The Development of a Predictive Damage Condition Model of Light Structures on Expansive Soils using Hybrid Artificial Intelligence Techniques.

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Dissertation

Submitted in fulfilment of requirements for the degree of

Doctor of Philosophy

Faculty of Engineering and Industrial Sciences

Swinburne University of Technology

2007

For my father, Osman Marzuki, with Love,

(28th August 1944 – 23rd August 2006)

If Only I knew…
I would change my actions
If Only I knew…
I would finish on time
If Only I knew…
I would work extra hard
If Only I knew…
I would free my time
If Only I knew…
I would listen more
If Only I knew…
I would make you more proud of me
If Only I knew…
I would express how I feel
If Only I knew…
I would take care of you
If Only I knew…
I would hug you tighter
If Only I knew…
I would tell you to forgive me
If Only I knew…
I would remind you how much I Love you
If Only I knew…
I would Thank You from the bottom of my heart
Now I know…
I will miss you immensely

By: Linda Osman

I Love You Papa
&
Thank You Greatly

ABSTRACT

Expansive soils have damage light structures due to movement of soil which was a common problem all around the world. Soils exhibiting expansive properties were common throughout Australia. The damage to light structures founded on expansive soils in Victoria occurred mainly in properties built on quaternary basaltic clays and Tertiary to Ordovician clays. A review of existing literature in the area of expansive soils showed a lack of a thorough scientific diagnostic of the damage to light structures founded on expansive soils. Very few studies had been performed on damage to light structures on expansive soils in Victoria.

There were no models so far to predict damage condition to light structures. More over, most of the reports on damage to light structures on expansive soils in Victoria were poorly documented. The aim of this research project was to develop a model to predict the damage condition of light structure on expansive soils in Victoria.

A hybrid Neural Network trained with Genetic Algorithm was adopted for the development of the Predictive Damage Condition model. The Neural Network and Genetic Algorithm toolboxes from MATLAB® version 7.1 were used. The development of a Predictive Damage Condition model was driven by the shortage of defined quantitative studies and methods of selecting the factors that influenced the damage to light structure on expansive soils.

The data used was based on information extracted from the Building Housing Commission which was recorded by different engineering companies based only on the tenants complain and site investigation of the properties. A series of factors that were believed to be dominant in influencing damage to light structures were chosen including: structural type, foundation, the presence of vegetation, soil type, age, and climate change.

The model showed that it was able to resolve the problems facing light structures on expansive soils. First and foremost, the Predictive Damage Condition model was able to predict the damage condition or damage class using different combinations of factors. It was also possible to identify the factors contributing to the damage of the structure and to assess their relative importance in causing damage to light structures on expansive soil. It was found that the *construction footing* and *vegetation* were the most important among all the other input parameters. *Change in Thornthwaite Moisture Index* or climate was ranked second. *Construction wall* and *age*, were ranked third and fourth respectively while both *region* and *geology* were ranked fifth. In addition, *Change in Thornthwaite Moisture Index* was noted to have the strongest correlation with other input parameters.

ACKNOWLEDGEMENTS

First and foremost, I would like to dedicate this thesis to my father, *Osman Marzuki*, who did not have the chance to see its completion. Papa, without you none of this would happen. I wish you could see this. Your everlasting love, encouragement and support have motivated me to pursue this path. Thank you so much for everything that you have given me all my life. I miss you tremendously and I hope I have made you proud. I love you Papa.

My gratitude and love also goes to my mother, *Sylvia*, my brother, *Qamal*, my two sisters, *Irma* and *Rina* and the rest of *The Osman* clan. Your support and love have helped me cope with my ever changing motivation level.

To my supervisor, *Dr Kerry McManus, A.M.*, who believed in me from the beginning. Thank you, *Kerry*, for always understanding my situation especially when dealing with my father's passing. Thank you also for your support and assistance throughout my journey. You have been a great supervisor and a father figure to me.

Thanks also to my second supervisor *Dr Anne Ng* for her support. I would also like to express my gratitude to *Mr Dominic Lopes, the USL Group Pty Ltd., the Foundation and Footings Society and the Swinburne library staff (especially Ms Mez Wilkinson).* To *the anonymous reviewers* who have taken their precious time to review this thesis - Thank you in advance.

Last but not least to my friends who have helped me deal with PhD pressure and assisted me in any way they could both academically and emotionally. Special Thanks to *Mr Tino Schlegel, Mr Huu Dung Tran, Dr Jarek Bosko, the Kanyan family* (*Freda and Louis*) and *Mr Guido Farnell*. You guys have been a great help.

DECLARATION

I hereby declare that the thesis entitled "The Development of a Predictive Damage Condition Model of Light Structures on Expansive Soils Using Hybrid Artificial Intelligence Techniques" submitted in fulfilment of the requirements for the Degree of Doctor of Philosophy in the Faculty of Engineering and Industrial Sciences of Swinburne University of Technology, is my own work and that it contains no material which has been accepted for the award to the candidate of any other degree or diploma, except where due reference is made in the text of the thesis. To the best of my knowledge and belief, it contains no material previously published or written by another person except where due reference is made in the text of the thesis.

Norhaslinda Yasmin Osman

July 2007

PUBLICATIONS

The following publications have been based on part of this work:

Refereed Conferences:

1. McManus, K J, Lopes, D & **Osman, N Y** 2003, 'The Influence Of Drought Cycles On The Thornthwaite Moisture Index Contours in Victoria Australia' an International Conference on Problematic Soils, Nottingham, United Kingdom, 28 – 30 July 2003, CI-Premier, Singapore pgs 357.

2. McManus, K J, Lopes, D & **Osman, N Y** 2004, 'The Effect oThornthwaite Moisture Index Changes in Ground Movement Predictions in Australian Soils', Proceedings of the 9th Australian New Zealand Conference on Geomechanics, Auckland, New Zealand, 2004, pgs 555-561.

3. **Osman, N Y**, McManus, K M, Tran, H D & Krezel, Z A 2005, 'The Prediction of Damage Condition in Regards to Damage Factor Influence of Light Structures on Expansive Soils in Victoria, Australia' International Symposium on Neural Networks And Soft Computing in Structural Engineering, Waszczyszyn, Z, Cracow, Poland, 2005, Eccomas C7.

4. **Osman, N Y** & McManus, K J 2005, 'The Ranking of Factors Influencing the Behaviour of Light Structures on Expansive Soils in Victoria, Australia' Proceedings of the Eighth International Conference on the Application of Artificial Intelligence to Civil, Structural and Environmental Engineering., Topping, B H V, Rome, Italy, 2005, Civil-Comp Press, Paper 56.

5. **Osman, N Y**, McManus, K & Ng, A W M 2005, 'Management and Analysis of Data for Damage of Light Structures on Expansive Soils in Victoria, Australia' Proceedings of the 1st International Conference on Structural Condition Assessment, Monitoring and Improvement, Perth, Australia, 12-14th December, 2005, CI-Premier, Singapore 283-290.

6. **Osman, N Y**, Ng, A W M & McManus, K J 2006, 'Selection of Important Input Parameters Using Neural Network Trained With Genetic Algorithm for Damage to Light Structures' Proceedings of The Fifth International Conference on Engineering Computational Technology, Topping, B H V, Montero, G And Montenegro, R, Las Palmas De Gran Canaria, Spain, 12-15 September 2006, Civil-Comp Press.

7. **Osman, N Y**, Lopes, D & McManus, K J 2006, 'An Artificial Intelligence Examination of the Influence of Geological Conditions and Changes in Climate on Damage to Light Structures in Victoria' Proceedings of the 7th Young Geotechnical Professionals Conference, Adelaide, 18-21 October 2006.

8. **Osman, N Y**, & McManus, K J 2007, ' Analysis of a Model of Damage Condition to Light Structures Using Clamping and Pruning Techniques' Proceedings of the Ninth International Conference on the Application of Artificial Intelligence to Civil, Structural And Environmental Engineering,Topping, B H V, Civil-Comp Press, Stirlingshire, Scotland.

Refereed Journal:

9. **Osman, N Y**, McManus, K J, Tran, H D, and Krezel, Z A 2007, The Prediction of Damage Condition in Regards to Damage Factor Influence of Light Structures on Expansive Soils in Victoria, Australia Computer Assisted Mechanics and Engineering Sciences (CAMES). Vol. 14, No. 2, Poland.

10. **Osman, N Y**, and McManus, K J, Predicting the Damage Classifications for Light Structures on Expansive Soils in Victoria, Australia, Using a Neural Network Approach. Advances in Engineering Software, Elsevier. (Submitted 2006 and Under Review)

11. **Osman, N Y**, & McManus, K J, 'The Analysis of a Predictive Damage Condition Model for Light Structures Using Various Techniques' Computer-Aided Civil and Infrastructure Engineering, Blackwell Publishing. (Submitted 2007 and Under Review)

12. **Osman, N Y**, & McManus, K J, 'Artificial Intelligence Approach for Analysing and Testing a Predictive Damage Condition Model for Light Structures on Expansive Soil' Applied Artificial Intelligence, Taylor & Francis Group. (Submitted 2007 and Under Review)

13. **Osman, N Y**, & McManus, K J, 'The Prediction of Damage Condition for Light Structures with Hybrid Artificial Intelligence' Journal of Artificial Intelligence Research, AAAI Press. (Submitted 2007 and Under Review)

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14. **Osman, N Y**, McManus, K J, House Distressed Research Findings, Foundation and Footings Society – ACSEV Joint Workshop "Raising The Standard", 11th October, 2005, Box Hill Institute, Foundation and Footings Society, 2005.

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16. McManus, K. J, Lopes, D, and **Osman, N Y**, Thornthwaite Moisture Index As a Guide to the Effects of Soil Changes in Victoria. R.M.I.T. Climate Change Project - Section 2, RMIT, ***In Process***.

Other publication not based on this thesis by the author:

17. Tran, D. H., Ng, A W M, **Osman, N Y** & McManus, K J. 2006, 'Application of Neural Networks in Modelling Serviceability Deterioration of Concrete Stormwater Pipes,' 7th WSEAS International Conference on NEURAL NETWORKS (NN'06), Cavtat, 12-14th June, 2006, WSEAS. *{Won Best Student Paper Award Based on Originality and Scientific Impact, Good Presentation (Presented By **Osman, N Y**), and Paper Presented by a Student}.*

18. Tran, D. H., Ng, A W M, McManus, K J. & **Osman, N Y** 2006, 'Prediction Model Using Probabilistic Neural Network for Serviceability Deterioration of Stormwater Pipes,' Proceedings of the Fifth International Conference on Engineering Computational Technology, Topping, B H V, Montero, G and Montenegro, R, Las Palmas De Gran Canaria, Spain, 12-15 September 2006, Civil-Comp Press.

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NOTATION AND SYMBOLS

Abbreviation

A	Age
BHC	Building Housing Commission
ChgTMI	Change in Thornthwaite Moisture Index
CF	Construction Footing
CW	Construction Wall
df	degree of freedom
Ep	Evapotranspiration
G	Geology
IM	Inner Melbourne
mse	mean squared error
msereg	mean squared error with regularisation
msw	mean squared network weights and biases
R	Region
RS	Raft Slab

SF	Strip Footing
TMI	Thornthwaite moisture index
TMIN	Thornthwaite moisture index (1960-1990)
TMIO	Thornthwaite moisture index (1940-1960)
V	Vegetation
WM	West Melbourne

Roman Letters

$\boldsymbol{D}$	deficit
$\boldsymbol{d}$	surplus
do_k^p	network output value for pattern
dx_i^p	input value for pattern
$gp\left(x\big\|_{xi=\bar{x}i}\right)$	generalisation performance of network
$\boldsymbol{H_s}$	design suction change
$\boldsymbol{h}$	maximum number of hidden neurons
$\boldsymbol{h_i}$	hidden layer input
$\boldsymbol{i}$	number of neurons in the input layers

I_n	number of indicator
I_{max}	maximum value of numeric indicator
I_s	shrink-swell index
m	number of fitted coefficients
n	number of data point
o	number of neurons in the output layers
S_i	sensitivity of input
p	pattern
pF	soil suction
PN	total number of data pattern
w_{ji}	input weights
w_{jo}	output weights
$\bar{x}_i$	mean value
y	response value
$\hat{y}$	predicted response value
y_s	surface movement

Greek letters

γ	regularisation parameter
$\xi(x_i)$	impact ratio

Chapter 1

INTRODUCTION

Expansive soils were responsible for billions of dollars worth of damage to man-made structures, such as buildings and roads. They had been identified as the most common cause of ground movement around the world. According to the American Society of Civil Engineers, one of the most common and least recognised problems causing severe structural damage to houses lies in expansive soils. For example, expansive soils could exert uplift pressures of as much as 250 kPa, which could do considerable damage to lightly-loaded wood-frame structures (Rogers et al. 1993).

Expansive soils were strong enough to support light structures on a simple foundation. However, these soils posed a significant hazard especially to foundations for light buildings. Foundations were considered the most susceptible to damage due to swelling and shrinkage. These phenomena were caused by the reduction and increased in the moisture content of the soils, which occurred seasonally. This effect was even worse during seasons of drought or flood. A slight movement of the light structures founded on this type of soil could be expected. The volume changing effect of expansive soils to light structures could lead to severe damage such as cracking of the walls, uneven doors and deformation.

Soils exhibiting expansive properties are common throughout Australia. Richards et al. (1983) estimated that 20 percent of the surface soils of Australia could be classified by moderately to highly expansive soil with related damage ranging from minor cracking to irreparable destruction of buildings. Six out of eight of Australia’s largest cities were significantly affected by clay foundation soils (Fityus et al. 2004). Approximately half of the surface area in Victoria was covered by moderate to highly expansive soils; mostly derived from tertiary, quaternary and volcanic deposits (Mc Andrew 1965).

Victoria is the smallest and most densely populated Australian mainland state with a size of 228,000 sq km. The damage to light structures founded on expansive soils in Victoria occurred mainly in properties built on quaternary basaltic clays and Tertiary to Ordovician clays. The dark clays formed on basalt in western Victorian volcanic plains were the most affected by ground movement. Areas where swelling clays developed in unconsolidated sedimentary deposits were extensive over the Wimmera and Riverine plane (Dahlhaus 1999). Most of the hilly north-eastern parts of Melbourne have sodic duplex soils on Silurian sedimentary rocks. The eastern suburbs were capped by tertiary sediments, which have acidic duplex soils while the western suburbs were rich with clays on basaltic plains. The danger zones for foundation failures in Victoria, according to Archicentre Ltd. (2000), were concentrated in the western and north western suburbs with an average of 50% of the houses affected.

Numerous light structures founded on expansive soils in Victoria suffered from ground movement due to edge heave or under floor drying settlement in the clay beneath them. This movement was caused by swelling and shrinkage of the expansive soils underlying the property. The sole presence of expansive soil was not necessarily the main cause of this problem. Other factors such as vegetation, pipe leakages, climate factors, types of construction materials, geology type and workmanship may also have contributed to the damage. However, three quarters of damage to light structures on expansive soils in Victoria resulted from local drying settlement caused by trees and shrubs planted too close to the structures (Cameron and Earl 1982).

1.1 Importance of the Work

A review of existing literature in the area of expansive soils showed a lack of a thorough scientific diagnostic of the damage to light structures founded on expansive soils. Very few studies had been performed on damage to light structures on expansive soils in Victoria. The work done so far did not provide adequate information and nor were there available models predicting the damage condition. Although much assumption and guess work had been made in regards to damage to light structures on expansive soils, few researches had been done to distinguish the important factors that cause the damage. More over, most of the reports on damage to light structures on expansive soils in Victoria were poorly documented. There were no models so far as to predict damage condition to light structures. In addition, the factors for such a prediction and their importance were currently unknown. The only solution for unknown factors that influenced damage was to inspect the damage and to make a judgement of the problems.

The aim of this research project was to develop a model to predict the damage condition of light structure on expansive soils in Victoria. In order to do this, a thorough analysis of the environmental factors was necessary for a precise damage prediction and ranking their importance. The main challenge or problem for any inspector was to investigate technically which one of these factors was predominant in any particular case. The research project demonstrated that the model was able to resolve the problems facing light structures on expansive soils. First and foremost, the model was feasible to predict the damage condition or damage class using different combinations of factors. Secondly, it was possible to identify the factors contributing to the structure damage and their relative importance in causing damage to light structures on expansive soil. Thirdly, correlations between those contributing factors were able to be distinguished. Lastly, the developed model could be applied to other data sets throughout the world.

The development of this model was useful to analyse the long term behaviour of light structures on expansive soils in Victoria in order to enable the government to better maintain social housing building stocks. The model in turn could assist the government or the building trade authorities to finally recognise and identify the parameters that most affect damage to light structures on expansive soils. In addition, the model could help to predict the damage class of the light structure. This helped to identify if any serious and urgent repairs were necessary and immediate actions could be initiated without delay.

1.2 Hypothesis and Objective

The hypothesis was:

That a Predictive Damage Condition model can determine the class of damage based on selected important parameters that influence damage to light structures on expansive soils.

The main objectives of the research project were:

- *To study the behaviour of expansive soils including their mineralogy and their volume change properties in order to identify and understand the parameters that are responsible for soil movement.*
- *To study and understand the factors that influence the movement of light structures founded on expansive soils and identify existing correlation between those factors*
- *To develop a Predictive Damage Condition model and consecutively to study and evaluate the performance of such a model. Hence predict damage to light structures.*

1.3 Research Methodology

The Predictive Damage Condition model was developed based on data that was extracted from reports given to Swinburne University by the Building Housing Commission of Victoria. The Building Housing Commission owned and managed over 73,000 properties across Victoria. Over 200 comprehensive damage were reported annually with an annual budget of $1Million (Department of Human Services 2004).

In order to develop the Predictive Damage Condition model, an investigation on a number of the more significant of the potential parameters that affected damage to light structures was performed. This included an investigation of available information regarding expansive soils and light structures on expansive soils. The results were reported in literature review in **Chapter 2**.

Since the reports were not uniform, a thorough diagnostic of the available reports had to be performed. A considerable amount of time was devoted to extract and select useful information from the reports in order to develop a uniform database. This process was discussed in detail in **Chapter 3**.

Chapter 4 discussed the techniques required for the development of the model including all necessary information about the techniques and their applications.

Chapter 5 covered the analysis of the Predictive Damage Condition model. It reported on the conducted analyses of the model and its performance. The model was then validated using different data marts and the results from **Chapter 6** to check the accuracy and reliability of the Predictive Damage Condition model using data that has never been used in the model. **Chapter 6** also demonstrated a possible outcome of the Predictive Damage Condition model. An interactive web-based map using the results obtained from the model was developed.

Finally, **Chapter 7** covered the conclusion and recommendations summarising the research work from the previous chapters. Figure 1 shows the process involved in the development of a Predictive Damage Condition model including the analysis and testing (**Chapters 3 to 6**).

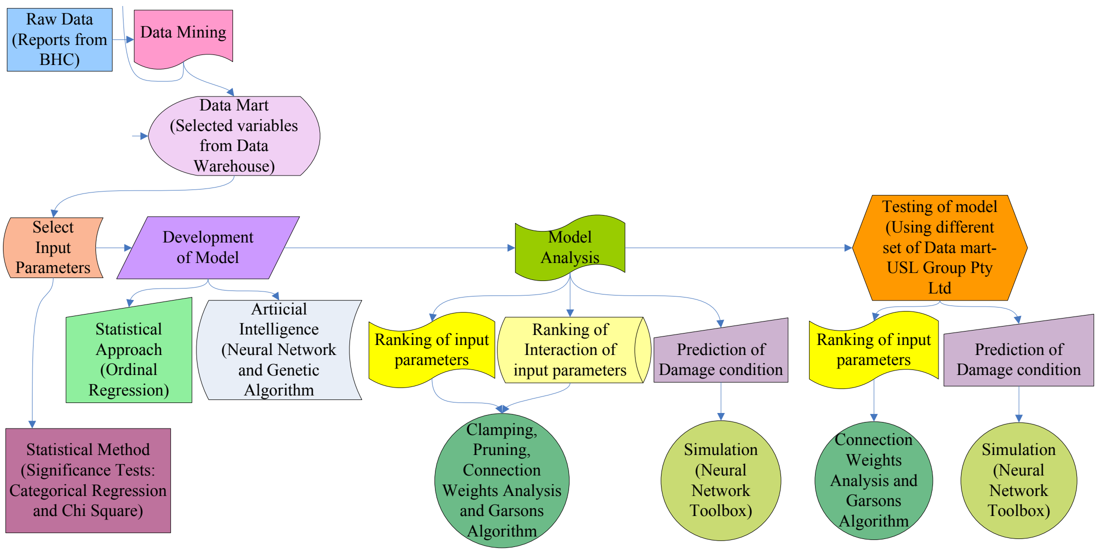


Figure 1: Process for the Predictive Damage Condition Model

Chapter 2

LITERATURE REVIEW

The thesis focused on damage to light structures on expansive soils. Throughout this chapter, relevant literature of damages to light structures relating to expansive soils was reviewed. To better understand the fundamentals of expansive soil as well as damage to light structures, examinations of existing models were undertaken. This included existing models and algorithms to predict damage by either soil movement or building damage due to changes in the influencing factors over the life of the structure.

The literature review was also undertaken to study the factors influencing the behaviour of light structures on expansive soils in Victoria and to provide a framework of available information regarding both expansive soils and light structures. It was because of the lack of available information from the literature review that the theoretical, conceptual and methodological background of the entire research was established.

2.1 Review of Expansive Soil and Its Behaviour in Victoria

"Each soil has its own history. Like a river, a mountain, a forest, or any natural thing, its present condition is due to the influences of many things and events of the past" (Kellog 1956).

Expansive soil, which was also known as swelling, heaving or volume change soil, is clay soil. Swelling clays could control the behaviour of virtually any type of soil if the percentage of clay was more than about 5 percent by weight (Rogers et al. 1993). This may cause damage to structure due to the magnitude of the ground movements associated with shrinkage or swelling phenomenon (Gray and Frost 2003; Padfield and Sharrock 1983; Sorochan 1991; Hudyma and Burcin Avar 2006).

Expansive soils were spread widely all over the world in:

- ***Asia*** *- (Fujita et al. 1998; Ilamparuthi et al. 1998; Nagaraj et al. 1998; Ohri 2003; Rama Rao and Krishna Roa 1998; Sako and Kitamura 2003; Shahu and Hayashi 1998; Sivapullaiah et al. 1998; Sridharan 1998; Sudakhar Rao and Revanasiddappa 2000);*

- ***Australia*** *- (2006b; Aitchison 1972, 1965; Aitchison and Richards 1965a; Aitchison and Richards 1969; Aitchison and Woodburn 1969; Evans et al. 1998; Fityus et al. 2004; Grayson et al. 1997; Holland 1981, 1979; Holland and Cameron 1981; Holland et al. 1975; Jaksa et al. 2002; Jayasekera 2003; Lopes and Hargreaves 2004; McManus 1983; McManus and De Marco 1996; McManus et al. 2004, 2003; McPherson and Swarbrick 1995; Osman et al. 2006a; 2005a; 2005; 2005b);*

- ***Canada*** *- (Poorooshasb 1998; Poorooshasb and Noorzad 1998; Canada Mortgage and Housing Corporation 2005);*

- ***Europe*** *- (Afes et al. 1998; Biddle 2001, 1998c; Bilsel and Trucer 1998; Cheney and Burford 1975; Driscoll 1984, 1983; Entwisle and Kemp 2003; Gray and Frost 2003; Greene-Kelly 1974; Jaremski 2003; Meisina 2003; Page 2003; Popa et al. 2003; Shadunts 1998; Sultan et al. 1998; Toll 2003; Vaughan 1998; Ward 1975, 1954; Wijeyesekeera 1998);*

- ***Middle East*** *- (Abdullah 2003; El-Sohby et al. 1998; Keskin and Uzundurukan 2003; Nusier and Alawneh 2002; Taher 2003);*

- ***South Africa*** *- (Blight and de Wet 1965; Jennings et al. 1973; Wawaru et al. 1998);*

- ***South America*** *- (Camapum de Carvalho et al. 1998; Conciani et al. 1998; Farias et al. 1998; Ferreira et al. 1998); and*

- ***The United States of America*** *- (Department of the Army USA 1983; Noe 2003; Sullivan and McClelland 1969).*

2.1.1 Geology of Victoria

Soils in Victoria derived mainly from the weathering of the underlying rocks and the local geomorphic history (Jenkin 1999b). Victoria is bounded on the south and east by the Indian Ocean, Bass Strait, and the Tasman Sea. Melbourne is the capital city of Victoria. Approximately 50% of the surface area in Victoria is covered by moderate to highly expansive soils; mostly derived from Tertiary, Quaternary and Volcanic deposits (Mc Andrew 1965).

About 50% of the housing failures in Victoria investigated by Holland (1981) occurred in Quaternary basaltic clays (moderately to highly expansive), 40% occurred in the Tertiary to Ordovician clays (low to moderately expansive) and the rest occurred in potentially highly expansive clays. Almost all the failures in the Quaternary basaltic clays were caused by edge heave or under flooring drying settlement in the clay beneath the structures (Holland 1981). According to Holland (1981), three quarters of failures which occurred in Tertiary to Ordovician clays resulted from local drying settlement caused by trees and shrubs planted too close to the structures.

Victoria is divided into four major physical divisions (Hills 1955; Jenkin 1999a; Singleton 1973). The different combination of geomorphic processes were due to different landforms and soils of the divisions (Jenkin 1999a). Figure 2 and Figure 3 show the physiography and geology of Victoria. The classification for geology type in the map can be found in Appendix 1. The four major physical divisions are described below:

The Murray Basin Plains

The Mallee, the Wimmera and the Riverine Plains comprise the Murray Basin Plains. The Mallee is underlain by marine Tertiary rocks (Singleton 1973). The clay plains of the northern and eastern Wimmera are a mixture of aeolian, lake and swam deposits (Jenkin 1999a). The Wimmera plains are covered by grey, brown and red calcareous clay soils (Jenkin 1999a). The Riverine Plains consists of alluvium (Hills 1955; Singleton 1973).

The Central Highlands

The Central Highlands extends from east to west through central Victoria (Hills 1955; Singleton 1973). The bedrock throughout the eastern highlands is made up of various palaeozoic sedimentary, igneous and metamorphic rocks (Jenkin 1999a; Hills 1955).

Most of the north eastern part of Melbourne, which is the hilly area, has sodic duplex soils on Silurian sedimentary rocks. These soils swell and shrink on wetting and drying and especially great during unusually dry summer. The eastern suburbs of Melbourne are capped by Tertiary sediments which has acidic duplex soils. These soils provide stable foundations for houses.

The western highlands is similar to the eastern highlands although volcanic rocks are also prominent in the landscape (Hills 1955) . The western suburbs of Melbourne are rich with clays on basaltic plains. These soils are particularly prone to soil movement on wetting and drying. This causes much damage to buildings (Rowan 1999).

The Western District Plains

The western district plains stretch westward from Melbourne almost to South Australia border (Jenkin 1999a). This plains are underlain by Tertiary rocks, covered in places by Volcanic lavas, elsewhere by sandy soil (Hills 1955). The dark clays formed on basalt in West Victorian Volcanic plains are the most affected by ground movement. Areas where swelling clays developed in unconsolidated sedimentary deposits are extensive over the Wimmera and Riverina plane (Dahlhaus 1999).

