analyse and exhibit the prediction fuzzy model and validate against the real and theoretical data.

Fuzzy logic model is a subset of Matlab, which is a program that provides GUIs to perform fuzzy system development and pattern recognition. This Neuro-adaptive fuzzy inference system analyses the findings using both theoretical and real time data. This model was developed to predict wildfire using variables such as temperature, humidity, wind speed, soil moisture, amount of rain and number of days since the last rainfall to calculate the Fire Danger Index (FDI).

Each component in this model interprets the values in the input vector and, based on the defined rules, assigns values to the output vector. The theoretical values obtained using the FDI formula are used to train the system. This training is at various estimated levels using both the minima and maxima methods. This method will enhance the accuracy of the module. The data used in the research are largely compatible with the FDI formula generated [1,2]. The prime idea is to develop an accurate fuzzy system to compute any given weather condition in order to predict the severity of fire danger at that location.

Using the adaptive Neuro-Fuzzy Inference System (ANFIS), the model is designed with input/output data. This system’s learning enables an understanding of the fire danger from different views, such as the rule viewer and surface viewer. By this method, wildfire hazard is estimated by using an absolute multiplicative model where the impact of each variable is understood separately [4].

1.3 Research Objective

In this research, the main objective is to define the conditions prevailing during a wildfire and its significant reactions and impact on the nearby locations. Severe deforestation and degradation over the past two decades has acted as the primary and the most significant factor for wildfires, even today. Other causes include lightning, volcanic eruption, sparks from rock falls and spontaneous combustion [5, 7].

The other main cause of wildfires is, surprisingly, human carelessness. Carelessness can constitute handling fireworks, debris burning and arson, etc., all of are examples of human activities that often result in wildfires.

Another reason for wildfires is the slash and burn form of farming, which is a common practice of cutting and burning woodlands and vegetation in order to clear the land. Quite often, the slash-and-burn practices result in catastrophic wildfires [8]. Volcanic activity is another reason, creating favourable conditions for the ignition of wildfires in nearby areas [9].

Underground coal fires are slow and flameless forms of combustion, below the earth's surface. Such fires continue to burn for many years, resulting in the release of toxic fumes which lead to the destruction of vegetation and human property.

Although, in most cases, natural disasters and human activities cause wildfires, it has been estimated that 90 per cent of cases of wildfires are mainly caused due to human interaction with nature, either directly or indirectly [10,11]. See Figure below [FIG 1.1].

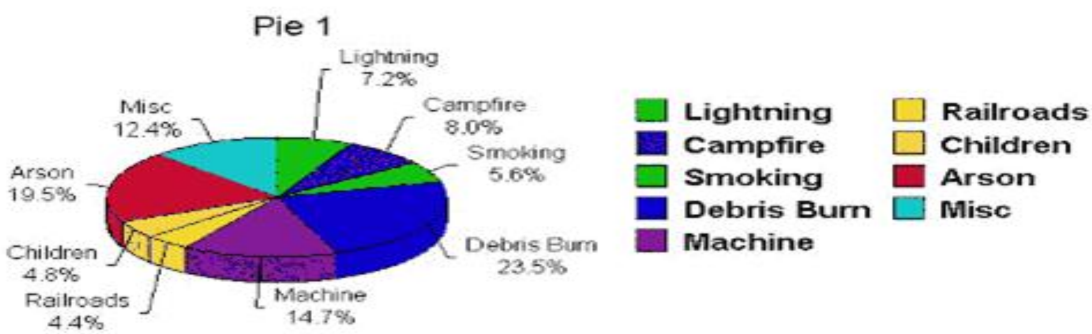

Figure 1.1 Chart representing the different modes of wildfire causes

Wildfires are more predominant in the summer and autumn seasons. They are also common during droughts, when the fallen branches and leaves become dry and flammable. The overall spread of wildfires depends on:

1. Weather.
2. Type of vegetation.
3. Geography and topography.
4. Strong Winds.

An accurate estimation of wildfire hazard is tremendously important to aiding officials in preparing supplies and staff in preventing, combating, and controlling large wildfires. One way to obtain estimates of wildfire hazard would be to produce a statistical model that uses weather variables such as relative humidity, temperature, and precipitation in forecasting total daily burn area due to wildfires. While a variety of models are used to predict wildfire incidences of human or lightning-caused ignition, and other possible factors which are used to model the spread of existing fires, possibly relying on physical characteristics of the fires and the landscape, the prime focus here is on the forecasting of wildfire activity solely using meteorological variables. Such statistical forecasts may be useful, not only for planning and preventive purposes, but also for the sake of understanding the critical role that these weather variables can play in affecting wildfire incidences and behaviour [14,15].

Thus, the main objective of this research project is to develop a wildfire prediction system, with accuracy also playing a significantly important role.

1.4 Early Warning system

At a time of global changes, the world is striving to adapt to inevitable natural disasters.

An Early Warning System (EWS) enables humans to detect any undesirable situation early on. Current gaps are investigated continuously with the goal of laying out guidelines for developing a global multi-hazard early warning system.

Early warning systems help to reduce economic losses and alleviate the number of injuries or deaths from a disaster by providing information that allows individuals and communities to protect their lives and property. Early warning information enables people to take action when a disaster is about to happen. If well integrated with risk assessment studies, communication and action plans, early warning systems can lead to substantive benefits. As stated by Glints: "*predictions are not useful, however, unless they are translated into a warning and action plan the public can understand and unless the information reaches the public in a timely manner*".

AN effective EWS embraces all aspects of emergency management, such as risk assessment analysis and prediction techniques An EWS is designed to focus on monitoring and predicting the location and intensity of the natural disaster, alerting authorities to respond to the disaster. Commonly, early warning systems lack one or more elements. After reviewing research projects on existing early warning systems, in most cases communication systems and response plans are not handled in the most efficient manner. Monitoring and predicting has only been a key part of the early warning process. This provides the input information for the early warning process that needs to disseminate to those whose responsibility it is to respond to monitoring and predicting systems, and is closely associated with the communication system and response plans. It may be helpful for this information to be communicated efficiently with the targeted users, communities, regions, or to media (regional or global early warning applications).

This information makes it possibile to take action to initiate mitigation or security measures before a catastrophic event occurs. The main goal of an EWS is to take action to protect life, reduce loss of life, lessen damage and lessen economic loss by taking measures before the disaster occurs.

Nevertheless, this warning must be timely in order to provide enough lead-time for responding, so that those responsible for responding to the warning will feel confident in taking action. Predictions become more reliable and accurate with time, when more observations work with the prediction system. There is, therefore, an inevitable trade-off between the amount of warning time obtainable and dependability on the predictions provided by the EWS. An initial alert signal sent is gives the maximum amount of warning time with a minimum level of prediction accuracy.

However, the prediction accuracy for the location and size of the event will continue to improve as more predictions continue with the monitoring system as part of the EWS network. It is quite evident that every prediction is associated with uncertainty. Because of the uncertainties associated with the predicted parameters that characterise the incoming disaster, a wrong decision may be made. Two kinds of wrong decisions occur in most cases [16]. These are:

1. Missed Alarm (or False Negative) - when the mitigation action is not taken.
2. False alarm positive - the action takes place when it should not have been.

Finally, the message communicated at such level of uncertainty must be communicated with clarity to those who are at the receiving end. Very often, there is a communication gap between EW specialists and the users themselves. EW specialists have the technical knowledge, whereas the users are not completely aware of all the technical aspects. To avoid this, these early warnings need to be reported concisely in layman's terms and without scientific jargon [17]. The overview of an EWS constitutes various criteria [see Fig 1.2].

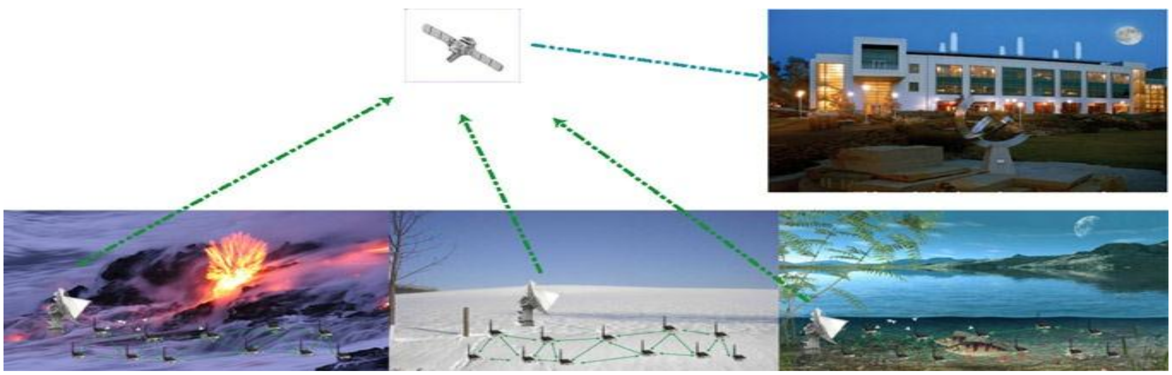

Figure 1.2 Early Warning Systems

Early warning (EW) as defined by the UN is "*the provision of timely and effective information, through identified institutions, that allows individuals exposed to hazard to take action to avoid or reduce their risk and prepare for effective response*" [11].

1.5 Fuzzy Development

A Fuzzy Logic Toolbox provides MATLAB functions, graphical tools and a Simulink block for analysing, designing, and simulating systems based on fuzzy logic. Behavioural functions provided in this study cater to many methods, including fuzzy clustering and Adaptive-Neuro Fuzzy.

For this research, fuzzy inference systems are applied to model systems using input vectors (Weather variables) in order to understand the behaviour of the prediction system.

The toolbox used will outline complex system behaviours using simple logic rules and then implement these rules in a fuzzy inference system. The ANFIS is used all through the research for design, development and validation. The model is trained using synthetic data attained by using an established FDI formula. After training and testing the fuzzy controller, the fuzzy model is ready to work with any raw data in order to understand the Fire Danger.

The final fuzzy model developed is for viewing, analysing and comparing various results. This is to cultivate an understanding of the model's reliability.

CHAPTER 2: Wildfire Early Warning System: A literature review

2.1 Introduction

This chapter reviews the various conditions of the wildfire and its phenomenon leading to the importance of the existence of an early warning system to detect a wildfire before the occurrence.

Towards attaining this goal, the most important aspect is to analyse the importance of the research. Various research articles and publications reviewed emphasise past projects and their findings. This chapter aims to understand and review the literature already published in order to provide a clearer outlook of this research.

2.2 Overview of sensing parameters for prediction

Among the most basic references towards attaining knowledge on the sensors, Miao [3] defines the sensor networks as a computer network composed of a large number of sensor nodes. This research article also explains the sensor capabilities in terms of resources, memory, computational speed and bandwidth. Further, the author writes about the various sensors that are available such as pressure, accelerometer, camera, thermal, microphone, etc., in order to understand the main aspects. All the weather variable capabilities used in this article are related to wildfire prediction directly or indirectly. However, if all the sensors are to be used for the fuzzy model, the result system will risk having a greater error percentage.

The sensors within this article monitor different conditions at various locations, such as temperature, humidity, vehicular movement, lightening condition, pressure, soil makeup, noise levels, the presence or absence of a certain kind of objects, the current characteristics such as speed, direction and size of an object. Not all the sensor capabilities are completely associated with this study. However, some of the weather sensor information is valuable as it gives an understanding of the hardware capability of such a product.

The applications of the sensors are military, environmental, health, home, etc. The author [3] brought up the various applications and the necessary data ffor each scenario. This helped to understand the importance of various factors over others for different categories of applications (in this case, wildfire hazard prediction).

The report by ITU-T technology [4] reported on a Ubiquitous Sensor nNetwor (USN) which showed another perspective of the sensor networks. Such an enhancement would allow anyone to interact with the network with compactness and effectiveness. The report further delivers the nature of such sensor networks and complexity that can be included in such a network. The basic characteristics of USN[4], which set it apart, are its requirement of small-scale sensor nodes, and limited power requirements that can be stored or harvested.

This report also emphasises the use of compact sensors over a high range, which would provide dependability for a vast area. Further, the sensor nodes used can be reduced, improving the effectiveness of each node rather than having numerous sub-nodes. Working on nodes covering a vast area was a very significant input of this article, but the aspects of accuracy over these ranges are not discussed in detail. Some factors about the use of compact sensors to improve effectiveness caught my interest [FIG 2.1]:

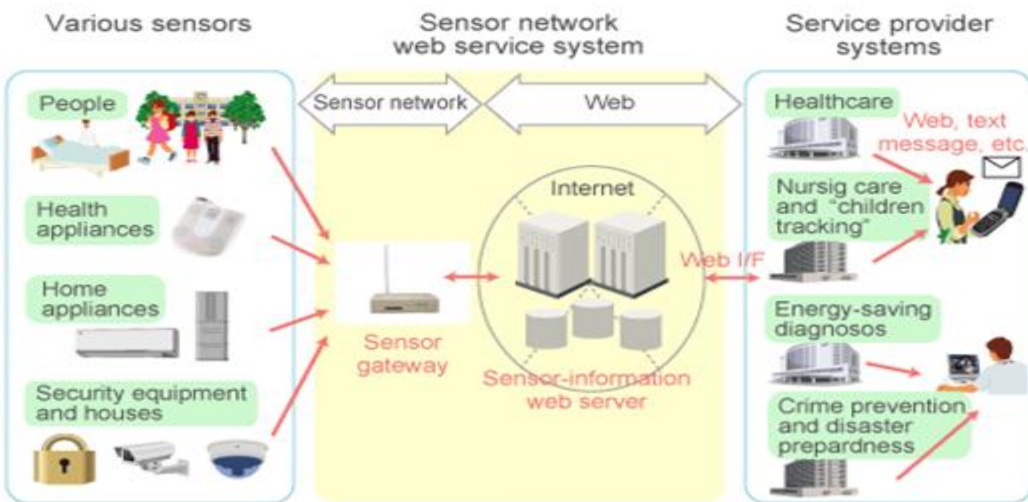

Figure 2.1: Overview of Sensor system

The technical aspect of such sensor networks using Zigbee, an implementation of the IEEE 802.15.4 standard for wireless personal area networks (WPAN), provides a suite of communication protocols [4]. Extension to the knowledge established via this paper gives an insight into the possibilities of sensor applications. However, the main concern with this paper is the main prediction system, which could be discussed in detail providing a deeper understanding of the sensors.

Various papers explained the design methods of the concept with the possible errors that could prevail. An article by Chu [5] explained very well the design methods for a bushfire sensor system. The author explained about the nodes placed accordingly to pass the data to a base station. The sensors used consist of various aspects and levels of detection. These include detection of fire, gathering climate data and gathering fire behaviour data. The wireless sensors are suitable for bushfire or wildfire monitoring; this is because wireless sensor networks are of lower cost, finer grain, and greater coverage (time/space). Moreover, the wireless sensors have a lower delay, are automatic, and more reliable. All these positive aspects regarding the use of WSN make them a better method of monitoring wildfire [5] [FIG 2.2].

Chu [6] explains the technology used in developing a wildfire sensor and related modeling procedures. The author explains the monitoring equipment requirements for wireless sensing such as the processor unit, radio, memory and the various necessary sensors. The different members of the wireless sensor networks (WSN) are defined as normal, super, and base station [6]. It has been said that the networks can be chosen as required. For instance, greater radio range, longevity, and cost are a few of the factors to consider [6].

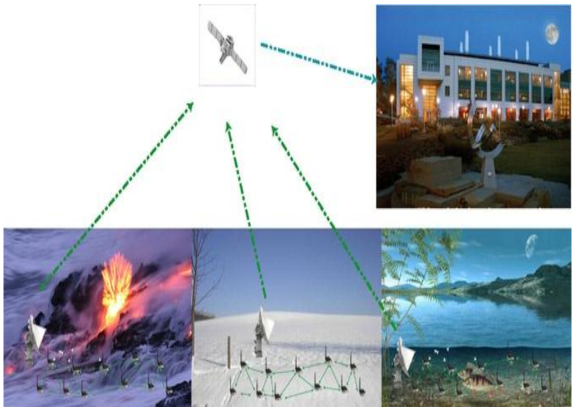

Figure 2.2: Sensors used for various hazard prediction systems

Both these authors describe the advantages of wireless technology when it is used more efficiently. All these factors are reassessed while choosing the best network for monitoring. The author explained about the importance of bushfire sensing and modelling equipment in order to perform experiments in a virtual environment that would otherwise be impossible in a reallife situation due to cost, danger, and lack of control [6].

The author further explained the use of a multilayered model for simulating the overall system. In such a way, the determination of each layer could capture the behaviour of each component. This technique is discussed in a very structured manner, without explaining the risks to the prediction system itself in different weather conditions. A multilayer system is indeed a great idea when a system is built for inevitable conditions such as wildfire prediction, which requires maximum accuracy and efficiency.

To enable more clarity towards the prediction model, Power [7] proposed a method of mapping a potential bushfire hazard. The method the author specified focuses on the benefits of using the mapping method by deploying derivations. This can be done by mapping objectives, such as predictive fuel load modelling and the rate of spread modelling. Mapping of the data itself gives an in-depth idea of what to expect, but the author fails to extend the topic to real-life mapping, which would also be a significant improvement in the area of prediction modelling.

Usage of remotely sensed data also assists in addressing the remote sensing of the fire risk mapping, which is manifold and advancing at an enormous rate [7]. The author illustrated the entire framework which maps the risk areas in order to predict a bushfire hazard. Li et al. [8] provided useful information about the use of GPS signals to map and monitor bushfires. This article provides a different perspective in order to understand bushfire monitoring. The author explains about the DGPS/INS integrated system. This includes the system design tightly coupled with integration software implementation, differential GPS, and particular methods for reconstructing the trajectory of the host vehicle based on the GPS data [8].

Three methods considered by the authors included the optimal Kalman predictor, the optimal smoother and the least-squares polynomial fitting method. All these methods were followed to gain the respective results in accordance with the factors given. They described this method by using GPS with various hardware and software equipment. The static and kinematic tests have demonstrated the functioning of the TCIKF software used in the experiments, followed by the authors. The authors concluded that the least-squares polynomial fitting method gives better solutions than the other two proposed methods used for assuming the bushfire condition to prevail in mathematical terms [8]. These terms set a basic matrix format for the formula to calculate the fire danger indices. This indicates the complexity of the various inputs provided, depending on the weather conditions of each scenario [8]. The percentile error can be calculated for the research to understand the accuracy of the fuzzy system modelled. The only aspect the authors fail to discuss in detail is the calculation technique impact on the existing prediction systems and the systems yet to come. Consequently, all the major variables were not quantified enough to understand the concept better.

With further research, a project progress report by Bushfire Cooperative Research Centre (CRC) [9] provided a concrete approach of projecting a high fire risk project and its progress. This report reviews and compares the various formal methods employed to correct the rate and direction of bushfire spread in the presence of both wind and slopes. The researchers claim these methods are critical, as are dealing with the natural resources. This paper draws together and explains those elements of mountain meteorology that have the potential to affect fire behaviour. The mountain meteorological literature has been extensively consulted and condensed into an easily readable form and is relevant to Bushfire CRC stakeholders and researchers [9]. However, the research has been carried out taking all aspects into consideration, while the comparison between studies does not allow it to be examined in a practical environment. Overall, the research article provided a great deal of computed information that made it easier to understand prediction systems better.