The Southern Upland and Lowland

This covers the country between Geelong and the south west Victorian coasts, and between the south eastern side of Victoria and Wilsons Promontory (Jenkin 1999a). The south western part is underlain mainly by Jurassic sandstones, mudstones and shales (Hills 1955). Here; older Volcanic basalts are widespread (Ellis and Ferguson 1976; Hills 1955). Wilsons Promontory is mainly underlain by granite (Singleton 1973). The Southern lowland plain is underlain by Tertiary sediments.

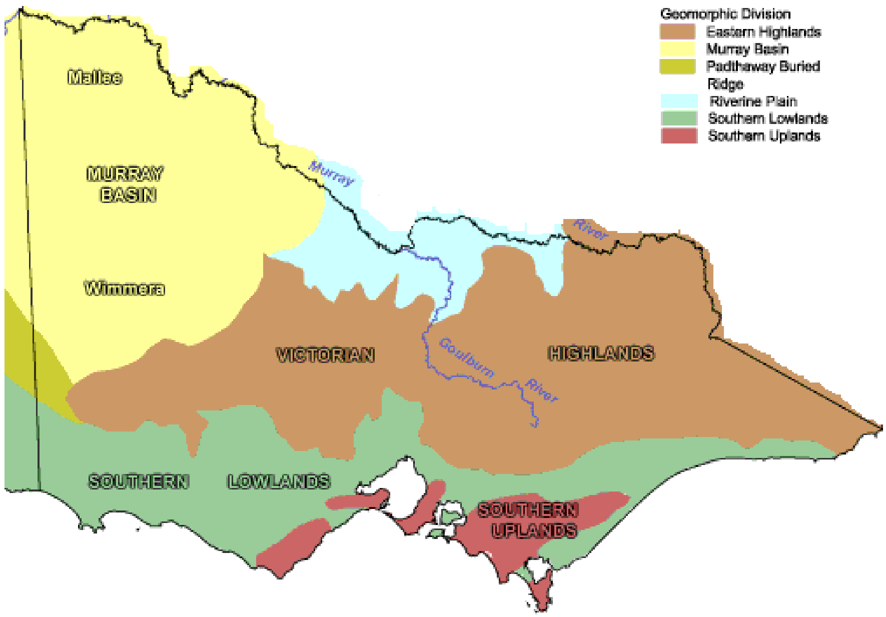


Figure 2: Physiography of Victoria

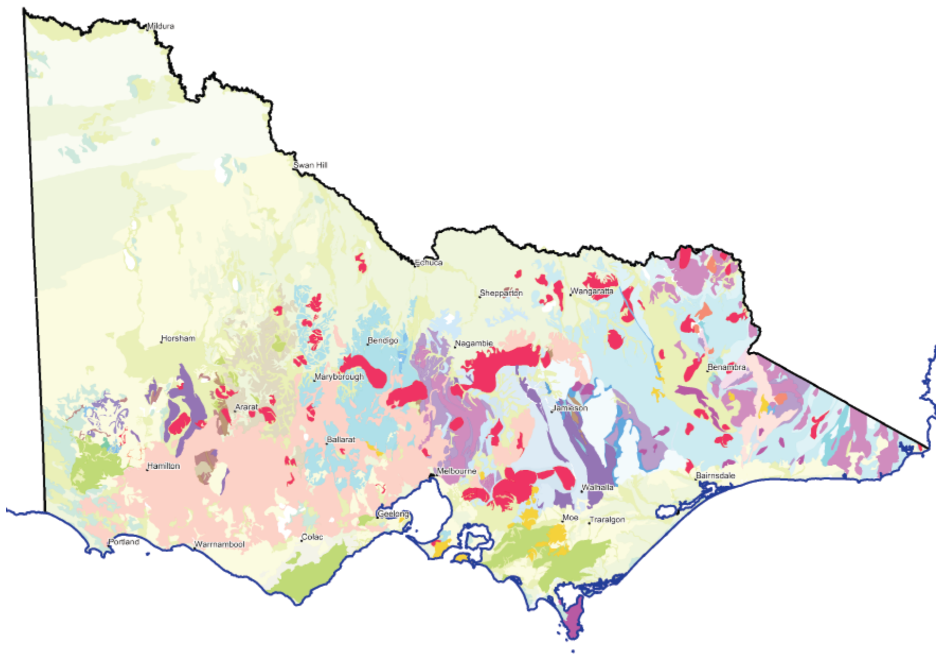


Figure 3: Geology of Victoria

2.1.2 Expansive Soil Classification of Victoria

Expansive clay sites in Australia are classified in accordance with the Australian Standard 2870-1996 base on its reactivity as:

- *Slightly (S) with only slight ground movement from moisture changes*
- *Moderately (M) which can experience moderate ground movement from moisture changes*
- *Highly (H) which can experience high ground movement from moisture changes or*
- *Extremely (E) which can experience extreme ground movement from moisture changes.*

These site classifications depend on the amount of the design ground surface movement, y_s, expected over the 50 year design period in an urban environment. Table 1 shows the surface movement values for the following site classification. Expansive site classification in Melbourne is typically (Standards Australia 1996b) Class H for Basaltic clays, and Class M for other clays. These classes can drop down to Class M for basaltic clays and Class S for other clays for shallow (0.6m) clay sites.

Classification	**Surface Movement, y_s**
S	0 mm < y_s ≤20 mm
M	20 mm < y_s ≤40 mm
H	40 mm < y_s ≤70 mm
E	y_s >70 mm

Table 1: Surface Movement for Different Site Classification (Standards Australia 1996a)

Soil profiles at a site can vary markedly, leading to differences in movement across a site, even if the site experiences a uniform change in soil moisture condition (O'Malley and Cameron 2002). The theoretical depth of movements for all clays in the Melbourne area in accordance with the Australian Standards varies between 1.5 and 3.2 m, depending on the climatic zone (Standards Australia 1996b). Outside the Melbourne area, movement depths of more than three meters were possible in regions where more semi-arid conditions apply (Horsham, Mildura and Wodonga) (Standards Australia 1996b). For example, suburbs located in Silurian and Tertiary clayey soils were severely affected by long drought in 1982-1983, especially where large trees are present (Dahlhaus 1999).

2.1.3 Climate of Victoria

Climate Zone

Victoria has a temperate climate, which varies according to region. Melbourne has generally a dry, hot summer and a wet winter (Cameron and Walsh 1984). The climate of Victoria is characterised by a range of different climate zones, from the hot, dry Mallee region of the northwest to the alpine snowfields in the northeast of Victoria (Bureau of Meteorology 2007). A soil classification based on typical profiles and climatic zone for Victoria can be seen in Table D1 in AS2870 (Standards Australia 1996a) as shown in Appendix 2.

Thornthwaite Moisture Index (TMI)

Thornthwaite Moisture Index is the climate classification based on rainfall and evapotranspiration. Thornthwaite Moisture Index could be used to determine the type of soil at a particular climate zone and the effect of climate to expansive soils. The overall availability of moisture during the year could be assessed by using Thornthwaite Moisture Index formula by Thornthwaite (1948) as in equation (1) where D is deficit, d is surplus and Ep is evapotranspiration.

$$\mathrm{TMI} = \frac{100\mathrm{D} - 60\mathrm{d}}{\mathrm{Ep}} \tag{1}$$

The climate classification of Victoria is shown in the Thornthwaite Moisture Index 1940-1960 map Figure 4 (Aitchison and Richards 1965b; Standards Australia 1996a) and the new modified Thornthwaite Moisture Index 1960-1990 map (Figure 5) (McManus et al. 2004, 2003).

Figure 4: Thornthwaite Moisture Index (1940-1960) (Aitchison and Richards 1965b)

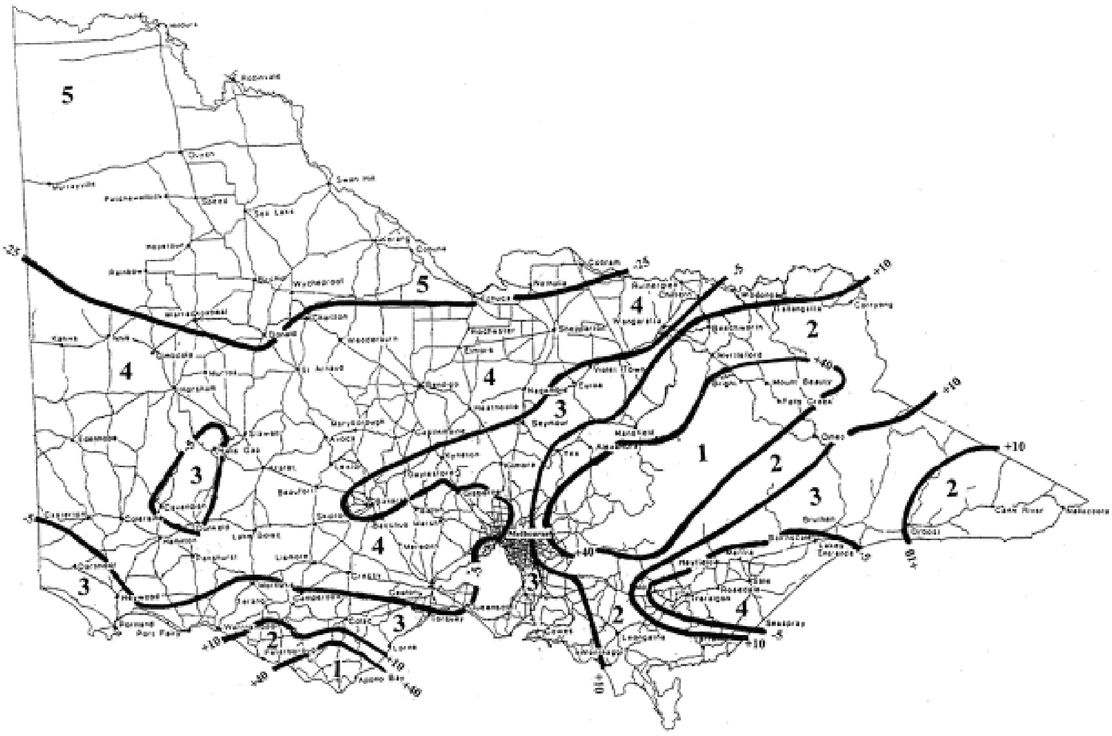


Figure 5: Thornthwaite Moisture Index (1960-1990) (McManus *et al.* 2003)

2.1.4 Soil Behaviour

2.1.4.1 Soil Mineralogy

Expansive soils owe their characteristics to the presence of swelling clay minerals (Rogers et al. 1993). Clay soils were made of very fine particles less than 0.2 µm in diameter packed together which demonstrate plastic properties when wet and composed mainly of aluminosilicate mineral such as feldspar.

Expansive soils developed wherever geological processes allow accumulation of predominantly silt and clay sized particles that contained large quantities of expansive minerals (Rollings and Rollings 1996). The entire physical behaviour of clay soil was strongly influenced by the water content (Hillel (1980) cited in (Barlow 1998) which depended on the clay minerals. Clay minerals were crystalline, and they generally arise from the chemical decomposition of mainly igneous rocks. They were usually present in combination with larger particles (Padfield and Sharrock 1983). Sheet arrangement within aluminosilicate layers that predominate the clay-sized fraction of the soil varied between clay mineral types (Barton and Karathanasis 2002).

The major clay mineral groups were Kaolinite, Illite and Smectite that vary in physical and chemical properties. Clay mineral have different affinities for the absorption of moisture, which cause shrinking and swelling (Thomas *et al.* (2000) cited in (Hudyma and Burcin Avar 2006). The basic building blocks of clay minerals comprise of silicon-oxygen tetrahedra, aluminium-oxygen octahedra and magnesium octahedra which carry net negative charges (Wu 1969; Taylor and Cripps 1984). The combination of these materials form silica, brucite and gibbsite (Wu 1969; Taylor and Cripps 1984; Barton and Karathanasis 2002). Figure 6 shows the structure and building blocks of clay minerals.

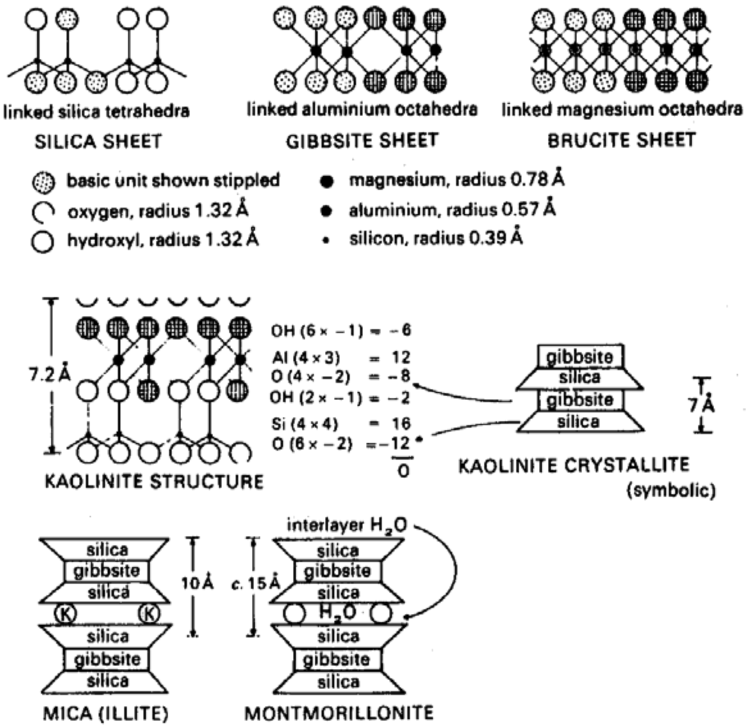


Figure 6: Basic Building Blocks and Sheet Structure of Clay Minerals (After: Taylor & Cripps, 1984)

Kaolinite

Kaolinite was formed by stacking of 70 to 100 or more 7Å thick sheets as a book of gibbsite and silica sheets together with 1:1 layer bonded by hydrogen bonds and Van Der Waals forces (Gillott 1987; Taylor and Cripps 1984). It resulted in considerable strength and stability with little tendency to swell (Bowles 1984). The hydrogen bonding which held the layer tightly together restricted expansion and limited the reactive area to external surfaces (Barton and Karathanasis 2002). Kaolinite was the most uniform crystal, which was often hexagonal plates with typical diameters of 0.3 to 0.4μm and specific surface area in the range of 10 to 30 m^2/g (Entwisle and Kemp 2003). It was the least active clay mineral with lower plasticity and had lower capacity for adsorbing cations thus exhibit lower swelling potential (Barton and Karathanasis 2002). Kaolinite shrink and swell the least of the three types of clay soils.

Illite

Illite had one layer of octahedral (gibbsite sheet) sandwiched between two layers of tetrahedra (silica sheets) with thickness of 10Å (Addison 1996; Bowles 1984; Taylor and Cripps 1984; Sowers and Sowers 1970). It had lower plasticity and lower swelling potential due to its low specific surface area of about 30 m^2/g. It shrink and swell a little more than kaolinite, but considerably less than the Smectite clays.

Smectite

Intersheet bonding due mainly to the Van Der Waals forces of one gibbsite sheet sandwiched between two layers of silica sheets with the absence of potassium between the sheets formed smectite (Sowers and Sowers 1970; Wu 1969). Two types of smectites that were commonly found were montmorillonite and bentonite. These cause the most trouble to residential and light commercial structures. Due to its large negative charge, and its clay percentage of more than 5 percent by weight and its osmotic pressure, montmorillonite was capable of swelling when water was available (Rogers et al. 1993; Ohri 2003). However, potential of swell in clay soils was not only due to the presence of montmorillonite (Entwisle and Kemp 2003; Ohri 2003; Wawaru et al. 1998; Wijeyesekeera 1998) but was also directly related and highly influenced by the chemistry of pore fluids (Abdullah 2003).

Smectite particleswere typically around 3mm thick, 0.1 to 1μm in diameter and have a specific surface area of about 740 to 800 m^2/g. They have high plasticity, high activity and high swell/shrink potential due to their high specific surfaces area (Entwisle and Kemp 2003; Whitlow 1983). When large amounts of water were adsorbed to the surfaces, the spacing unit sheets of montmorillonite was variable and may increased from 9.6Å to almost complete separation (Wu 1969). The result of the separation of two montmorillonite sheets which were stacked together with very weak secondary bonds swell due to the water molecules and cations which occupy the space in between (Bowles 1984).

Smectite clays showed extremely high plasticity due to its high average specific surface area (Whitlow 1983). Any soil with high plastic clay minerals generally those with liquid limits exceeding 50 percent and plasticity index over 30 changes in volume when its moisture content changes and usually have high inherent swelling capacity (Rollings and Rollings 1996; Rogers et al. 1993).

The reactivity of the clay soil or the size of movements depended on the mineral structure, or bonding, of the clay plates (Masia et al. 2004). The interaction of clay minerals with water determined the direction of ground movement. It varied with the amount and type of clay minerals in the soil. When water content increased, the soil swell and when it decreased, the soil shrink (Ferreira et al. 1998; Ilamparuthi et al. 1998).

The study by Lytton (1997) indicated that that foundation damage was over three times more likely to occur on the montmorillonitic soils with higher shrink-swell potentials. This gave the greatest effect on the movement of structures built on it. The water molecules were taken up between the sheets of ions when these clays become wet. They effectively pushed the other ions apart which resulted in the montmorillonite to swell. The clay ions returned to their previous size when they dry out (Dahlhaus 1999). On the other hand, swelling was least noticeable in kaolonite clay derived from granite as it was a non- swelling variety (Dahlhaus 1999).

Swelling pressure was influenced by initial density and water content, testing time, stress path followed during testing and type of clay mineral (Ohri 2003). A modified triaxial testing system was used by Keskin and Uzundurukan (2003). They observed that the lateral swelling pressure slightly decreased because of mineralogical effect. In Melbourne, the soils that swell and shrink, causing failure of building foundations were those derived from basalt and the clay was predominantly smectite (Norrish and Pickering 1993). Other soils in Melbourne overlie Silurian shale and Pliocene sandstone and contained illite and kaolin respectively as their clay minerals (Norrish and Pickering 1993)

2.4.1.2 Swelling and Shrinkage

Highly reactive soils experienced extensive volume changes related with swelling and shrinkage. When water content increased, the soil swell and when it decreased, the soil shrink (Ferreira et al. 1999; Ilamparuthi et al. 1999). Volume changes in soils were important because they determine settlements due to shrinking, heave due to swelling, and contribute to deformations caused by shear stress (Mitchell and Soga 2005). Predicting shrink–swell potential accurately required both the knowledge of which soil properties influence shrinking and swelling and the magnitude of these parameters (Thomas et al. 2000). Many researchers studied and experimented upon the potential of swelling and shrinkage of expansive soils using methods such as free swell test (Sridharan 1998), unit swell test (Golait 1999), odometer test (Erzin and Erol 2004; Jennings et al. 1973), a simple diffusion equation (Mitchell 1980) and many more.

Soil swelling would take place when there was an environmental change such as pressure release due to excavation, desiccation caused by temperature increase, and volume increase caused by introduction of moisture (Chen 1988b). The amount of suction change determined the depth to which the upward movement or swelling occurred (Lytton 1997). The amount of swelling of soils depended on the size of the load on the soil and the magnitude of the change in soil moisture content. Detrimental swelling could occur due to slight changes in moisture content, in the magnitude of 1 to 2%. Most of the swelling had already taken place and further expansion would be small at moisture content above 30%. Very dry clays would absorb moisture as high as 35%, resulting in swelling thus causing damage to structures (Chen 1988a; Meisina 2003).

Wetting of the dry soil from the bottom of a crack could cause swelling of the soil in a restrained environment (Kodikara et al. 1999).

Soil shrinkage was the result of loss of water in the soil. However, like swelling, clay with high content of montmorillonite was susceptible to shrinkage (Ohri 2003; Wawaru et al. 1998). When there was a severe loss of water, the tiny plate-like particles of clays collapse, leading to a reduction of soil volume and soil shrinkage (Canada Mortgage and Housing Corporation 2005). Soil shrinkage resulted in differential settlement. This may be due to dramatic change in underground conditions such as the loss of moisture. Water could be removed from soil by a wide variety of mechanisms, such as excavation or other works that lower ground water levels, prolonged periods of low rainfall, or low rainfall in combination with mature trees with a high water demand (Canada Mortgage and Housing Corporation 2005; Chen 1988a).

2.4.1.3 Soil Suction

Swelling and shrinkage of soil depended on soil suction. All engineering structures on expansive soils were subjected to variations of suction at the soil surface (Lytton 1997). Soil suction was a measure of the tendency of the soil to undergo a change in moisture content within a time period and it depended on climate, vegetation , drainage, site cover and watering patterns (Bulut et al. 2001; Cameron and Walsh 1984; Chen 1988c; Mitchell 1980; Nelson and Miller 1992; Whitlow 1983; Aitchison 1993). Soil suction was useful in the analysis of reactive clays because it was more strongly a function of the climate and vegetation than it was of soil type (Standards Australia 1996a).

Soil suction testing was a powerful tool for investigating expansive soil behaviour for use in selecting foundation type and making design decisions (McKeen 2001). The knowledge of the soil suction and water flow of the expansive soil enabled the prediction of the behaviour of swelling and shrinkage. Many researchers (Bulut et al. 2001;

Chandler et al. 1992; McKeen 2001; Fredlund et al. 1996; Fredlund et al. 1998, 2002; Fredlund et al. 1997; Miller et al. 2002; Vanapali and Fredlund 1999, 2000; Vanapali et al. 1998; Van Genuchten 1980; Zhou and Yu 2004; Blatz 2000; Juca 1993; Meilani et al. 2002; Likos et al. 2003) (Arampatzis et al. 2001; Baumgartl and Kock 2004; Van Wambeke 2000; Wray et al. 2005; Xu 2004) have made use of soil suction testing to determine the behaviour of expansive soils in the laboratories or in the fields using various methods.

Variation in Soil Suction Profile

Soil suction profile (Figure 7) was a representation of a state of physical balance between various processes operating to add or to subtract water at any part of the profile (Aitchison and Woodburn 1969). The flow of moisture through the soil was controlled by the suction gradient of the soil profile from low suction regions to high suction regions (Mitchell 1980).

Changes in soil suction were greatest at the soil surface where soil moisture fluctuations occurred and reduced with depth to zero at the bottom of the active zone (Fityus et al. 1998a; Masia et al. 2004). The active zone could extend from 1 to 12 m deep depending on the soil and climate (Sorensen and Tasker 1976 cited in (Masia et al. 2004; Department of the Army USA 1983; Rogers et al. 1993). The active zone was affected by time, climatic variations, the presence of ground cover and vegetation (Hamilton 1977). A closed-formed solution indicated that 80% of the total heave occurred within 50% of the active depth (Rama Rao et al. 1988). Hence, the replacement of the top portion of the expansive soil depth could significantly reduce the potential heave that could occur during the lifetime of the structure.

Structures founded directly in the active zone of the expansive soil profile could suffer serious cumulative damage (Terzaghi et al. 1996). For example, if the foundation system was in the active zone (a shallow foundation), the foundation would move as moisture conditions change in the active zone. This was due to the volume change as a result of seasonal moisture changes (Poorooshasb 1998; Justino da Silva and Marinho 2003; Rogers et al. 1993). Cyclic shrink or swell behaviour of expansive soil usually occurred in the active zone near this layer which could result in damage to structures due to movements (Nelson and Miller 1992; Poorooshasb 1998; Rogers et al. 1993; Cerato and Lutenegger 2006). Changes in the pore-water pressure could occur because of variations in climate, change in the depth to water table, water uptake by vegetation, removal of vegetation or the excessive watering of a lawn.

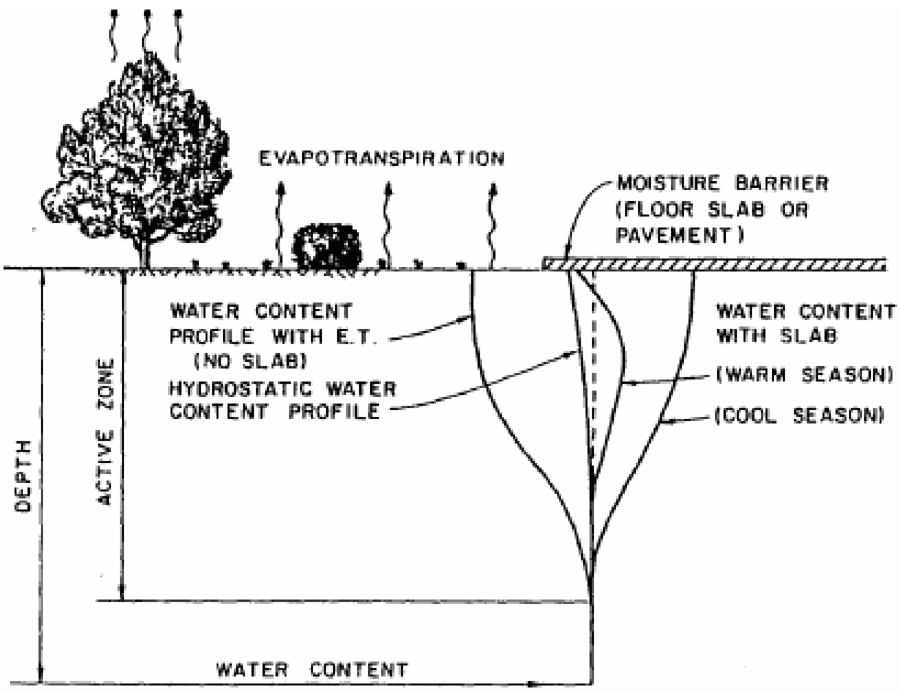


Figure 7: Soil Suction Profile

Soil Suction Value

Soil suction could reach values of several thousands of atmospheres in a dry soil and was expressed on a logarithmic scale termed pF (Gillott 1987). The range of equilibrium suction values recorded was very wide (from less than pF 2.5 to more than pF 5.5). To engineers, it indicated a wide range in value of soil strength and volume change in soils (Aitchison 1993).

Australian Standard, AS2870 1996, used equation (2) for the measurement of soil suction. In most situations according to McKeen (2001), a range of 3pF (98kPa) to 5pF (9800kPa) were reasonable for wet and dry boundaries for suction at the soil surface. For clay soil, the soil water content at wilting point was 39% and 54% for the field capacity (Raes 2002).