Pook [50] explained the empirical model formulations to predict fine fuel moisture content, and also discussed fire prediction models. The author incorporated the methods, analysing the performances of temperature and relative humidity inspired by McArthur's models. [50] On the same grounds, Pook [51] explains the empirical formulation and some prominent features and procedures of the prediction models.

Fire Hazard Analysis is discussed by Buklowski [10], who explained the risk analysis of fire and predicted a few approaches in order to potentially prevent a fire hazard. The author also wrote about the quantitate fire hazard analysis as the most fundamental tool of modern fire safety practices [10]. The analysis addressed all the salient scenarios and likely events, where all the assumptions were justified to provide a comfort level with all the code requirements [10].

The indices described the requirement for the application of designing a structure, briefing the understanding of the structure to design a wildfire early warning system. The different conditions provide an understanding of the various responses of different factors. The various factors affecting the fire dander index as described would be the wind, fuel moisture, and fuel availability conditions. In these various conditions, the given set of inputs using various sensors according to the requirement is a critical aspect. This idea is developed further throughout the research.

2.3 Overview of an Early Warning Systems

Early warning (EW) is "*the provision of timely and effective information, through the identified institutions exposed to hazard to take action to avoid or reduce their risk and prepare for effective response*" [11].

Various types of early warning systems include Tsunami EW system, Earthquake EW system, Flood EW system and many more disaster EW systems. With the knowledge of all such systems, this allows an understanding of the importance of accuracy when developing an EW system for wildfire prediction. A report by the United Nations [11] provided a global survey of EWS. This report provided an assessment of capacities, gaps and opportunities toward building a comprehensive EWS for all natural hazards.

The report speaks about the many gaps and shortcomings that have prevented the occurrence of EWS. In addition, the survey described that global systems for all hazards are not yet ready to be in place. More positively, there are committed capacities and strengths available upon which truly effective globally comprehensive early warning systems can be built, but as a network of interacting systems and components, drawing on the expertise and technical capacities of the different hazard fields and the knowledge and insight of the relevant associated social and economic fields.[11]. A vast study was conducted to give an understanding of the early warning systems. However, consideration of the various locations that could be an impact to the hazard is not given. Nevertheless, the report specifies that all the EWSs are supposed to be people-centric, and that there are four elements that every EWS

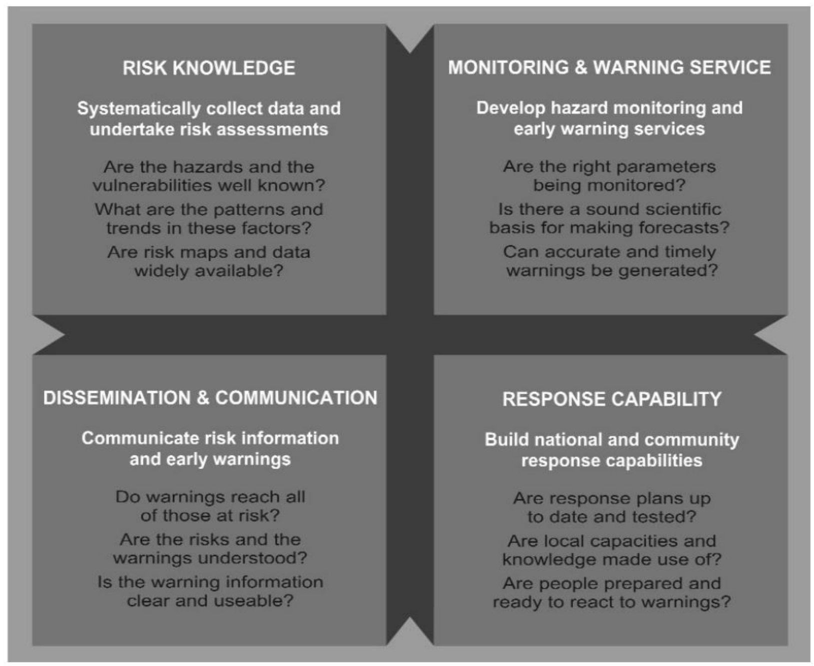

Figure 2.3: Four elements of EWS

should abide by in order to gain maximum usability, as follows: i) Risk knowledge; ii) Monitoring & warning service; iii) Dissemination & communication; and iv) Response capability [Figure 2.3].

Similarly, a research report by NOAA science board [12] had an in-depth view about the catastrophic destruction causing loss of life, destruction of property and critical infrastructure, and widespread environmental damage. In the United States, human population densities in wildfire-prone areas are increasing. In particular, areas of intersection between human populations and wild land, called the “wildland urban interface” (WUI), has been increasing, with 2000 Census data showing that 100 million people now live in WUI areas [12]. Consequently, the vulnerability of communities to the incursion of wildland fire, both in human and economic terms, is escalating [12].

The report also produced numerous examples in recent years of the exceptional fires that caused death and destruction at remarkable levels. Moreover, the report emphasises the significant role of the weather in the initiation of fire. Much of the historical research on fires has focused on surface conditions, but there is increasing recognition that the three-dimensional atmosphere also plays a key role. While the specific effects of climate change on wildfire occurrence, extent, and severity are likely to vary in different regions of a country, there is growing scientific evidence that climate change will increase the number and size of wildfires [12].

An integrated approach to bushfire management by the Bushfire CRC [13] states the damage caused by bushfire is estimated at $29 million. In addition, the report describes the fire behaviour as eucalypt dominant ecosystems and exhibits some remarkably different and yet imperfectly understood characteristics. The nature of fires in forests and woodlands significantly depends on the dynamics of available fuels [13].

The Bushfire CRC is further undertaking two projects that will considerably enhance the capacity of existing bushfire management decision support tools. In addition, most other CRC projects have the capacity to feed directly into these models [13].

The bushfire risk model provides data in a fire manager-friendly fashion. This report has provided a clear view on the risk management of bushfires by providing the estimations of loss due to wildfires [13].

A report by Ensis [14] on forest security and protection explains the vital contribution to the economy and environmental protection. It also explains the key factor in taking effective management action before and during fires is high-resolution fire behaviour prediction. The report emphasises the effects of seasonal to decadal climate variability on fire climate and fire danger trends.

It also determines that the degree of grass curing (or percentage dead) is a hugely significant determinant fire danger and fire behaviour potential in grasslands. It is a critical input required for the Australian and New Zealand fire danger rating systems. Current visual assessments in the field are largely inaccurate, and remote sensing techniques need to be updated with newer technology. Using remote sensing to assess curing across both countries with confidence requires the development of separate relationships for the different grassland regions [14].

Further, an article by Oldford et al. [15] discusses predicting slow-drying fire weather. The article states that the fire danger predicted by the Canadian Fire Weather Index, a system based on point source weather records, is limited spatially. NOAA AVHRR images used to model two slow-drying fuel moisture codes, the duff moisture code and the drought code of the fire weather index, in boreal forests of 250,000 sqkm portions of northern Alberta and the southern Northwest Territories, Canada. Temporal and spatial factors affecting both codes and spectral variables (normalised difference vegetation index, surface temperature, relative greenness, and the ratio between normalised difference vegetation index and surface temperature) are identified. Models were developed on a yearly and seasonal basis. They were strongest in spring, but had a tendency to saturate. Drought code was best modelled (R^2 = 0.34-0.75) in the spring of 1995, when data are categorised spatially by broad forest cover types [15]. These models showed improved spatial resolution by mapping drought code at the pixel level compared with broadly interpolated weather station-based estimates [15].

Harttung, Han and Holbrook [16] discussed a multitier portable wireless system for monitoring weather conditions in wildland fire environments. In this article, the authors discussed wireless technology as a means of bringing communications to remote areas, while short-range sensor networks were seen as a means of gathering large amounts of data from small areas. The authors blended these two ideals into an actual real-world deployment that combines the best of both technologies. In so doing, the authors built a system that successfully presented an elevation gradient of environmental conditions in wildland fire environments. This previously unattainable information would help fire behaviour analysts make better predictions about fire conditions and create a more aware environment in the fire community which will, in turn, help make fighting forest fires safer in the future [16].

Mills [17] discussed the improvement and understanding of fire weather, which is the main cause of wildfires. In this article, the author suggests a way of improving the operational utility of fire weather forecasts and outlooks, by providing better knowledge and understanding of wind, temperature and humidity structures and distributions, on the short-term, and seasonal through to climate, time-scales[17]. This article further explained the medium-range predictability and possible application of seasonal prediction. Fire databases and outcomes were also discussed [17].

Keenan [18] closely relates the research proposal by testifying that a global early warning system is a very valuable benefit to humankind. The significant ecosystem destruction, which is caused by hazards like wildfire, has a negative impact. Regarding this, the significant loss of life, including the negative social impact and economic losses, are also discussed. The potential impact on climate change by the increased use of aerosols was also a matter discussed without proper consideration of the prime causes of the hazard, but which would have been of value to the research work conducted by the author [18].

Information from all the research publications and surveys resulted in an understanding of the concept of EWS. The current status was best summed up in a report by the United Nations [11], which conducted a comprehensive survey in 23 countries involving 20 international agencies. The findings obtained mainly synthesised the gaps in the field of EWS. It can be seen that considerable progress has been made in developing the knowledge and technical tools to assess risks and to generate and communicate predictions and warnings, particularly as a result of growing scientific understanding and the use of modern information and communication technologies.

However, EW systems are available on a limited basis on both the natural hazards and the operating countries. Use of a scientific understanding of the natural hazards themselves and predicting them accurately is the key. In this research, the focus is to design the prediction system after understanding the causes of wildfire and predict their occurrence as accurately as possible.

2.4 Overview of Wireless sensors and smart environments

Smart environments represent the next evolutionary development step in building, utilities, industrial, home, shipboard, and transportation systems automation. Such environments were clearly reviewed and discussed by F.L. Lewis in the article produced by the Automation and Robotics Research Institute. Like any other organism, the smart environment relies mostly and foremost on the sensory data from the real world. Sensory data can be obtained from multiple sensors of different modalities in various locations [9].

Lewis further explained the various challenges in the hierarchy of detecting the relevant quantities, monitoring and collecting the data, assessing and evaluating the information, formulating meaningful user displays, and performing decision-making and alarm functions. The information needed by smart environments is provided by Distributed Wireless Sensor Networks, which are responsible for sensing as well as for the first stages of the processing hierarchy. The number of recent funding initiatives, including the DARPA SENSIT program, military programs, and NSF Program Announcements, highlights the importance of sensor networks. Figure 2.4 shows the

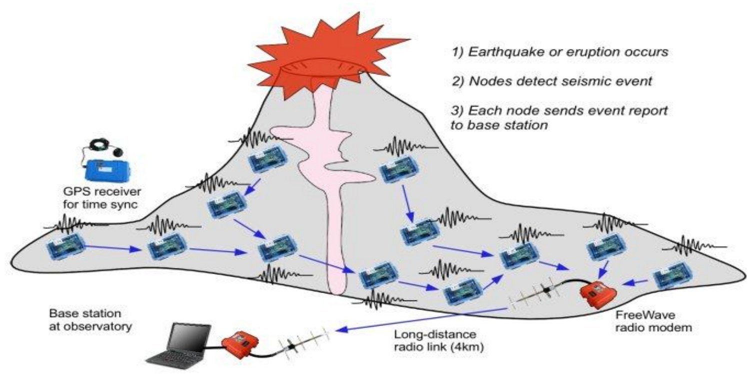

Figure 2.4: Sensor system used in earthquake warning system [19]

complexity of wireless sensor networks, which generally consist of a data acquisition network and a data distribution network, monitored and controlled by a management centre.

In the project, looking at all the required sensors in the prediction of the fire danger index is the key aspect. To get the prediction accurate, fuzzy inference systems are used to relate each sensor capability to the outcome - the FDI. The study of the sensor technology creates a degree of flexibility when deciding on the sensors according to the requirements.

2.5 Real life wildfire data – An analysis

A brief report by Bushfire CRC [19] on the Lake Taylor project: "Project Fuse: Fire Shrub land Experiments" with attention to wind, aims to continue the development of the heath/shrub fire behaviour model by conducting experiments in different heath/shrub/scrub fuel structures at different sites in Australia and New Zealand. These experiments examine how fire spread is affected by slope, as well as other factors like ignition pattern. The Lake Taylor New Zealand burn experiments, the first stage of Project Fuse, were carried out in March 2005 in thick shrub vegetation on very steep slopes. These experiments add to the scientific understanding of fire behaviour in scrub fuels enhancing fire fighter safety, public safety, prescribed burn planning and wildfire management [19].

The elements comprising the fire environment like the topography, fuels and weather are discussed. With respect to wildland fuels, we consider fuel models, live and dead fuels, and the role of remote sensing in this arena. Weather, both current and forecast, are seen to be crucial and the one element common to all operational systems. Considering the fire models, which utilise the environmental input and produce fire danger output related to either fire potential or behaviour, is critical.

2.6 Summary

This chapter gives an overview of the different sensing parameters required for an effective sensing of fire danger. In addition, an understanding of the early warning systems for different natural hazards is also discussed in order to improvise the efficiency of the research.

CHAPTER 3: A Framework for Wildfire Prediction methods - An Architectural view and Methodology

3.1 Introduction

In this chapter, the wildfire prediction system and its methodology is discussed in detail. This chapter explains the methodology used while developing the prediction system, as well as explaining each of the weather variables used in a descriptive manner.

In addition, this chapter gives an overview of the complete system mainly focusing on the block system and the formulae used to analyse the findings.

3.2 System Architecture

Predicting wildfire constitutes various inputs that are used together to develop a model. This model will be capable of predicting the wildfire occurrence according to the data it receives.
A wildfire prediction system is integrated with a variety of input factors that cause the wildfire and produce a trained system. This would give the EWS a reliability and consistency.

While outlining the exact concept on which the system would run, there were various implications that could be related to the WPS. This is so as the concept is related to expectations and forecasting. In addition, this should be very strong with significant progress towards producing a consistent, reliable and objective prediction system. Lack of infrastructure and a variety of modelling tools and information technology ideas could be the only drawbacks of producing such system. However, this idea has a key element in producing the application models, which would suit the needs of the environment at a global level [24, 25].

Producing an early warning system provides the decision makers and users with an insight into the future status of the wildfire ecosystem and its evaluation. By gathering the real time data of the various wildfire analyses of selected scenarios, this would provide us with measurements related to the WPS that we are to produce [25, 26]. For any key research, preparing the raw factors is a key factor. Various observations through this concept globally provided the decision-making tool by which to understand the natural hazards in the exploitation of economically advantageous trends.

Recent advances in climate forecasting have elicited strong interest in a variety of economic sectors: agriculture [30], and health and water resources [32]. The climate forecasting capabilities of coupled ocean-atmosphere global circulation models (GCMs) have steadily improved over the past decade [33]. Given observed anomalies in sea-surface temperatures (SSTs) from satellite data, GCMs are now able to forecast general climatic conditions, including temperature and precipitation trends, 6 to 12 months into the future with reasonable accuracy [32,28].

While such climatic forecasts alone are useful, the advances in ecosystem modelling allow specific exploration of the direct impacts of these future climate trends on the ecosystem. One-day predictions made in March might accurately forecast whether Montana's July winter wheat harvest will be greater or less than normal and whether the growing season will be early or late.

Figure 3.1 shows the block diagram of the WPS, which is designed in stages. In the initial stage, all forms of raw data related to wildfire either directly or indirectly, along with the boundary values, are formulated into an initial model, which takes place in the “model” section of the block diagram. This model developed is used for four main actions, which are prediction, assimilation, monitoring and verification. All these are directly communicated to the users. WPS is designed in such a way that the user is able to access all the necessary areas of the system to get information. As seen in the diagram below, the user has the ability to carry on the main actions with a WPS. For example: the user is able to access the “model” for information on the actual design, “prediction” for the result which can be in the form of graphs or indices, “verification” to verify the output of the whole system, and “monitoring” or “assimilation” to finally check the data which was used by the model. A WPS is to be modelled in such a way that the end user can easily access any part of the information in the system to judge and take necessary action accordingly.

During this research, the prediction block is experimented thoroughly for a potential fire hazard indication. The “**Prediction”** block is defined, verified and validated in the further chapters of this research [Figure 3.1].

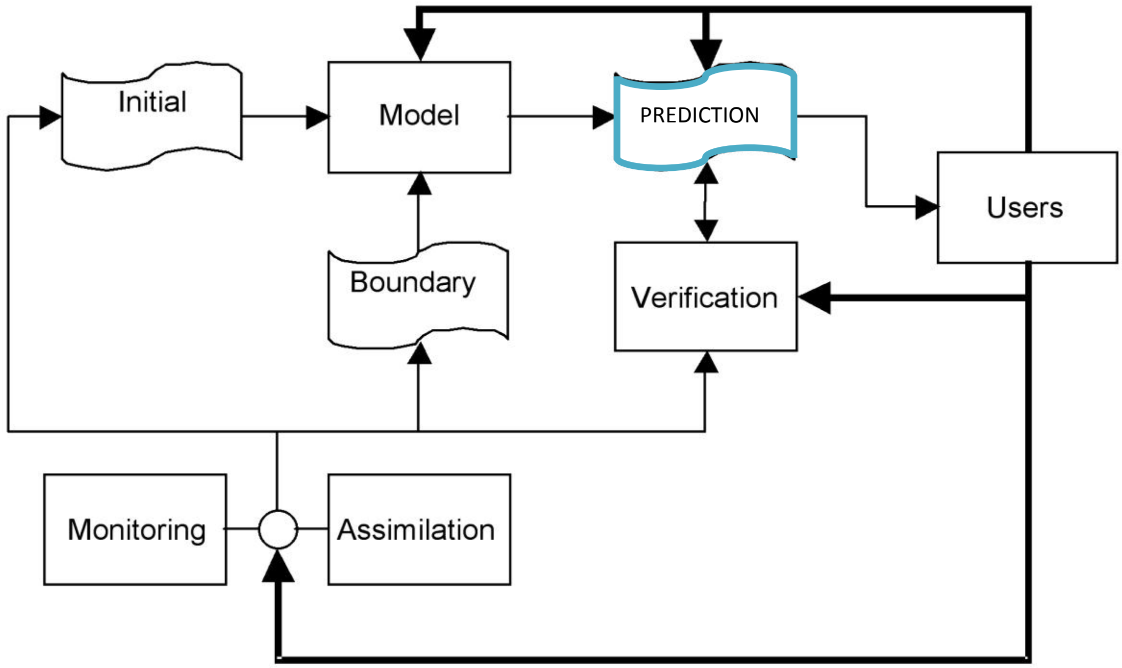

Figure 3.1: Prediction, monitoring and verification of the WPS

One of the key problems in adapting climate forecasts to natural ecosystems is the "memory" that these systems carry from one season to the next. Simulation models are often the best tools to carry forward information about this Spatio-temporal memory [34].

The ability of models to describe and to predict ecosystem behaviour has advanced dramatically over the last two decades. This has been driven by major improvements in process-level understanding, climate mapping, computing technology, and the availability of a wide range of satellite and ground-based sensors. In this chapter, we summarise the efforts of the Ecological Forecasting Group at NASA Ames Research Center over the past six years to integrate advances in these areas and develop an operational ecological forecasting system.

3.3 Setting and Operations

3.3.1 Fire Danger- Factors and Weather conditions

The potential for the occurrence and development of bushfires is dependent upon the interaction of fuels with a number of weather elements that vary over long and short timescales. Consequently, various methods have been developed around the world to combine information on weather and fuels into a fire danger prediction system index. Fire danger indices provide a measurement of the chances of a fire to occur. Various other impacts can also be studied concerning fire danger, such as:

1. Rate of spread.
2. Intensity.
3. Difficulty to suppress.

The above can be studied with a combination of weather factors such as temperature, relative humidity, wind speed and the drought effects.