The suction values for different conditions of unsaturated soil are shown in Table 2.

$$Soil\ suction\ (pF) = 1 + \log_{10}\left|\left[soil\ suction\ (kPa)\right]\right| \quad (2)$$

Condition	Soil Suction (pF)	Reference
Saturated Soil	0	(Taylor and Cripps 1984)
In Melbourne at Hs=1.9m and $\Delta_u = 0.25$	1.2	(Masia et al. 2004; Standards Australia 1996a)
Soil Desiccation	2.0	Reynolds(1979) in (Driscoll 1983)
Field Capacity of clay	2.3	(Raes 2002)
Wet soil in semi arid climate	3.0	(O'Malley and Cameron 2001)
Lifting a low-rise building	3.0	Reynolds(1979) in (Driscoll 1983)
Ponding of water	3.1	(Lytton 1997)
Desiccation for eucalyptus species in Adelaide	4	(Richards et al. 1983; McKeen 2001; Cameron 2001)
Jacaranda	4.2	(O'Malley and Cameron 2001)
Wilting point	4.2	(Van Genuchten 1980)
Clay	4.2	(Raes 2002)
Blue gum	4.3	(O'Malley and Cameron 2001)
Desiccated tree in UK	4.6	(Bryant et al. 2001)
Dry soil in semi arid climate	5.0	(O'Malley and Cameron 2001)
Dry Soil	7	(Raes 2002; Taylor and Cripps 1984)

Table 2: Soil Suction Values in Different Condition

2.1.6 Summary

In this section, the geology, climate, classification of soil and behaviour of expansive soils for Victoria were discussed. The behaviour of soil was described including the mineralogy, volume change and soil suction. It was mentioned in the previous section that soils with abundance of montmorillonite mineral were the most prone to swelling and shrinking. Thus it made the mineral the most susceptible to greater effect on movement of the structures built on it. The behaviour of soil in terms of absorbing water was studied by looking at how soil suction occurred and the effect of it on the swelling and shrinking of the expansive soils. This included soil suction testing and classification of soil suction values. Soil suction values allowed the prediction of the behaviour of swelling and shrinkage of expansive soil. The understanding of the basic behaviour of expansive soils could be used to determine how the expansive soils influence the damage to light structures founded on them. Therefore, it was essential to include soil behaviour when reporting on damage to structures. However, this was usually not frequently done, as it took time and money. Nevertheless, the inclusion of soil behaviour such as mineralogy and soil suction values was beneficial to predict the magnitude of the soil movement. Not only could these parameters determine the behaviour of the soils but also the effect it had on the light structure.

2.2 Review of the Factors Influencing Damage to Light Structure in Victoria

"Home buyers should know that expansive means expensive, particularly if the problem is not taken into account during design and construction"(Handy 1995)

The unsatisfactory performance of light structures founded on expansive soils subject to seasonal movements were frequently reported since the early 1950's (Holland 1979). The expansive soils were ranked first worldwide of all the natural hazards in terms of damage to structures, and more so to light buildings in the form of cracks for light buildings, often, all attributed to differential movement within the foundations (Karuiki et al. 2002). Excessive movements have caused damages to numerous structures that had not been adequately designed to accommodate the soil volume changes. Types of damage include impaired functional usefulness of the structure, external and interior cracked walls, and jammed and misaligned doors and windows (Department of the Army 1990).

The presence of expansive soil could often be confirmed by the effect of excessive movements on garden walls and other structures on shallow foundations (Freeman et al. 2002). The highest risk situation was where clays extended from the ground surface to at least 2m depth (Cameron and Earl 1982). Experts suggested that changes in the water content of clay soil cause up to 90% of all the cracking problems in houses (Archicentre Ltd 2000). Damage due to expansive soils normally showed up after a long period of dry weather; close in winter, or wet periods, and may re-open during another dry summer (Freeman et al. 2002).

Damages in light structures vary from slight, moderate or severe. Categorization of visible damages in structures was critical for assessing the potential effect of expansive soils. The slight, moderate, and severe categories were in most cases based on crack size and pattern. The classification of damage to foundation movements with reference to walls and concrete floors can be seen in Table C1 and Table C2 in Australian Standard 2870 (Standards Australia 1996a), shown in Appendix 3 and Appendix 4.

In Melbourne, the analysis of damage to public housing stock in the western suburbs of Melbourne such as West Footscray and Maidstone showed increased damage in the last decade (McManus et al. 2003). Increasing complaints of damage in recent times had been reported to the building practitioners (McManus et al. 2003). The danger zones for foundation failures in Victoria according to Archicentre Ltd (2000) were concentrated in the western and north western suburbs with an average of 50% of the houses effected by foundation movement. It was predicted that approximately 30,000 new dwellings/annum will be affected by rising building costs, in Victoria alone, by $AUD 60-90 Million per annum which will increase up to $AUD 400 Million per annum if similar changes occur (McManus et al. 2004).

Researchers had been trying to predict structural movements on expansive soil for years. However, it was not easy as there were many factors that needed to be considered such as the type and behaviour of expansive soils, type of foundations, climates and the presence or removal of vegetations and other buildings. This section dealt with the factors affecting damage to light structures on expansive soils, which included the effect of damages due to structural characteristics, climate, vegetation and leakages.

2.2.1 Effect of Structural Characteristics on Performance

"Structures should be designed to withstand the worst conditions they are likely to experience" (Dahlhaus 1999)

The structural system for a light structure must be capable of transmitting both vertical and lateral loads. For all the loading conditions it was important that the structural system of the house be continuous from the roof through to the foundations with clearly defined load paths (Page 2001). Lightly loaded buildings such as houses were especially vulnerable to damage because these structures were less able to suppress the differential heave of the swelling foundation soil (Canada Mortgage and Housing Corporation 2005).

The types of structure that was usually susceptible to swelling and shrinkage of the soils were the foundations and walls of the light building (Cameron and Walsh 1984). Therefore, civil engineers design footings to counter the upward and downward movements in order to avoid large deflections of the structure, and hence distortion and cracking of walls (O'Malley and Cameron 2002).

2.2.1.1 Influence of Foundation Movements

The footing foundations experienced movements when they were built in and on high swelling clay (Terzaghi et al. 1996). One of the primary functions of the foundation was to transfer total load of the building to the soil as even as possible. It was also to provide resistance to soil movements such as that transmitted to the structures (South Australia Steering Committee 1981). Foundations constructed on highly expansive clay soils were usually susceptible to distress failures (Brown 1984). This depended largely on the amount and location of moisture changes in the soil beneath the foundation and the foundation stiffness (Pengelly and Addison 2001).

Foundation movement was one of the few processes that could cause cracking in both leaves of a cavity wall at approximately the same location (Freeman et al. 2002). It often resulted in cracks at weak points, such as window openings and doors, or at points where there was a change in foundation depth such as the junction bay or an extension with the main structure (Freeman et al. 2002).

The type of foundation was important to determine the stiffness of the structure founded on clay soils. Numerous footing systems and construction methods had been developed over the years to overcome damage to structures (Holland 1981). In Australia, the most common foundation systems used were Raft foundations for Class A and S, Stiffened slab with deep edge beams for Class M, strip footing foundation and strip and pad footings for Class M, H and S (Standards Australia 1996a). Only strip and raft footings were discussed in this section since they were the most commonly used and their performance were the worst in Melbourne.

Strip Footing Foundations

Strip footing foundations were generally constructed of reinforced concrete and support load bearing walls both internally and externally (Holland 1979). Strip footing foundations were vulnerable to sideways and twisting movements even though it could be founded where there was less moisture in the soil (Standards Australia 1996b). These movements caused damage to the light structures. The house perimeter and support strip footing foundations would be subjected to seasonal soil movements owing to annual moisture changes in the clay soil (Holland 1979).

Buildings founded on traditional strip footing foundations cracked badly (Cameron and Walsh 1984; Rogers et al. 1993). Failures of typically sized strip footing foundations as a result of localised swelling following brittle pipe breakages and drying due to adjacent trees were commonly experienced in the Quaternary basaltic clay in Melbourne (Holland et al. 1975).

A survey in Melbourne showed that strip and pad footing systems when combined indicated good performance when correctly specified (Standards Australia 1996b). However, early surveys in Melbourne indicated that 91% of the observed failures occurred in housing around clay soil sites in Melbourne used strip and pad footing systems (Holland 1981). The reason for the different results was that the design for footing foundations did not take into account the change in climate. Standards Australia (1996a) still used the old Thornthwaite Moisture Index map instead of the new modified map (Osman and McManus 2005).

An observation done by Ward (1975) of a 20 year record (1951-1973) of the narrow concrete strip foundations of a typical house at Hemel Hempstead, UK, showed that the settlement continued fairly steadily for the whole period at net rates between 0.12 and 0.39mm per annum with a mean of 0.22mm per annum. Since the house was kept clear of trees and large bushes either immediately prior to construction or subsequently, the settlement was due to movement associated with a major straining of the outer walls causing redistribution of foundation loading rather than seasonal moisture movement of the ground.

Raft Foundations

Raft foundations have the advantage of reducing differential settlements. Raft footings were better suited for reactive clay soils compared to strip footings as stated in Standards Australia (1996b) and Holland *et al.*(1975). The three dimensional action and strength of failure of raft foundations would efficiently defy localised drying effects (Holland et al. 1975). There were no reported tree damage to raft slab foundation in Melbourne owing to its strength (Holland 1979).

Very few failures on raft foundations have been reported in Melbourne since 1968 according to Holland (1975). However, things have changed over the years. In that era, there were no standard designs for foundations. Hence other methods of design were used such as Lytton (1970) and Walsh (1974) (cited in (Holland et al. 1975) theories until 1986 when Australian Standard; AS2870 – Residential slabs and footings construction, were developed.

In an analysis made by Osman *et al.* (2005a), it was found that raft foundations performed the worst in unsaturated soil though they were the most suitable for this type of soil where damage to light structures were concerned. The reason was that the size of the foundation was not sufficient to support the load of the building using the design requirement form AS2870-1996 which had not commented on the potential effect of possible climate change (Osman et al. 2005a). The Australian Standard AS2870 (Standards Australia 1996a) did not update the change in the climate since it was first calculated. It was obvious that the climate has changed over the years (McManus et al. 2003, 2004). However, the standard was still using the old Thornthwaite Moisture Index (1940-1960) instead of the new Thornthwaite Moisture Index 1961- 1990 for the purpose of designing the footings.

2.2.1.2 Influence of Wall Type

Most external walling elements were free to move in upward directions only as the soil and foundation restrains the downward movement (Addleson 1972). Damage such as cracking could only occur when there was settlement on the foundation due to soil shrinkage. However, the type of construction and materials of the wall may prevent its damage, as some of the materials used were flexible.

Usually, the buildings with masonry load bearing walls or frames with masonry in-fill walls were the most sensitive to settlement (Boone 2001, 1996). Walls constructed with Portland cement and harder plasters were stronger but brittle and were more sensitive to smaller differential movement of the foundations (Pryke 1975). Walls constructed with timber or bricks with soft lime mortar could accommodate substantial movement without cracking, as they were relatively flexible.

"Many old houses, such as Victorian and Edwardian ones, were built using lime mortar, which allows bricks to move relative to one another and makes the walls quite flexible. Houses built using lime mortar can often cope with differential settlements of 40mm or more without showing any obvious signs of distress, such as cracking. However, if substantially refurbished, such houses may be as sensitive to movements as modern ones" (Freeman et al. 2002).

Brick veneer constructed houses were not as prone to cracking as solid brick houses in reactive soil areas. Solid brick houses were brittle as it was prone to cracking even when the walls had undergone only small distortion. On the other hand, brick veneer construction with its internal timber framing and plasterboard skin was more capable of absorbing flooring movements particularly within the interior of the house, as it was more flexible.

2.2.1.3 Influence of Vegetation

While vegetation could provide many benefits such as increasing the value of properties and keeping the sites cooler in summer due to their shade, it could contribute problems to properties. During summer, the trees generated large pore water suctions, particularly near the surface causing the ground to shrink and subside. In turn, during winter, the suctions drew water back to the soil allowing the surface soil to recover to its original volume (Page 2003). Vegetation caused moisture depletion from the soil (Sorochan 1991). In the clay soil area of Melbourne, tree drying damage to foundations was very common during late summer and early autumn (Holland 1979). Holland (1979) also stated that a prolonged dry periods significantly reduced the amount of soil water available to the tree and foundation damage may occur due to the likely extended zones of tree desiccation.

Understanding how trees absorbed and removed water could help the engineers in identifying the cause of the structural failure of light structures without jumping to conclusion that it was always due to the presence of trees. However, most of the cases associated with downward ground movement (settlement or shrinkage or desiccation) were caused by the presence of trees. Damage of light structures due to trees was widespread all over the world. Many researchers (Amokrane and Villeneuve 1996; Bryant et al. 2001; Cameron and Earl 1982; Cameron 2001; Cameron and Walsh 1984; Chang and Corapcioglu 1997; Driscoll 1983; Fredlund and Hung 2001; Legget and Crawford 1965; Roose and Fowler 2004; Ward 1954; Wray 1995) have studied the influence of trees to light structures.

A study built on the work of Cameron (2001) related to soil movement was conducted by Jaksa *et al.* (2002). It indicated that tree effects extend beyond the measured depth of 4m and was likely to continue to 6m below the surface. Chandler *et al.* (1992) indicated a depth of up to 8m due to desiccation caused by trees in south east England. Cases of foundation movement in South Eastern England mostly due to trees reported by Driscoll (1984) concluded that 75% fell within and below Damage Category 2, 20% category 3 and the remaining 5% in Category 4 and 5. From an onsite investigation done over the years, tree drying was found to be as deep as 3.6 m in the Melbourne region (Brown 2003). Damage to housing caused by trees generally developed in February to May in Melbourne which was the end of long dry and hot periods (Holland 1979; Cameron and Earl 1982).

In order to gain a better understanding of the effect of vegetation, this section was divided into distance, type, removal and root system of vegetation. These factors were considered to be the most important factors related to vegetation where damage to light structures was concerned.

Distance

Cases of damage to single storey brick veneer construction founded on strip footings and stiffened concrete footings in eastern and south eastern suburbs of Melbourne had been reported most frequently where trees were closer to the building than 0.5 times their height (Cameron and Earl 1982). Ward (1954) stated that on the highly shrinkable clays, trees that transpired large quantities of moisture in summer could damage buildings at distance up to the height of the tree. A survey of 574 buildings conducted in Ottawa, Canada showed differential settlements varying up to 0.3m where rows of large trees were growing nearby (Legget and Crawford 1965). The results of a numerical model based on the general theory of unsaturated soil behaviour demonstrated that the magnitude of structures and soils close to the trees decreased with decreasing water uptake and with vertical and horizontal distance from trees (Fredlund and Hung 2001).

Desiccation due to single or rows of trees can suddenly develop structural damage to structures adjacent to them even though there were no sign of tree damages for many years (Cameron and Earl 1982; Holland 1981). Normally, trees at corners of buildings caused the corners to settle (Cameron and Earl 1982). A case study by

Driscoll (1983) indicated that the rows of trees of heights to up to 20m adjacent to the building were the major cause of damage and the removals could caused further heave hence increased the damage.

The measurements related to a group of large spotted gums in Adelaide, indicated that the trees influenced soil suction when the lateral distance to height was less or equal to 0.8 for a group of trees, was less or equal to 0.5 for single trees (Jaksa et al. 2002). Holland (1979) observed that trees in rows increased the zone of soil drying influence. It was assumed in the foundation design guide that trees in rows will dry the clay to one and a half times their height compared to single trees, which dry clays to their height (Holland 1981). If large bushes or shrubs planted directly along the outside of the building were not watered regularly, they could withdraw water from the edge of the building (Wray 1995).

Type

Driscoll (1983) presented a case study for damage to light structures influenced by vegetation on swelling and shrinking of clay soils in Britain. The case study showed that even though the five London planes were within the zone of influence, they still have an effect on the building nearby. The trend of increasing crack width with time was attributed to the increasing water demand of the growing London plane planted on the pavement near the building. A study in Adelaide, Australia, by O'Malley and Cameron (2001) found that both young and mature trees dry the underlying soil at depth and gave evidence of significant movements.

Removal

Case studies conducted by Richards *et al.*(1983) in Adelaide, demonstrated that vegetation caused movements of buildings of up to 150mm settlement and 100mm heave. In some cases, the removal of vegetation acted as a partial recovery of the differential settlement. Driscoll (1983) showed the influence of the removal of a group of trees nearby the building resulted in heave which caused damage category 3 to most part of the building.

Root system

Studies of soil moisture conditions, ground movements and physical evidence of roots had shown that vegetation could influence the soil under covered areas to a much greater extent than variation in climate alone. Any influence of trees was entirely seasonal; the root activity would create a cycle of seasonal soil drying during the summer and recovery during the winter (Biddle 1998a). Climatic moisture withdrawal from supporting soils was frequently caused by root systems of nearby large vegetation (Pengelly and Addison 2001). The roots of a tree within the moisture active zone could cause extreme variations of suction in the soil, ranging from very wet to the wilting point. During dry season, tree roots draw moisture from the soil (Cameron and Walsh 1984). In dry conditions, roots extended towards more moist ground; the root systems advances relatively fast, 1- 1.5m per season, whereas in wet seasons they may wither back (Pryke 1975). For example, the seasonal fluctuations of suction in the root zone would affect the movement of the soil for a distance of 0.3m to 3.0m from the root zone (Lytton 1997).

A great number of studies performed on root systems of trees to determine the influence, the rate and the part of root systems that take up water. Ward (1954) found that the height of the trees was roughly the guide to the spread of the roots and the extent of damage to brick dwelling houses near trees in the UK. The analysis of root influence model performed by Bryant *et al.* (2001) indicated that the influence of tree roots was a function of the soil type and the influence at the extreme perimeter of the structure was as significant as the penetration of the tree roots significantly beneath the foundation with differential downward movements. Bryant *et al.*(2001) also indicated that the movement was in the order of 127 to 152mm at the perimeter moving from a wet condition ($pF=3$) to a desiccated tree condition ($pF=4.6$) reducing to approximately 5.1cm or less when the tree roots were at least 0.6m from the structure perimeter.

The information on distance, type, removal and root system of vegetation were important in terms of their influence on damage to light structures. A number of studies had been performed on these factors, which indicated the effect they had on soil movement. Therefore, it was useful to incorporate this information to predict damage to light structures. However, not all the information was easy to acquire. For example, it was difficult to distinguish whether vegetation had been removed unless there were reports on the removal or there was evidence of stumps where trees had been cut down. Another difficulty was that the inspection of the root systems was not easy to perform. Usually an expert such as an arborist was needed to perform the task. The information of the trees such as the type, height and age were required in order to make an estimation of the direction and the depth of the root system. Some roots could grow as deep as the tree was high. Knowledge of the in situ soil suction changes around trees was also essential to reliably estimate the ground movement in expansive clay soils (O'Malley and Cameron 2002).

2.2.1.4 Influence of Climate

Seasonal changes in rainfall were typically the principal cause of the change of soil moisture. This led to downward movement during summer and upward movement during winter (Sorensen and Tasker (1976) cited in (Masia et al. 2004; Freeman et al. 1994; Smith 1993; O'Malley and Cameron 2002). The consequent rising and settling of ground surface occurred in the dry and wet seasons resulting in seasonal subsidence and seasonal recovery respectively (Biddle 1998b; Terzaghi et al. 1996).

The results and observations by most of the researchers (Al-Hamoud et al. 1995; Grayson et al. 1997; Albrecht and Benson 2001; Fleureau et al. 2002; Kodikara et al. 1999; Sheng et al. 2004; Sudakhar Rao and Revanasiddappa 2000; Sudhakar Rao et al. 2001;

Tripathy et al. 2002) suggested that expansive soils which experienced periodic swelling and shrinkage during alternate wet and dry seasons caused considerable damage to structures founded on them. The damage to structures built on expansive soil in wet climates usually occurred during drought period. Cracks appeared in the walls of thousands of Melbourne houses built on expansive soils during the long drought in 1982-1983 with the worst being those underlain by basalt (Dahlhaus 1999).

Expansive soils that occurred in arid climates typically did not cause much damage to structures constructed over them unless the clay experienced a major wetting period (Wray 1995). In an arid climate, clay soils were normally very dry with high soil water suction all year round (Holland 1981). Structures in regions, which experienced a semi-arid climate, suffer damage because of annual cyclic rise and fall of the structures. This was due to periods of rainfall followed by long periods of no rainfall. During the rainfall period, the soil became wetter and swells which led to the rise of structures.

The semi-arid regions of the country were much more prone to damage from expansive soils than regions that maintained moist soil conditions throughout the year. Masia *et al.* (2004) successfully measured the unpredictability in ground movements due to seasonal and long term climatic effects and due to the construction date using a numerical model that was capable of generating continuous records over time of 3D soil suction profiles beneath the structure.

The Thornthwaite Moisture Index maps in Figure 4 and Figure 5 showed that the climate had changed over the years and that it was getting dryer. Thus, the structures founded on expansive soils in this region suffered more damage than for which they were first designed. It was known that foundations in expansive soils experienced severe distress in arid and semi-arid areas characterised by Thornthwaite Moisture Index more negative than -10 (Lytton 1997). It had been suggested by Jayatilaka *et al.* (1993), cited in (Evans et al. 1998), that regions whose Thornthwaite Moisture Index lies between -5 and -15 would produce the greatest seasonal vertical movement. These regions were located in the Melbourne area and areas to the west of Melbourne.

The knowledge of climate was vital in the prediction of damage to light structures on expansive soils. It was shown in the previous section that climate was changing over the years thus influencing the design of the structures. The disadvantage of this was that it was intricate to obtain information on climate. For example, the most accurate way of taking climate into account in damage prediction was to observe the damage over a long period of time taking into consideration other natural disasters such as flooding and drought. This way, a more accurate estimate of the level of damage due to climate change could be estimated. Nonetheless, other means of information on climate such as the average rainfall (over a period of time or seasonal) or Thornthwaite Moisture Index maps and the change in Thornthwaite Moisture Index (change in climate) could also be used for this purpose as was done in this research project.

2.2.1.5 Influence of Broken Drainage Pipe

Plumbing leaks, bad drainage, site aspect, and garden watering could lower soil suctions under a building, and were the contributors to foundation movement (Pengelly and Addison 2001). If water or sewage pipes break, then the resultant leaking moisture could exacerbate swelling damage to nearby structures. For example, shallow pipes, especially plastic pipes, buried in the zone of seasonal moisture fluctuation, were exposed to enormous stresses by shrinking soils (Rogers et al. 1993). This could lead to structural damage to the light structures such as cracks, floor humps, and movement of foundation due to localized heaving near the leak. For cases such as a poor drainage, it could result in a condition where the entire depth of potential heave was wetted during the life of the structure (Overton et al. 2006).

Soils with both low and high percent swell potential have reached approximately 97% of their maximum heave in 100 years as the case for sites with poor drainage

(Overton et al. 2006). The effect of a leaking water line was dependent on the soil moisture condition in the supporting expansive soil mass prior to the leaking occurring (El-Garhy and Wray 2006). Dishing of floor systems due to clay heave under the footings could occur when excessive water was present due to site leakage at the edges of the structure. This may continue for 4 to 5 years unless the leakages are fixed (Holland 1981).

A site leak near light structures, particularly near foundations was severe especially during rainy seasons. However, during dry weather, a leaky drain may protect the foundation that was surrounded by water during wet weather (Pryke 1975). The expected heave rate for a site with poor drainage may be almost an order of magnitude greater than that for a site with a good drainage (Chao et al. 2006). A two-dimensional finite element model experimented by Li (2006) indicated that a leaking underground water pipe could cause more severe distortion of the footing than the seasonal climate changes. It also showed that a water pipe leaking beneath the footing could cause a much larger distortion in the slab than if it had leaked outside of the footing (Li 2006).

Even though important, it was hard to judge whether the damage was due to leakages or broken pipes. This was because a thorough investigation was needed to be conducted, as the cause of the leakages usually was not present overnight. The "distortion" due to leakages usually occurred over a period of time. Hence, unless swelling was still present during dry season, then it could only be assumed that there was a leakage nearby the foundation or the light structure. Even so, it was essential to include this parameter as it was considered to have a dramatically effect on the movement of light structure.

2.2.2 Summary

The factors influencing movement of light structure in Victoria were reviewed in this section. The change in climate, site factors such as presence of vegetation and leakages, and the structural characteristic were the factors that have the most influence on the movement of light structures. Changes in climate influenced the seasonal and long-term effect of the volume change of the soil thus leading to movement. In addition, vegetation caused movements of buildings of up to 150mm settlement and 100mm heave. Clay heaved under the footing due to pipe leakage to continue for 4 to 5 years unless the leakages were fixed. Another factor that influenced the movement of structure was its structural characteristic. These factors depended on the ability of the structure to absorb movement. Raft foundations have the advantage of reducing differential settlements and they were the most suitable foundation in expansive soils. However, in one of the analysis done by Osman *et al.* (2005a), it was found that raft foundations performed the worst in unsaturated soil. The reason stated that the design requirement did not take into account the climate change over the years. As for the wall type, brick veneer was less prone to damage due to its capability of absorbing flooring movements.

2.3 Review of Application of Artificial Intelligence Techniques

Various approaches were considered by researchers such as mathematical and statistical methods to predict the damage to structures and to predict the design requirements of the construction types to resist such damage. However, there were limitations to the models mentioned. The main disadvantage of statistical methods was that the data was usually sparse, especially for general concepts in technical texts or technical concepts in general or irrelevant texts. Another disadvantage was that it was very specific in identifying only one parameter or factor. For example, during the data exploration the user had to perform repeatedly a set of some elementary operations to obtain different results for different parameters. Different tools were needed to perform more fine-grained architectural analysis of network structure and performance

Many statistical methods required assumptions to be made about the format of the data to be analysed. There were situations in which even transformed data may not satisfy the assumptions. Its accuracy could not be improved because predictive variables could not be added to the model without increasing the model's complexity to the point where it was not longer useful. This method may only be applied to networks that were sufficiently large to provide statistical significance, eliminating consideration of this type of analysis for many network models. On top of that, it did not combine parameters that may influence damage to structures. For example, most of the soil suction testing performed only one task which was determining the behaviour of soil in terms of the change in volume.

Fortunately, there were other alternative approaches in analysing and developing a model. With the advance of computer technologies and available softwares, it was essential to look at other methods related to these advances. Combining many simple processing units together could lead to an overall increase in computational power McCulloch and Pitts (1943) (cited in Demuth, H and Beale, M (2001). The results obtained using Artificial Intelligence techniques in terms of the ability to predict an outcome was promising. It could learn unknown functional relationship that was difficult to predict compared to more conventional methods such as statistical method. Due to the many advantages of Artificial Intelligence techniques, they were chosen to develop a Predictive Damage Condition model in this research project. A brief background and related models were discussed further in the next section.

Artificial intelligence techniques were used in predicting the behaviour of expansive soils and the location and time of damage to light structures founded on expansive soils. Most of the studies involved the investigation and prediction of movement of individual structure in a building, for example beams and footings caused by seismic movement and founded on non-expansive soils such as sand. The techniques were however, seldom used to predict settlement of foundation on cohesive soils such as clay. A hybrid Neural Network trained with Genetic Algorithm was adopted in this research project.

2.3.1 Neural Network

A Neural Network is a computing paradigm inspired by the human brain. It consists of an interconnected group of simple processing elements, called neurons that are working together to generate an output function. McCulloch and Pitts (1943) (cited in Demuth, H and Beale, M (2001) were generally recognised as being the designers of the first Neural Network. As in nature, the Artificial Neural Network changed its connection structure based on information that flows through the network. The output function was largely determined by the connections between the processing elements. The goal of the network was to learn or to discover some association between the input and output patterns, or to analyse, or to find the structure of the input patterns (Abdi 2003). Figure 8 shows the relationship between biological and artificial neurons.

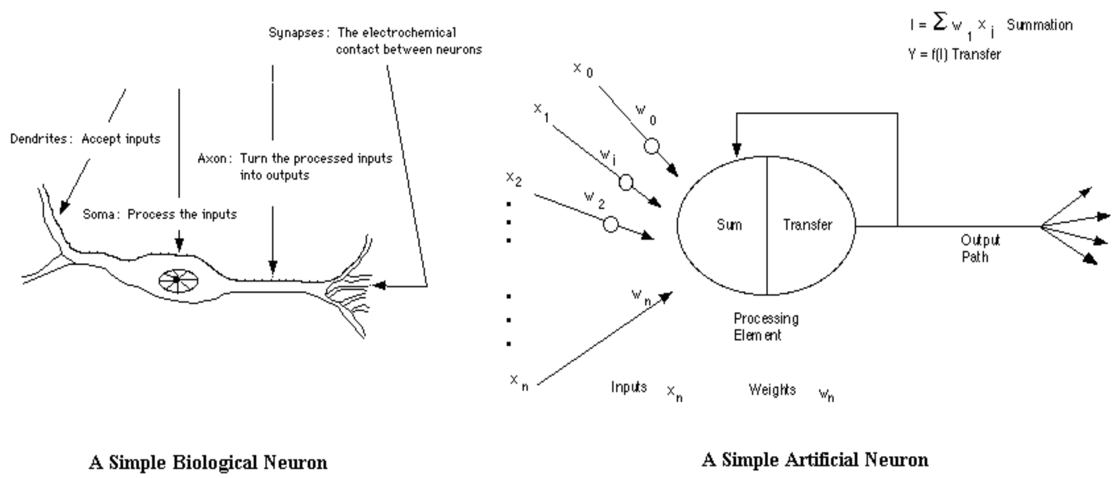


Figure 8: A Comparison of a Biological and an Artificial Neuron

The learning or training process was achieved through the modification of the connection weights between units. Given a sample of input and output vectors, a Neural Network "learns" this relationship, and stores this learning into their parameters (Maqsood et al. 2002). Neural Networks could also be used to determine, which variables or parameters were important and to build a model relating to those parameters (Bigus 1996). This was the key aspect of the Neural Network that were used in this research project as one of the objectives of the research study was to rank parameters that caused damage to light structures. The ability of Neural Network to learn automatically from examples made it attractive (Knutti et al. 2003).

2.3.2 Genetic Algorithm

Genetic Algorithm, based on a Darwinian-type survival of the fittest strategy was invented by John Holland in the 1960's (Mitchell 1996). Most organisms evolved by means of two primary processes: natural selection and sexual reproduction (Holland 1992). The first determined which members of population survived and reproduced, and the second ensured mixing and recombination among the genes of their offspring. Potential solutions to a problem compete and mate with each other (cross-over) in order to produce increasingly stronger individuals. This mixing allowed creatures to evolve much more rapidly than they would if each offspring simply contained a copy of the genes of a single parent, modified occasionally by mutation (Holland 1992). Genetic Algorithm worked on a random set of points in the population by using a set of operators that were applied to the population. The different operators were scaling, selection, reproduction, crossover, migration and mutation. The specific properties of the operators and the dependencies between the operators to produce Genetic Algorithm for this research project were discussed in detail in this section. This was to better understand how the relationship of these properties and dependencies defined an optimization algorithm with certain properties. Along with the choice of an optimisation algorithm (combination of operators), the behaviour of the optimisation algorithms could be controlled via a number of options (Pohlheim 2005).

The application areas of Genetic algorithms were numerous as they have a number of advantages including the following (Kalate et al. 2003):

- *Genetic algorithms perform global search as against the local one performed by the gradient-based methods. Thus, Genetic algorithm was most likely to arrive at the global optimum of the objective function.*
- *The Genetic algorithms search procedure was stochastic requiring only values of the function to be optimized and it did not impose preconditions such as smoothness, derivability, and continuity, on the form of the function.*
- *Genetic algorithms could easily handle functions that were highly non-linear, complex, and noisy; in such cases the traditional gradient-based methods were found to be inefficient.*

2.3.3 Models Using Artificial Intelligence Techniques

Examples of Artificial intelligence techniques using Neural Network and Genetic Algorithm included work by Habibagahi and Bamdad (2003), Hao and Xia (2002), Maity and Saha (2004), Ratnam and Parameswara (2004) and Shahin *et al.* (2001; 2005). Maity and Saha (2004) presented a model to locate and assess the damage occurring at any position in a cantilever beam by back-propagation Neural Network considering displacement and strain as input parameter to the network. From the review conducted by Shahin *et al.*(2001), it was evident that Neural Network were applied successfully to many geotechnical engineering areas which included pile capacity prediction, settlement of foundations, soil properties and behaviour, liquefaction, site characterisation, earth retaining structures, slope stability and the design of tunnels and underground openings.

Ratnam and Parameswara (2004) proposed a technique for the detection of macroscopic structural damage in elastic structures performed with Genetic Algorithms. While Hao and Xia (2002) have demonstrated that the method with a real-coded Genetic Algorithm gave better damage detection results in a laboratory tested cantilever beam and a frame structure. Neural Network was also used to predict the settlement of shallow foundation on cohesionless soils by Shahin *et al.* (2005; 2002). The satisfactory results from Neural Network indicated that Neural Network outperformed the traditional methods by Mayerhof (1965), Schultze and Sherif (1973) and Schmermann et.al (1978) (All cited in (Shahin et al. 2002).

The studies showed that the uses of Artificial Intelligence technique were numerous. It demonstrated that the techniques gave more accurate and better results compared to more conventional methods such as statistical methods. Even though these techniques were found to give more reliable results than the conventional methods, only few studies have been done on expansive soils. Most of the studies focused mainly on cohesion-less soil such as sand. All the results were outstanding and the techniques were applied successfully in most of the engineering fields. Hence, it should be used extensively in the engineering field especially with problem soils such as clay. Therefore, due to the lack of these techniques used in predicting damage condition of light structures on expansive soils, it was adopted in this research project.

2.4 Review of Australian Standard AS2870 and Its Shortcomings

Australian Standard AS2870 was used in the design of light structure since 1986 and was included under the Building Code. Most local authorities have adopted it as part of their standard of building practice. Prior to this, other standards such as Uniform

Building Regulations and Victoria Building Regulations were adopted. The much older Victorian Uniform Building Regulations came into force in 1958. Victorian Building Regulations was enacted in 1984.

Australian Standard was used to establish performance requirements and specific designs for footing systems for foundation conditions. It particularly focused on the design of reactive clay sites susceptible to ground movement due to moisture changes (Standards Australia 1996a). There were four amendments from 1997 to 2003. However, the amendments did not take into account the change in climate and surface movement, y_s. The assessment of the depth of design suction change, Hs, was needed in residential footing design, surface movement and site classification and could be estimated by using Thornthwaite Moisture Index (Smith 1993; Walsh et al. 1998).

2.4.1 Climate

The extent of the moisture change that the clay would undergo was largely a function of the prevailing climate (Standards Australia 1996b). The change in climate may affect the performance of standard footing and slab designs in the Australian "Residential Slabs and Footing" Standard. The changes in climate definitely have an effect on light structures founded on expansive soils in Victoria. There was evidence of damage to light structures especially in the western part of Victoria. Analysis of damage to public housing in the western suburbs of Melbourne showed increased damage in the last decade with increasing complaints reported by building practitioners (McManus et al. 2004).

The climatic zone and Thornthwaite Moisture Index map that were used in AS2870 was from the Year 1940-1960. McManus *et al.*(2004; 2003) showed that the climate of Australia have changed over the years since it was last calculated by Stephens (1964) (cited in (Aitchison and Richards 1965b). McManus *et al.*(2004; 2003) have calculated new Thornthwaite Moisture Index values for 1961-1990 which indicated that the climate was drying out throughout Australia. The new Thornthwaite Moisture Index calculations confirmed the belief that the Australian climate has generally became drier since the last period (1940-1960) calculated by Stephens (1964) (cited in (Aitchison and Richards 1965b).

There were significant changes between the old map (1940-1960) and the new modified map (1960-1990) as in Figure 4 and Figure 5 respectively. The positive values of the Thornthwaite Moisture Index indicated that the area was relatively wet while the negative values showed the relatively dry areas. In the new Thornthwaite Moisture Index map, the gaps of the isopleth were bigger compared to the old ones. For instance in the west of Victoria where there used to be 4 lines of isopleth (TMI -25,-5, +120 and +40) it had became only two lines; TMI -25 on the North and TMI -5 on the south of Victoria. It was also noted that on the east of Victoria, TMI +40 in the old map had changed to TMI +10 in the new map, which indicated the drying out of the climate in Victoria. Another example of the change in climate could be seen on the south west Victoria where TMI +40 in the old map changed to TMI – 5 in the new map.

The change in Thornthwaite Moisture Index resulted in the change in climatic zone. These changes in climate affected the performance of “deemed to comply” footing and slab designs. Where the climate zones have become one category drier, the Characteristic Surface Movement have increased by about 50% (McManus et al. 2003).

2.4.2 Design Suction Change (Hs) and Surface Movement (Ys)

The degree of clay movement depended on the nature of the clay, its depth, change in moisture content, and the ease with which water can soak into the clay (Standards Australia 1996b). The Standard described the properties of the foundation by the expected surface movement. This was the vertical movement range expected during the life (50 years) of the house (Standards Australia 1996b). The assumption was from a reasonable estimate of dry conditions to a similar estimate of wet conditions. It did not take into account the moderating effect of the footing system.

The theoretical depth of surface movement in Melbourne according to AS2870 (1996) varied between 1.5 and 2.3m, depending upon the climatic zone. Deep-seated movements of greater than 3m were possible outside Melbourne area, where semi-arid regions occurred, especially in the west of Victoria (AS2870, 1996). The change in climate may affect the performance of standard footing and slab designs in the Australian "Residential Slabs and Footing" Standard. Where the climate zones have become drier, the y_s would increase. A change in the climatic zone from zone 2 to zone 3 increased the Hs from 1.8m to 2.3m. Thus, increased in the y_s , by 28%. Where there had been a change from zone 2 to zone 4, the Hs increased from 1.8m to 3m increasing the y_s to 67% (McManus et al. 2004).

Fityus *et al.*(1998b; 1998a) discussed in detail of the development of a contour plan of Thornthwaite Moisture Index for the Hunter Valley which provided improved estimates of design suction change needed for estimating surface movement and defining site classification in accordance with AS2870. Water balance method, a representation of moisture movement, provided a rational means for predicting soil suction, pF, changes due to climatic condition. Two study areas in Newcastle, Australia showed identical values to that predicted using AS2870 where the maximum change in pF corresponding to movement was 1.5pF and the predicted surface movement of 65mm (McPherson and Swarbrick 1995). Contrary to this, the change in pF for another site in Newcastle completed by Fityus *et al.* (2004; 1998a) exceeded 0.5pF compared to the one given in AS2870 which stated that the value suggested by AS2870 was not appropriate for Newcastle region.

The same method was used by Fox (2000) to assist practitioners in all states in Australia in the calculation of surface movement to determine the classification of sites under AS2870. An example of surface movement calculated using the map was done for a house site at Biloela, Queensland in climate 4 zone with Hs = 3.0 m, changed in Hs of 1.2pF and shrink-swell index, Is, of 2.5% which gave results of 55mm for surface movement indicated that the site to be a class H according to AS2870-1996. Walsh *et al.* (1998) recommended value of Hs for Perth to be 1.8m, a significant decreased from 3.0 m given by AS2870. Due to the very arid conditions, the value of Hs could be even greater than 4m hence an additional Zone 6 for Western Australia should be included.

If these new Zones were to be accepted, many building sites would require more costly footings. More over, footings for existing structures may be subjected to soil movements greater than anticipated when constructed (McManus et al. 2004). Therefore, amendments of the Australia Standard, AS2870; taking into account the change in climate, surface movement and design suction changes would be required.

2.5 Available Database Formats and Their Influences on A Potential Model

Unfortunately, there were very few instances in Australia in which a desirable level of complete investigation of damage to light structures on expansive soils were performed. Aitchison *et al.* (1965a; 1969; 1969) reported studies of shallow foundations on expansive clays in the Adelaide region and Holland *et al.* (1979; 1981; 1981; 1975) reported on housing foundation failures on expansive soils in Melbourne region. Few more recent studies were performed on the damage of light structures on expansive soils in Australia by researchers such as (Brown 2003; Brown and McManus 1996; Cameron and Earl 1982; Cameron 2001; Cameron and Walsh 1984; Cameron and Yttrup 1992; Jaksa et al. 2002; Lopes and Hargreaves 2004) as mentioned in the previous sections.

The worldwide interest in research on expansive soils in the last four decades resulted in numerous methods being proposed for the prediction of soil movement (SoilVision Systems Ltd. 2005). Although an analytical tool for the prediction of movement was extremely important, there had been a slow advancement in the development of such a tool for solving practical engineering problems. Historically, there did not appear to be a computer program that were written and widely accepted for the prediction of movement in expansive soils. The non-existence of organised database or collated account of defined reports on damage to light structure on expansive soil was a major factor for the development of a predictive damage model.

The main objective of the research project was the development of a Predictive Damage Condition model for light structures on expansive soils in Victoria. The limited studies available were still insufficient to permit the compilation of an overall pattern of the factors attributing to damage to light structures on expansive soils in Victoria based upon quantitative data. However, the incomplete data that exist were sufficient to permit an assessment of these attributes. The assessment was best presented through observation or reports on the frequency and severity of occurrence of damage to light structures on expansive soils in Victoria. In the absence of specific work in the studies on damage to light structures founded on expansive soils, previous studies in different parts of the world had been extensively reviewed.

It was expected that the predictive model for light structures founded on expansive soil could assist the practitioners in predicting the damage condition of any type of light structures. The model was developed by using a hybrid Artificial Intelligence technique. These techniques were chosen due to the lack of this method being used to predict damage to light structures founded on expansive soils. Neural Network was chosen because it is robust when faced with a small number of data points. It was also fault tolerant and can work even with noisy, overlapping, highly non-linear, missing data and non-continuous data because processing was spread over a large number of processing entities (Garson 1998a). Genetic Algorithm was chosen because it is heuristic, derivative-free optimisation method compared to conventional programs.

2.6 Conclusion of the Literature Review

The review of the factors influencing damage to light structure in Victoria, application of Artificial Intelligence techniques, Australian Standard AS2870 and their shortcomings as well as available database format and its influence on the development of models were performed.

The geology, climate, classification of soil and behaviour of expansive soils for Victoria were discussed. The mineralogy and the ability of the soil to undergo a change in moisture content or soil suction were discussed. The methods for the expansive soils behaviour and its identification were examined. The methods covered were the indirect and direct tests to identify the behaviour and the potential severity of swelling and shrinking of clay soils such as filter paper and Soil Water Characteristic Curve. Artificial Intelligence methods, Neural Network and Genetic Algorithm were studied in terms of determining the behaviour of the soil and the damage identification of structures. However, the limitation in these methods was that only a few of the studies observed relate to expansive soils.

It was shown in the literature review that effect of climate and vegetation contribute greatly to the behaviour and the movement of the light structures on expansive soils. The structural characteristics for the light structures were also studied. The influence and the ability of the type of foundation and walls in terms of the severity of the damage caused by the soil movement were noted.

It was also noted from the previous sub-sections that various approaches had been considered by some researchers such as mathematical and statistical approaches to predict the damage to structures and to predict the design requirements of the construction types to resist such damage. Other studies showed that the use of Artificial Intelligence techniques gave more accurate and better results in complex engineering problems compared with conventional methods. Hence, the later method was chosen for the development of the Predictive Damage Condition model.

The shortcomings from a simple model such as AS2870 and the non-existence of organised database were also noted. Among all the models, approaches and case studies performed by researchers, there had never been any development done on a Predictive Damage Condition model of light structure on expansive soils any where in the world. The existing models mentioned do not satisfactorily resolve the problem in damage to light structures in Victoria, thus a development of a model was required. The development of a Predictive Damage Condition model was drawn by the shortage of defined quantitative studies and methods of selecting the factors that influenced the damage to light structure on expansive soils. Therefore, there was a need to consider these factors which were mentioned earlier in the development of a Predictive Damage Condition model.

The following chapters of this thesis included the database management, development, analysis, testing and outcome of a Predictive Damage Condition model, as well as conclusion and recommendation.

Chapter 3

DATA MINING

"Data mining is the efficient discovery of valuable, non-obvious information from a large collection of data. Data mining centres on the automated discovery of new facts and relationships in data" (Bigus 1996)

This chapter placed emphasised on the preparation and management process of the data obtained from Building Housing Commission reports. There was no existing specific and fully relevant database readily available from Building Housing Commission, except for the incomplete paper-based and electronic-based reports. It was mentioned that the Building Housing Commission reports have some shortcomings, which would need to be resolved before the data could be used to create a Predictive Damage Condition model. Data mining or knowledge discovery was used for this purpose. It was the search for the discovery of valuable information in large volumes of data that were previously unknown (Cabena et al. 1998; Weiss and Indurkhya 1998).

Two databases were proposed to assist in the selection process of the data from the reports. One was called “Data Warehouse” that stored all the information from the Building Housing Commission reports. The other was called “Data Mart”, a “compressed” version of the data warehouse and was mainly used for analysis. A clear statement of the objective was always an advantage in order to set up the analysis correctly (Giudici 2003). The objective of this research project as mentioned earlier was to develop a Predictive Damage Condition model for Light structures on expansive soils in Victoria.

Two main steps in the process of data mining were used for Building Housing Commission reports. Data mining started from a massive quantity of data which would then be selected and pre-processed in a database which was called the “Data warehouse”. The data from the Data Warehouse was to be transformed into a smaller database called the “Data Mart”, which focused on the main subject for analysis. These two processes refer to Data Preparation. The second step to data mining was the development of a data mining algorithm which was used to check whether the factors chosen in the data mart were correct. This was done using two statistical methods; categorical regression (CATREG) and a Chi-Square test.

This chapter of the thesis examined the existing database for deficiencies and then proposed a database which could assist the Building Housing Commission to perform a simple and uniform data entry of reported damage to buildings. It included data preparation, data coding, management of missing values or data, as well as checking the accuracy of the chosen factors or parameters in the data mart. First, the shortcomings of the Building Housing Commission reports were discussed to understand the need for a data mining process.

3.1 Building Housing Commission Reports and Its Shortcomings

More than 600 reports dating from 1980 to 2003 were reviewed for the purpose of analysing damage to light structure due to soil movement. The condition of the building assets was not monitored on a regular basis. The problems of the reports were that the reports were (i) not scientific and uniform, and, (ii) not consistent where some of the reports had missing attributes.

The Building Housing Commission reports were recorded by different engineering companies based only on the tenants complaints concerning damage and site investigation of the properties. This resulted in a series of disparate reports containing dissimilar information. The damage was inspected by internal Building Housing Commission inspectors who reported on the deterioration in terms of which building trades would be involved in the repair works and the extent of their involvement. A thorough diagnosis of the damage and geological site investigation was then conducted by Consulting Engineers using their own version of a paper-based report. Therefore, it was expected that the information in the reports were different and some would be lacking important information such as structural systems, footings and foundations, climate, soil classification or geological site, vegetation, leakages and many more. This in turn made it difficult to analyse the data with as many possible factors and as accurate as possible.

Since the reports were not consistent, some information extracted from the Building Housing Commission reports was omitted or more information added in order to produce a quality database. In the case of missing attributes, an alternative way of gathering information was used. Relevant and useful factors in predicting the damage to light structures had to be compensated by other means such as using Geological (Mc Andrew 1965), Thornthwaite Moisture Index (Aitchison and Richards 1965b; McManus et al. 2003), and vegetation (Bureau of Rural Sciences 2003) maps. These are shown in Figures 2, 5 and 6 as well as Appendix 5 respectively. With the combinations of the readily available and additional information, the development of the model and its analysis was able to be performed.

Even though the reports were collected from one source (Building Housing Commission), different engineering consultants were appointed to investigate different properties that were reported damaged. In the 1980 to early 1990's, the reports were hand-written or typed using a typewriter. Hence only hard copies were available. In the mid 90's, the reports were typed using a computer and some of the reports were stored in both soft and hard copies. Therefore, reading and extracting all required data from different forms of report was a difficult part of the data preparation. In order to produce a quality database, one must know which information was relevant, redundant or suspicious. A major source of error in the data gathering stage was the manual entry of the data, which can result in mistyped data or lead to incomplete or missing data (Tamraparni 2003). Possible solutions for handling missing data are discussed in section 3.4.

As mentioned earlier there were shortcomings of the Building Housing Commission reports that had to be resolved. The shortcomings can be summarised as follows:

- ***Structural System*** – *The structural system here referred to the wall and frame system of the light structures. The types of walling or frame system of the light structure were essential to determine why the damage was slight or severe. Brick for instance was brittle and the most vulnerable to cracks due to foundation movement. Therefore, knowledge of the type of the structural system could assist in assessing the severity of the movements and the damage that occurred. It would be useful if all the reports included structural system of the property. However, only few reports placed emphasised* *on the information on structural system, both interior and exterior wall as well as the frame system.*

- ***Footing and Foundation*** *– The most vulnerable to expansive soil movement was the footing and foundation of the light structure. Therefore, knowing the type, depth and the size of footings and foundation was very useful in order to examine how different types of foundations were more vulnerable than the other. Unfortunately, not all the Building Housing Commission reports included the foundation types. Almost all of the reports did not have information on the sizes of the footing and foundations. Hence, the lack of vital information would influence the analysis. It was recommended that this information be added in future reports to improve the analysis and the accuracy of damage to light structures.*

- ***Climate*** *– Another essential factor was the climate. Climate influenced expansive soils greatly in terms of seasonal shrinkage and swell tendency of the expansive soils. No records on climate conditions at the time of inspection could be found in the Building Housing Commission report. However, an alternative way of including the climate in the database was by referring to the Thornthwaite Moisture Index map (Aitchison and Richards 1965b) (Figure 5) that was readily available. A new Thornthwaite Moisture Index map modified by McManus et al. (2003) (Figure 6) was also used for the sake of comparing the effect of climates on the damage to light structures on expansive soils.*

- ***Soil Classification or geological Site*** *– Even though this information was very essential to indicate the soil or geology type of a site, unfortunately not all the Building Housing Commission reports have included them. This information could distinguish the cause of the severity of the damage. For example, a site H was more prone to movement than site S or a site with*

Tertiary rock was more prone to damage than a Silurian site. A geological map (Figure 1) was used for ease of analysis due to the lack of information on this factor in the Building Housing Commission reports.

- ***Vegetation*** *– Most of the reports did not specify the existence of vegetation or gave more detailed information on the vegetation, which should include the type, size, and distance of the vegetation to the house. This particular information was very important as these are the factors that can be the main cause of the movement to a property. Since this information was useful, a relevant vegetation map as shown in Appendix 5 (Bureau of Rural Sciences 2003) was used to compensate the lack of information.*

- ***Leakages*** *– Information of leakages such as pipe burst, water main cracks etc. would be useful in understanding why damage occurred. However, most of the Building Housing Commission reports were totally lacking this information. Unfortunately, there was no alternative way to include this useful factor. Hence, it could not be included in the database for analysis.*

- ***Age/Year*** *– Other information that was lacking and should be incorporated in the Building Housing Commission reports included the age of the structure, the construction year and the year the tenant complained. Age of the structure was useful because, from this information, the design standard, types of materials used for the structures could be determined. The quality of the materials and the design standard, for example, during and before World War II was much different compared to recent time. Construction year and the year the tenant complained were other factors that were lacking in the Building Housing Commission reports. Had these factors been included, there would be a better chance in knowing the time the damage occurred; for instance whether during flooding or drought seasons.*

3.2 Data Preparation

Ideally, a good database contained consistent and quality data collected by a trained team of experts based on uniform standards. The first step towards the development of a database was to identify and define the objectives of the analysis. Definition of the objectives involved defining the aims of the analysis. The objective of this thesis was mentioned earlier; to develop a Predictive Damage Condition model for light structures on expansive soils in Victoria. Hence, the important factors and the interaction between the factors (if any) that influenced damage to light structures on expansive soils would be essential. The selection of data from the report was crucial for the analysis of the database. It provided the fundamental input for the subsequent data analysis (Giudici 2003).

3.2.1 Data Warehouse

A data warehouse is a central storage of data that has been extracted from operational data (Weiss and Indurkhya 1998). The key idea of a data warehouse was to make critical information available that can be used for further analytical processing and decision making (Weiss and Indurkhya 1998). The data warehouse contains very large data set since the information in it is subject-oriented, non-volatile, and of an historic nature (Adriaans and Zantinge 1996).

The available raw data, from approximately 600 reports from Building Housing Commission were transformed into a common data format. This was simply done by identifying and extracting the most common information plus other information that might be of importance from all the reports. This included other information such as climate and geological condition that might be useful for the analysis. Since the reports were not uniform, it was useful to include the most common and useful information extracted from the reports in the database even though not all the information would be used for the development or the analysis. These data from different sources were then integrated into a central database. The data warehouse stored all information that could be extracted from the reports.

The Building Housing Commission reports contained information of the damage properties which included the following categories as shown in Appendix 6:

- ***Consultant's detail*** *–included the name and address of the consultant who was responsible or appointed to inspect the property*

- ***Property Information*** *– included the Local Government Authority number and the address of the house*

- ***Building Information*** *– referred to the type of building, year built or age of the property, year of first inspection and the construction type including types of foundations, slabs and walls of the property*

- ***Site Information*** *– included the soil class, presence of trees, height, location in regards to the house, and type of trees*

- ***Consultant's diagnosis*** *– referred to the consultant's diagnosis on the condition of the property such as cracks; size, severity and location of cracks in the house, settlement of foundation, other problems with the property and also the damage classification of the property according to AS 2870, 1996 (Standards Australia 1996a, b). Here, the causes of the damage were also assessed for instance due to heave or nearby trees (Standards Australia 1996a)*

- ***Schedule of work*** *– referred to the consultant recommendation of the work that needed to be done to the property and the priority of the repair*

- ***Estimated cost of repairs*** *– referred to the consultant's estimated cost of repairs on the property valid at the time of the inspection.*

All relevant information from the above mentioned categories in the reports were included in the data warehouse. The consultant's details and schedule of works were not included. These categories were not relevant as they were only recommendations for possible repairs. A few other categories such as the climatic zone and the source of report (electronic or paper-based) were also included in the data warehouse. The later helped to trace back the original report just in case there was a dispute in data entry. The categories in the Building Housing Commission reports were used to group the data

3.2.2 Data Mart

From the data warehouse, a new database called data mart was created. Data Mart was a subset of data warehouse and it focused on a particular subject. Data extracted from the data warehouse might need additional transformation to produce a uniform and standard database for preliminary analysis. Only relevant categories from the data warehouse were chosen and included in the data mart. The important categories for the analysis were chosen based on studies of relevant and related work performed on expansive soils. This was referred to in chapter 2: literature review.

New variables had to be included since the analysis was dealing with damage to light structure in regards to soil moisture; the factors influencing the damage had to be considered. This included climate (Thornthwaite Moisture Index), structural system (Wall Construction), foundation system, age, soil characteristics (Geology), vegetation, site leakages and pre and post construction. From the literature review section of the thesis and the Building Housing Commission reports, these factors proved to be the most common damage factor potential.

The data and variables of the data warehouse (Appendix 6) underwent transformations before they can be inserted in the data mart as foundation of further analysis. Table 3 lists the recommended categories and variables that were adopted in the data mart.

CATEGORY	VARIABLES
Property Information	Geographical region (GR)
	Construction Footing (CF)
Building Information	Construction Wall (CW)
	Age of building (Age)
	Climate
Site Information	Geology
	Vegetation
Consultant’s diagnosis	Damage Classification (DC)

Table 3: Categories and Variables for the Data Mart

- *Category: Property Information*

This category included all general information for identifying, locating and describing the property. This information was relevant for the purpose of analysis to indicate the frequency of the damage taking place in a particular region or suburb. This allowed the creation of reports showing the vulnerability of particular suburbs or other regions to damage caused by expansive soils. The variables in the category “Property Information” had to be transformed into a new variable called region according to their postcodes, which allowed a sufficient granularity for the damage analysis caused by expansive soils. Different regions would have more than one postcodes. However, an analysis found that the suggested categorisation was too detailed for analysing the available data, so that a coarse grouping according to the regions in Victoria, shown in Figure 9 was used in the Datamart.