As fire prediction is probably the most efficient means of protecting forests, suitable methods are developed for estimating the fire danger. Fire danger is composed of ecological, human and climatic factors. Therefore, the systematic analysis of factors includes forest characteristics, meteorological status, and topographic conditions causing forest fire danger; it is the result of both constant and variable fire danger factors affecting the development, spread and difficulty of control of fires and the damage they cause. Constant factors are those that change slowly and vary with location, e.g. slope and fuel. Variable factors change rapidly with time but can influence extensive areas, such as wind speed, relative humidity and temperature [21].

Fire danger indices (FDI) are used as a measure to inform the public of bushfires in addition to assessing a fire behaviour potential in an operational setting. In south-eastern Australia, fire danger is determined using McArthur's forest and grassland fire danger metres [1]. The metres take the form of circular slide rules according to the type of fuel under consideration. The content of the metres can be expressed as equations [1,2], which express fire danger as exponential functions of temperature, relative humidity, precipitation, wind speed, grass curing, fuel moisture content and drought factor. The equations provide a way of including the fire danger metres in computer systems, which allow for an advanced modelling of the fire system.

3.3.2 Fuzzy modelling - An overview

Fuzzy inference systems interpret the values of the various input factors, namely temperature, soil moisture, humidity, gas and wind speed, which lead to the wildfire in any form of atmospheric factors.

The fuzzy logic model for this project is built using the MATLAB 7.0 software. The fuzzy logic toolbox leads us to build the FIS based on the rules set, the membership functions, which are provided to the system using the input modelling according to the formulae that we use to gain the FDI for the system.

Due to the flexibility of the FIS, the information given to the system can be edited and displayed at any point of the structuring. In addition, the 3D display and surface gives us a clearer picture of the output of the system.

Three different scenarios are used to test the formulae on the ANFIS structure modelled. The simultaneous use of the FIS is structured to interpret the prediction system three times with the input of the formula and the various datasets of the scenarios.

3.3.3 Formulation of FDI – Mathematical theory

The equations of Noble et al. [1,2] provide an optimal fit to the circular slide rules developed by McArthur, but are not intuitive. The prevalence of tools such as the Tolhurst Fuel Moisture Meter opens up opportunities for the development of new intuitive approaches to modelling fire danger that generally reproduce what is in current use. As a starting point, we consider the factors known to affect the fire danger directly.

Wind is the most critical meteorological factor affecting fire potential and is one of the main components determining the rate of spread and direction of a fire. Moreover, it aids combustion by causing the flames to lean towards unburnt fuel, supplying the fire with oxygen and carrying moist air, which would otherwise restrict the amount of heat available to ignite un-burnt fuel.

The fuel moisture content also directly influences fire potential. The fuel moisture content is a combination of a long-term dryness component and a component of dryness governed by the ambient air. The long-term dryness of fuel affects the flammability of fuels. It is a measure of the proportion of the fine fuel that is able to become flammable. The moisture in the ambient air will also affect the flammability of fuels, as it is a measure of the efficiency with which flammable fuel will burn.

Other factors such as temperature and relative humidity have direct and indirect effects on fire danger. It is also pertinent to note that site-specific factors such as terrain and fuel are not listed. These have a role in fire behaviour, not in fire danger, which is a regional tool [25].

Intuitively, then, fire danger should increase as wind speed increases and should decrease as fuel moisture content increases. Thus, in basic terms, a fire danger index should be something along the lines of [20, 21]:

$$FDI \approx \frac{U_f}{FMC} \quad (1)$$

Where U_f is the wind speed at the fire and FMC is the fuel moisture content.

3.3.3.1 Wind

A fire is directly affected by wind at the fire front. Typically, the most relevant part of the wind is at a height of approximately 2m. Meteorological wind, on the other hand, is defined to be the wind measured at 10m above the ground, in a clear site. The wind at the fire front U_f can be estimated from the meteorological wind by means of a canopy reduction factor (γ), which ranges from 0 to 1:

$$U_f = \gamma U_{10} \quad (2)$$

Where U_{10} is used to denote the meteorological wind. All wind measurements have units of kilometers per hour. The canopy reduction factor is a term that describes attenuation of the wind by vegetation. Typically, for a forest $\gamma \approx 0.3$. In other words, 70% of the wind speed is attenuated by the canopy and does not affect the fire.

A further consideration is the in draughtU_{in} created by the fire. Air heated by a fire will rise and expand, causing the surrounding air to flow in to replace it. The net effect at the head fire is a counter-wind that alters U_f,

$$U_f \mapsto U_f - U_{in} \quad (3)$$

Typically, $U_{in} \approx 3$ km h-1 for grassland and $U_{in} \approx$ 0.2km h-1 for forest. However, for the purposes of determining fire danger, U_f cannot fall below a minimum value U_b, which corresponds to the rate of spread of a backing fire [21]. Hence:

$$U_f = \max\,(U_b, \gamma U_{10} - U_{in}) \quad (4)$$

3.3.3.2 Fuel moisture content

Fuel moisture content is expressed in percentiles. It is the moisture weight of a fuel sample expressed as a percent of the oven-dried weight. For example, if a kilogram fuel sample is dried and weighs 900g, then the fuel moisture content is 11%. Fuel moisture content is affected by three sources of moisture - air, soil and rainfall.

The influence of the air on fuel moisture content can be approximated with the following basic expression [21]:

$$FMC_a = 10 - \frac{(T - H)}{4} \qquad (5)$$

Where T is air temperature (°C) and H is the relative humidity (%). Equation (5) implies that hotter and drier air lowers FMC_a, which specifies the fuel moisture content in %. In addition, it was mentioned in [21] that equation (5) is an approximation based on the regression results in [50, 51] and the coefficients have been rounded for the sake of convenience. There is approximately a 1.5-hour lag time for fuel moisture content to respond to major changes in the air.

As this study is purely based on the prediction model derived by McArthur [1], the above equation is used to understand the impact of each variable only.

The soil and rainfall influences on long-term moisture are handled by the drought factor (*DF*) and curing (*C*), for forest and grassland, respectively. This changes much more slowly than the moisture content of the air. Drought factor ranges from 0 (lowest) to 10 (highest), and curing ranges of 0% to 100%.

The influence of the drought factor (or equivalent) is given by the long-term dryness factor D_{LT}, which can be estimated via the drought factor as:

$$D_{LT} = \frac{7}{DF} \quad (6)$$

Combining the long-term dryness and the influence of moisture in the air, we can express the net fuel moisture content as the product:

$$FMC = D_{LT}\ FMC_a \quad (7)$$

3.3.3.3 Fire danger index

A fire danger index is then a combination of wind, long-term dryness and the fuel moisture content of the air [21]:

$$FDI = \frac{\alpha U_f}{D_{LT}\ FMC_a} \quad (8)$$

Note that this equation possesses a calibration constant α, which needs to be approximately 20 to provide reasonable agreement with the McArthur models.

Equation (8) can be combined with equations (4) and (5) results in:

$$FDI = \frac{\beta \max\left(U_b, \gamma U_{10} - U_{in}\right) DF}{40 - T + H} \quad (9)$$

Where $\beta = 4\alpha/7$ is another calibration constant that needs to be determined. In what follows, the calibration constant α (and hence β) will be selected to give the best agreement with the McArthur Fire Danger Indices.

Even though the above FDI formula derivation agrees with the McArthur derivations, the above equations were primarily used to understand the impact of each variable only as each variable was rounded to the convenience of the author [21]. To further research on the FDI and its overall impact, the more established and widely accepted formulae by McArthur are used in our case studies.

Fire danger ratings are used to indicate the type of threat that wildfires may pose given the forecast weather conditions. The fire danger ratings provide the community with an indication of the sort of wildfire behaviour that could be experienced on that day. The FDI usually ranges from 1 to 100, with 1 being the least likely condition for a wildfire and 100 being the most likely. However, there are instances for a FDI to be above 100. Such ranges where the FDI is above 100 are classified as catastrophic wildfire. Under these types of weather conditions, fires will be unpredictable, uncontrollable and fast moving. The Fire Danger Index from 1 to 35 are categorised as being low probability, 35-50 being high probability and over 50 being highly probable for this project. Thus, a FDI value of 35 is used as the boundary line to distinguish between safe and unsafe conditions using the fuzzy system.

The Bureau of Meteorology uses consistent language and terminologies familiar to the community in their fire weather forecasts in order to facilitate their understanding about the severity of the threats from wildfires.

According to McArthur's derivations, the fire danger index (FDI) is defined as [1]:

$$\mathbf{FDI = 1.275\, D^{\wedge}\, 0.987 * [exp(0.0338T - 0.1345H)] * [exp(0.0234V)]} \tag{10}$$

Where,

D (or DF) = Drought factor

T = Maximum air temperature (°c)

H = Minimum relative humidity(%)

V = Daily mean wind speed

The fire danger index (FDI) is categorised into three zones according to the severity of fire danger that it predicts.

Firstly, FDI ranging from **0 to 18** is considered as the safe zone where there are almost nil chances that a wildfire will take place. Whereas, **19 to 35** FDI mean that the wildfire has the probability to occur but has little chance. At this stage, the other factor, the drought factor, is considered to understand the severity of the wildfire.

However, **FDI of 35** and above is considered dangerous to extremely dangerous, and the wildfire is most likely to appear in this range [20].

Synthetic data is created using equation (10) for calculating the FDI. Synthetic data is chosen over actual data to enable a more flexible incorporation of various ranges for all weather variables. This way, the ANFIS model can be trained more extensively, thus result in a better prediction accuracy. The relationship between each variable and FDI is also discussed in the following sections. The synthetic data obtained is as follows:

DROUGHT FACTOR	TEMPERATURE	HUMIDITY	WINDSPEED	FIRE DANGER INDEX
3	29.8	20	30.2	10
5	50.5	30	10	34.1
6	12.3	2	50	19.4
10	42.6	22.3	15.9	45
2.7	21.3	23.4	34.2	7
9.7	30.1	10.02	19.3	34
3	30.8	4.98	25.6	15
1.8	34.9	4.3	1.6	5
6.7	19	51.9	18.9	5
5.8	23	34.6	17.8	11
8.4	32.2	23.3	20.2	27
6.8	29.9	24.0	12	18
3.	29.7	50.9	40.4	8
4.6	49.8	3.284	32.9	34

Table 1: Sample FDI

3.3.3.3.1 Temperature

Each sample location, with the maximum temperature occurring during the last days directly proportional to the humidity, is to be calculated to an accuracy of (±2°c) in order to attain the final accuracy, as explained by Mills [17]. Therefore, it is essential that the temperature accuracy should be within ±2°c at all instances to maintain an accurate output. This is because, if the temperature increased over the acceptable range, there would be a risk in the resulting FDI becoming inaccurate.

The FDI is plotted against a range of temperatures in order to understand the effect of the various ranges, and whether they are to be considered safe or unsafe considering different variations. The FDI 1, 2 and 3 are plotted against the temperature while understanding the range.

The conditions through which the FDI's are plotted are:

1. FDI 1 - Low DF (3), Low RH (15%), Low WS (23m/s).
2. FDI 2 - High DF (10), Medium RH (35%), Medium WS (76m/s).
3. FDI 3 - Medium DF (5), High RH (76%) and High WS (60m/s).

The FDI of Plot 1, 2 and 3 is integrated to form an output graph in order to understand the complexity of FDI under all conditions [Figure 3.2]:

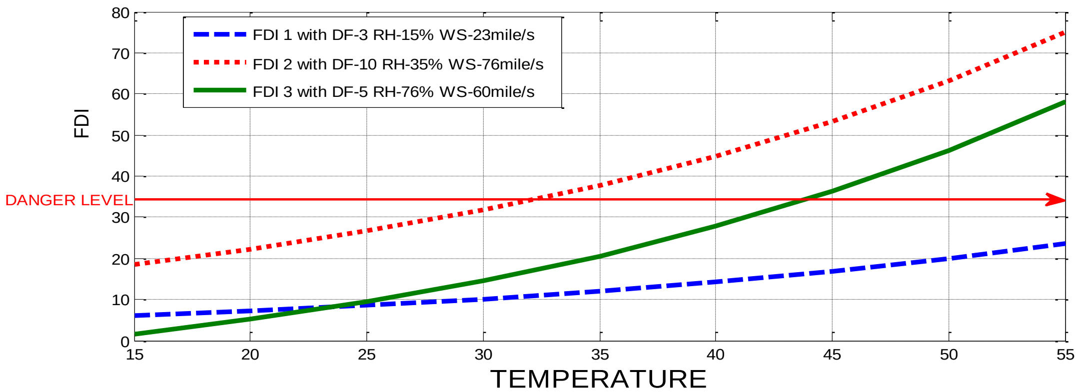

Figure 3.2: FDI 1, 2 and 3 integrating with varying temperature

The above graph represents the mapping of the FDI plotted against a range of temperatures (15°C to 55°C). The aim is to understand the behaviour of the other factors at different instances and their correspondence to the behaviour on the FDI.

The graph also emphasises that FDI 2 with a high DF will significantly increase the risk of wildfire. On the contrary, the graph also Emphasises that a low DF does not present any risk of a wildfire at any temperature level up to 55°C.

The temperature ranging from **0˚C to 25˚C** is considered a very safe environment, where there is no chance of a fire unless other factors lead to fire danger.

The temperature ranging from **26˚C to 35˚C** is considered as a moderate environment where there is a minor chance of a fire danger. This depends on the severity of the other parameters leading to fire prediction.

A temperature above **35˚C** is considered highly dangerous and such condition is optimum and it is likely that a wildfire may follow.

The above conditions will be carefully considered when the research proceeds to train the ANFIS structure in the following chapters.

3.3.3.3.2 Relative humidity

Relative humidity could be sensed in the sampled location by measuring relative humidity in the range of 0-100%. This factor can be calculated at an accuracy of ± 5–6% as explained by Mills [17]. Therefore, it is essential that the Relative Humidity accuracy should be within ±5% at all instances to maintain an accurate output. This is because, if the temperature increased in the acceptable range, there is a risk for the resulting FDI to become imprecise.

Relative humidity also plays a crucial factor in the development of wildfire. The humidity that is used in this research ranges from 2 to 80%. The humidity from **40 to 80%** is considered as a safe environment and would clearly not lead to a wildfire provided other parameters are not out of range.

Moderate environment is when the humidity falls between **18 to 39%** where there are very minor chances that the wildfire may occur, depending on the other parameters.

The range from **2 to 18%** is considered an extreme condition, where wildfire is most likely to take place [17].

The conditions through which the FDIs are plotted are:

1. FDI 4 - Low DF (3), Low Temp (20 C), High WS (70m/s)
2. FDI 5 - Med DF (4), Medium Temp (27 C), Medium WS (30m/s)
3. FDI 6 - High DF (9), Medium Temp (31 C) and High WS (72m/s)

The FDIs of Plot 4, 5 and 6 is integrated to form an output graph in order to understand the complexity of FDI under all conditions [Figure 3.3]:

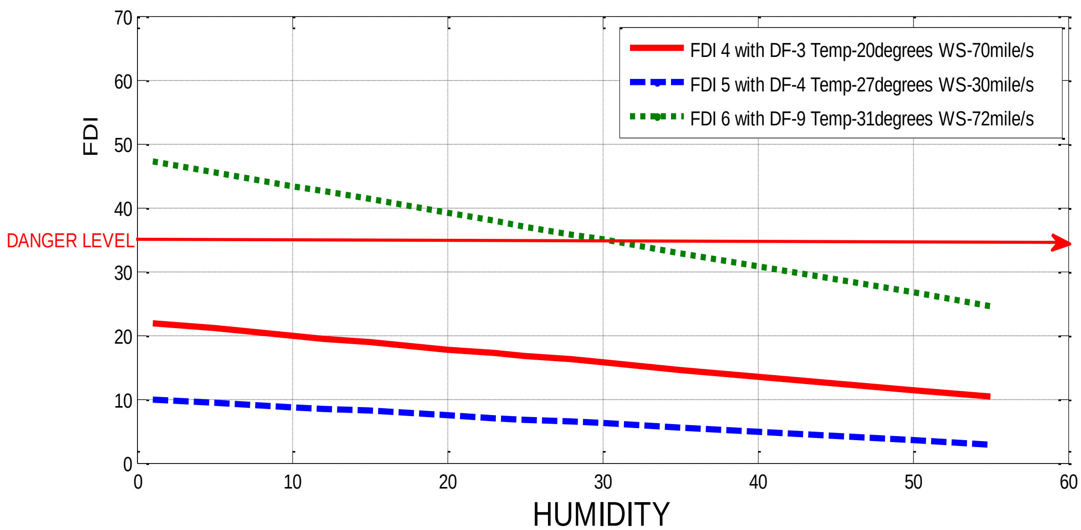

Figure 3.3: FDI 4, 5 and 6 integrated with varying humidity

The above graph represents the mapping of the FDI plotted against a range of humidity in the air (0 to 60). The aim is to understand the behaviour of the remaining factors at different instances and their correspondence to the behaviour on the FDI [Figure 3.3]

The graph emphasises that FDI 6 with a high DF will significantly increase the risk of a wildfire. On the contrary, the graph also emphasises that a low DF does not present any risk of a wildfire at any humidity level in the air.

The above conditions will be carefully considered when the research proceeds to train the ANFIS structure in the following chapters.

3.3.3.3.3 Wind Speed

The wind speed sensor is a four-blade helicoids propeller. Propeller rotation produces an AC sine wave voltage signal with frequency directly proportional to wind speed. Slip rings and brushes are eliminated for increased reliability. The wind direction sensor is a rugged yet lightweight vane with a sufficiently low aspect ratio to assure proper fidelity in fluctuating wind conditions.

The wind speed from **15 to 25 m/sec** is considered as a safe environment and would certainly not lead to a wildfire, provided other parameters are not out of range.

Moderate environment is when the wind speed is between **25 to 50 m/sec** where there are very minor chances that the wildfire may occur depending on the other parameters.

The range from **50 m/sec and above** is considered an extreme condition where the wildfire is most likely to take place.

The conditions through which the FDIs are plotted are:

1. FDI 7 - Med DF (5), Medium Temp (30 C), Low RH (15%)
2. FDI 8 - High DF (9), Low Temp (10 C), Low RH (20%)
3. FDI 9 - Low DF (3), Medium Temp (35 C) and High RH(76%).

The FDI of Plot 7, 8 and 9 is integrated to form an output graph in order to understand the complexity of FDI under all conditions [Figure 3.4].