Figure 9: Victoria's Regions

- *Category 2: Building Information*

The type of construction was significant to identify which type of construction was most suitable for a particular geological site. Therefore, the indication of types of footings, walls and age of buildings were valuable for identifying which type of construction was more susceptible to damage. The information of the sizes of the footing was also an advantage. The age of the building or the year built was also useful as they indicated how old the building was and the availability of the building materials used and also the site conditions. Only three were taken into account which were *the* type of footings, *type of walls* and *age.* These variables were the only variables that were the most reported, though not by all engineering firms. These variables were valuable to predict the damage to light structures. Age could indicate the availability of the materials and the change in climate during construction.

- *Category: Site Information*

Vegetation – Only 10% of all reports mentioned detailed information on type, distance and size of vegetation on the site. Indeed, it would be better to have more details on the type of vegetation as different vegetation has different root types where some of them can tolerate drought while others cannot. However, since the report was not uniform, most of the reports were lacking this information. Therefore, since this was one of the damage factor potential, the data of the vegetation covers was extracted from a vegetation map (Bureau of Rural Sciences 2003) according to regions instead as this map gave an idea of the type of vegetation covers.

Geology – Again only 10% of all reports have mentioned the type of geology or the soil classification of the sites. Therefore, the information on geology was extracted from the Geology of Victoria Map (Mc Andrew 1965) based on the geographical region. The geology was the major implication of the type of rocks in the region. The type of rocks was useful to denote the type of soil in the region whether it was unsaturated or saturated. Rock type relates to residual soil type, which relates to expansive nature of the soil. Unsaturated soil derived from sedimentary rock, which was widespread in Victoria, was the common causes of damage to structure.

Climate – There was no information on climate in any of the investigated reports. Since this information was useful in determining the behaviour of soil for shrinking and swelling potential as well as the magnitude, it was essential to include this information in the data mart. The Thornthwaite Moisture Index was chosen as a measure of the influence of climate on damage to light structure. This was because, the information on Thornthwaite Moisture Index was readily available on maps where it was easily extracted according to regions or a particular site. The Thornthwaite Moisture Index is a long term effect on climate change and it can estimate the design suction change, *Hs,* that are needed in residential footing design which is most vulnerable to movement. The Thornthwaite Moisture Index ranges from –

40 for the driest and 40 for the wettest part of Victoria respectively. The Thornthwaite Moisture Index 1940-1960 (Aitchison and Richards 1965b; Standards Australia 1996a) and the Thornthwaite Moisture Index 1961 to 1990 (McManus et al. 2003) were used in the data mart according to the region. The two maps were used to indicate the change in the climate at a different time period.

- *Category: Consultant's Diagnosis*

Only damage category was adopted because the purpose of the analysis was to predict and model the damage potential of light structures. A detailed diagnosis of the damage structure was important to identify types of damage of the structure. Preferably a detailed measurement showing the size of cracks for instance would also be useful to indicate the severity. In the Building Housing Commission report, there were three types of consultant's diagnosis; first was the type of damage (i.e.; cracks, heave etc), second was the classification of damage (i.e.; priority A, B, C etc) and last but not least the damage category as per AS2870. Damage Classification (AS2870) was chosen as the classification was in accordance to AS2870 which was more precise and reliable.

- *Category: Schedule of works*

This category was not considered at all in the analysis as the design objective of the data mart was to analyse the variables in order to predict and develop a model for the damage factor potential for light structures. The variables of this category represented the remedial work of the damage, which was applicable only when one would do the repair of the building. Since the objective was not to predict or model the factors for the remedial work, this category was omitted altogether and was not included in the data mart.

- *Category: Estimated Cost of repairs*

This indicated an estimate of the costs of repair if it was to be done. However, at this stage, this was not very useful as the prices were not consistent and uniform with different consultants. Besides, another quotation had to be done if Building Housing Commission decided to repair the property. However, this category could be useful in future to show the cost incurred in the analysis.

The categories *schedule of works* and *estimated cost of repairs* respectively were not taken into account in the creation of data mart as they were not significant in predicting and modelling damage potential of light structures. However, they might be useful in future for another kind of prediction and model developing, which was out of the context of this research project.

3.3 Data Coding

A unified information system for Building Housing Commission was recommended since it would assist in the organisation of the data into an ordered and high quality database. Qualitative and quantitative variables were developed using the selected information from the reports. Qualitative variables were classified into levels, sometimes known as categories while quantitative variables were linked to intrinsically numerical quantities (Giudici 2003). The selected variables in the data mart were further refined to suit the input format requirements of the particular data mining process.

Since most of the information in the data mart was in qualitative (text) form it was essential to transform this into quantitative (numeric) form. Text form was not usually preferred and was considered far from a standard form and suggested great difficulties for analysis purposes. Since most of the variables in the categories were not similar and have different formats such as text, numbers and units, it was recommended to code the variables accordingly so that they appeared uniform. This was to ensure that there would not be any bias in the outcome resulting from different range of values in the variables.

Normalisation was chosen for this task. Normalisation is the process of efficiently organizing data in a database where it eliminates redundant data and ensures data dependencies make sense (Nardo et al. 2005). The first step was to set the quantitative and qualitative variables in the data mart in numeric format. This transformation applied to the sub-variables from each category. The numerical setting was then coded into {0, 1} interval so that all the values will fall between 0 and 1. This was to ensure uniformity in the values of all the categories. Since the values were between 0 and 1, there would not be any discrepancy or bias towards larger values. In other words, it was to avoid bias in learning errors to weights of numerically large valued parameters.

"Experience has shown that normalized numbers scaled similar to the output values, lead to a better training"(Weiss and Indurkhya 1998).

A simple mathematical formula was used to code the numeric variables for all sub-variables in each category as in equation (3) where I_n is the number of indicator and I_{max} is the maximum value of numeric indicator.

$$Code = \frac{I_n}{I_{\max}} \tag{3}$$

The following tables (Table 4 to Table 12) show the codes for the selected categories.

Category: Property Information

Region (R)

Sub- Variable	Indicator	Code
Missing Data	0	0.00
Inner Melbourne	1	0.07
Inner Eastern Melbourne	2	0.14
Outer Eastern Melbourne	3	0.21
Western Melbourne	4	0.29
South Melbourne	5	0.36
South East Melbourne	6	0.43
North Melbourne	7	0.50
North East Melbourne	8	0.57
Mornington	9	0.64
South East Victoria	10	0.71
North East Victoria	11	0.79
West Victoria	12	0.86
North West Victoria	13	0.93
South West Victoria	14	1.00

Table 4: Codes for Region

Category: Existing Damaged Building Information

Construction Footings

Sub-Variable	Indicator	Code
Missing Data	0	0.00
Concrete Slab on Ground	1	0.25
Strip Footing and Stump	2	0.50
Raft Slab	3	0.75
Bluestone	4	1.00

Table 5: Codes for Construction Footings

Construction Walls

Sub-Variable	Indicator	Code
Missing Data	0	0.00
Brick Veneer	1	0.20
Cavity Brickwork	2	0.40
Concrete	3	0.60
Double Brick	4	0.80
Weatherboard	5	1.00

Table 6: Codes for Construction Walls

Age

Sub-Variable (years)	Indicator	Code
Missing Data	0	0.00
1 to 10	1	0.17
11 to 20	2	0.33
21 to 30	3	0.50
31 to 40	4	0.67
41 to 50	5	0.83
>50	6	1.00

Table 7: Codes for Age

- *Category : Site Information*

Vegetation

Sub-Variable	Indicator	Code
Missing Data	0	0.00
Built Up	1	0.20
Annual Crops & Highly Modified pastures	2	0.40
Native Grass & minimal Modifies pastures	3	0.60
Native Forests & Woodlands	4	0.80
Horticultural Trees & Shrubs	5	1.00

Table 8: Codes for Vegetation

Geology

Sub-Variable	Indicator	Code
Missing Data	0	0.00
Quaternary	1	0.14
Tertiary	2	0.29
Volcanic	3	0.43
Silurian	4	0.57
Upper Devonian	5	0.71
Jurassic	6	0.86
Ordovician	7	1.00

Table **9**: Codes for Geology

Climate

Two different formats for climate were used in the analysis. One format was listed in Table 10 which showed the actual values for the Thornthwaite Moisture Index. The other format was listed in Table 11 which showed the difference of the old and new Thornthwaite Moisture Index, which only showed whether the climate was dry or wet.

Sub-Variable	Indicator	Code
Missing Data	0	0.00
-25	1	0.11
-20	2	0.22
-15	3	0.33
-5	4	0.44
0	5	0.56
5	6	0.67
10	7	0.78
30	8	0.89
40	9	1.00

Table 10: Codes for Climate

Sub-Variable	Indicator/Code
Dry	0
Wet	1

Table 11: Codes for Change in Climate

- *Category: Problems*

Damage Classification

Sub-Variable	Indicator	Code
Missing Data	0	0.00
1	1	0.25
2	2	0.50
3	3	0.75
4	4	1.00

Table 12: Codes for Damage Classification

3.4 Missing Data

Many practical problems suffered from data that was unreliable. Some variables measured or recorded by human were subjected to an observational error. They might be corrupted by noise, or values might be missing altogether. When the data from the Building Housing Commission reports was loaded into the data warehouse and data mart, it often contained missing or inaccurate data. Approximately one third of the data were missing in mostly every line from the Building Housing Commission reports which were incorporated in the database. For instance, some reports did not take into account the type of wall construction but included other factors or it could be the case where there was no information on the age of the building. Since there were only about 600 lines of data available in the database, it was a crucial decision to delete or omit the entire line of data as this might reduce the amount of data available for analysis. This would influence the accuracy of the results from the analysis if not enough data were used.

"Although this data loss may be less of a problem in situations where data volumes are large, it certainly will affect results in mining smaller volume …….. In these circumstances we may well be throwing away the very observations for which we are looking."(Cabena et al. 1998)

Some of the data mining tools have a minimum and maximum number of data required for the analysis in order to get accurate and unbiased results. However, more data did not guarantee accurate or good results. The approach to dealing with missing values or incomplete data was to go through a "cleansing" process; either to drop them from the analysis or substitute typical values for them (Bigus 1996; Tamraparni 2003). The lines in which there were missing data might be useful for the prediction of damage. Therefore, it might be useful to substitute the missing values instead of omitting the entire lines with missing one or two data. However, most programs for analysis do not manage missing values very well as a missing value cannot be multiplied or compared to other values (Weiss and Indurkhya 1998).

There should be a rule of thumb when dealing with missing values as it was important to judge whether the complete set of data with missing data was relevant or not in the analysis.

"A general rule states that any deletion of data must be a conscious decision, after a thorough analysis of a possible consequences" (Adriaans and Zantinge 1996)

Two ways to deal with missing data were to; (1) omit (2) replace it with a default value.

Omit – "If there are a significant number of observations with missing values (undefined variables) *for the same variable, it may be an option to drop the variable from the analysis" (Cabena et al. 1998).* However, as stated previously, the data sets where the missing values were omitted might be useful for the analysis. Therefore, it was very important to decide whether or not to omit the data sets with missing values or to substitute the missing values with a default value.

Replace – By replacing the missing values with a default value such as the constant feature mean or a few values, the data would be biased. If missing values were replaced, an unknown value might be implicitly made into a positive factor that was not objectively justified. In general, it was speculative and often misleading to replace missing values with any default value (Weiss and Indurkhya 1998).

"It is best to generate multiple solutions with and without missing values …" (Weiss and Indurkhya 1998).

It was decided in this research project, to adopt the suggestion by Weiss and Indurkhya (1998) to compare the results with and without missing values to avoid any bias or misleading results. For the replacement of missing values, the numeric value, 0, is used because this value would not affect the outcome of the analysis. The best results from the two would be chosen and used for the entire analysis in this research project. The following section discussed the technique used to determine the accuracy of the chosen factors using the data mart with missing values.

3.5 Data Mining Algorithm

To enhance the quality of the data mart, it was essential to quantify whether the selection of factors or the input parameters made were precise. A categorical regression (CATREG) and a Chi-Square test using the commercial software package, SPSS version 14 for Windows were selected to check the significance of the chosen parameters. The data mart with missing values was adopted to check the accuracy of the chosen factors.

CATREG was a variant which can handle nominal independent variables and was used to find the best-fitting model. A CATREG was used to predict a dependent variable (the Damage Condition) from a set of independent variables (the selected parameters) (Meulman and Heiser 2004). Table 13 shows the significance of the factors chosen using categorical regression analysis. All the chosen factors except for *Age* were significant where the significant values were less than 0.05 ($P<0.05$). This indicated that the factors were correctly chosen for the purpose of predicting the damage condition (without considering other possible factors). *Age* could be eliminated. However, it would be still used together with the other factors in this stage. These factors will be evaluated later in the final stage of the analysis.

Factors	**Standardised Coefficients**		**df**	**F**	**Sig.**
	Beta	Std. Error			
Region	-.125	.045	2	7.848	.000
Wall	.133	.042	2	9.938	.000
Footing	.116	.042	3	7.570	.000
Age	-.039	.040	2	.935	.393
Geology	.107	.048	4	5.055	.001
TMI 1940-1960	.202	.064	2	10.034	.000
TMI 1960-1990	-.222	.058	1	14.674	.000
Vegetation	-.091	.045	2	4.017	.019

Table 13: Coefficients in Regression of Categorical Data

Another test to check the accuracy of the chosen factors was done using a significance test. Significance tests were used to determine whether or not a finding was the result of a genuine difference between two (or more) factors, or whether it was just due to chance or random selection of a value. Here the widely used Chi-Square test was chosen. The significance values shown in Table 14 indicated that the factors were significant with $P<0.001$. This denoted a 99% chance that the factors chosen were true.

This meant that it had a significant affect on the outcome which was damage condition. The computed value for Chi Square exceeded the value indicated in degrees of freedom. Thus, it could be assumed that the observed relationship between the factors exists.

	R	CW	CF	A	G	TMIO	TMIN	V
Chi-Square	286.9	664.3	311.1	198.5	606.9	1288.6	972.1	1982.1
df	13	5	3	6	6	7	5	4
Asymp. Sig.	.000	.000	.000	.000	.000	.000	.000	.000
99% Confidence	.000	.000	.000	.000	.000	.000	.000	.000

Table 14: Chi-Square Test

3.6 Conclusion of Data mining

This chapter covered all parts required for the preparation of the data mining processes. This chapter included data preparation including data coding and the management of missing values. It also dealt with the solution of transforming the qualitative data into quantitative data and resolving missing data. Normalisation which was capable of organizing data in a database was chosen for the purpose of transforming the data before inserting them into the data mart for further analysis.

As for the missing values, it was decided in this research project, to compare both the results with and without the missing values to avoid any bias or misleading results. The best results from the two were chosen which was the data mart without missing values. This data mart was used for the entire analysis in this thesis.

The data used was based on information extracted from 600 reports from the Building Housing Commission reports. The extraction and addition of information from the Building Housing Commission reports had not been smooth sailing at all with many shortcomings encountered. Therefore, the management of extracting the information from the reports had to be done thoroughly in order to include all the necessary information needed for the development and the analysis of the proposed model. The selections of the relevant information in the reports were based on the studies and investigations done by other researchers on expansive soils behaviour in terms of ground movement which in turn lead to damage to structures. However, not all the information needed was available in the Building Housing Commission reports. Therefore, an alternative way of obtaining the important information such as climate, geology and vegetation had to be extracted from relevant maps. Realistically, a proper investigation of the site regarding these factors was better compared to extracting the information from a general maps.

Where vegetation was concerned, the vegetation at a particular property in the same suburb need not necessarily be the same with the neighbouring property. Therefore, it was much better to report on any presence or removal of the vegetation in the engineering reports so that at least the right information can be added in the data warehouse hence data mart. Not only should the presence or the removal of vegetation be reported on, but the type, height and distance of the vegetations should be mentioned as well. These were proven to have an effect on the properties thus useful to have in the reports.

It is the same case as the information extracted from geology map. It was much better if all reports included soil classification. The information for geology was generalised for all the sites according to the regions. Logically, not all the sites have the same soil classification even though their geology was the same. A soil investigation should always be performed to acquire more accurate information on a particular site. Furthermore, a neighbouring property for instance could have different soil classification from the other property.

Other shortcomings of the Building Housing Commission reports were the lack of detailed information on the structural characteristics of the damaged properties. The most important aspects that need to be reported on were the type, size and depth of footings and foundations and also the type of external walls used. The lack of this information was unfortunate as it would have been very useful to distinguish whether the design of the structures were inadequate or it was merely due to the other factors influencing movements such as climate or vegetation.

The other disadvantage of the Building Housing Commission reports was that not all the engineering firms have included the year in which the structure was built and the year the first damage was reported. This information was relevant in order to determine whether those years were subjected to environmental condition such as drought or flood. This way, at least it was certain that the damage caused was especially due to expansive soil movements. The other cause would of course be the material used or the standard design requirements.

In order to check whether the factors chosen were correct, the factors were tested for their significance in predicting the damage condition. The significance test showed that all the chosen factors except for *Age* of the light structures were significant. However, this factor would still be retained and checked for its usefulness later in the following two chapters. The development of a data warehouse hence the data mart enabled Building Housing Commission to evaluate the usefulness of the reports prepared on the reported damage properties. It could also assist them in re-evaluating the information given by the engineering firms. This enabled them to distinguish between any additional or relevant and non-relevant information needed in analysing damage to light structures on expansive soils in Victoria.

The data in the data mart could be used to undertake different analysis such as analysing the important factors causing particular types of damage, predicting the future development of damage, generating detailed reports with substantial filtering options and many more. This analysis could assist in the asset management of the housing stock that needs maintenance, reconstruction or demolition. Time and money would be saved as the database would not only be easy to use but also be readily available for any kind of data analysis using any type of programs or software such as Artificial Intelligence or any statistical software.

The next chapter covered the development of the Predictive Damage Condition model using the chosen factors.

Chapter 4

DEVELOPMENT OF A PREDICTIVE DAMAGE CONDITION MODEL

The lack of a predictive damage model for light structures on expansive soils in Victoria was the motivation for developing the proposed model. The previous chapter dealt with the data mining process of the Building Housing Commission reports. This together with the proposed model could assist the Building Housing Commission and other building trades authorities to finally recognise and identify the parameters that were most affecting damage to light structures on expansive soils. In addition to that, the model could help to predict which class the damage condition of the light structure with only a click of a button. That way, any serious and urgent repairs could be identified and preventive action can be taken without delay.

The data mart in the previous chapter was used to develop the model. The data mart were divided into two sets; *original* and *complete* as shown in Table 15. The *original* data mart consisted of missing lines of data while *complete* data mart consisted of non-missing lines data. The data marts were tested for their performance or goodness of fit using two methods. Ordinal regression was chosen for statistical method. To check the accuracy of findings using this conventional method, a newer Artificial Intelligence method was adopted. A hybrid approach using Neural Network and Genetic Algorithm was the most promising approach for the task of analysing the data dependencies and function approximation in order to allow a reliable damage prediction. The data mart that produced the best performance for both methods and the method that gave the highest precision was used for the development of the Predictive Damage Condition model.

4.1 Data Marts

The preparation and the selection of the data from the Building Housing Commission reports have been described in the previous chapter. Since the *original* data mart mentioned in the last chapter contained missing values, another data mart was created without the missing values which was called *complete* data mart. This was to determine whether there was any discrepancy when using data mart with and without missing values.

Both the *original* and *complete* data marts have 600 and 350 lines of data respectively. The *original* and *complete* data marts were replicated into two as shown in Table 15. These were referred to as *Original A* (OA), *Original B* (OB) and *Complete A* (CA), *Complete B* (CB).

Original A (OA) was the initial data mart created from the data in the data warehouse. It contained all data from the data warehouse that were transformed into a new format that suited the requirement of the algorithms for further analysis. It consisted of approximately 600 lines of data including lines with missing values. There were eight variables in the original data mart. These were *Region (R), Construction Wall (CW), Construction Footing (CF), Geology (G), Thornthwaite Moisture Index 1940-1960 (TMIO), Thornthwaite Moisture Index 1960-1990 (TMIN), Vegetation (V)* and *Age (A)*

Original B (OB) was derived from the original A data mart. There were seven variables in this data mart. *Region (R), Construction Wall (CW), Construction Footing (CF), Geology (G), change in Thornthwaite Moisture Index (ChgTMI), Vegetation (V) and Age (A). Thornthwaite Moisture Index 1940-1960 and Thornthwaite Moisture Index 1960-1990* were substituted with a new parameter; *change in Thornthwaite Moisture*. This is the difference between *Thornthwaite Moisture Index 1940-1960* and *Thornthwaite Moisture Index 1960-1990*. A negative value of change in Thornthwaite Moisture Index indicated that the climate was getting dryer. A positive value indicated that the climate was getting wetter. Zero meant that no change occurred. Since the literature review proved that climate was one of the major factors influencing the behaviour of expansive soils, it was essential to analyse the relationship between the climate or the change in climate with damage condition. The reason for having this data mart was to investigate if there was a difference in using these parameters as a reflection of climate conditions in their influence to damage caused to structures built on expansive soil.

Complete A (CA) data mart was a subset of original A data mart with approximately 350 lines of data. It had the same variables as the original A data mart but all lines of data with missing values were removed.

Complete B (CB) data mart was a subset of complete B data mart. It had the same number of variables as original B except that all lines of data with missing values were removed in the data mart. This data mart has approximately 350 lines of data.

Data mart	Variables							
OA & CA	R	CW	CF	G	V	A	TMIO	TMIN
OB & CB	R	CW	CF	G	V	A	ChgTMI	

Table 15: Variables in The Original and Complete Data Marts

4.2 Statistical Method

An ordinal logistic regression method was used to model the relationship between the outcome variable which was the damage condition and the influence factors of damage condition. The influence factors included *Region*, *Construction Wall*, *Construction Footing*, *Age*, *Thornthwaite Moisture Index (1940-1960)*, *Thornthwaite Moisture Index (1960-1990)*, *change in Thornthwaite Moisture Index*, *Geology* and *Vegetation*. Ordinal logistic regression for SPSS version 14 was used.

All the data marts were used for checking the goodness of fit of the data to the model. Three results from the ordinal logistic regression method were interpreted. Firstly, the model fitting information which referred to the log likelihood ratio where it looked at whether the null hypothesis of the model can be rejected. Secondly, goodness of fit which determined whether the data fit the model well. Lastly, Pseudo R square test which indicated the performance of the model in terms of the prediction of damage condition.

4.2.1 Model Fitting Information (Log Likelihood Ratio Test)

Likelihood ratio test could be used for assessing the significance of logistic regression, A well-fitting model was significant at the .05 level or better (Garson 1998b). A chi-square probability of 0.05 or less was commonly interpreted as the justification for rejecting the null hypothesis. This meant that the variables were unrelated and not only randomly related. Table 16 shows that all data marts are highly significant (less than 0.05).

Data mart	-2 Log Likelihood	Chi Square	df	Sig.
OA	1220.189	92.571	45	0.000
OB	1236.924	75.836	42	0.001
CA	544.916	68.392	41	0.005
CB	548.040	65.268	39	0.005

Table 16: Model Fitting Information

4.2.2 Goodness of Fit Test

Table 17 represents the Chi-square test of goodness of fit. If chi-square goodness of fit was not significant, then the model had adequate fit. From Table 17, it was obvious that the original data marts had higher significant chi-square values compared to the complete data mart. It was also noted that the degrees of freedom of all data marts were less than the chi-square values. As a rule of thumb, a good fit was provided by a model when chi-square for a model was not substantially larger than the degrees of freedom (Garson 1998b).

In Table 17, it was apparent that the complete data marts were a better choice compared to the original data mart. In other words, the model based on the data in the complete data marts was statistically significant.

Data mart	Chi Square	df	Sig.
OA	1428.008	1319	0.019
OB	1477.088	1322	0.002
CA	531.841	511	0.253
CB	541.095	513	0.189

Table 17: Results of Goodness of Fit

4.2.3 Pseudo R-Square Test

Pseudo R-Square test was applied to know how the model improved prediction capability. It takes values between 0 and 1, becomes larger as the model "fits better", and provides a simple and clear interpretation(Shtatland et al. 2000). In terms of the capability of predicting damage condition, the complete data marts were better as shown in Table 18. This could be seen from the higher values of Cox and Snell, Nagelkerke and McFadden Pseudo R square values. In McFadden Pseudo R square, the values for complete data mart were nearly doubled. This indicated that the complete data marts were capable of predicting damage condition accurately compared to original data marts. The values in Cox and Snell and Nagelkerke also showed the values for complete data marts were much bigger compared to the original data marts. Thus it could be concluded that complete data marts were the better choice in maximising the capability of Predicting Damage Condition model.

Data mart	Cox and Snell	Nagelkerke	McFadden
OA	0.148	0.158	0.058
OB	0.123	0.131	0.047
CA	0.184	0.203	0.086
CB	0.177	0.195	0.082

Table 18: Pseudo R-Square Values

4.2.4 Summary

An ordinal regression for SPSS version 14 for Windows was chosen and described. Three results from the ordinal regression were examined. Both the likelihood chi-square test and the chi-square goodness of fit test showed the same results. They showed that the complete data mart (CA and CB) was highly significant in both cases and more significant than both original data marts (OA and OB). This indicated that the complete data mart (CA and CB) fit the model well. In terms of the capability of predicting damage condition, again complete data marts showed an advantage.

The results obtained however were not conclusive as it demonstrated a limitation when using statistical methods. In general, all statistical method required complete data in order to produce useful results. Undefined or missing values cannot be handled using these kinds of approaches. Therefore, other alternative methods (Artificial Intelligence) were considered and used to see the accuracy of these methods and whether the missing values were significant.

4.3 Artificial Intelligence Methods

Neural Network and Genetic Algorithm have been established as two major research and application areas in Artificial Intelligence. Neural Network was of particular interest because of its robustness, parallelism, and its abilities (Weiß 1994). Genetic Algorithm on the other hand was robust and could deal with a wide range of problem areas including those which were difficult for other methods to solve as a global search method (Beasley et al. 1993).

In this section, a brief background of the applied Artificial Intelligence methods, namely Artificial Neural Network and Genetic Algorithm were discussed. In order to use these methods efficiently, suitable variables and operators had to be selected. The performance of Artificial Intelligence method was mainly influenced by the selection of the available variables and operators. This would be done using trial and error approach. The rest of the section examined and compared the performances of a pure Neural Network approach and a hybrid technique using a Neural Network trained by a Genetic Algorithm. The technique that gave a better performance was chosen for the development of a Predictive Damage Condition model.

Two major steps were undertaken in this method. Firstly, Original A data mart was used to select the options in both Neural Network and Genetic Algorithm. For the Neural Network, this was done by comparing the performance of the settings such as training and transfer functions as well as the number of neurons in the hidden layer. For Genetic Algorithm, the performance was determined by comparing different settings. These included using different combination of options such as population size, crossover, fitness scaling, mutation, reproduction and selection. The best performances for the settings from Neural Network and Genetic Algorithm respectively were then chosen for training.