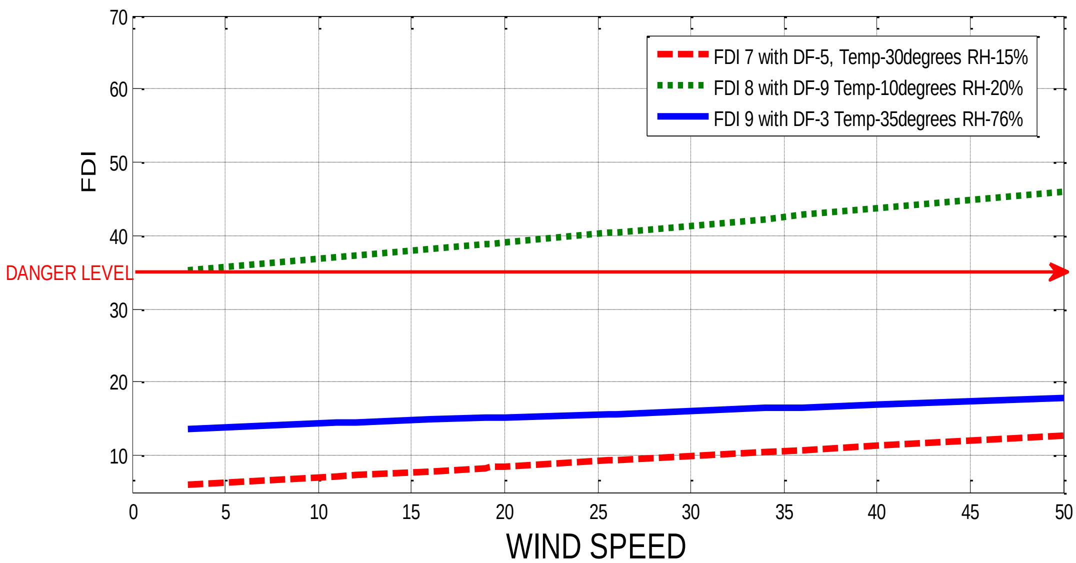

Figure 3.4: FDI 7, 8 and 9 integrated with varying wind speed

The above graph represents the mapping of the FDI plotted against a range of wind speed (0 to 50). The aim is to understand the behaviour of the rest of the factors at different instances and their correspondence to the behaviour on the FDI.

The graph emphasises that FDI 8 with a high DF will significantly increase the risk of wildfire. On the contrary, the graph also emphasises that a low DF does not present any risk of a wildfire at any wind speed up to 50 m/s.

The above conditions will be considered when the research proceeds to train the ANFIS structure in the following chapters.

3.3.3.4 Drought factor

Drought factor is a broad measure of fuel availability as determined by seasonal severity and recent rain effects [1]. Drought is also known as a condition of dryness in the duff and upper soil layers that progress from total moisture saturation to an absence of available moisture. The Keetch-Byram Drought Index is defined as "*a number representing the net effect of evapotranspiration and precipitation in producing cumulative moisture deficiency in deep duff and upper soil layers*". It is a measure of moisture in the tested layers of soil, and is based on an arbitrary 8 inches of water in the litter/duff/soil column. When the full 8 inches of water are available, the Index value is 0. As water is removed from the soil column by evapotranspiration, the numerical value of the Index can increase to a maximum value of 800, which is the condition when the 8 inches of water will have been removed completely. Thus, an Index of 250 means there is a deficit of 2.5 inches of water out of the original 8 inches, leaving a content of 5.5 inches of water. The KBDI attempts to measure the amount of precipitation necessary to return the soil to full field capacity. It is a closed system ranging from 0 to 800 units and represents a moisture regime from 0 to 8 inches of water through the soil layer. At 8 inches of water, the KBDI assumes (by definition) saturation. 0 is the point of no moisture deficiency and

800 is the maximum drought that is possible. At any point along the scale, the index number indicates the amount of net rainfall that is required to reduce the index to zero, or saturation. Where the effect of one rain period is superimposed on another, the lowest drought factor should be used. This is used as a measure of seasonal severity and fuel availability. It is derived from daily records of maximum temperature and rainfall.

The conditions through which the FDIs are plotted are as follows:

1. FDI 10- Med Temp (30 C), High RH (75%), Low WS (20m/s)
2. FDI 11- High Temp (40 C), Low RH (15%), High WS (55 m/s)
3. FDI 12- Med Temp (30 C), Medium RH (25%), High WS (60m/s).

The FDI of Plot 10, 11 and 12 is integrated to form an output graph in order to understand the complexity of FDI under all conditions [Figure 3.5]:

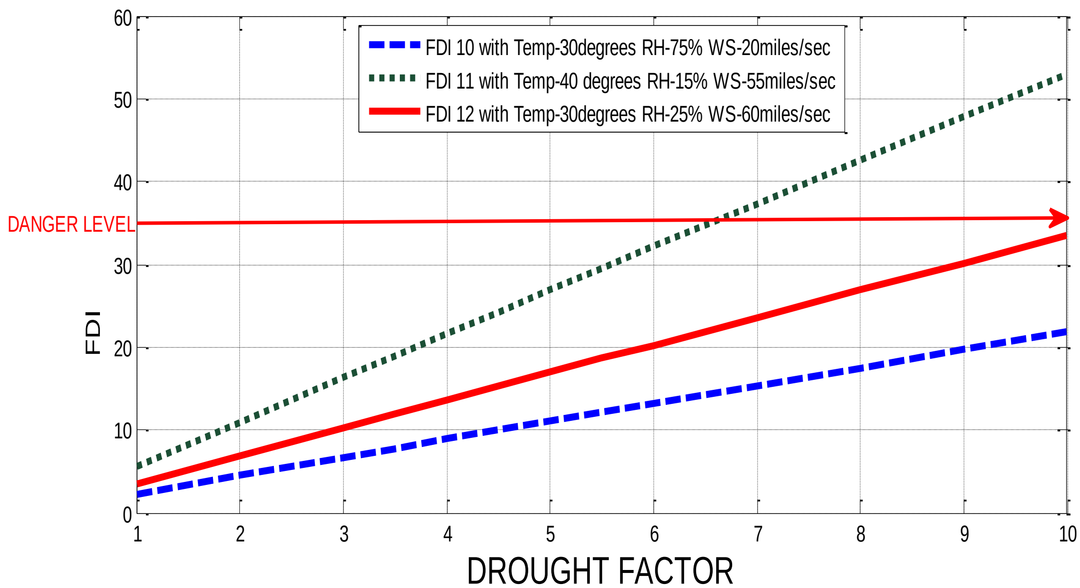

Figure 3.5: FDI 10, 11 and 12 integrated with varying drought factor

A Drought Factor of 5 is intended to indicate that about 50% of the fine fuel should be available to burn, while a Drought Factor of 10 is intended to indicate that 100% of the fine fuel should be available to burn**.**

The Drought factor is a broad measure of fuel availability as determined by seasonal severity and recent rain effects. Where the effect of one rain period is superimposed on another, use the lowest drought factor.

The equation for Drought factor (D or DF) is defined as [1]:

$$\mathbf{D = [0.191(I + 104)(N + 1)^{1.5}]/[3.52\ (N + 1)^{1.5} + R - 1]} \qquad (11)$$

Where,

D (or DF) = Drought factor

N - Number of days since last rain

R - Total rain in the most recent 24 hours with rain (mm)

I - Amount of rain needed to restore soil moisture to 200mm (also known as KBDI)

The Drought factor index lies in the range of 0-10 with 10 being the most favourable condition for a fire danger. This is because the drought factor of 10 indicates an almost nil moisture level in the soil and a dry atmosphere plays an important role leading to wildfire. Different means of moisture days since last rain, soil moisture and the amount of rain are used to calculate the DF to maximise efficiency, resulting in more accurate FDI finally.

A set of synthetic data [Table 2] is generated covering the maximum range of the result DF to implement the ANFIS accurately. This table is further analysed very thoroughly in order to understand the effect of each parameter when determining the overall FDI.

I (mm)	N (No. of days- numeric)	R(mm)	Drought factor
4.98	5.76	6.9	5.7
3.98	4	5	5.8
39.98	1	0	8.6
3	0	2	4.8
56.78	9.8	4	8.2
61.23	30.9	3.4	8.8
12.75	15.7	8.0	5.8
43.52	26	2.21	7.9
10.98	2.1	3.43	5.4
28.09	1.1	2.154	6.4
65.7	0.4	6.98	5
23.98	3.67	3.43	6.3
80.8	0.12	9.8	4
70.8	1.2	7	6.2

Table 2: Sample DF

Using the formula, graphs are plotted in the section below to understand each of the parameter's capability towards each other and to the overall estimation of the Drought factor. Each parameter is discussed below.

3.3.3.4.1Soil Moisture (I)

The Soil Moisture ranging **above 100** is considered a very safe environment, where there is no chance of a fire unless other factors leading to fire danger might constitute dangerous conditions.

The Soil Moisture ranging from **71 to 100 mm/sqm** is considered as a moderate environment where there is a minor chance of a fire danger. This depends on the severity of the other parameters leading to fire prediction.

The Soil Moisture above the range of **0 to 70 mm/sqm** is considered highly dangerous. Such condition is optimum and it is likely that a wildfire may follow.

3.3.3.4.2 Number of Days since last rain (N)

The N ranging from **0 to 5 days** is considered a very safe environment where there is no chance of a fire, unless other factors leading to fire danger are in dangerous conditions.

The N ranging from **6 to 20 days** is considered as a moderate environment where there is a minor chance of a fire danger. This depends on the severity of the other parameters leading to fire prediction.

The N above **30 days** is considered highly dangerous and such condition is very optimum and it is likely that a wildfire may follow.

3.3.3.4.3 Total rain (R)

The Rain ranging from **13mm and higher** is considered a very safe environment where there is no chance of a fire unless other factors leading to fire danger might be in dangerous conditions.

The Rain ranging from **4 to 12 mm** is considered as a moderate environment where there is a minor chance of a fire danger. This depends on the severity of the other parameters leading to fire prediction.

The Rain ranging from **zero to 4 mm** is considered highly dangerous and such condition is optimum and it is likely that a wildfire may follow.

3.3.4. Organisation for calculating the Fire Danger Index

After understanding the different inputs and elements of the evolution of FDI and DF, a block diagram is provided. The block diagram emphasises the different elements that formulate the outputs.

The complete model is structured into two different formulations that are used later for the fuzzy system. The Drought factor is calculated from three input factors: amount of rain, number of days since rain, and Soil moisture. The D or DF then extracted is fed to evaluate the FDI. Apart from the DF, Wind speed, Humidity and Temperature are used to compute the FDI. The FDI then calculated is identified to understand the criteria to which the severity of the Danger is predicted [Figure 3.6].

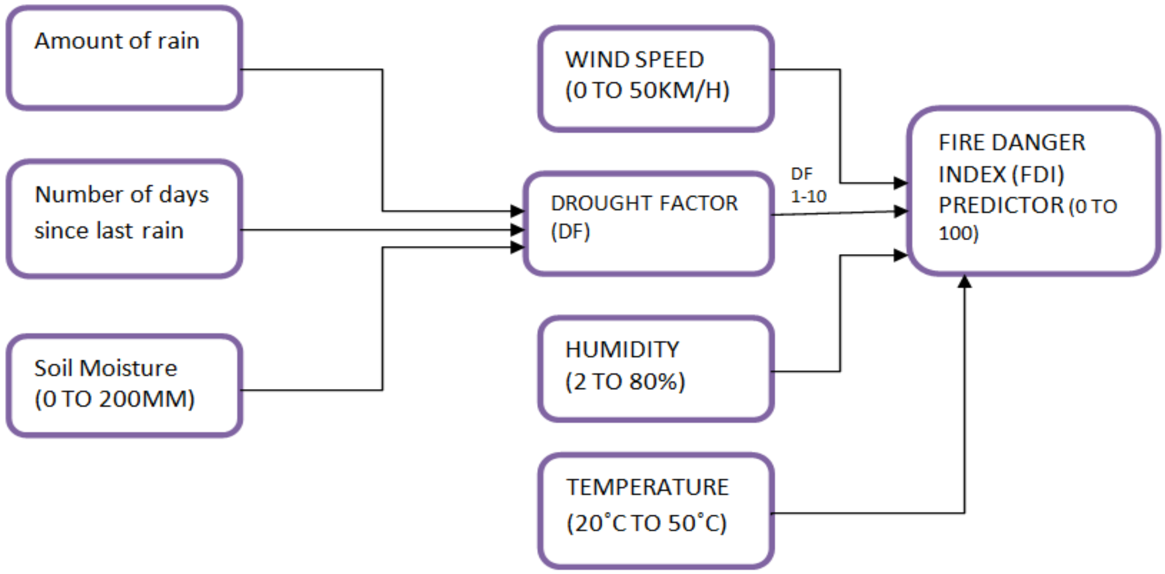

Figure 3.6: Fire Danger Index computation system

The above model is used for the project to predict the fire danger of any specified area. The above block layout is divided into two different fuzzy systems to calculate the Fire Prediction. In the block diagram layout, the input vectors amount of rain, number of days since last rain and Soil moisture are used to compute Drought factor. The Drought factor computed lies in a range of 1-10. The Drought factor mainly calculates the moisture level of the area. Drought factor attained here is used as one of the input vectors to further compute the FDI. Along with the DF, the other input variables used are the Wind Speed, Humidity and Temperature. All these variables are computed to result in FDI. The FDI lies in the range of 1-100.

CHAPTER 4: Fire Indices Fuzzy Models

4.1 Introduction

In this chapter, the layout of the Wildfire Prediction System (WPS) is modelled through the development of fuzzy models for Fire Danger Indices. The modeling in this research is carried out using the fuzzy logic toolbox of MATLAB. Through the FDI formulations, synthetic data is generated which is used to train the fuzzy system, and evaluate its accuracy for wildfire prediction.

4.2 Development of Fuzzy Model for Fire Danger Indices

Fuzzy logic is a form of multi-valued logic derived from any fuzzy set theory to deal with reasoning. The fuzzy logic variables have binary sets, having a truth-value that ranges between 0 and 1. The linguistic degrees are also a mode of understanding the range of the fuzzy logic implementation. Fuzzy implementation always has a value ranging from low to medium to high [24].

FL emerged as a result of the 1965 proposal of a fuzzy set theory. Fuzzy logic is applied to many fields, from control theory to artificial intelligence. It remains the most preferred form of prediction tool for many engineers and researchers. Even though various kinds of theories are available to be worked on, especially in the area of artificial intelligence or Neuro-Adaptive networks, fuzzy logic is evaluated to be the best suitable option for this research. After thorough consideration, FL had all the features that are required for the implementation of a prediction system. One of the prime reasons is the multi-tier capability of the ANFIS method, which can compute and link multiple models both simultaneously and collectively to produce a result. In this project, where DF and FDI are to be implemented, DF (or D) as one of the input variables to the ANFIS model of FDI proved to be a huge advantage. Apart from that, the flexibility of adding raw weather data and training the system accordingly is also an added advantage of fuzzy logic implementation over other forms of robotic and artificial intelligence methodologies.

Depending on the system, it may be necessary to evaluate every possible input combination since some seldom occur. By making this evaluation, fewer rules are used, thus simplifying the processing logic and perhaps even improving the fuzzy logic system and its performance [25].

In this project, the input membership function is divided into three linguistic values, denoted as low, medium and high. The determination of the membership functions are prepared by using the help of the ANFIS Toolbox in MATLAB. For this, the synthetic data is used to train the fuzzy system with limited membership functions, mostly covering all the probabilities of occurrence. Furthermore, as the system is trained, the Neuro-adaptive technique is used automatically by the system. This technique means that the first set of data is completely new to the system but, as the synthetic data is loaded, the fuzzy system already learns from previously fed data. This improves the efficiency of the system itself.

The membership functions and set of rules are fed into the system in determining the response for each set of data obtained synthetically. Each rule in the system is considered critical in order to generate the predictions in numeric form. The snapshot of the membership function plot and rules fed into the system are shown in Figures 4.3 and 4.5 in the section 4.3.1.1 and 4.3.2.2 respectively.

All the membership functions and the rules develop the fuzzy system and the factors act in combination to provide a result. After the formulations using these variables, the FDI is calculated by which the rate of danger is estimated according to a scale of 1 to 100 with 35 being a safe mode.

The data included various parameters: Temperature, Relative humidity, Soil Moisture and Wind speed. Moreover, these parameters varied over a period of 48 hours.

In order to create a fuzzy inference system, mamdani architecture is used to develop and model an ANFIS system for wildfire modelling.

4.2.1Model development using Adaptive-network-based fuzzy inference system

This section presents the architecture and learning procedure underlying ANFIS, which is a fuzzy inference system implemented in the framework of adaptive networks. Using a hybrid learning procedure, an input-output mapping can be constructed based on both human knowledge (in the form of fuzzy if-then rules) and stipulated input-output data pairs [42]. By using the fuzzy model for this research, a range of inputs can be fed into the system, which will return a FDI through which the fire danger can be easily recognised. Using a formula, such as the McArthur formula, it is possible to calculate fire danger only at a single point in time, i.e. the time at which the data used by the formula was captured. For better accuracy, the average values of the data can be used, but this requires the user of the formula to perform data averaging over a sufficient time window. However, by using a fuzzy model that has been adequately trained using historical data sets, anyone who has the real-time data, which are available in the meteorological bureaus, can utilise them directly to make accurate predictions. This also enables the system to be more user-friendly.

In this perspective, the aim of this research is to use ANFIS architecture to develop a fuzzy model, which can serve the basis of calculating the Fire Danger Index using real-time weather data captured at any time.

The fuzzy model is further developed using the multi-level functionality to attain the maximum accuracy possible. One level uses input vectors to calculate the DF and the other used a few more input vectors, along with the DF, to calculate the FDI. Using the multi-level functionality was an idea developed while reviewing the literature articles. The flowchart below presents the method used to identify the ANFIS modelling approach using multiple level formulations [Figure 4.1].

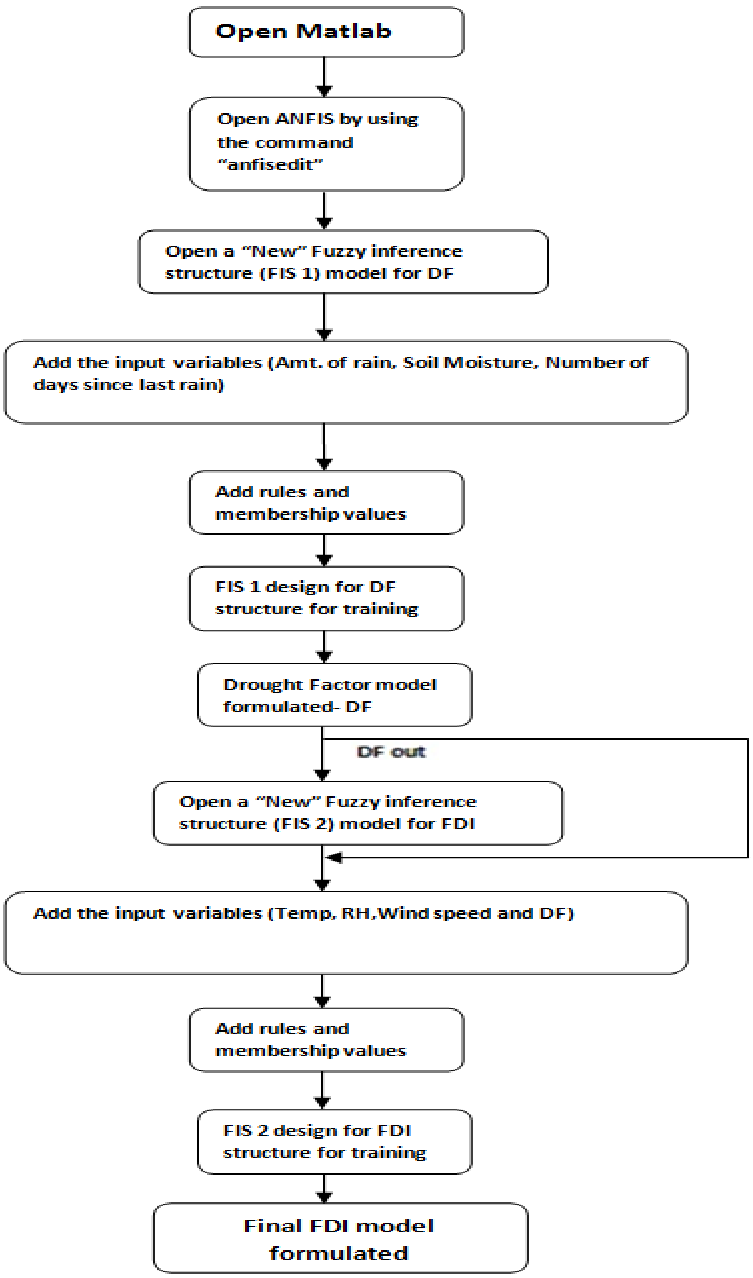

Figure 4.1 Flowchart representations of the ANFIS modeling approach

The ANFIS modelling approach is used with the WPS to predict the wildfire occurrence ahead of time.

Firstly, a parameterised model is hypothesised. This model structure relates the inputs to the membership functions. After this, the input and the output data, which were gathered from the National Climate Centre, New Zealand, are entered in the system using the table.

The system is trained with the FIS model to emulate the training data presented to it by modifying the membership function according to its structure and the requirement. In general, this type of modelling works well if the training data presented to ANFIS for training (estimating) membership function parameters is fully representative of the features of the data that the trained FIS is intended to model.

4.2.1.1 Model Development for Drought Factor (DF)

The fuzzy index processor is grouped to two different projects to attain the highest accuracy with the fire prediction.

The data is used to calculate the fire prediction with the highest perfection. To test the ANFIS model, the data used are the first 20 sets based on the formula for the Drought factor, as shown in equation (11) [1].

The ANFIS model is designed based on the above formula generating the data used for training. The complete step-to-step method to model the structure is explained below.

DF is first generated by giving the I, N and R inputs to the FIS structure with the specific range. The range further defines different low, moderate and the high membership function according to their range [Figure 4.2]:

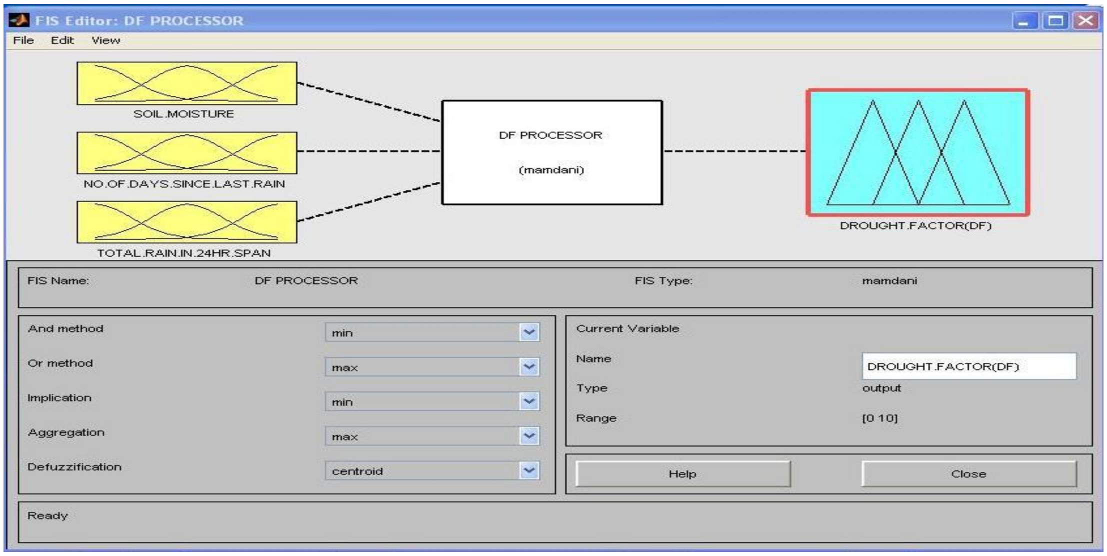

Figure 4.2: DF processor Structure

The DF processor is then trained with the same set of theoretical data to verify the final model and the effect of each of the inputs to the DF calculation. The set of rules are shown in Figure 4.3

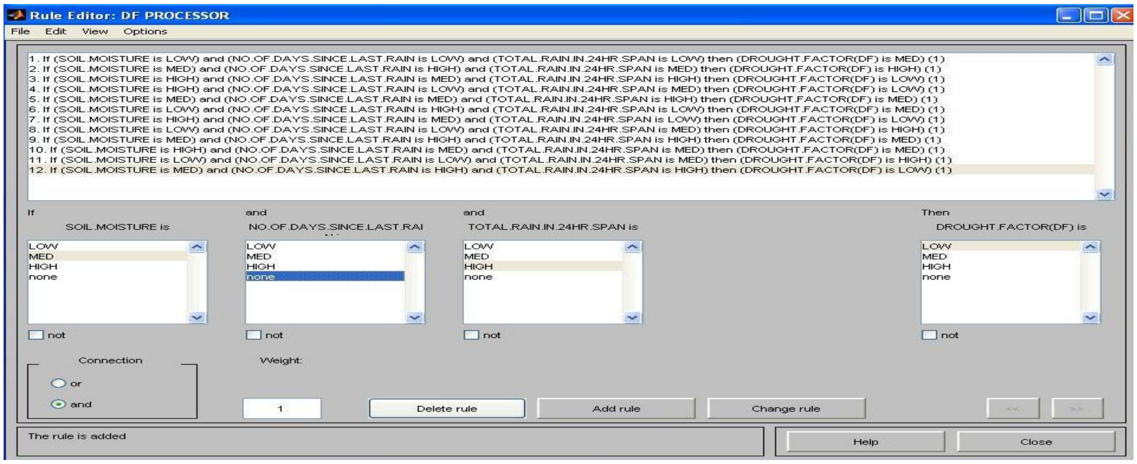

Figure 4.3: Set of rules for DF

The above sets of rules are placed by understanding each of the criteria of the parameters in the fuzzy processor. Few rules were exempted during this process as the scenarios were providing negligible variation in the output. These rules are then used to generate the DF. The rules are formatted as below:

Soil Moisture (mm/sqm)	No. of days since last rain	Total rain (mm)	Drought factor (1-10scale)
L	L	L	M
M	H	M	M
H	M	H	L
H	L	M	L
M	M	H	M
L	H	L	M
H	M	L	L
L	L	M	H
L	H	H	M
M	M	M	M
L	L	M	H

TABLE 3: Ranges used for DF

Using the above data with the ANFIS model, each of the input effects are then plotted.

4.2.1.2 Model Development for Fire Danger Index (FDI)

The data are used to calculate the fire prediction with the highest perfection. To test the ANFIS model, the data used are the first 20 sets based on equation 10.

The above attained DF is then fed as an input to the FDI processor with the other inputs used, and the set of rules are also placed as used to analyse each of them [Figure 4.4]. The set of rules are also added for the FDI [Figure 4.5].

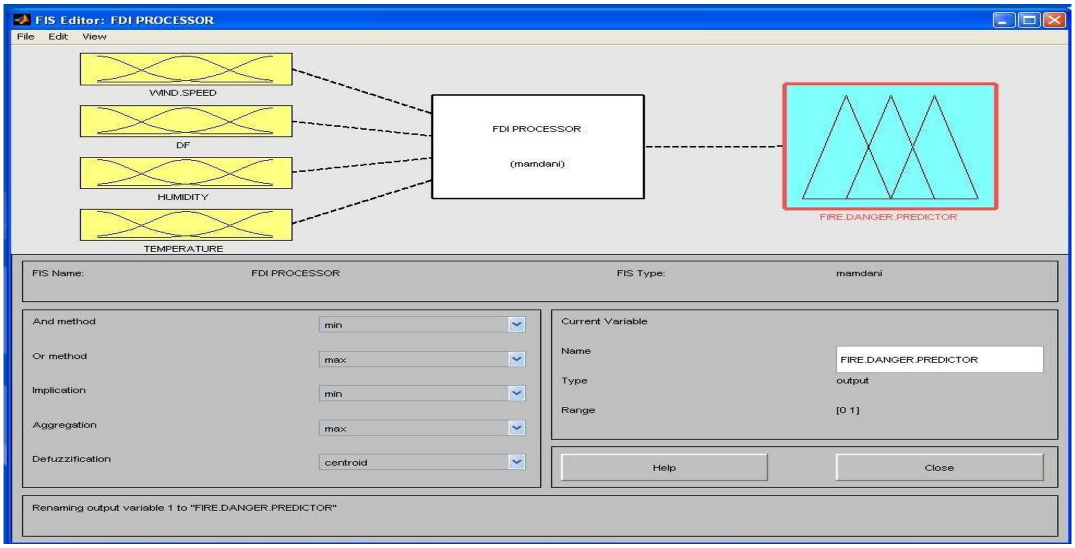

Figure 4.4: FDI processor structure

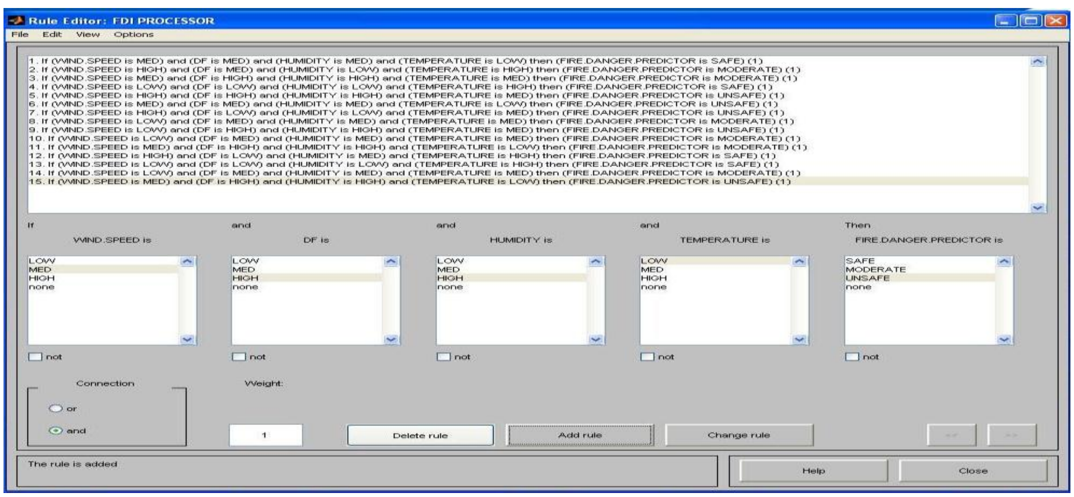

Figure 4.5: Set of rules for FDI

Now, the set of data [Table 4] is used to train the ANFIS structure.

DROUGHT FACTOR	TEMPERATURE	HUMIDITY	WINDSPEED	FDI
3	20	58.01	17	**1.3**
4	23.5	51	20	**4.4**
5	51.8	18	24	**35**
5	34	17	23.5	**19**

5.5	54	23	30	**40.5**
6	34.6	31	45	**23.2**
6	52.3	34	32.2	**39**
6	45.6	33	30	**30.6**
7	32	36	42	**22.7**
8	38	39	19.5	**26**
9	51	41	23	**50.7**
9	32	42	45.6	**27.07**
9.5	55.5	43.4	30	**64.7**
10	45.5	32.6	50	**56.9**
6	45.5	55.1	34	**25.5**
7	52.2	52.6	12	**35.6**
1	27	23	43	**3.47**
9	43	44.6	43	**40**
10	22	21.6	23.6	**22**
5	0	21.6	32	**6.3**
7	10	12.3	12.4	**10.6**
3	15	2.4	23.7	**7.5**
4	27	21	35.8	**12.7**
7	35	23	61.5	**33.7**
8	32	43	32.4	**21.7**
3	21	43	17	**3.2**
2	30	42	18.5	**4.6**

TABLE 4: Training data

The above training data are used to train the ANFIS model. By training, the model, the structure will be ready for further testing of the data. The model that is trained constitutes the data that is put into the model in the form of providing structured data.

Such data used will train the model at 5 epochs in order to acquire all the information sent in a timely manner.

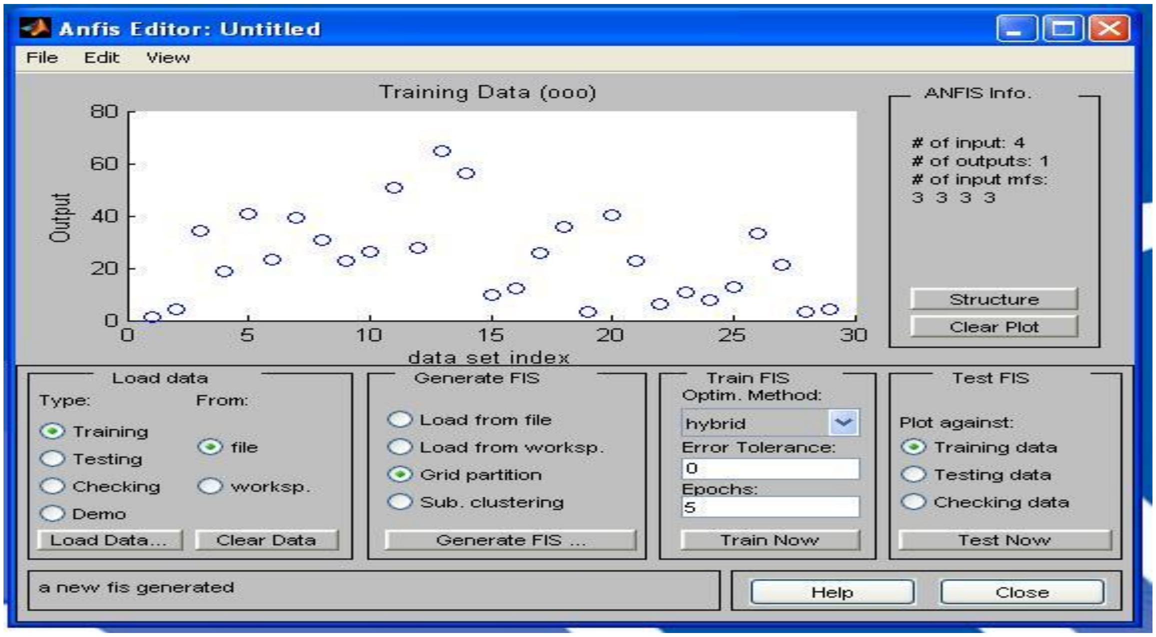

Figure 4.6: ANFIS training process

Further, to enhance the fuzzy model, the training data is checked for any error formed while training. This is done in order to maximise the accuracy of the model. When the training data was checked for any error formation, the training error pointed to ‘Zero’, which means that the training has no error and is sent in the fuzzy without any error formation [Figure 4.7].

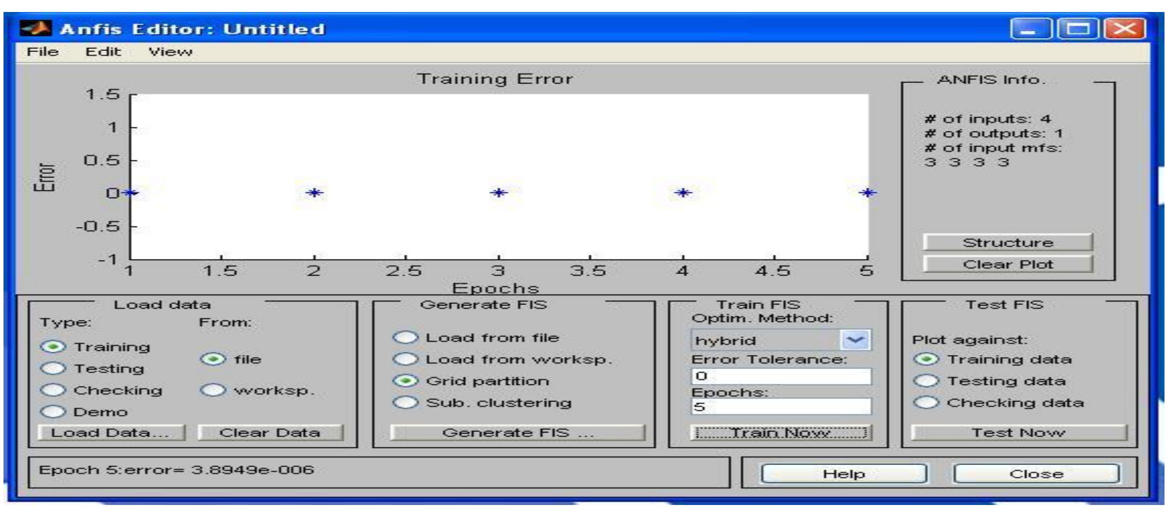

Figure 4.7: Training error output

The FDI processor has the inputs and its effects are thus analysed. FDI is then plotted against temperature to understand the effect of the various ranges of temperature to be considered safe and unsafe based on different variations.

The conditions through which the FDIs are plotted are as the graph below [4.8]:

1. FDI 1- Low DF, Low WS, Low RH
2. FDI 2-High DF, High WS, Med RH
3. FDI 3- Med DF, High WS, High RH

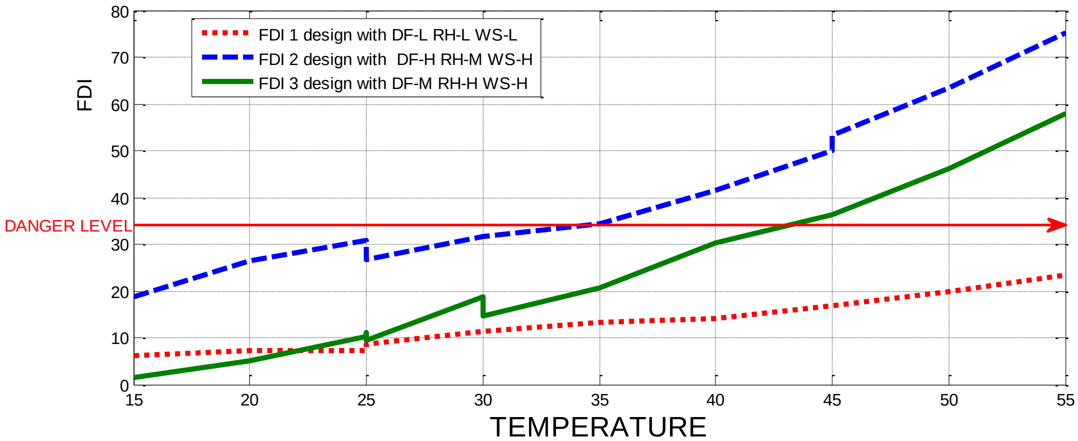

Figure 4.8: FDI 1, 2 and 3 integrated with varying temperature using FIS

The Humidity is then analysed with the other input factors to the final FDI, as shown below [Figure 4.9].