Secondly, all the data marts were used to compare the performance of the two Artificial Intelligence techniques. This was done by comparing the performance using only one Artificial Intelligence which was Neural Network. The other was comparing this with a hybrid method which was Neural Network trained with Genetic Algorithm. The reason for having two comparisons was to select the method that gave the best performance for analysis.

4.3.1 Neural Network

Artificial Feedforward Backpropagation Neural Network had been widely used in many applications in recent years. It had shown strength in solving hard problems in Artificial Intelligence (Plagianakos et al. 1998). A Feedforward Backpropagation network (as in Figure 10) trains the network by iteratively adjusting all connection weights among neurons. It is a gradient descent search algorithm, which tries to minimise the total mean square error between actual output and target of Neural Network (Yao 1993). It derived from the process of propagating the error information, the mean squared error backward from the output nodes to the hidden nodes (Smith 1996). The goal was to find a set of connection weights that minimizes the error of network (Olden 2000).

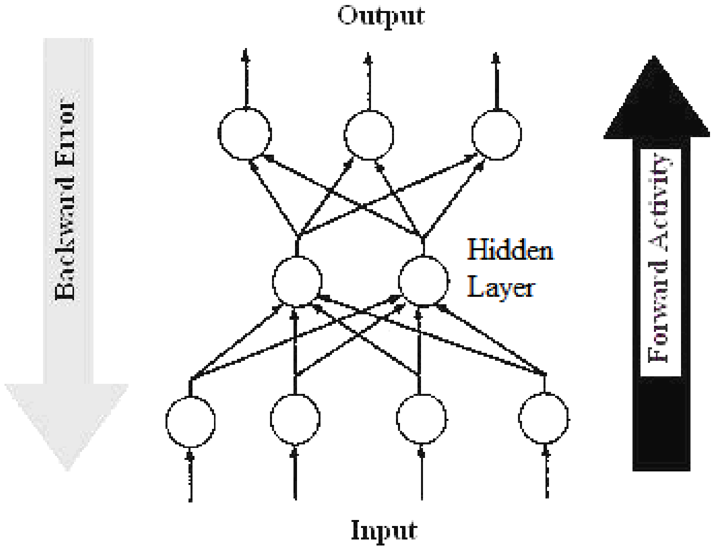


Figure 10: Feedforward Backpropagation Network

Learning in Neural Network is an optimisation process by which the error function of a network is minimised (Rojas 1996). Before Neural Network can perform anything reasonable, it had to go through training or learning phase. Here, the connection weights, w_j were continuously updated so that the network can efficiently perform a specific task. Instead of following a set of rules specified by human experts, the Neural Network appeared to learn the underlying input-output relationship from the examples presented to it in a training set (Knutti et al. 2003).

Choosing appropriate training patterns of the Neural Network was crucial. Too few or poorly selected training samples would prevent the network from learning the whole input-output relationship (Knutti et al. 2003). Thus only part of the presented input would be recognised correctly. Too many training samples on the other hand though would not do any harm; it increased the computational cost dramatically. Best practice showed that a Neural Network should be created by dividing the available data into three sets before training or learning begins.

In this research project, original A data mart was used to select the options for Neural Network. The reason for using the data mart with missing lines of data was that the relevance of the data in the data mart was not known and this method was known for its ability to handle missing lines of data. The data mart was divided randomly into three sets for training, testing and validation respectively. A randomly chosen sample would ensure an approximately even distribution and good performance in the whole parameter range of interest (Knutti et al. 2003).

The training set contained 50% of the data mart, 25% of the data mart was used for testing and the rest of 25% was used for the validation of the Neural Network. The testing data set was used to compare the generalisation of the network with the training data set (Smith 1999). The goal was to make sure that the errors in the testing data set were smaller than the one produced by the network in the training set. Otherwise, the network had not learnt to generalise the values other than the learnt input values. The validation set was used to stop training sooner before overfitting starts. This was to test the performance of the network. Typically, the error of the validation data set would begin to rise when the network began to overfit the data (Heaton 2005). Overfitting caused the network to lose its ability to generalise and correctly predict the output from an input it had not been trained with (Knutti et al. 2003).

Fortunately, the validation error for original A data mart did not show any sign of overfitting. The error in the validation set was consistent with the training and testing sets. This showed that the number of neurons and layers used in the Neural Network is sufficient as not to over fit the network.

A two layer network using log sigmoid and the resilient Backpropagation training function (Demuth and Beale 2001) was the most efficient training algorithm for this research project due to its extremely fast convergence. *Sigmoid transfer functions* take some input, and shrink its output to fit between the two limits (0 and 1) (Profitt and Riebe 2003) and is calculated using Equation (4). The transfer function was chosen as it gave more stable results than Tan Sigmoid transfer function as shown in Figure 11. The equation of Tan Sigmoid transfer function was similar to Log Sigmoid transfer function.

$$\log sig(x) = \frac{1}{1+e^{-x}} \tag{4}$$

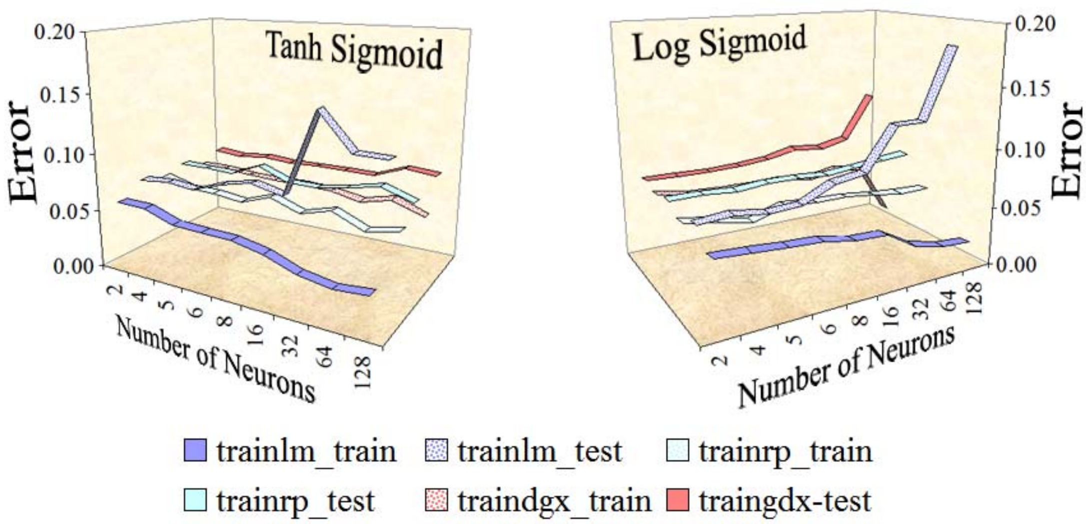


Figure 11: Training Function Using Tanh Sigmoid and Log Sigmoid Transfer Function

A detailed introduction to Neural Networks architectures, learning rules, training methods and application was written by Demuth and Beale (2001). Below is the description of the process for selecting the options for the Neural Network

4.3.1.1 Processes for Selecting the Neural Network Options

The efficiency of supervised learning in Feedforward Backpropagation Neural Network strongly depended on the network architecture, the neurons or the hidden layers and learning rules (training functions). Therefore, before adopting a network for training, the selection of architecture and training function needed to be initialised. The graphical user interface of the Neural Network Toolbox for MATLAB® version 7.1 was used and shown in Figure 12.

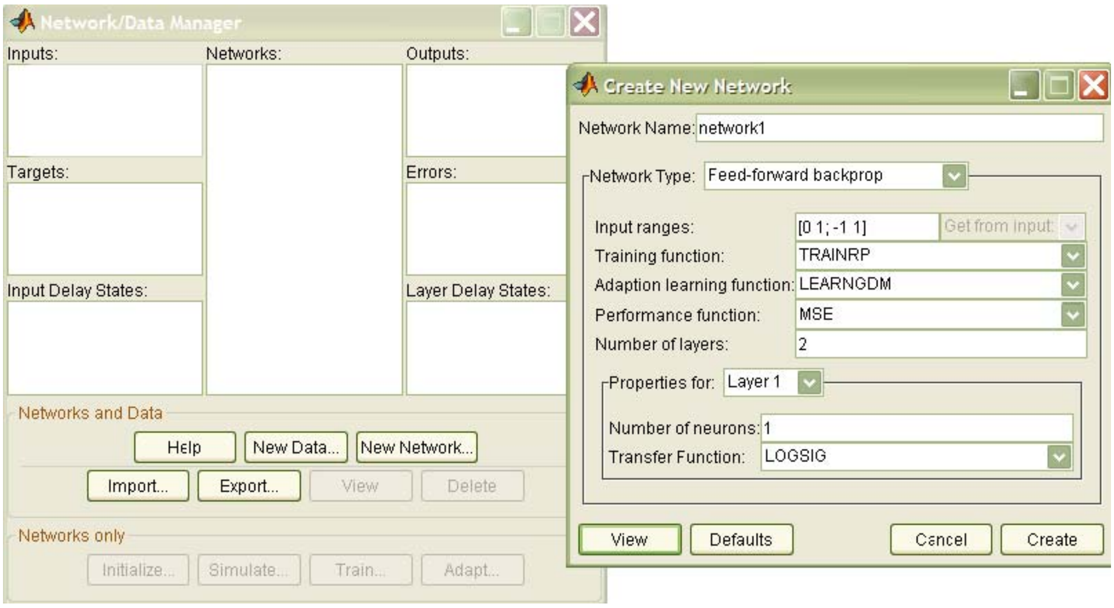


Figure 12: Neural Network Toolbox for MATLAB® Version 7.1

Neural Network Architecture

The arrangement of neurons into layers and the connection patterns within and between layers is called the net architecture (Fausett 1994), which is shown in Figure 13. Ideally, the number of layers of the network should also be established. The size of the Neural Network was critical for performance as well as for efficiency reasons. If the network was too small, it had too few degrees of freedom, to learn the desired behaviour and would do a poor approximation of the input-output relationships (Knutti et al. 2003). The most common Neural Network architecture consisted of two layers: the input was connected to a layer of hidden neurons, which was connected to the output layer.

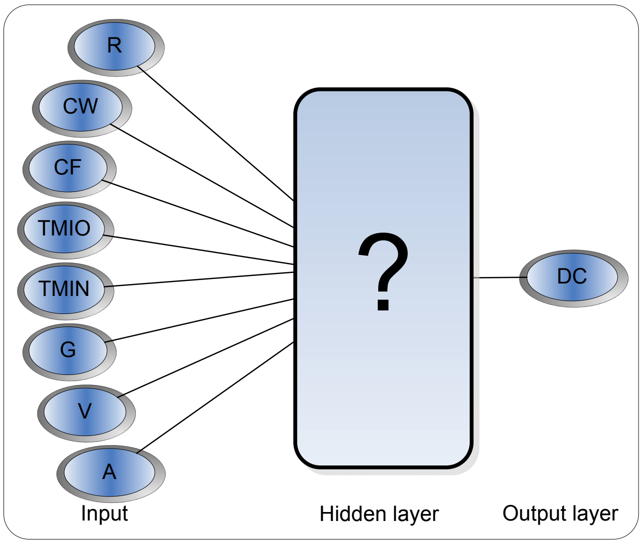


Figure 13: Neural Network Architecture

Input

It should be noted that the input acts as a buffer to hold the input vector. Therefore, it had no weights assigned, which needed to be modified. In the rest of this research project, it was not referred to as a layer. The Neural Network in this research project had eight input parameters. The eight input parameters used were the *Region (R)*, *Construction Wall (CW)*, *Construction Footing (CF)*, *Geology (G)*, *Thornthwaite Moisture Index 1940-1960 (TMIO)*, *Thornthwaite Moisture Index 1960-1990 (TMIN)*, *Vegetation (V)* and *Age (A)*.

Output Layer

The output layer of the Neural Network presented a pattern to the external environment. The behaviour of the output units depended on the activity of the hidden neurons and the weights between the hidden and output layers. The output parameter for this research project is the *Damage Condition (DC)* of the light structure.

Hidden Layer

The hidden layers do not directly interact with the external environment. However, they have a tremendous influence on the final output. The number of hidden neurons affects how well the network is able to separate the data (Smith 1999). A single hidden layer was adequate to approximate any continuous function. However, more accuracy could be gained using more than one hidden layer. The rule-of-thumb method for determining the best number of neurons to use in the hidden layers was that the number of hidden neurons should be in the range between the size of the input layer and the size of the output layer. Moreover, the number of hidden neurons should be 2/3 of the input layer size, plus the size of the output layer and the number of hidden neurons should be less than twice the input layer size (Heaton 2005). Most of the time, trial and error approaches were used to determine the number of hidden layers and neurons in the network, which was very time consuming but was the current best practice.

In this research project, the number and size of the hidden layer and its neurons were calculated using the trial and error method in combination with the formula by Garson (1998a) as shown in equation (5). It was assumed that the given data from the reports was in the middle between clean and noisy, where *r=9*, which resulted in a number of 5 neurons for the hidden layer. The Neural Network was also tested with different number of neurons ranging from 2 until 128 as trial and error method.

$$h = \frac{n}{[r(i+o)]} \tag{5}$$

Figure 14 and Figure 11 show the performance values of the training and test set using different numbers of neurons in hidden layer. The performance of the number of hidden neurons had to be considered before choosing the number of neurons. It can be seen that the more neurons the better would be the performance. However, the analysis of the network would be slowed down dramatically. In this research project, 5 neurons were chosen as the analysis should be completed within a practical amount of time to be implemented in a real-life application. This decision was made even though the performance in the training set was better compared to the testing set. The mean squared error or the performance increased and decreased when another neuron was added in the training and testing sets respectively. The number of neurons with a lesser mean squared error for the testing set will be adopted. This was because the testing set was used to measure the performance that was expected from the network when it was put into service. The training set on the other hand was used to calculate the changes in weights. The selected number of neurons in hidden layer also proved the accuracy of Garson's formula.

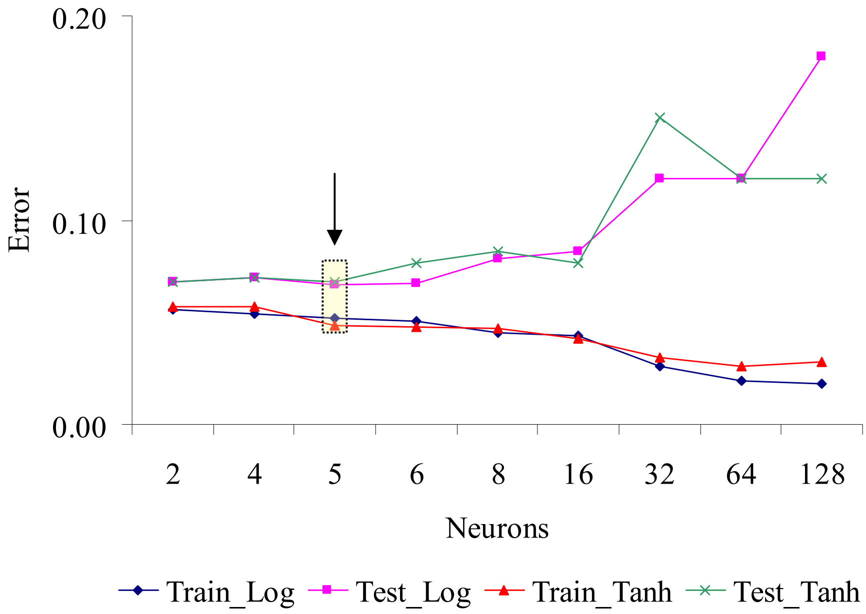


Figure 14: Selection of Number of Neurons in Hidden Layer

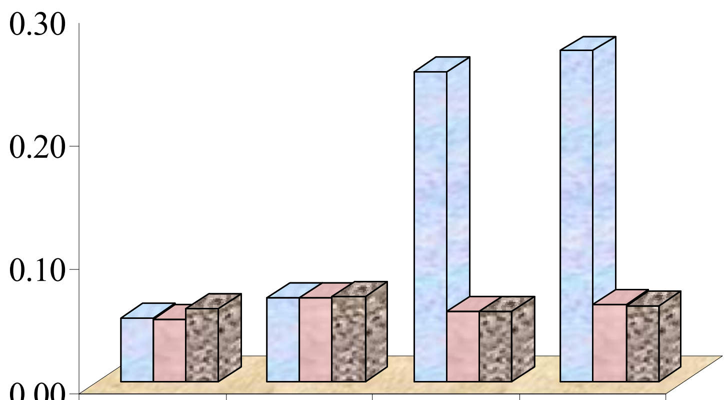
Training Function

Training function is the algorithm which efficiently modifies the different connection weights to minimise the errors at the output. Three training functions, *Variable train-*

ing rate (Train GDX), *Resilient Backpropagation* (Train RP) and Levenberg-Marquardt Backpropagation (Train LM) were compared. Only one training function was chosen in the model development according to its performance. *Train RP* was chosen as it was the most efficient training function based on its performance functions. The performance functions of the network used were the mean squared error (*mse*) and mean squared error with regularisation (*msereg*) as in equation (6) and (7) respectively. The regulation, γ was used to improve the performance. However, the mean squared error seemed to be a more stable indicator for errors compared to the mean squared error with regularisation as seen in the obtained values of Figure 15.

$$mse = \frac{\sum (y_1 - \hat{y}_i)^2}{n - m} \tag{6}$$

$$msreg = \gamma \cdot mse + (1 - \gamma) \cdot msw \tag{7}$$



	MSE train	MSE test	MSEREG train	MSEREG test
trainlm	0.0521	0.068	0.2514	0.2684
trainrp	0.0512	0.068	0.0576	0.0630
traingdx	0.0594	0.069	0.0575	0.0620

Figure 15: Performance of different Training Function in Neural Network

One of the disadvantages of Feedforward Backpropagation was the "scaling problem". It could easily get stuck in a local minimum (Yao 1993) of the error function because the steepest descent and conjugate gradient Backpropagation based training methods were local minimisation algorithms. This meant that the training process may not be perfect. Another disadvantage of Feedforward Backpropagation was the slow convergence and sensitivity to the settings of the training rate (Bigus 1996). There was no mechanism that allowed the training to escape such a local minimum (Heaton 2005). Another problem with Feedforward Backpropagation was that it cannot handle discontinuous optimality criteria or discontinuous node transfer functions (Montana and Davis 1989).

One way to overcome Backpropagation's shortcomings was to consider the training process of Genetic Algorithm. Genetic Algorithm could be used to initialise good connection weight values before training the network. It could be used when no information was available about the gradient of the function at the evaluated points (Rojas 1996). The main idea was to use Genetic Algorithm as function optimisers to maximise fitness functions (minimise mean square error). This was because Genetic Algorithm was capable of dealing with large, complex, non-differentiable and deceptive space (Yao 1993). Eventhough, the function was not continuous, Genetic Algorithm could still achieve good results even in case in which the function had several local minima or maxima (Rojas 1996). The following section discussed the options in Genetic Algorithm

4.3.2 Genetic Algorithm

"Genetic Algorithms are a class of search algorithms modelled on the process of natural evolution and have been shown in practice to be very effective at function optimization, efficiently searching large and complex (multimodal, discontinuous, etc.) spaces to find nearly global optima" (Montana 1995).

Genetic Algorithm generally improved the current best candidate monotonically by keeping the current best individual as part of its population while it searches for better candidates (Montana and Davis 1989). Unlike Backpropagation, Genetic Algorithm was generally not concern with local minima. When a Genetic Algorithm was run using a representation that usefully encodes solutions to a problem and operators that can generate better children from good parent, the algorithm could produce populations of better and better individual, converging finally on results close to a global optimum (Montana and Davis 1989).

The Genetic Algorithm toolbox for MATLAB® was used. Figure 16 shows a screenshot of the graphical user interface with a variety of settings and options. The selection of the best operators for the initialisation of the connection weights for the Neural Network was done using experimentation. This was the best practice way to choose a good set of operators for a given problem. The combination of the available options was chosen based on their behaviours in optimising the Genetic Algorithm. However, choosing different operators may or may not improve the best fitness value. Therefore, trial and error was used for configuration of the Genetic Algorithm in this research project. A Genetic Algorithm could quickly scan a vast solution set. Bad proposals did not affect the end solution negatively as they were simply discarded. The inductive nature of the Genetic Algorithm meant that it did not have to know any rules of the problem - it worked by its own internal rules. This was very useful for complex or loosely defined problems.

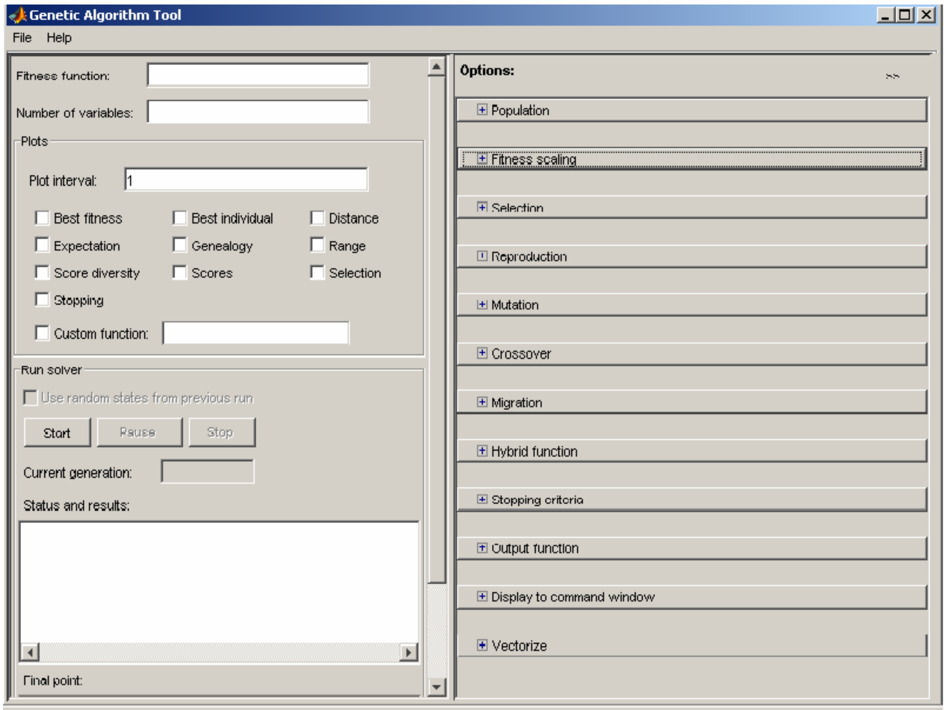


Figure 16: Genetic Algorithm Toolbox for MATLAB®

4.3.2.1 Processes for Selecting the Genetic Algorithm Options

Initially the default values for all the options for the operators were used in order to assess the behaviour of the default options in optimising the algorithm. Default values made two essential contributions by showing a representative and a frequent value. It could also help reduce errors. However, default values were not always the best choice. The default values for each operator are shown in Appendix 7 which gave a fitness function value of 0.0613. Only the Population size did not use a default value as the default value 20 was too small compared to the number of variables used. Even though the fitness function value was quite small, it did not mean that the default value was the best alternative as mentioned earlier. To check the accuracy and sensitivity of the combination of options in the toolbox, different options have been examined for all possible combinations. The following sections aimed at describing the operators and their options based on their optimisation ability. Since the Genetic Algorithm starts with a random initial population which was created using MATLAB® random number generators, the Algorithm was run twice to get the average values. This was also to avoid any bias towards the results. Note that all the results shown in this research project were the average values.

Options for Genetic Algorithm

From the trial and error methods used in this research project, many options of Genetic Algorithm could be adjusted to very sensible and robust values, without having to be readapted to every problem. The settings of all the options are shown in Table 19. The options were chosen according to the best performances (Lowest fitness functions). "*A fitness function is a particular type of objective function that quantifies the optimality of a solution (that is, a chromosome) in a genetic algorithm so that that particular chromosome may be ranked against all the other chromosomes"* (Wikipedia 2007). The fitness function values or the performance for different options are shown in Figure 17 and Figure 18. A detailed introduction to Genetic Algorithm and options was written by Holland (Holland 1992) and Goldberg (Goldberg 1988).

Most options for the setting of the *Population* used the default value in MATLAB® except for population size and type. The population size of each generation was set to 51, which was equal to the number of connection weights required for the Neural Network. The population size should at least be the value of number of variables (The Mathworks Inc 2005). This was to ensure that the individuals of each population span the space being searched. Increasing the population size enabled the Genetic Algorithm to search a broader space and thereby increasing the chance to obtain better results. The initial range (0,1) was chosen to restrict the range of the candidate solution for the connection weights in the initial population from 0 to 1. Since the target values were real values *double vector* was chosen. On top of that *double vector* produced a smaller fitness value.

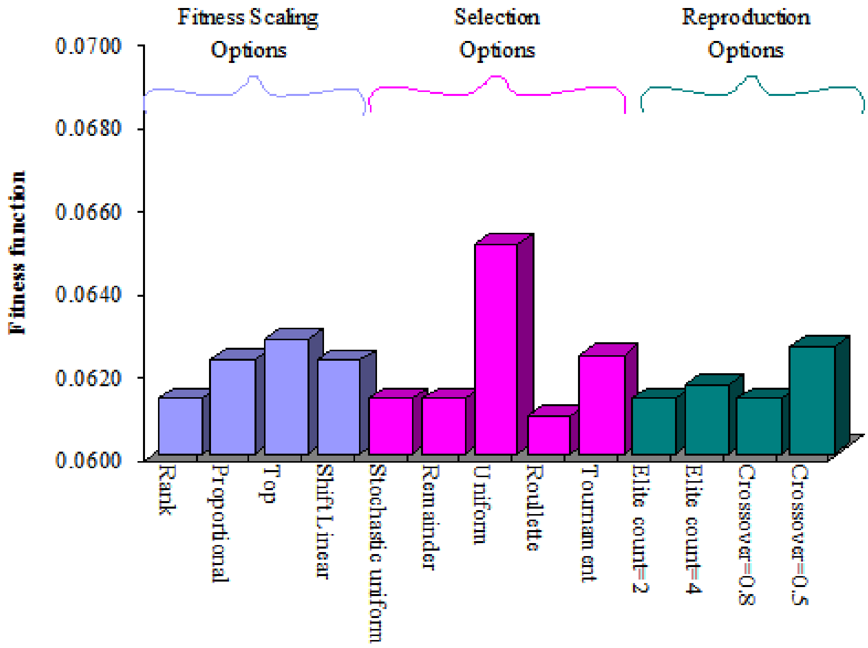


Figure 17: Performances for Fitness Scaling, Selection and Reproduction Options

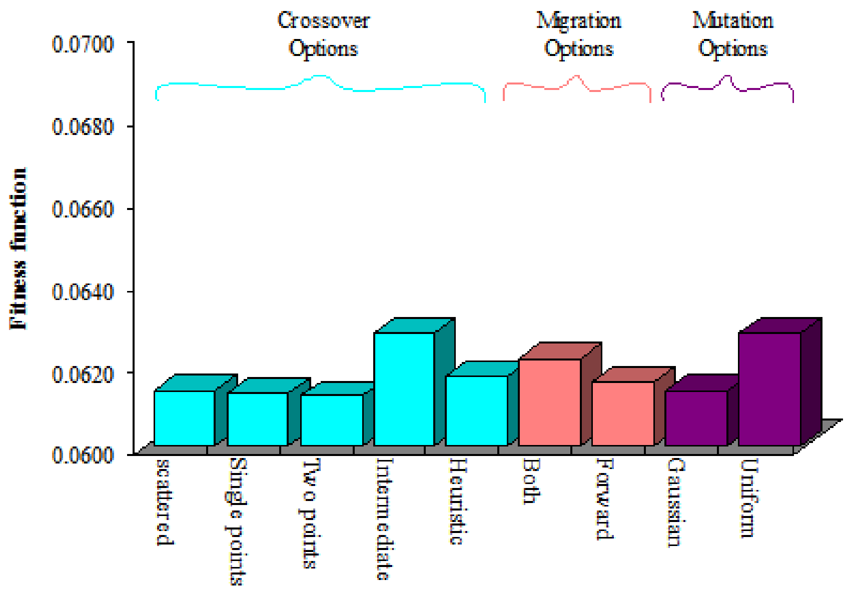


Figure 18: Performances of Crossover, Mutation and Migration Options

Operator	Options
Population	
Population Type	Double Vector
Population Size	51
Fitness scaling	
Scaling Function	Rank
Selection	
Selection Function	Roulette
Reproduction	
Elite Count	2
Crossover Fraction	0.8
Mutation	
Mutation Function	Gaussian
Crossover	
Crossover Function	Two Point
Migration	
Migration Direction	Forward
Migration Fraction	0.2
Migration Interval	20
Hybrid Function	fminsearch

Table 19: Chosen Options for the Operators for Genetic Algorithm

4.3.3 Hybrid technique: Neural Network trained with Genetic Algorithm

The use of both, Genetic Algorithms and Neural Network (hybrid technique) was originally motivated by the astonishing success of these concepts in their biological counterparts. Despite their totally different approaches, both can merely be seen as optimisation methods which were used in a wide range of applications, where traditional methods often proved to be unsatisfactory (Omer 1995). The primary motivation for using a hybrid technique laid in the inherent problems associated with Backpropagation approach which was easily trapped in local minima or maxima. Furthermore, it had been shown that Backpropagation was sensitive to the initial condition of the Neural Network and it was hard for it to find an optimal solution if the function was non differentiable (Curran and O'Riordan 2002).