The conditions through which the FDIs are plotted are:

1. FDI 4- Low DF, High WS, Low Temp
2. FDI 5-Med DF, medium WS, Med Temp
3. FDI 6- High DF, High WS, Med Temp

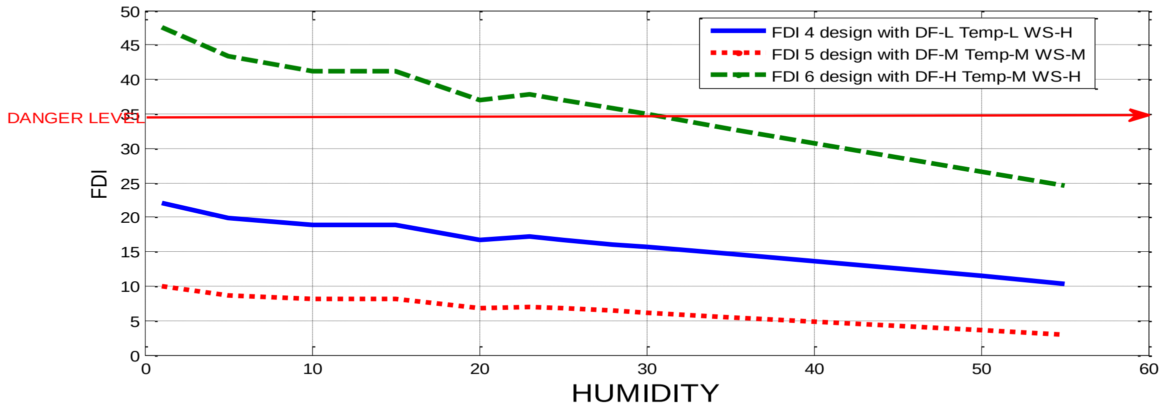

Figure 4.9: FDI 4 ,5 and 6 integrated with varying humidity using FIS

The Wind Speed is then analysed with the other input factors to the final FDI, as shown below [Figure 4.10].

The conditions through which the FDIs are plotted are:

1. FDI 7- Med DF, Med Temp, Low RH
2. FDI 8-High DF, High Temp, Low RH
3. FDI 9- Low DF, Med Temp, High RH

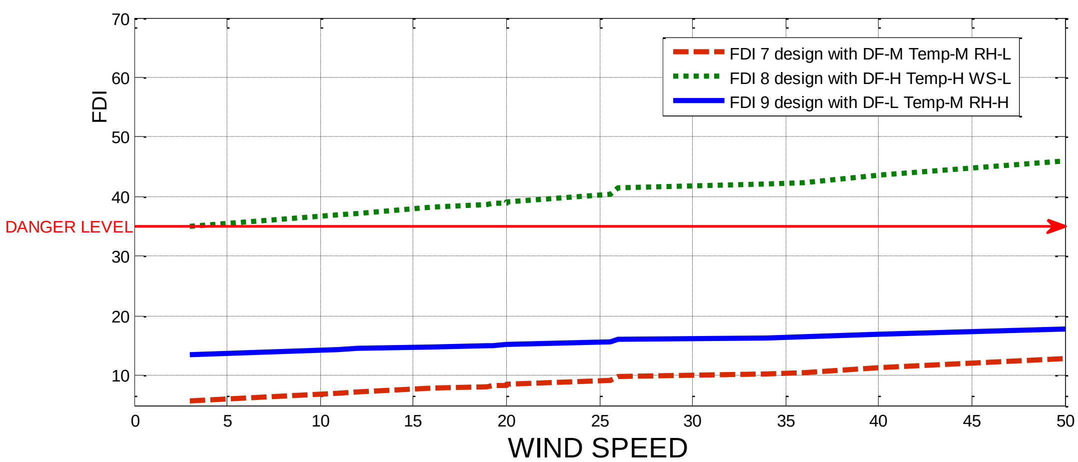

Figure 4.10: FDI 7, 8 and 9 integrated with varying wind speed using FIS

The Drought Factor is then analysed with the other input factors to the final FDI, as shown below [Figure 4.11].

The conditions through which the FDIs are plotted are:

1. FDI 10- Med Temp, High RH, Low WS
2. FDI 11-High Temp, Low RH, High WS
3. FDI 12- Med Temp, Medium RH, High WS

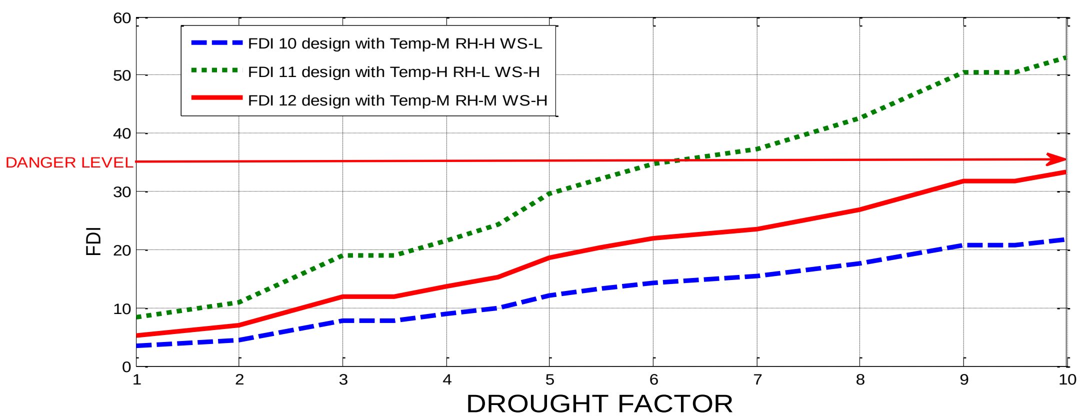

Figure 4.11: FDI 10, 11 and 12 integrated with varying Drought factor using FIS

By taking certain sets of data from training, the same is checked in fuzzy for validation. A single set of the training data is used here to crosscheck the training data sent to the model. The Training set is given as input to the fuzzy to check the output FDI. By checking the FDI, the training is validated. The training set 1 used here has a DF of 6, Temperature of 45.5˚C, Humidity of 55.1% and Wind speed of 34 m/s. This set of data has theoretically given a value of **25.6 FDI**. By cross-checking, the fuzzy provided similar outcome. Hence, training is provided in an accurate manner as seen below.

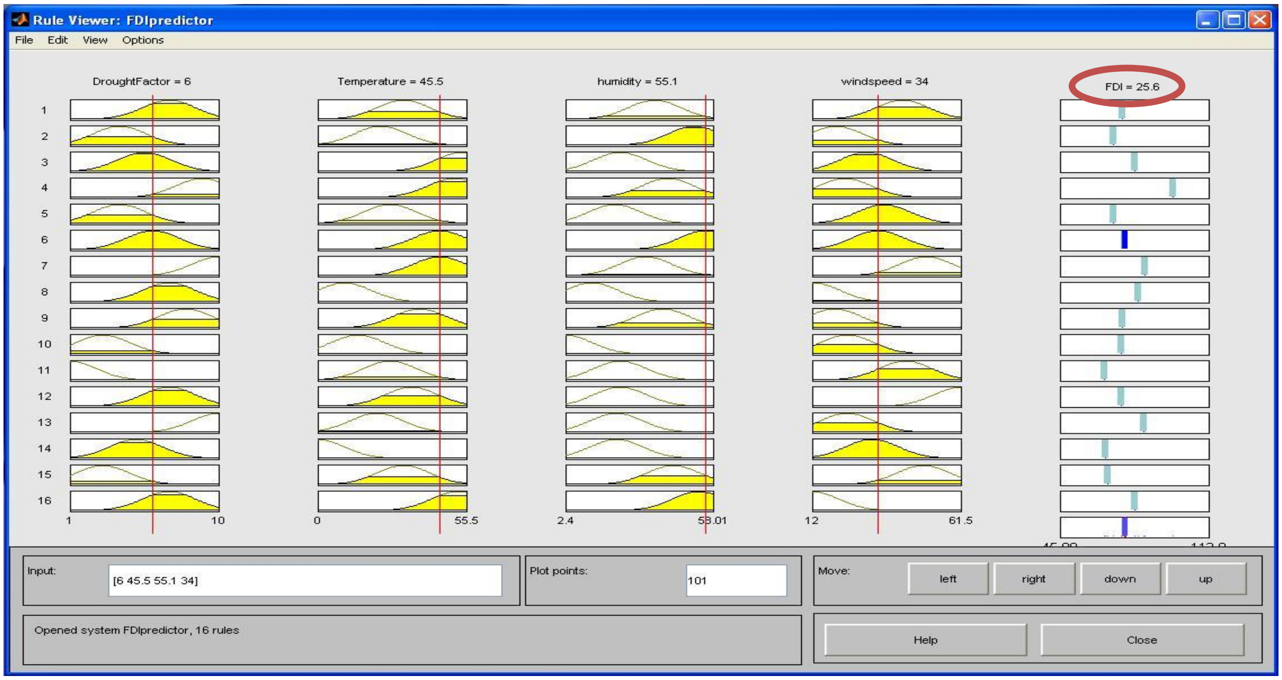

Figure 4.12: Checking training set in FIS (Check 1)

By taking certain sets of data from training, the same is checked in fuzzy for validation. A single set of the training data is used here to cross-check the training data sent to the model. The Training set is given as input to the fuzzy to check the output FDI. By checking the FDI, the training is validated. The training set 2 used here has a DF of 1, Temperature of 27˚C, Humidity of 23% and Wind speed of 43 m/s. This set of data has theoretically given a value of 3.41 FDI. By cross-checking, the fuzzy provided a similar outcome. Hence, training is provided in an accurate manner as seen below in Figure 4.13.

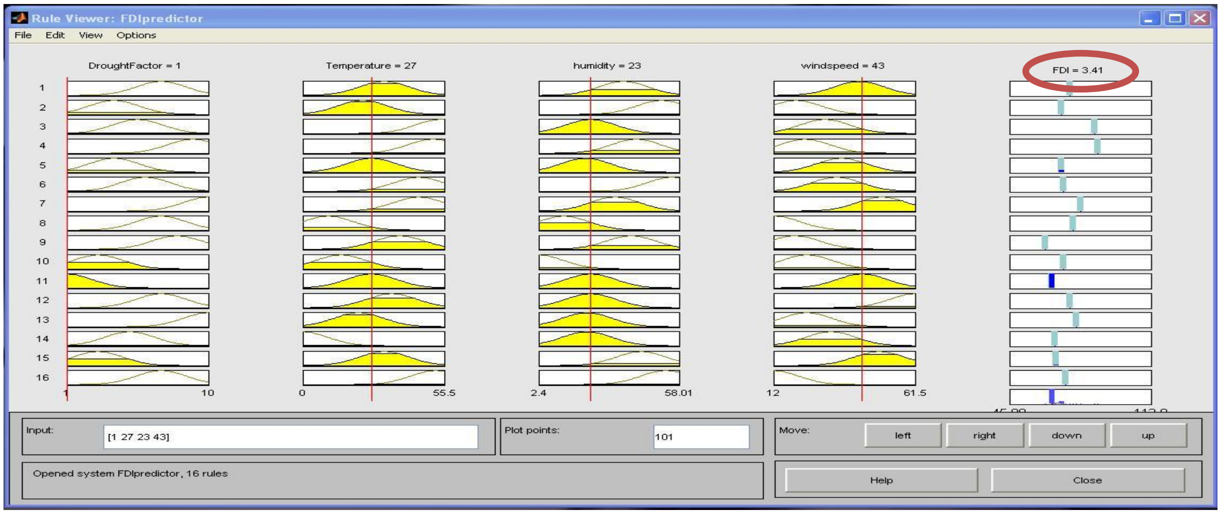

Figure 4.13: Checking training set in FIS (check 2)

After cross-checking the training set of data in the fuzzy for maximum accuracy, the next step is to test the fuzzy with a new set of data as shown in Table 5.

Drought factor	Temperature	Relative Humidity	Wind speed	FDI
4	43	21	15.7	**19.089**
7	21	23	13.7	**13.18**
10	34	44	22	**25.623**
3	43	23	23	**14.786**
5	15	80	45	**0.367**
6	32	21	34.6	**22.051**
5	51	44	12.7	**26.426**
1	21	43	33	**1.66**
2	2	12	42	**4.097**
9	15	25	21	**13.95**
4	43	21	15.7	**19.08**
7	21	23	13.7	**13.18**
10	34	44	22	**25.62**
3	43	23	23	**14.78**
5	15	80	45	**0.36**
6	32	21	34.6	**22.05**

5	51	44	12.7	**26.42**
1	21	43	33	**1.6**

TABLE 5: Testing data

The Testing set is given to the fuzzy to check the output FDI. By checking the FDI, the testing error is validated. The testing set 1 used here has a DF of 4, Temperature of 43˚C, Humidity of 21% and Wind speed of 15.7 m/s. This set of data has theoretically given a value of **19.08 FDI**. By cross-checking, the fuzzy provided 20.8 FDI. Hence, the testing error is calculated as 1.72 (1.09% error) point FDI scale (20.8-19.08). This error is due to the variation of the data structures used for training, which are not in the complete range of operation.

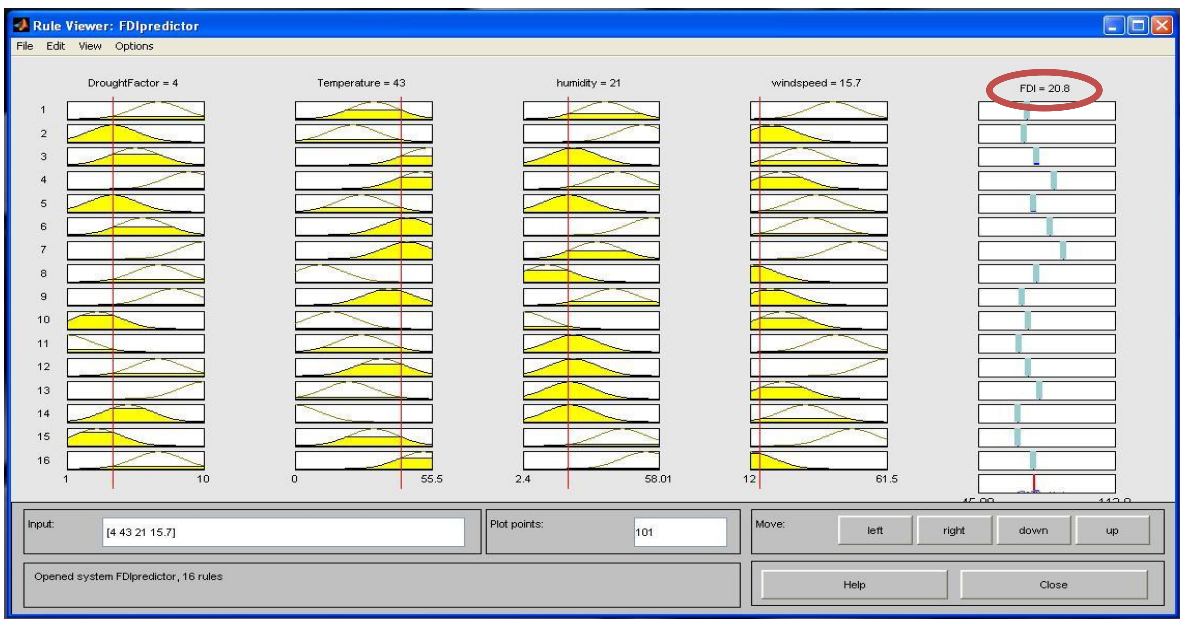

Figure 4.14: Checking test data in FIS (Test 1)

Another testing set is applied on the fuzzy model to check the output FDI. For example, the testing set 2 used here has a DF of 5, Temperature of 51˚C, Humidity of 44% and Wind speed of 12.7 m/s. This set of data has theoretically given a value of 26.5 FDI. The fuzzy model for the same set provides an **FDI of 30**. A testing error of 3.57 (1.13% error) point FDI scale is obtained. This error is due to the variation of the data structures used for training, which do not cover the complete range of operation.

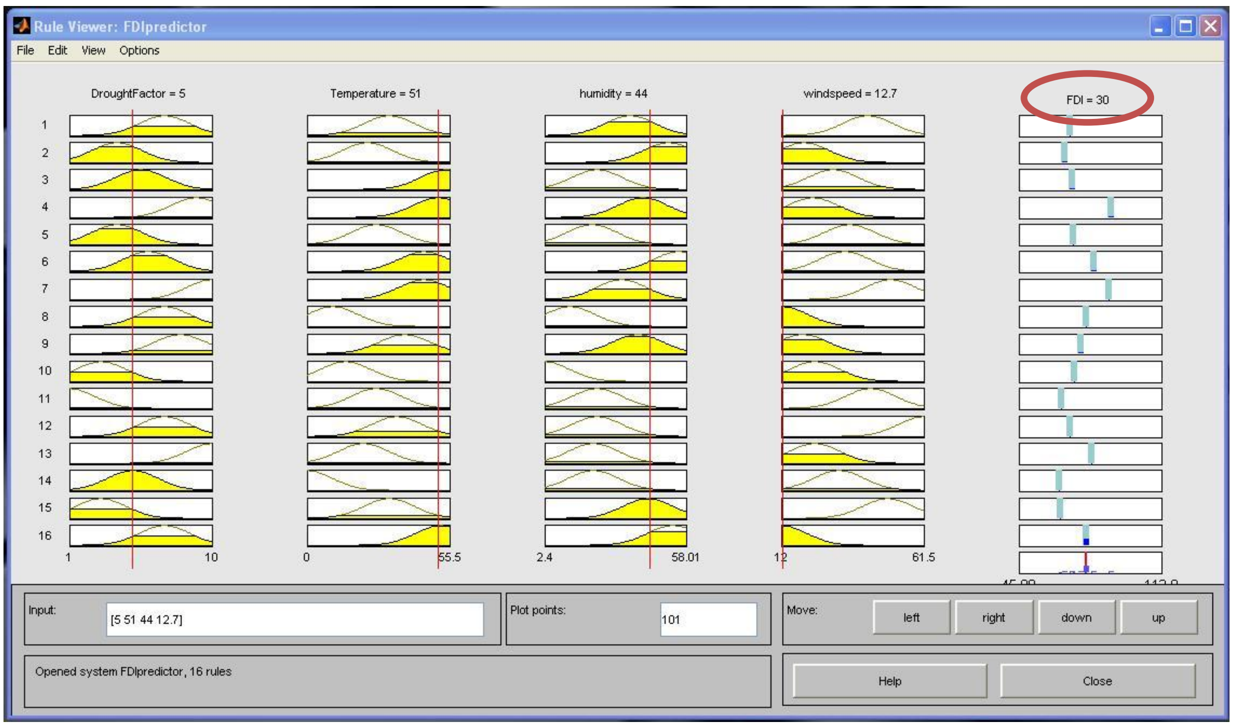

Figure 4.15: Checking test data in FIS (Test 2)

The model is then plotted against the testing data to calculate the average testing error. The error came out to be **0.13007** on average over the whole set of the testing data.

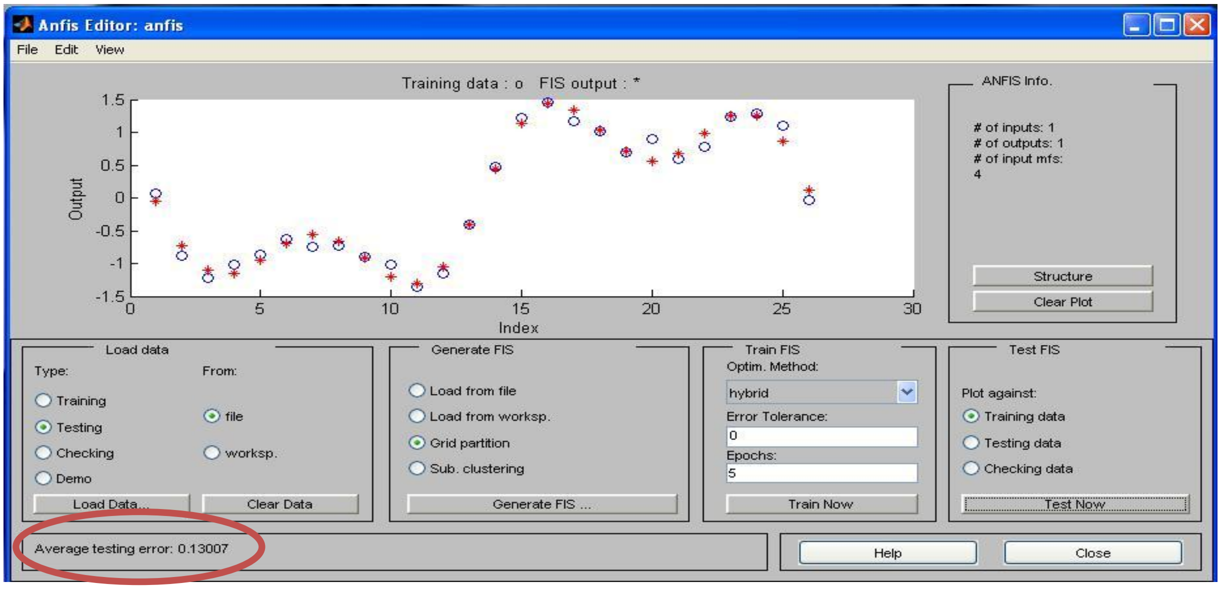

Figure 4.16: Checking the final error (training v/s testing)

The trained fuzzy model is used for predicting wildfire risk in terms of the FDI using the generated synthetic data set.

Graph 1: Both the theoretical and fuzzy predicted outputs as a function of temperature are plotted and the error is checked to find the accuracy.

The average error rate = {(Maxima (range) – Minima (range))/Total set of data values} [49]

= (30.12+29.7)-(50.2+53)/(30set of values)

= 1.446 FDI scale value (0.12% average)

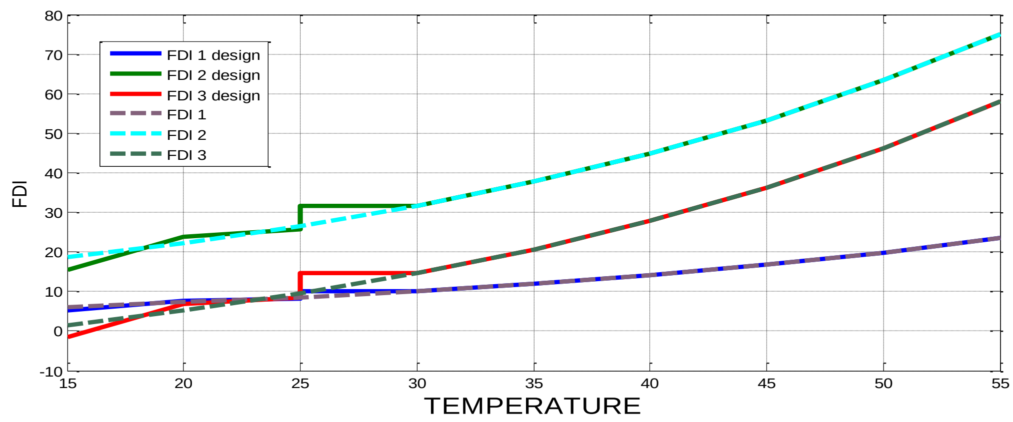

Figure 4.17: Overall FDI check (Fuzzy and theoretical towards temperature)

Graph 2: Both the theoretical and fuzzy predicted outputs as a function of humidity are plotted and the error is checked to find the accuracy.

The average error rate = {(Maxima (range) – Minima (range))/Total set of data values}[49]

=(26+29.7)-(0.2+0)/(30set of values)

= 0.883 FDI scale value (0.029% average)

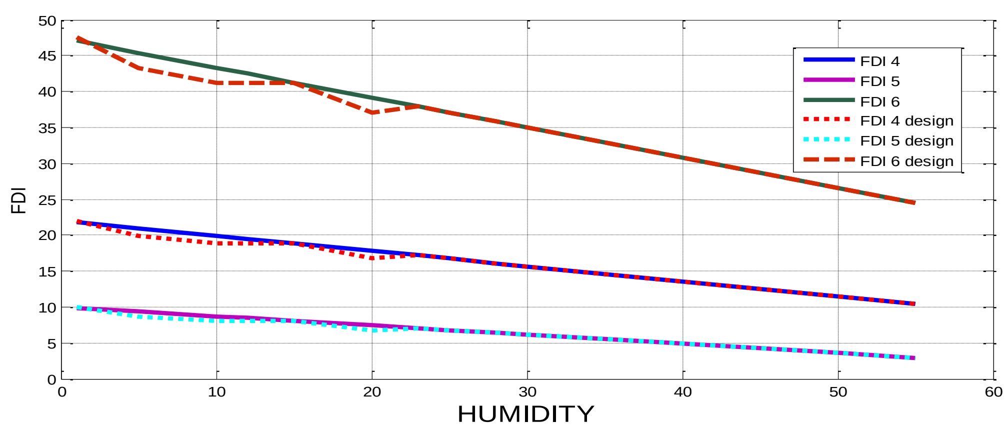

Figure 4.18: Overall FDI check (Fuzzy and theoretical towards humidity)

Graph 3: Both the theoretical and fuzzy predicted outputs as a function of wind speed are plotted and the error is checked to find the accuracy.

The average error rate = {(Maxima (range) – Minima (range))/Total set of data values}[49]

=(5+6)-(0.12+0.03)/(30set of values)

= 0.361 FDI scale value (0.012% average)

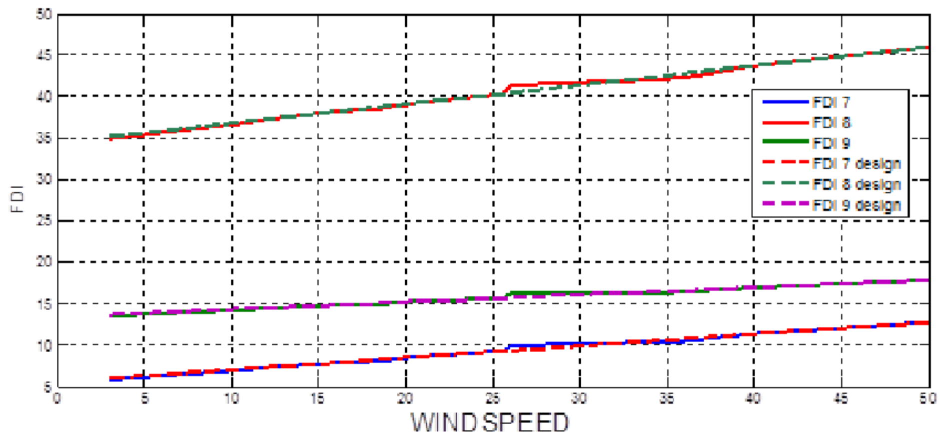

Figure 4.19: Overall FDI check (Fuzzy and theoretical towards Wind speed)

Graph 4: Both the theoretical and fuzzy predicted outputs as a function of drought factor are plotted and the error is checked to find the accuracy.

The average error rate= {(Maxima (range) – Minima (range))/Total set of data values}[49]

=(11+22.1)-(21.09+34.2)-(20.9+21.1)/(30set of values)

= (32.1-55.29-47.47)/3

= 1.50 FDI scale value (0.05% average)

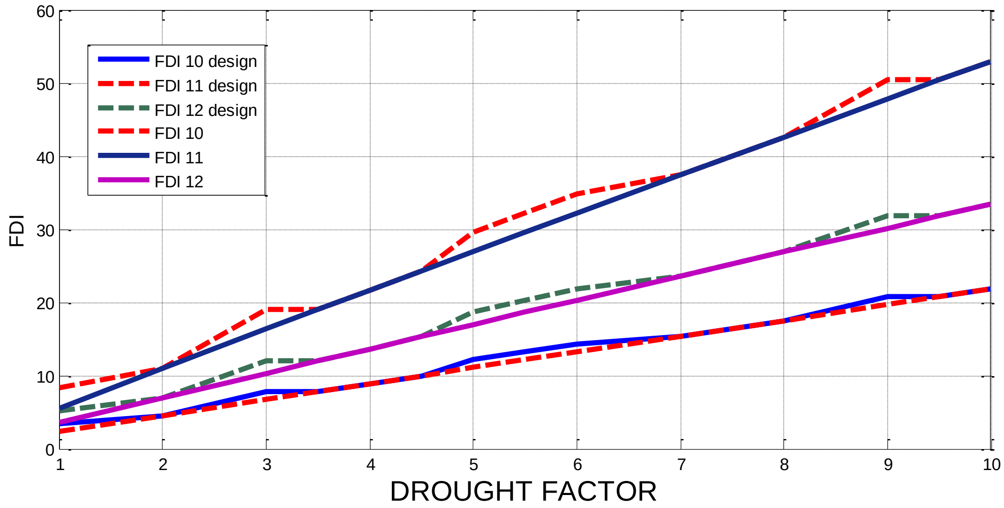

Figure 4.20: Overall FDI check (Fuzzy and theoretical towards Drought factor)

4.3 Summary

The formulae by McArthur have been used to develop synthetic data for both DF and FDI, which is chosen to train the ANFIS model across a wide range of input variables. The ANFIS structure is further explained clearly using a flowchart, which uses the multitier system to compute the FDI.

The ANFIS Design model is used to attain the graphs where the FDI is plotted against the other input variables to estimate the danger level, thus comparing each variable to the FDI to understand the accuracy level. After training the system completely, the trained model was tested against raw weather data resulting in an overall error of +/- 0.13007.

CHAPTER 5: RESULTS, TESTING AND VALIDATION

5.1 Introduction

In this chapter, the fuzzy model that has been trained and tested is subjected to some real-life weather data from the past. The prime reason for this is to validate the fuzzy model against a concrete set of data.

Raw weather data from NRFA (New Zealand Rural Fire Authority) is collected for two set dates during the summer months where the risks of wildfire are potentially high. This range of data is fed into the fuzzy system to predict the fire risk in accordance with the training that was provided to the system. In addition to this, Fire danger maps are also used to understand the area with a high risk of wildfire.

Furthermore, the relationship between the predicted outcome and the different factors (e.g. temperature, humidity, rainfall, and wind speed) is analysed. Finally, a comparison is made between the predicted outcome and that calculated using the FDI formula and real-time in order to validate the developed fuzzy model.

5.2 Implementation of Fuzzy Model on NZ National Weather data

There are two main scenarios that have been considered for this research experiment. The scenarios have been chosen in order that two different locations with different weather conditions and, therefore, presenting different levels of wildfire risk, are considered to evaluate the fuzzy system.

The aim is to validate that the fuzzy model can predict the Fire Danger with the raw data provided under all circumstances.

5.2.1 New Zealand wildfire history

Under section 14 of the Fire Service Act, the NRFA is required to monitor fire danger conditions throughout the country. In partnership with Rural Fire Authorities and a number of other organisations, a national network of over 150 Remote Automatic Weather Stations has been established.

The network delivers information based on the current weather conditions at a given point. This information is used in conjunction with the Fire Weather Index System, which is used to calculate fuel (vegetation) moisture, and expected fire behaviour. This data is distributed to the fire managers as an aid to fire management, planning and suppression efforts. This information is based on the 12:00 NZST weather readings (1pm daylight savings time). The sooner they receive the warning of a potential hazardous situation, the better, as this would allow them some time to take precautionary measures and/or combat the situation

Weather readings are collected every day. Of the 150 weather stations, around 100 of these can be dialled directly by telephone modem in order to collect data. New Zealand's Met Service supplies the rest of the data. Each call can typically take anywhere between 30 seconds and 2 minutes.

This information is used to:

1. Provide rural fire decision support.
2. Guide rural fire prevention.
3. Assist in preparedness planning.
4. Predict potential fire behaviour.
5. Assist in risk assessment.

6. Analyse seasonal fire danger trends.
7. Meet the requirements of the Forest and Rural Fires Act 1977.

The new fire weather system will provide the following benefits including:

1. More timely information.
2. More accurate information.
3. Lower operational and support costs.
4. Provide better decision-making.

The NRFA maintains its own system for collecting, storing and distributing fire weather data. Until 1996, an application built around Fire Weather Plus (an early version of Weather Pro) was used. This was not an automated system and required an operator to be present throughout the summer to collect the data and facts reports.

In 1996, a fully automated system was built which made use of the "fledgling" Internet by distributing reports by e-mail and posting on the NRFA's new web site. Faxes were also automated, but were phased out as the Internet provided a cheaper, more reliable mechanism for distribution.

After six years of operation, the fire weather information provided by the NRFA could hardly be described as "state of the art". This, coupled with impending obsolescence and reliability issues, made for a compelling business case for the development of a new system. It is only natural that we look overseas at existing successful developments.

The British Columbia Ministry of Forests is responsible for an area of approximately the size of New Zealand and has around 200 fire weather stations, which they monitor every day.

They have an existing system built for their staff to provide them with access to the data and tools for querying and manipulating the data. This system is not available to the public and is accessed by authorised users such as NRFA, New Zealand.

New Zealand is now able to share the core of these systems by pooling all our resources, as well as making use of their expertise in developing specific enhancements for our situation.

Even with an ever-increasing network of weather stations, the Fire Weather Monitoring System will be able to provide the foundation for monitoring fire danger conditions throughout the country for some years to come.

5.2.2 Fire Weather mapping: New Zealand

Case study 1:

Location: Christchurch, New Zealand
Date: 1 January 2009

The data for Christchurch in South Island has been provided by NRFA. The data includes all the factors that are required for understanding the fuzzy model's reliability. The time-varying data for each of the factors is plotted and later mapped to understand the accuracy of the model.

The real-time data for Temperature, Relative Humidity, Rainfall and Wind Speed are plotted, along with the corresponding FDI, calculated using these data and the formula denoted as FDI (real time data) as shown below figure [5.1].

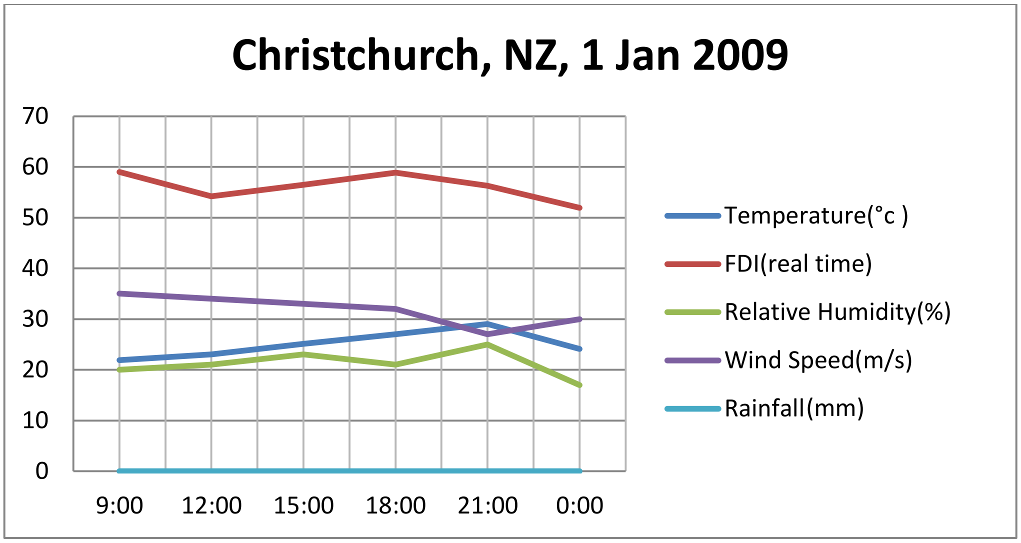

Figure 5.1: FDI plot Christchurch, 1 Jan 2009

In addition, the same inputs are mapped on the country's map in order to understand the spread of the danger. That is, the mapping has been used to determine the area with extreme to low fire danger.

The maps indicate towards the prime weather factors that may cause Wildfire, which can be seen very clearly with the help of the maps below in Figure 5.2.

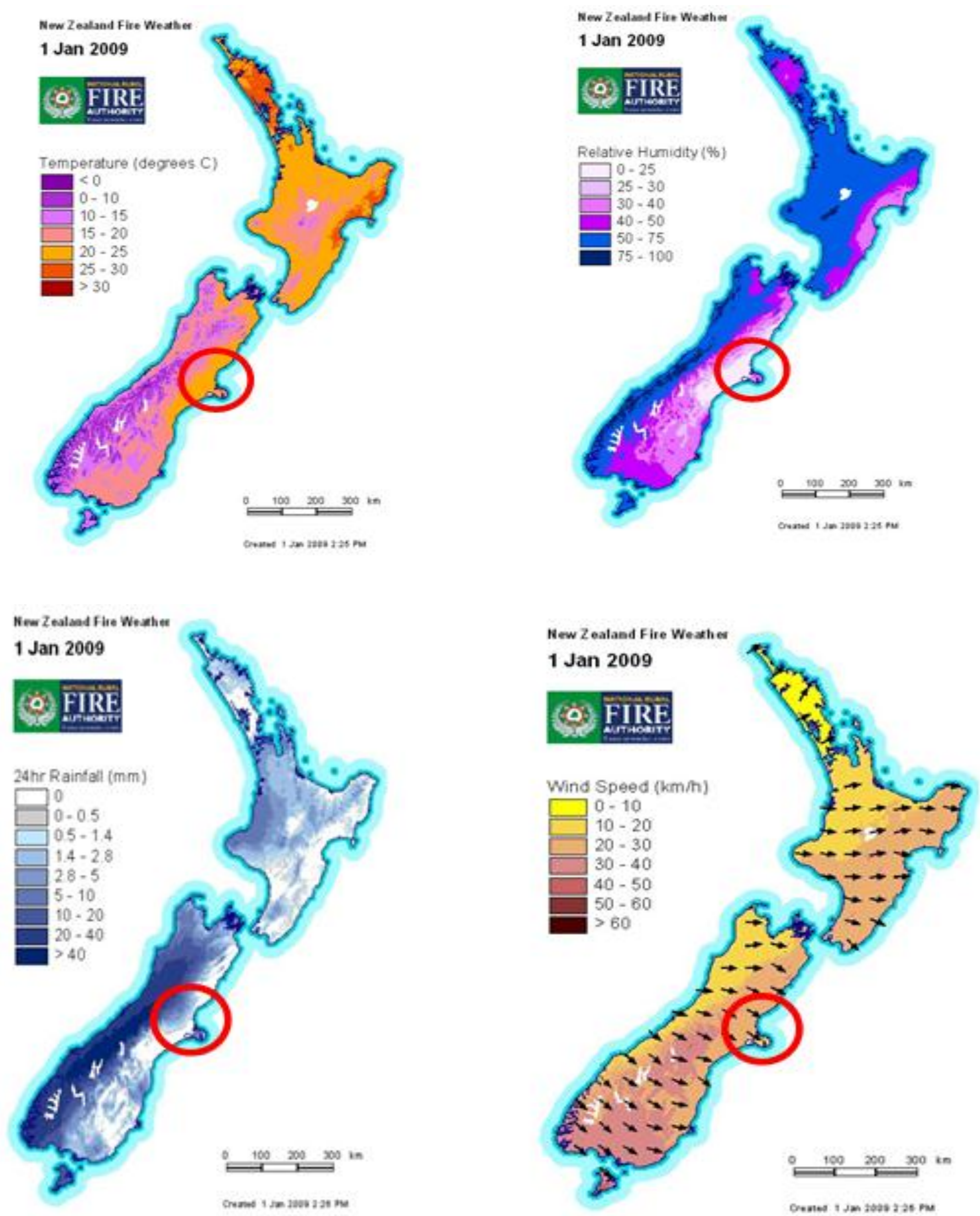

Figure 5.2: The impact of each weather variable to Fire Danger for Christchurch on 1 Jan 2009 *(from top left to bottom right)* a) Temperature mapping b) RH mapping c) 24hr Rainfall mapping d) WS mapping

The weather conditions across the few areas where Christchurch is located in South Island had certain weather conditions prevailing to cause wildfire. As seen in Figure 5.2, Christchurch and the surrounding area have higher temperatures and lower humidity levels, forming an ideal weather condition for the wildfire to occur.