The combination of Genetic Algorithm and Backpropagation Neural Network arose from the observations that the local search performed by Backpropagation was well complimented by the almost global search sampling performed by the Genetic Algorithm (De Castro et al. 1998). Backpropagation which is an example of gradient descent technique in Neural Network always attract some characteristics of local neighbourhood to determine the search direction to go through. Genetic Algorithm on the other hand, was effective because it ensured broad coverage over the entire domain where it worked by collecting information from the search space through generations, and then using this information to guide subsequent sampling towards promising regions (De Castro et al. 1998). Genetic Algorithm was able to optimise function even though the function was not continuous. This was because Genetic Algorithm employed fitness functions which could be tailored to suit the problem at hand and were not restricted in any way (Curran and O'Riordan 2002).

This research project dealt with the use of Genetic Algorithms for the training of Neural Networks. The general intention was to gain an optimal parameter tuning which improved the learning performance of conventional neural learning process which was Backpropagation in this research project. It was proven (Weiß 1994) that in almost all cases, the evolved networks (Genetic Algorithm and Neural Network) showed a significantly improved learning behaviour compared with using Neural Network alone. It had also been shown (Curran and O'Riordan 2002) that the hybrid technique was by far superior, both in terms of development time and performance.

The initial set of weights to be used in supervised learning for Neural Network had a strong influence in the learning speed and in the quality of the solution obtained after convergence (De Castro et al. 1998). An inadequate initial choice if the weight values might cause the training process to get stuck in a poor local minimum. Therefore, in this research project, a hybrid technique was used to create the initial population of Neural Network by means of mutation, recombination and fitness oriented selection at random. Another step was to use Genetic Algorithm to search the broad area of the weight problem space and then use Backpropagation as a local search to refine the weights. This approach ensured that the networks evolved were very accurate, more accurate than they would have been had Genetic Algorithm or Neural Network been used in isolation. (Curran and O'Riordan 2002).

In this research project, the performance of Neural Network was compared with the performance of hybrid Artificial Intelligence technique (Neural Network trained by Genetic Algorithm) using the settings from previous section. Two data marts; original (OA and OB) and complete (CA and CB) were used to identify the performances. Figure 19 shows Neural Network that was trained with Genetic Algorithm using the original data mart. The purpose of this experiment was to determine the significance of missing values in the data mart, since Neural Network was said to be capable of handling missing or noisy data (Garson 1998a). This was also to check whether the previously investigated ordinal regression method used was reliable.

The data mart with the best performance was used to determine the rank of the input parameters according to their performance and identified potential correlations between those parameters. The parameters that were vital in both the results (with the highest importance) were used for the development of the Predictive Damage Condition model. The development of the model is discussed in section 4.4.

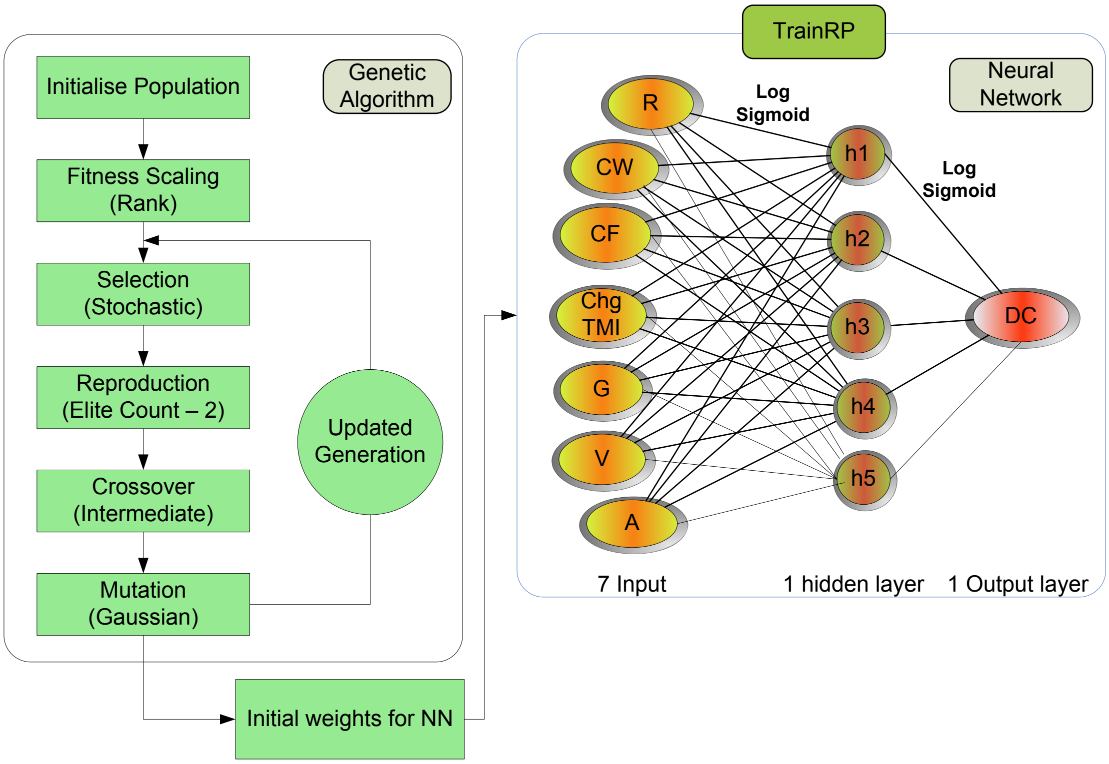


Figure 19: Hybrid Network: Neural Network Trained with Genetic Algorithm Model

From Figure 20, the performance of the trained and test sets of both data marts showed that the Neural Network trained with Genetic Algorithm produced a better performance compared to only using Neural Network. The performance was enhanced approximately 10%.

Figure 20 points out that the complete data marts performed better compared to the original data marts. Complete data mart A produced approximately 40% smaller mean square error values for the training set using the Genetic Algorithm for initialization of the Neural Network compared to the original data mart A. Complete B on the other hand performed 30% better than the original B data mart. These showed that the complete data marts with the input parameter change in Thornthwaite Moisture Index produced better results.

Overall, the complete B showed the best results by producing the smallest value of mean square error, which implied that complete B data mart was the most reliable data mart. It could also be observed that the complete data mart performed approximately 30% better than the original data mart. Even though the Neural Network approach was capable of handling data with missing data, it was essential to use complete data mart as it gave better performed network thus more accurate results.

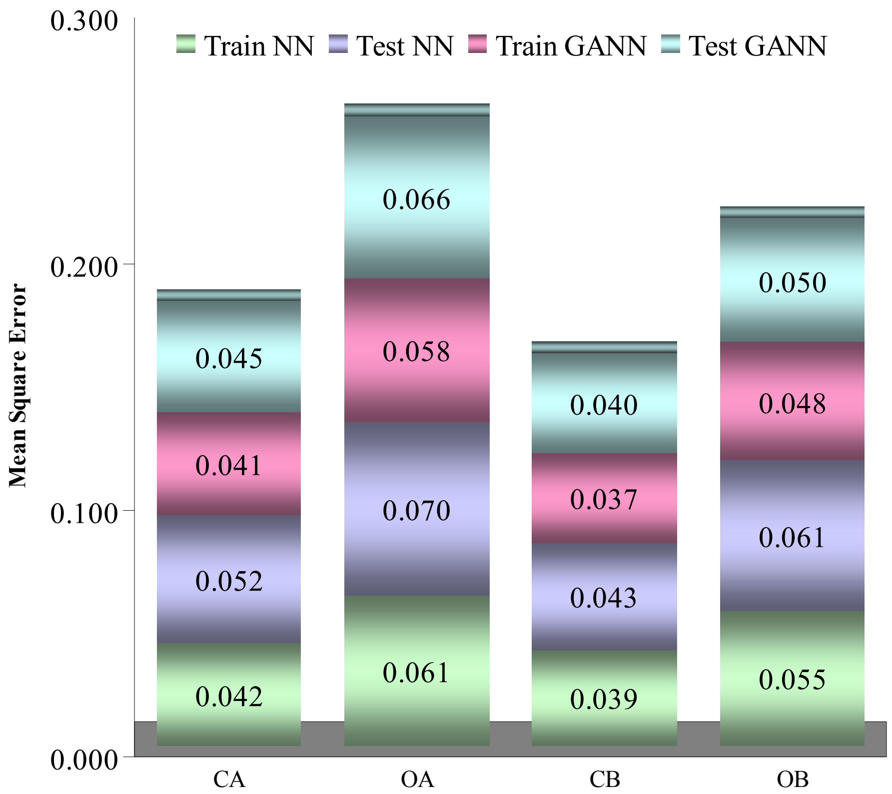


Figure 20: Performance of Neural Network Vs. Neural Network Trained with Genetic Algorithm

In order to select the most suitable data mart for the development of a model, another test was conducted. This test was to compare both performances of the complete data marts in terms of their accuracy in predicting the damage condition. Two networks were used to identify the input parameters used for the model. One network used the complete A as input and the other used complete B data mart as input data.

The performance was calculated using equation (8) (Tchaban et al. 1998), which was a measure for the sensitivity of the input parameters in relation to the damage condition.

$$S_i = \frac{1}{PN} \sum_p do_k^p \frac{\partial o_k^p}{\partial x_i^p} \quad (8)$$

Table 20 shows the sensitivity of both the networks. Both the networks did not give a perfect performance (i.e. 100%). This could be due to the fact that the database used is not the best database. The database had inadequate, inconsistent and noisy data. However, from these results and the size of the available data used, it was sufficient to say that the network using complete B data mart had the ability to predict with an approximately 10 percent higher accuracy than the original network. This performance value implied that around 58 percent of the output was predicted correctly.

Network using	Performance (%)
(i) Complete A	52.54
(iii) Complete B	57.63

Table 20: Performance of Different Networks

In this case, complete B data mart was better suited for the development of a model, due to its better performance compared to the other network. The input parameters for the model included *Region*, *Construction Wall*, *Construction Footing*, *Age*, *Geology*, *change in Thornthwaite Moisture Index* and *Vegetation*.

4.4 Predictive Damage Condition Model

The model was developed to predict the damage condition of light structures on expansive soil. It was assumed that the damage condition was influenced by the chosen input parameters. The Predictive Damage Condition model was based on the selected options and variables from the hybrid Artificial Intelligence technique as shown in Figure 21. The benefit of a hybrid Artificial Intelligence model lay in the fact that they could be used to derive a function from observations. This was particularly useful in the application of Building Housing Commission data marts because of the complexity of the data or task which makes the design of such a function by hand impractical.

The model was derived under the assumption that there was a functional relationship between the input parameters M and the damage condition as shown in equation (9).

$$f\colon M \rightarrow DC \tag{9}$$

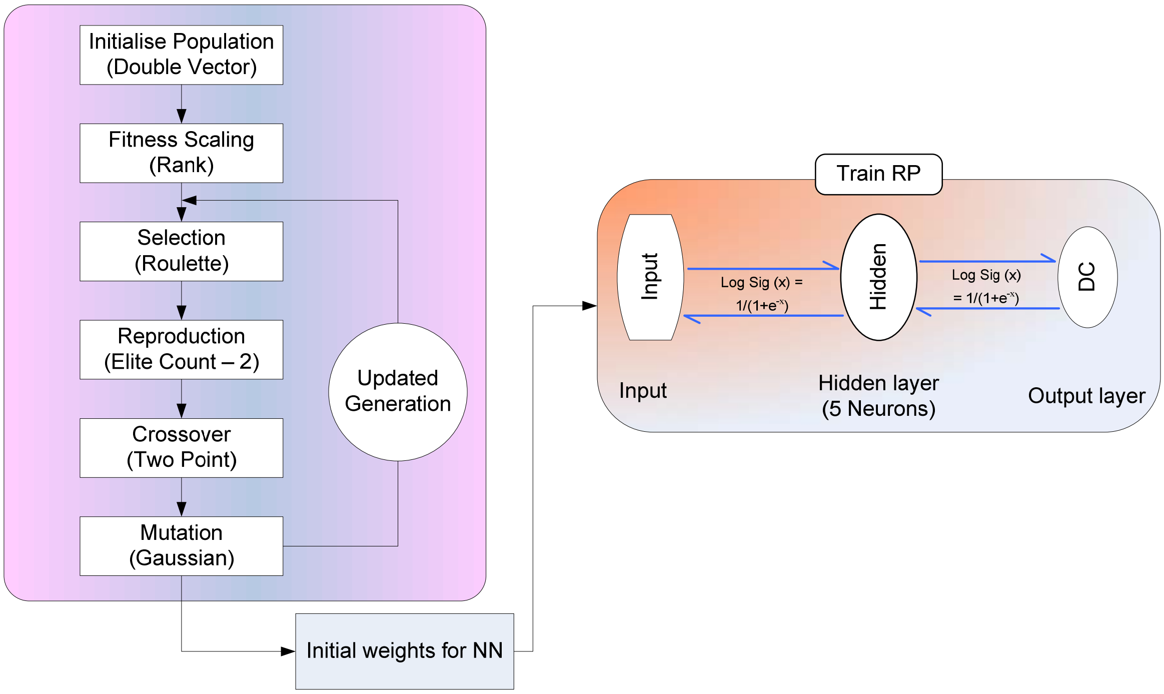


Figure 21: Predictive Damage Condition Model

A simulation function (Figure 22) in Neural Network toolbox was used to predict the damage class. A simulation function simulates the model (Demuth and Beale 2001). It simulated the input (the scenario) and the network (the predictive damage model), and returned an output (damage condition). A simulation is an imitation of some real thing or process. The act of simulating something generally entailed representing certain key characteristics or behaviours of a selected physical system. Simulation could be used to show the eventual real effects of alternative conditions and courses of action. In this case simulation was used to predict damage class of light structure using the available real life parameters. The outcome of the predictive damage condition was a combination of Table C1 (Appendix 3) and C2 (Appendix 4) in Standards Australia (1996a), which is described in Table 21.

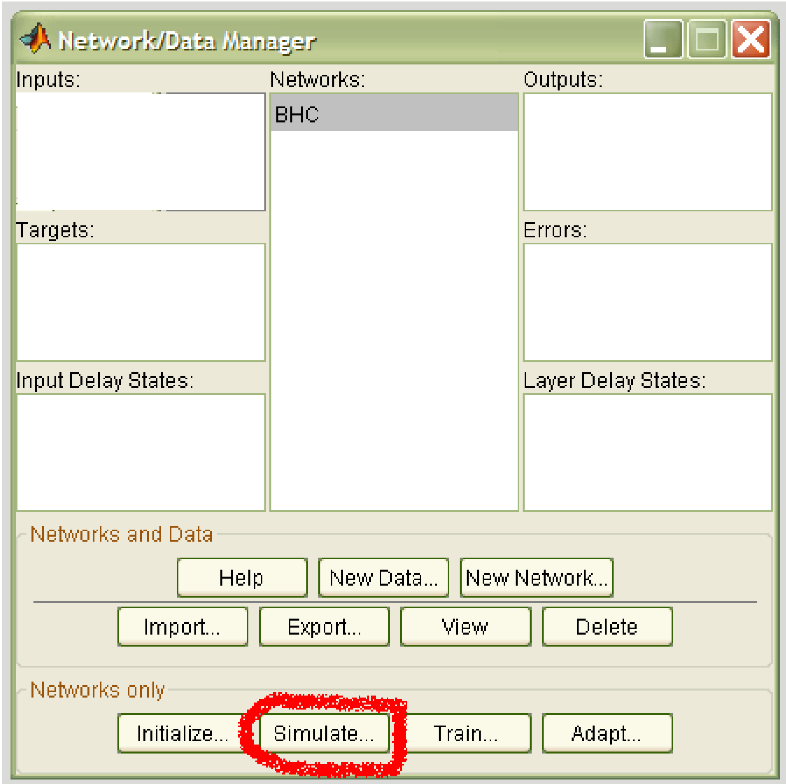


Figure 22: Simulation Function in Neural Network Toolbox

DC 0	0<PDC $\leq$ 0.125	Hairline cracks, insignificant movement of slab from level
DC 1	$0.125 < PDC \leq 0.375$	Fine cracks (do not need repair). Slab reasonably level
DC 2	$0.375 < PDC \leq 0.625$	Distinct crack. Change in level.
DC 3	$0.625 < PDC \leq 0.875$	Wide cracks. Change in level
DC 4	$0.875 < PDC \leq 1.00$	Extensive repair work. Gaps in slab. Change in level

Table 21: Damage Condition Levels of Light Structure

Figure 23 : Damage Class Scale for Light Structure

Since the output values after simulation would give a mean value, a scaled output values for each class of damage were developed as shown in Table 21 and Figure 23. The table and figure indicated that the output value would not fall on the exact whole value as the simulation would give a mean value. Therefore, the output values of the scenarios were scaled accordingly. A property would have damage class 0 when the output value was between 0 and 0.125. Damage class 1 when the output values fall between 0.125 and 0.375, damage class 2 between 0.375 and 0.625, damage class 3 between 0.625 and 0.875 and finally damage class 4 when the values fall between 0.875 and 1 respectively. The values would not fall below 0 or above 1 as all the codes were set up to have values between 0 and 1 accordingly. Therefore, damage class 4 with output values between 0.875 and 1 would be the damage class to avoid when designing a light structure as it was the most severe damage.

4.5 Conclusion of the Development of Predictive Damage Condition Model

This chapter described the use of different algorithms to select a suitable data set and algorithms to develop a Predictive Damage Condition model for Building Housing Commission Datamart. Two methods were used, one was using a conventional method which is the Statistical analysis and the other is using a more advanced Artificial Intelligence approach. An ordinal regression for statistical method was chosen to compare the performance with Artificial Intelligence methods.

Both the Original and Complete Data sets were used in Statistical and Artificial Intelligence methods to compare the performances. The results showed that the complete data mart gave better performances than the original data mart with missing lines of data. Statistical method showed that it could only handle complete data to obtain good performance of the model. Even though Artificial Intelligence method could handle missing values, complete data mart showed more promising results which are in agreement with statistical method. Thus the complete data mart was used using Neural Network trained with Genetic Algorithm.

The advantages of a hybrid Artificial Intelligence technique were numerous. A better understanding could be gained with respect to structure function connection of networks and the optimal parameter tuning of standard neural learning procedures when using a hybrid technique (Weiß 1994). Genetic Algorithm could be used to train all different varieties of the network where it could select initial weights for the recurrent network which was done in this research project. Genetic Algorithm could optimise not just weights but any combination of weights, topology and transfer functions (Montana 1995). Genetic Algorithm was particularly good at efficiently searching large and complex spaces to find nearly global optima. In this case, Genetic Algorithm was more attractive than Backpropagation which was used earlier to compare the performance of hybrid technique in this research project. More over, Genetic Algorithm was an excellent complement to Backpropagation for complex searchers (Montana 1995; Belew et al. 1990). In comparison, Genetic Algorithm was much better at locating good initial weights than Backpropagation approach. The results showed in the hybrid Artificial Intelligence technique was more efficient than using Neural Network alone.

This chapter also described the procedures for the selection of the options and variables needed in the development of the Predictive Damage Condition model. The network which used Complete B data mart was adopted to define the input parameters for the model. The input parameters include *Region, Construction Wall, Construction Footing, Age, Geology, change in Thornthwaite Moisture Index* and *Vegetation*.

The Predictive Damage Condition model using a hybrid Artificial Intelligence technique was developed. A simulation process would return an output value which indicated the damage class of a property. The damage class were based on output values in Table 21 and Figure 23. The next chapter described the analysis that could be performed from the model. The analysis of the data included the ranking of the parameters according to their influence to the damage condition and the relationship of the parameters with other parameters (correlated parameters). Another analysis which was the main reason to for this research project was to predict the outcome of the damage condition or class when used with various scenarios with particular sub variable of the chosen input parameters.

Chapter 5

THE ANALYSIS FROM THE PREDICTIVE DAMAGE CONDITION MODEL

This chapter examined on the analysis of the Predictive Damage Condition model developed in the previous chapter. This chapter was concerned with (i) the importance of the selected input parameters, (ii) the linking or correlation of the input parameters and (iii) generating a forecast of structure performance or predicting the damage condition of light structures.

The importance of the selected input parameters was evaluated using four methods; Clamping and Pruning methods as well as Connection Weights Analysis and Garson's Algorithm. Clamping and Pruning methods identified which parameters were the most important in the influence of damage to light structures. The performances of the pruning and clamping methods were evaluated using their generalisation performances. Their importance in terms of their performances or impact ratio was ranked accordingly. These methods were then compared with Connection Weights Analysis and Garson's Algorithm. These methods evaluate the input parameters of the Neural Network according to the weights of the input when trained using neural network. The methods were explained further in the subsequent sections.

The next concerned was the correlation of the input parameters. The direction and strength of a possible relationship between input parameters will be evaluated using Connection Weights Analysis and Garson's Algorithm. The bigger the weights obtained, the more related the parameters were to another. This indicated that they were not independent from each other. For example, it was expected the geology of an area was related to region as every region has different geology type. These methods were compared with a more conventional method, Spearman's rank correlation.

Finally, the last concern was the prediction of damage condition of light structures which was the most crucial part of the thesis. Section 5.2 covered the methodology for the prediction of the class of the damage condition using the Predictive Damage Condition model. Based on real life scenarios with particular input data, the application of the damage class prediction was demonstrated.

5.1 Importance of the Input Parameters

Clamping and pruning as well as Connection Weights Analysis and Garson's Algorithm were used to determine the rank of the input parameters. The final results were taken by averaging all the values from all the methods. Each method was further discussed. The ranking of the input parameters was validated or tested for their precision using different data marts.

5.1.1 Clamping Method

"If a parameter is redundant with respect to a classification of instances of a given problem, then clamping the corresponding network's input to a fixed value will have no adverse effect on the generalisation performance of a trained Neural Network compared to the same tests with it's original values"(Wang et al. 2000).

Wang *et al.* (2000) stated that the impact of an input has a severe effect on the performance of a trained network if this input is clamped using its mean value. Therefore, the input of the network was clamped using their mean value as in equation (10).

$$\bar{x}_i = \frac{1}{n}\sum_{n=1}^{n} x_{in} \tag{10}$$

To assess the impact of the input parameter quantitatively, the impact ratio, $\xi(x_i)$, of input parameters, x_i on the output was calculated using equation (11) (Wang et al. 2000). The higher the generalisation performances, (gp), of network, the more impact it had on the network. The input parameters were then ranked in descending order according to their impact ratio. A larger impact ratio indicates that the particular input parameter was more important and had a stronger impact on the output.

$$\xi(x_i) = 1 - \frac{gp\left(x\big|_{xi=\bar{x}i}\right)}{gp(x)} \tag{11}$$

A dummy input parameter was added to the Neural Network to show that it had no effect on the generalisation performance of the network. This technique was called clamping. Table 22 shows the clamped network. The dummy parameter had the same numerical value (in this case, numerical value 1 was chosen because 1 was the maximum value). All the clamped networks were trained individually using their clamped input parameters. The generalisation performance of the original network was evaluated in the previous chapter. The value for the performance for the network with complete B data mart was 57.63. Table 23 shows the generalisation performances of the clamped networks.

Clamped networks
Region clamped (CR)
Construction Wall clamped (CCW)
Construction Footing clamped (CCF)
ChgTMI clamped (CChgTMI)
Geology clamped (CG)
Vegetation clamped (CV)
Age clamped (CA)
Additional “dummy” feature

Table 22: Clamped Networks

In Table 23, it can be seen that the generalisation performance of the network with an additional dummy input parameter was the lowest. This indicated that the dummy input had no impact at all on the network. This was accurate as the dummy input was just to prove that it was redundant and it had no important value for the network. It could also be seen from Table 23 that all generalisation performances of the clamped networks were lower than the performance of the network of complete B data mart. This indicated that they have impacts on the network as the values were not constant with the network with complete B data mart.

Network	Generalisation Performance	Impact ratio
Region clamped (CR)	54.24	0.94
Construction Wall clamped (CCW)	54.24	0.94
Construction Footing clamped (CCF)	52.54	0.91
ChgTMI clamped (CChgTMI)	54.24	0.94
Geology clamped (CG)	54.24	0.94
Vegetation clamped (CV)	52.54	0.91
Age clamped (CA)	50.85	0.88
Dummy network	27.12	0.47

Table 23: Generalisation Performance Of Clamped Networks

The ranking of the input parameters according to their generalisation performance can be seen in Figure 24. The graph was based on the ranking according to the impact ratio with the highest being the most important. It showed that four of the input parameters have the highest ranks. These were *Change in Thornthwaite Moisture Index,* Geology, *Construction wall* and *Region*. The parameters *Vegetation* and *Construction footing* shared the second rank. The *Age* had the lowest rank among all input parameters, which was expected as the categorical regression test showed that *age* was not significant.