Case study 2

Location: Gisborne, New Zealand
Date: 19 February 2003

Similar to Case study 1, the real-time weather data for Gisborne in the North Island are obtained and plotted, along with the corresponding FDI, calculated using these data and the formula denoted as FDI (real time) as seen below Figure [5.3].

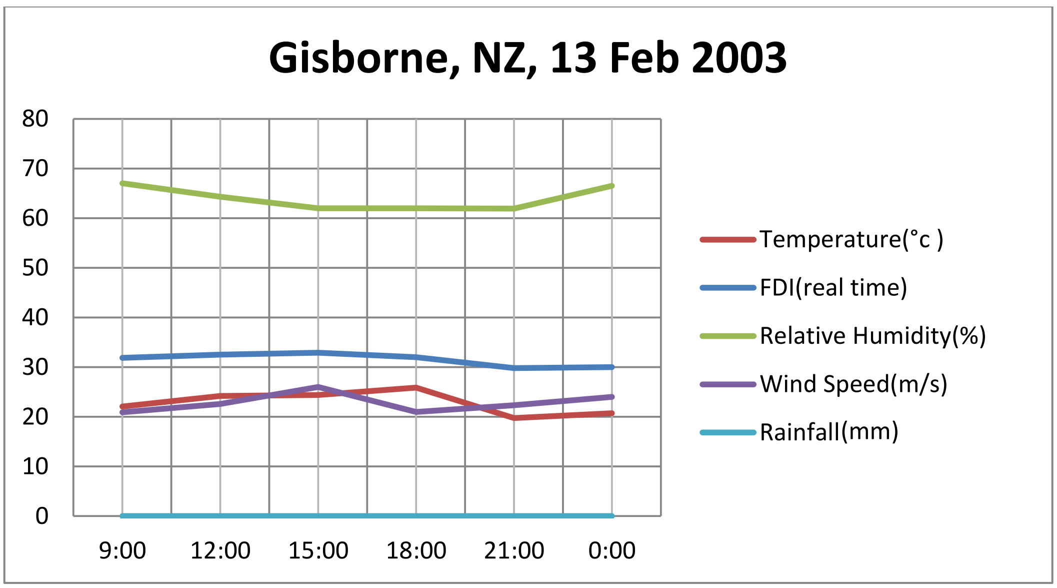

Figure 5.3: FDI plot Gisborne, 19 Feb 2003

The corresponding maps for each weather factor (Temperature, Relative Humidity, Rainfall, and Wind Speed) are also shown below in Figure 5.4.

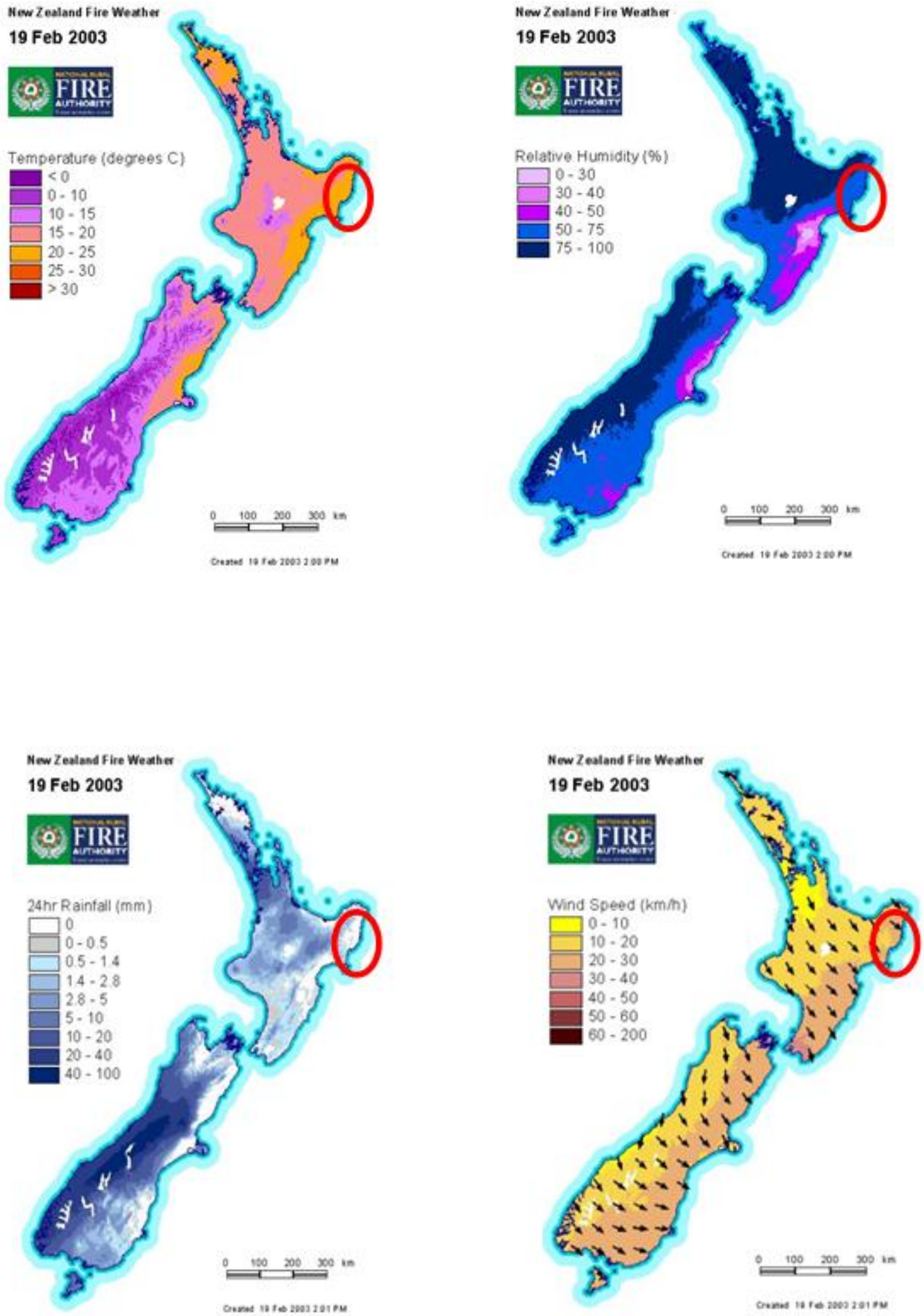

Figure 5.4: The impact of each weather variable to Fire Danger for Gisborne on 19 Feb 2003 *(from top left to bottom right)* a) Temperature mapping b) RH mapping c) 24hr Rainfall mapping d) WS mapping

In addition, similar to Christchurch, the Gisborne area located in North Island has favourable conditions for a wildfire to occur. As seen in Figure 5.4, Gisborne and the surrounding areas have higher temperatures and lower rainfall creating ideal conditions for wildfire.

5.2.3 Fire Danger mapping and final validation

In this section, two main criteria have been used to analyse and justify the fuzzy model made through this research. Firstly, the raw data taken from the NRFA on a particular day is used to calculate the FDI using the formula, which is shown in the plotted graphs as FDI (real time). The same raw data that was used for the first instance is fed into the trained fuzzy system to predict the wildfire risk similarly in terms of FDI for the same duration, denoted as FDI (Fuzzy model). The predicted FDI is then compared with the calculated result using the formula to verify the correctness of the developed fuzzy model.

The following plots the FDI (real time) and FDI (Fuzzy model) obtained under the two different scenarios as previously mentioned [Figure 5.5 and 5.6]. The results are compared and the error percentage between the two is found to be approximately 0.83%.

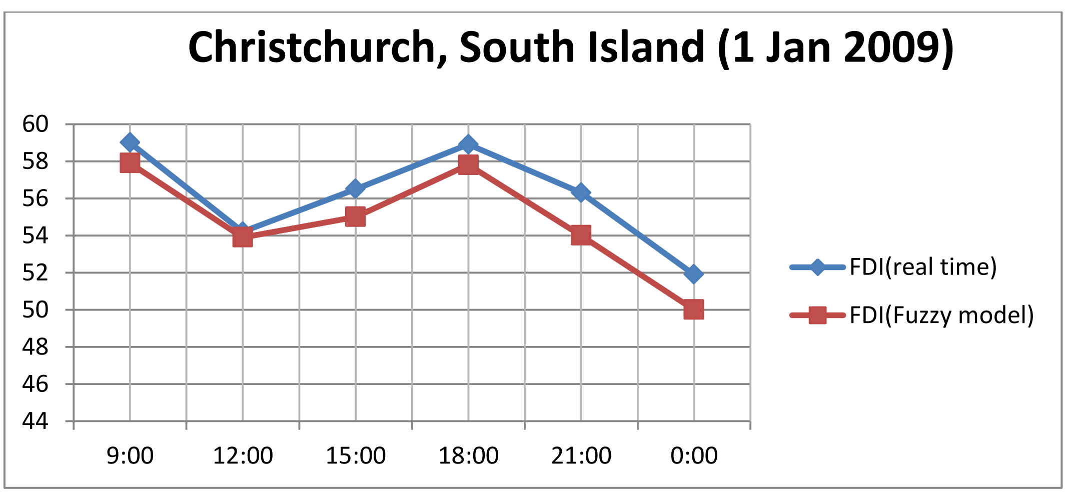

Figure 5.5: FDI comparison plot Christchurch, 1 Jan 2009

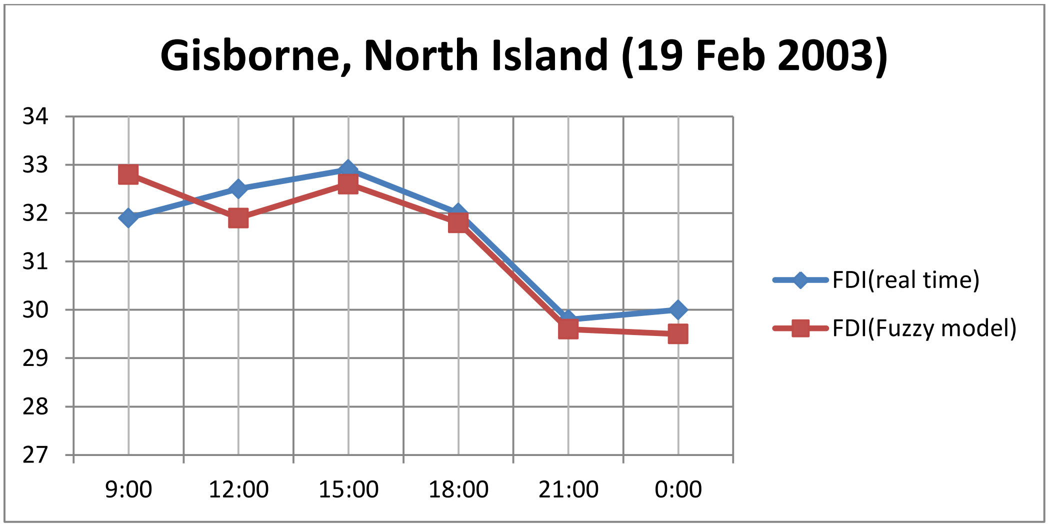

Figure 5.6: FDI comparison plot Gisborne, 19 Feb 2003

5.3 Summary

This chapter discusses the different scenarios checked across New Zealand in which the mapping is done. The data is checked for two different kinds of atmosphere in the chapter for the understanding of the changes according to the changing weather conditions. The mapping is plotted according to the results obtained from the equation. The purpose of such plots is to give an understanding of the impact of each of the factors and its role in causing wildfires.

CHAPTER 6: CONCLUSIONS AND FUTUREWORK

6.1 Conclusions

This study aimed to give an understanding of those weather factors that lead to wildfires and conducted ANFIS modelling to predict the hazard accurately. Towards understanding the core variables, extensive research is done to develop an understanding on early warning systems and their importance in predicting wildfire. In addition, accuracy of results in modelling the prediction system using MATLAB is also given significant importance in this research.

Using fuzzy logic, the ANFIS model was trained with a set of synthetic data derived from the formulae by McArthur, which are also used by the Australian meteorological bureau. The data used to train the ANFIS had been chosen such that it covered all the ranges of the weather parameters. The training proved to be efficient when an error of 0 was achieved during this research.

After coming to the conclusion that the training system was reliable, the ANFIS system was validated against past real-time data. By working with the past data, the solutions were comparable with the outputs of the ANFIS model. Overall, the error percentage was calculated to be +/-0.13007.

With the complete design system trained and tested, it was fed real-time raw weather data for two locations, Gisborne and Christchurch of New Zealand, during different time span and months. These were selected in order to validate the model against different locations and periods to ensure reliability.

Finally, the results of the ANFIS model have been graphed for the same period with the actual results provided by NRFA and NIWA. The error of the final plot comparing the design to the actual result is calculated to be 0.83% approximately. The main advantage of using the developed ANFIS model for predicting wildfire is that the user can directly utilise real-time weather data from meteorological bureaus to make accurate predictions, rather than having to perform data averaging when using the simple formula approach.

6.2 Future Work

This work initially appeared to be a straightforward research study but, along the way, it has led to the development of many new ideas. If time and resources were unlimited, the study would have been improved in several ways. This research was mainly focussed on the design of a fuzzy system to calculate FDI using raw weather data. The design was based on Matlab for execution on conventional computing platforms. It would be interesting to port the design for execution in an embedded hardware, such as a sensor node, in real-time. Although some initial code has been written in C language for a Chipcon processor, the code could not be completed due to the scarcity of time and resources. Another idea is to use wireless communication technologies such as Zigbee to communicate the predicted fire danger from the field to the user. This will elevate the usability of the model to a broader level.

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APPENDICES

APPENDIX A: OFFICIAL WEATHER DATA: NEWZEALAND

Max_min: Hourly

Station	Date(NZST)	Tmax(C)	Period(Hrs)	Tmin(C)	Period(Hrs)	Tgmin(C)	Period(Hrs)	Tmean(C)	RHmean(%)	Period(Hrs)	Freq
3925	20091016:0000	11.8	1	10.8	1	10.1	1	11.2	89	1	H
3925	20091016:0100	10.9	1	10.7	1	10.1	1	10.8	93	1	H
3925	20091016:0200	10.9	1	10.5	1	10.1	1	10.6	95	1	H
3925	20091016:0300	10.7	1	10.4	1	9.9	1	10.5	96	1	H
3925	20091016:0400	10.6	1	9.6	1	9.6	1	10.2	96	1	H
3925	20091016:0500	9.9	1	9.6	1	9.2	1	9.8	92	1	H
3925	20091016:0600	9.8	1	9.6	1	9.2	1	9.7	93	1	H
3925	20091016:0700	10	1	9.5	1	9.4	1	9.7	94	1	H
3925	20091016:0800	11.3	1	9.6	1	10.8	1	10.5	93	1	H
3925	20091016:0900	12.6	1	11.1	1	13.5	1	11.8	91	1	H
3925	20091016:1000	13.3	1	12.4	1	16.5	1	13	83	1	H
3925	20091016:1100	13.7	1	12.9	1	14.7	1	13.4	81	1	H
3925	20091016:1200	13	1	11.1	1	11.8	1	12.4	88	1	H
3925	20091016:1300	11.2	1	10.6	1	11.6	1	10.8	93	1	H
3925	20091016:1400	12	1	10.7	1	12.4	1	11.2	91	1	H
3925	20091016:1500	13.6	1	11.9	1	15.2	1	12.8	82	1	H
3925	20091016:1600	14.2	1	13.4	1	16.8	1	13.8	75	1	H
3925	20091016:1700	14.3	1	13.4	1	14.1	1	14	76	1	H
3925	20091016:18	13.5	1	12.2	1	12.4	1	12.7	89	1	H

	00											
3925	20091016:19 00	12.3	1	11.5	1	10.2	1	11.9	93	1	H
3925	20091016:20 00	11.6	1	11	1	8.4	1	11.4	88	1	H
3925	20091016:21 00	11.1	1	9.6	1	6.9	1	10.2	92	1	H
3925	20091016:22 00	9.7	1	8.5	1	5.4	1	9.3	95	1	H
3925	20091016:23 00	8.8	1	8	1	3.8	1	8.4	96	1	H
3925	20091017:00 00	8.3	1	7.7	1	4.4	1	8.1	97	1	H
3925	20091017:01 00	8.1	1	7.3	1	4.1	1	7.7	97	1	H
3925	20091017:02 00	8	1	7.3	1	5.6	1	7.7	98	1	H
3925	20091017:03 00	7.5	1	6.9	1	4.9	1	7.1	98	1	H
3925	20091017:04 00	7.2	1	6.8	1	5.3	1	7.1	98	1	H
3925	20091017:05 00	6.9	1	5.9	1	3.6	1	6.4	98	1	H
3925	20091017:06 00	6	1	5.2	1	2.4	1	5.7	98	1	H
3925	20091017:07 00	6.9	1	5.2	1	3.1	1	5.7	98	1	H
3925	20091017:08 00	8.7	1	6.8	1	7.6	1	7.9	98	1	H
3925	20091017:09 00	9.9	1	8.5	1	12.8	1	9.3	98	1	H
3925	20091017:10 00	11.4	1	9.8	1	14.7	1	10.6	93	1	H
3925	20091017:11 00	11.8	1	11.3	1	13	1	11.5	86	1	H
3925	20091017:12 00	11.8	1	11.2	1	12.6	1	11.5	87	1	H
3925	20091017:13 00	11.6	1	11	1	12.6	1	11.3	89	1	H
3925	20091017:14 00	11.4	1	11.1	1	12.8	1	11.3	88	1	H
3925	20091017:15 00	11.6	1	11.2	1	12.9	1	11.4	88	1	H
3925	20091017:16 00	11.5	1	10.9	1	12.2	1	11.2	88	1	H
3925	20091017:17 00	11.3	1	10.9	1	11.6	1	11.1	89	1	H
3925	20091017:18	11.1	1	10.9	1	10.8	1	11	92	1	H

	00											
3925	20091017:1900	11	1	10.2	1	9.8	1	10.5	94	1	H
3925	20091017:2000	10.3	1	9.8	1	9.3	1	10	94	1	H
3925	20091017:2100	9.9	1	9.4	1	9.2	1	9.7	95	1	H
3925	20091017:2200	9.9	1	9.4	1	9.1	1	9.6	95	1	H
3925	20091017:2300	9.6	1	9.2	1	9.1	1	9.4	96	1	H
3925	20091018:0000	9.6	1	9.2	1	8.7	1	9.3	95	1	H

UserName is = bhargavi@aut

Total number of rows output = 51

Number of rows remaining in subscription = 1957229

Comments to: cliflo@niwa.co.nz