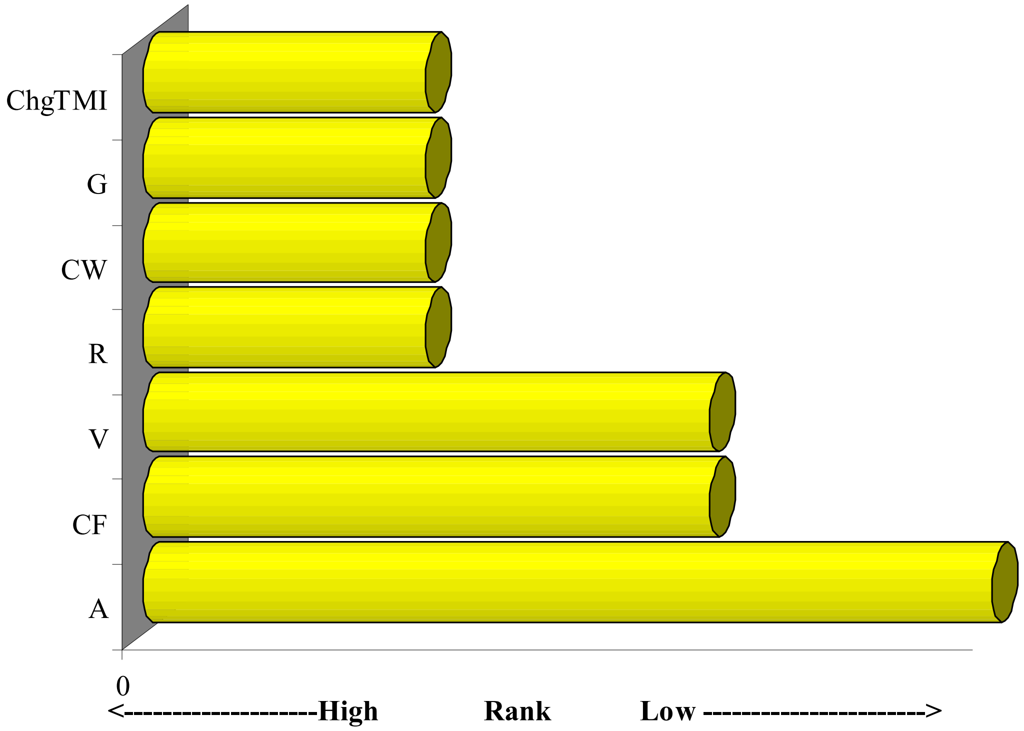


Figure 24: The Ranking of the Input Parameters Using Clamping Method

5.1.2 Input pruning

Pruning is a process where the neural network is made more efficient. The primary goal of pruning was to increase the amount of processing required of the neural network. Pruning methods usually either remove complete input or hidden nodes along with all their associated parameters or removal individual connections (Prechelt 1995). Pruning of the input was chosen in this research project. By pruning "unwanted" input the neural network can be made to execute faster. This allowed the neural network to perform more work in a given amount of time. Input pruning worked by analysing the connections of the neural network.

The individual input was analysed to determine which connections have the least impact to the effectiveness of the neural network. The method used in this research project was by removing input individually to observe the impact of each input on the performance of the neural network. Any modification to the input of a neural network would always have some impact on the accuracy of the performance of neural network. An input that has little or no impact on the neural network may slightly degrade the accuracy of the neural network's recognition. Removing such weak input parameters may improve the overall output of the neural network (Heaton 2005).

The pruning method involved pruning or removing the feature input of the network before training the network. The same networks for clamping method were used in the pruning method as in Table 24. As with the clamping method, if the input was of relevance to the network or other input, then the performance of the network would increase.

Pruned networks
Region pruned (PR)
Construction Wall pruned (PCW)
Construction Footing pruned (PCF)
Age pruned (PA)
Geology pruned (PG)
ChgTMI pruned (PchgTMI)
Vegetation pruned (PV)

Table 24: Pruning Network

The networks were trained using the same method as the clamping method. The performance of the results was also calculated using the same procedure as the clamping method. Table 25 shows the generalisation performance of the pruned networks. It showed that all generalisation performances of the pruned network were different compared to the network using complete B data mart with generalisation performance of 57.63. This indicated that all input parameters have impacts on the network even if some performances, e.g. *Construction wall* pruned and *Vegetation* pruned were very close to the performance of the network with complete B data mart.

Network	**Generalisation Performance**	**Impact ratio**
Region pruned (CR)	54.24	0.94
Construction Wall pruned (CCW)	55.93	0.97
Construction Footing pruned (CCF)	50.85	0.88
ChgTMI pruned (CChgTMI)	54.24	0.94
Geology pruned (CG)	52.54	0.91
Vegetation pruned (CV)	55.93	0.97
Age pruned (CA)	49.15	0.85

Table 25: Generalisation Performance of Pruned Networks

Figure 24 shows the ranking of the input parameters using pruned network. The ranking was based on the values of the impact ratio in Table 25. *Vegetation* and *construction wall* have the highest importance. These showed that the two input parameters were the most important among all the other. *Change in Thornthwaite Moisture Index* and *Region* were the second ranked. *Geology* was the third followed by *construction footing*. Again *Age* was the last ranked with impact ratio of 0.85. This showed that it was the least important.

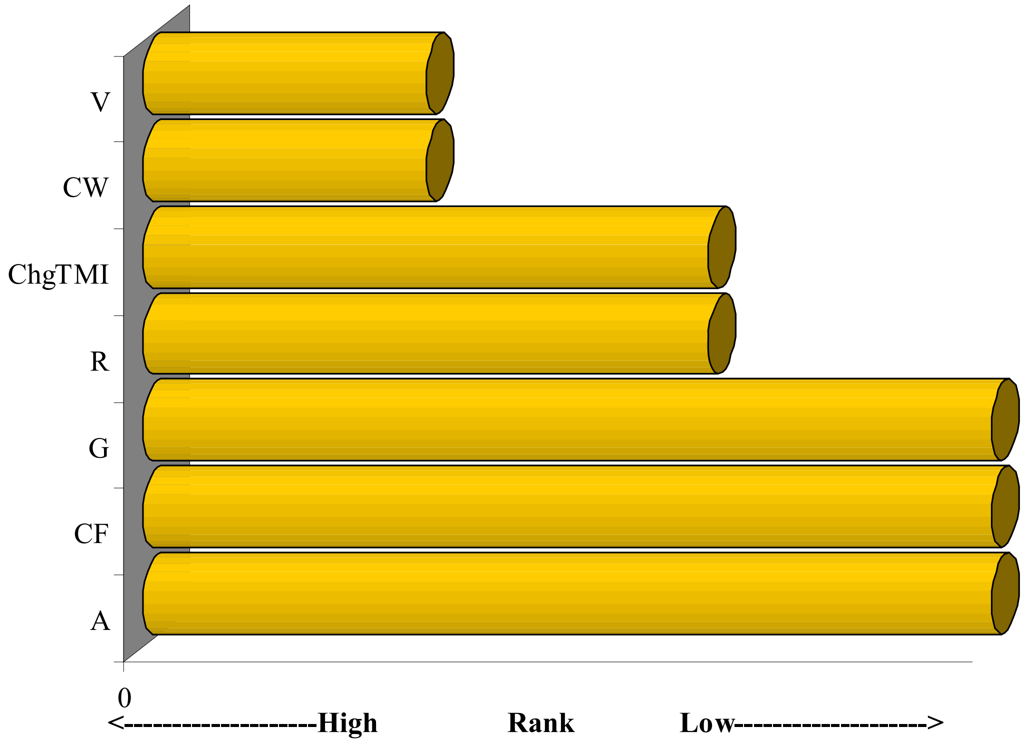


Figure 25: The Ranking of Input Parameters Using Pruning Method

5.1.3 Comparison of Input Pruning and Clamping Methods

From the two methods above, both pruning and clamping methods showed almost the same generalization performance values between 49 to 56 percent. It was clear from both the methods that *construction wall* was significantly affecting the network. This could mean that this input parameter was the most influential in predicting damage condition. *Change in Thornthwaite Moisture Index* and *Region* were the other two important ranks after *construction wall* which was shown by both methods. *Age* and *construction footing* seem to be the least important of all the input parameters.

The rank of *Geology* and *Vegetation* were different for both the clamping and pruning methods. In the clamping method, *Geology* was ranked first together with *construction wall*. However, in the pruning method, it was ranked third last *before construction footing*. *Vegetation* on the other hand was ranked first in pruning method while second in clamping method.

Since the results were still indecisive, Connection Weights Analysis and Garson's Algorithm were used to confirm the findings.

5.1.4 Connection Weights Analysis (CWA)

Connection Weight Analysis calculates the raw input-hidden and output-hidden connection weights between each input neuron and output neuron. The products were then summed up across all hidden neurons (Olden and Jackson 2002). The values calculated were converted into a percentage form. This form was the simplest way of expressing how large one parameter was in terms of another parameter. Figure 26 shows the values of the input parameters calculated using Connection Weights Analysis. The numbers indicated the percentage. The larger the percentages the more influential the input parameters were.

The *construction footing* has the largest percentages as seen in Figure 26. This indicated that *construction footing* was the input parameter that has the most influence in damage to light structure. *Vegetation* and *change in Thornthwaite Moisture Index* were two other input parameters that were fairly important before *Age*. Both *vegetation* and *change in Thornthwaite Moisture Index* shared the same percentage of 51%. This put *vegetation* and *change in Thornthwaite Moisture Index* in second ranked. With 42% and 22%, *Region* was the fourth and *geology*, fifth important respectively. The least important in this case is *construction wall* which was a contrast to the previous two methods used. *Construction wall* was the most important in the pruning and clamping methods. Figure 27 shows the ranking of the input parameter using Connection Weights Analysis.

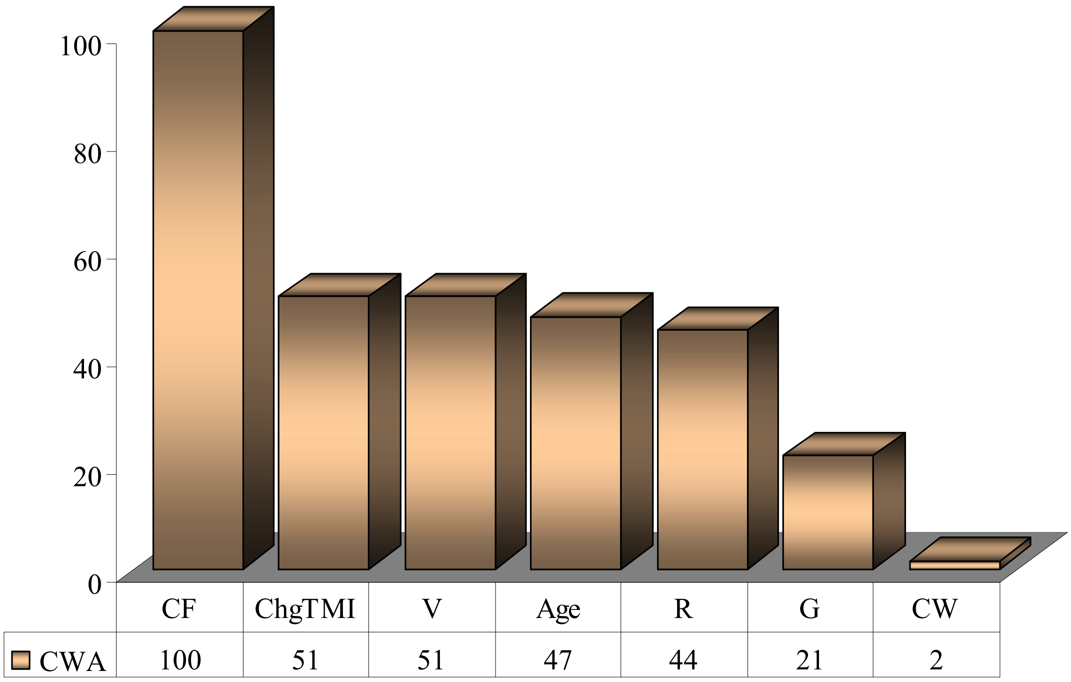


Figure 26: Percentages of Input Parameters Using Connection Weights Analysis

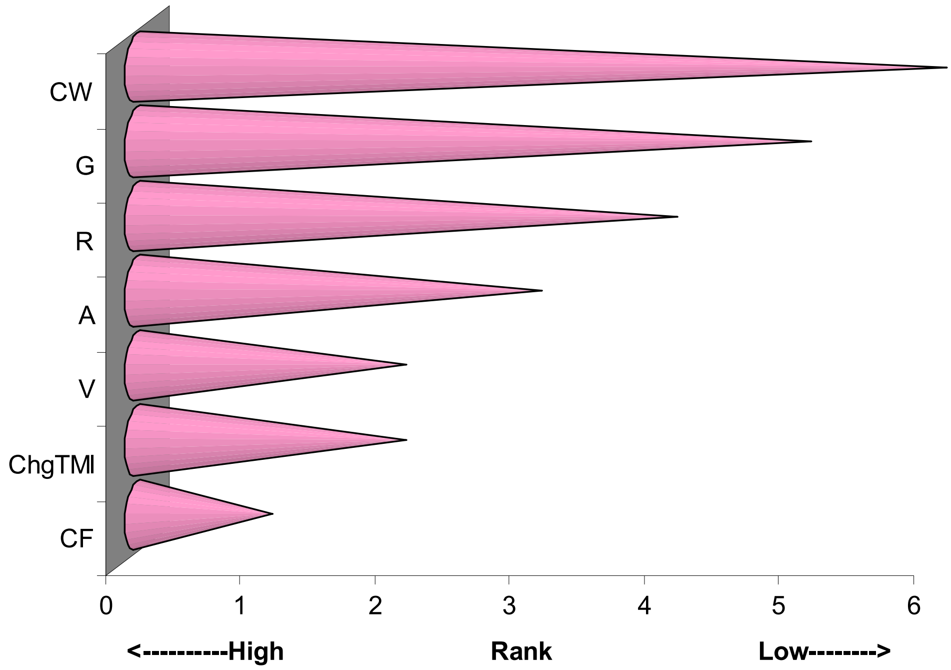


Figure 27: Ranking of Input with Connection Weights Analysis

5.1.5 Garson's Algorithm

Garson's Algorithm is similar to Connection Weights Analysis except that Garson's Algorithm calculates the absolute value of the connection weights when calculating the factors contribution. Hence, it does not provide the direction of the relationship between input and output factors (Olden and Jackson 2002). Each absolute value of input-hidden weight was divided by the sum of all the weights that were connected into the hidden neurons.

Figure 28 shows that most percentage values of the parameters were nearly the same except for *construction footing*. In the Connection Weights Analysis, *construction footing* was the most important input parameter. It could be seen in Figure 28 that the ranking of the input parameters have slightly changed compared to ranking in Connection Weights Analysis. The ranking order in Garson's Algorithm had the parameter

Age ranked second compared to third in Connection Weights Analysis. *Vegetation* was now ranked third. In Garson's Algorithm, *construction wall* was ranked fourth compared to last ranked in Connection Weights Analysis. *Geology* had the same spot as Connection Weights Analysis which was ranked fifth. *Change in Thornthwaite Moisture Index* was ranked sixth with a value of 41%. The least importance was the *Region* with 5% less than *change in Thornthwaite Moisture Index*. Figure 29 shows the ranking of input parameters using Garson's Algorithm.

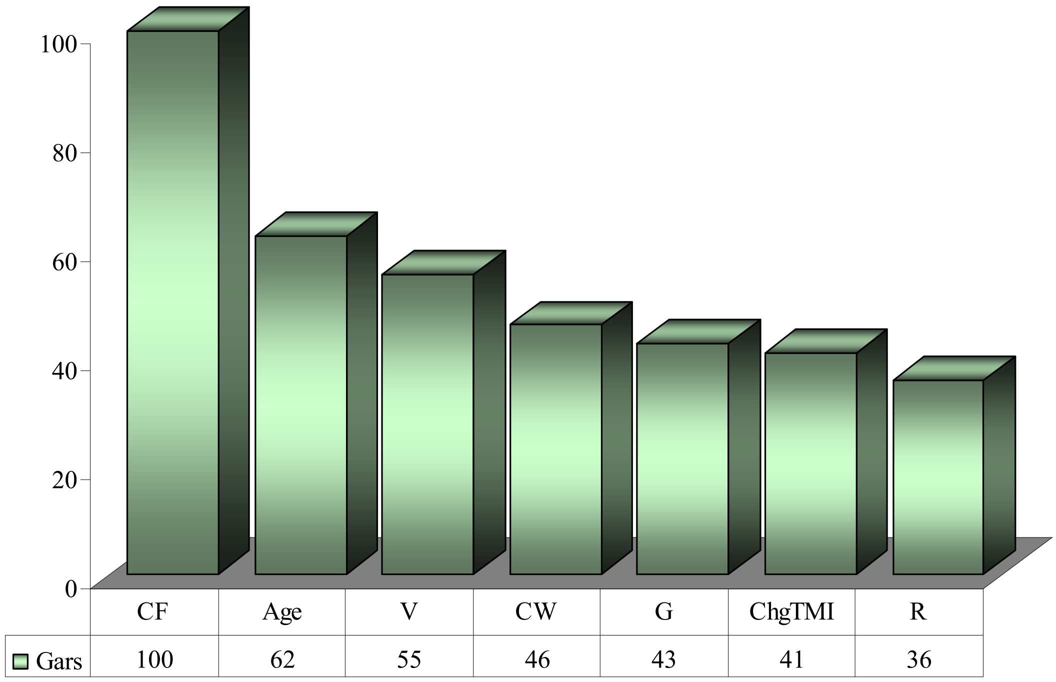


Figure 28: Percentages of Input Parameters Using Garson's Algorithm

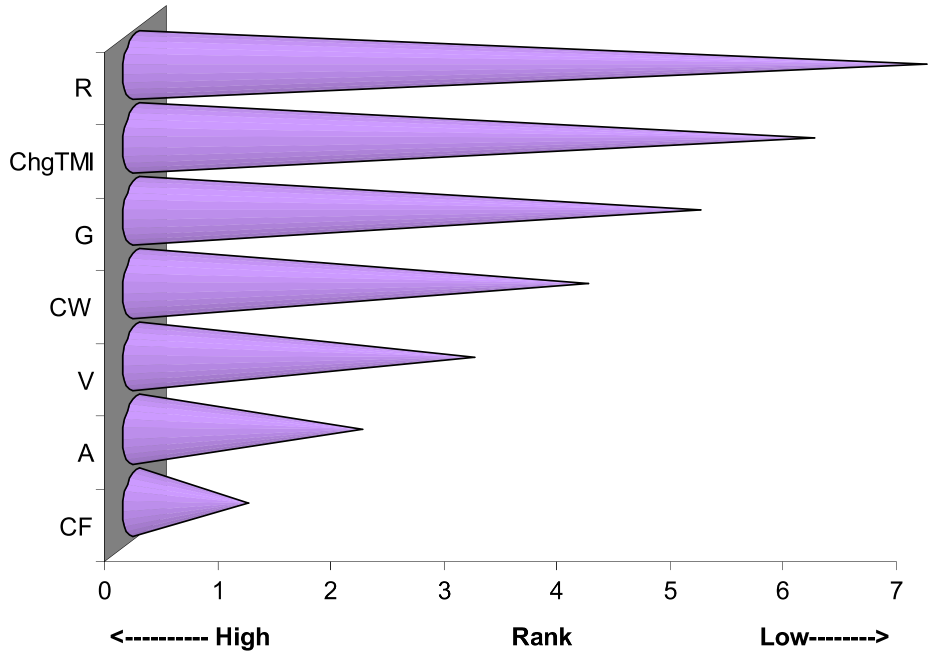


Figure 29: Ranking of Input Parameters with Garson's Algorithm

5.1.6 Ranking of Individual Input Parameters

The ranking of input parameters using the four methods were fairly consistent. Therefore, it was decided to take an average of all the ranks. Figure 30 shows the selected input parameters according to their ranking based on the average results of Pruning, Clamping, Connection Weights Analysis and Garson's Algorithm.

From Figure 30, *construction footing* and *vegetation* were the most important among all the other input parameters. This meant that damage to light structure on expansive soil was influenced by these two parameters. As predicted by researchers such as Holland *et al.* (1981; 1979), Driscoll (1983) and Biddle (1998b), *vegetation* influenced the extent of ground movement hence damage to light structures. A study done by Holland *et al.* (1981; 1979) also indicated that type of *construction footing* was also important in determining the cause of damage to light structures. Therefore, it could be said that *vegetation* (existing) and *construction footing* (type) were crucial in influencing damage to light structures. Hence it was not surprising that both were ranked first among all the input parameter.

Change in Thornthwaite Moisture Index or climate was ranked second. Climate was another parameter that may influenced damage to light structures according to researchers such as Masia *et al.* (2002) and Rogers *et al.* (1993). The importance of climate can be seen in the design of foundation. In accordance to the Australian Standards 2870 (Standards Australia 1996a), one of the factors that was needed to design foundation was the climate zone of the area. Therefore, the change in climate was crucial in deciding which type of foundation was suitable for a particular zone. Climate was also a major factor for the *vegetation*. The influence of *vegetation* on damage to light structures depended on the climate. This was mentioned in the literature review where Holland (1979) indicated that in Melbourne, tree drying damage to foundations was very common during late summer and early autumn.

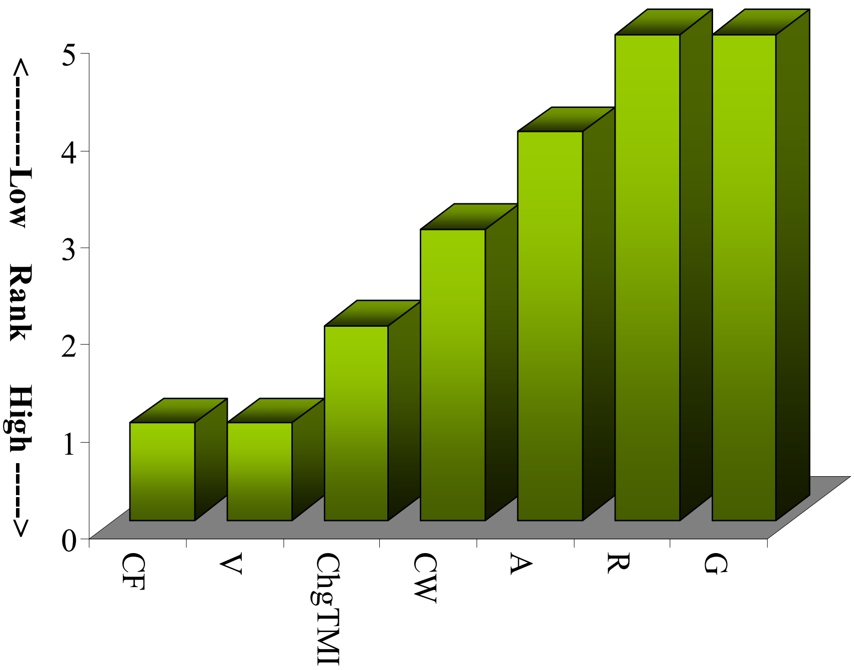


Figure 30: Average Ranking of Input Parameters

5.1.7 Correlated Input Parameters

Three methods were used to rank the correlated input parameters which were Connection Weights Analysis, Garson's Algorithm and Spearman's Rank Correlation. The later method was used to compare the other two methods.

5.1.7.1 Spearman's Rank Correlation

Spearman's Rank Correlation is a technique used to test the direction and strength of the relationship between two variables or parameters. Altman (1991) expresses Spearman's Rank Correlation, Rs as a technique used to test the strength of relationship between two variables/factors and would take a value between 1 and +1. A positive correlation was one in which the ranks of both variables increased together. A negative correlation was one in which the ranks of one variable increase as the ranks of the other variable decreased. A correlation of +1 or 1 would arise if the relationship between the two variable/factor was exactly linear. A correlation close to zero meant there was no linear relationship between the ranks. The further the coefficient was from 0, regardless of whether it was positive or negative, the stronger the relationship between the two variables.

Spearman's Rank Correlation, R_s uses equation (12) to calculate the rank of the variables/factors between two sets of data. However, the R_s only measures linear correlation between two sets of data where it treats all the factors equally without considering their relative ranking (Wang et al. 2000). Table 26 shows the summary of R_s value where n is the number of ranks and d is the difference between two ranks.

$$R_s = 1 - 6\left(\Sigma d^2 / n^3 - n\right) \tag{12}$$

R_s Value	**Description of R_s Between The 2 Sets of Data**
-1	Perfect negative correlation
-0.5 > R_s < -1	Strong negative correlation
-0.5 > R_s < 0	Weak negative correlation
0	No correlation
0.5 > R_s < 0	Weak positive correlation
0.5 > R_s < 1	Strong positive correlation
1	Perfect positive correlation

Table 26: Summary of R_s Values between 2 Sets of Data

The range for the correlation was from -0.339 to 0.350. This indicated that the most of the correlation have weak (positive and negative) correlation. However, since the aver*age* value was 0.360, any value above 0.300 was considered to have strong correlation and any value below 0.300 was considered to have weak correlation. The following were the Spearman's correlation for the input parameters.

- *Region*

Figure 31 shows the correlation of *region* with all the parameters. It showed that *Region* had a strong correlation with most of the parameters especially with change in Thornthwaite Moisture Index. This indicated that *region* "rely" on other parameter in terms of influencing damage to light structures. In other words, damage may occur at any *region* with the presence of other parameter such as *vegetation* and change in Thornthwaite Moisture Index for example.

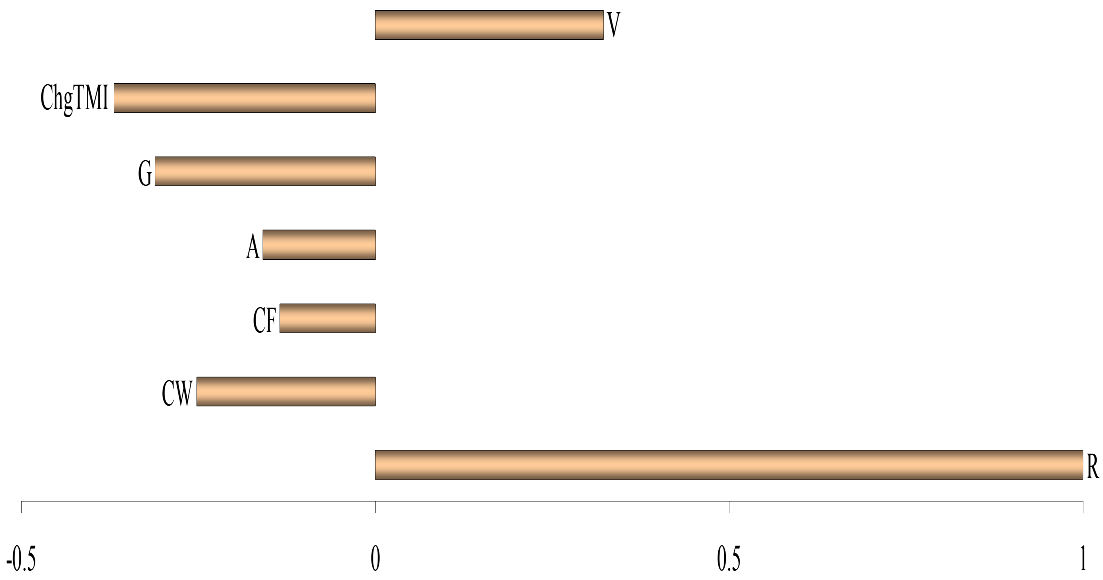


Figure 31: Correlation with *Region*

- *Construction Wall*

From Figure 32, *Construction wall* had strong correlation with four parameters in particular. These were *age*, *change in Thornthwaite Moisture Index*, *geology*, *region* and *vegetation*. The influence of *construction wall* to damage to light structure did depend on the five parameters. For instance, the correlation of age, change in climate and *construction wall* showed that the wall may crack or deteriorate to some extent due to the change in climate over time. The weakest correlation was with *construction footing*. This showed that when movement occur on *construction wall*, it did not cause *construction footing* to experience movement. Thus, there was no correlation with the two parameters.

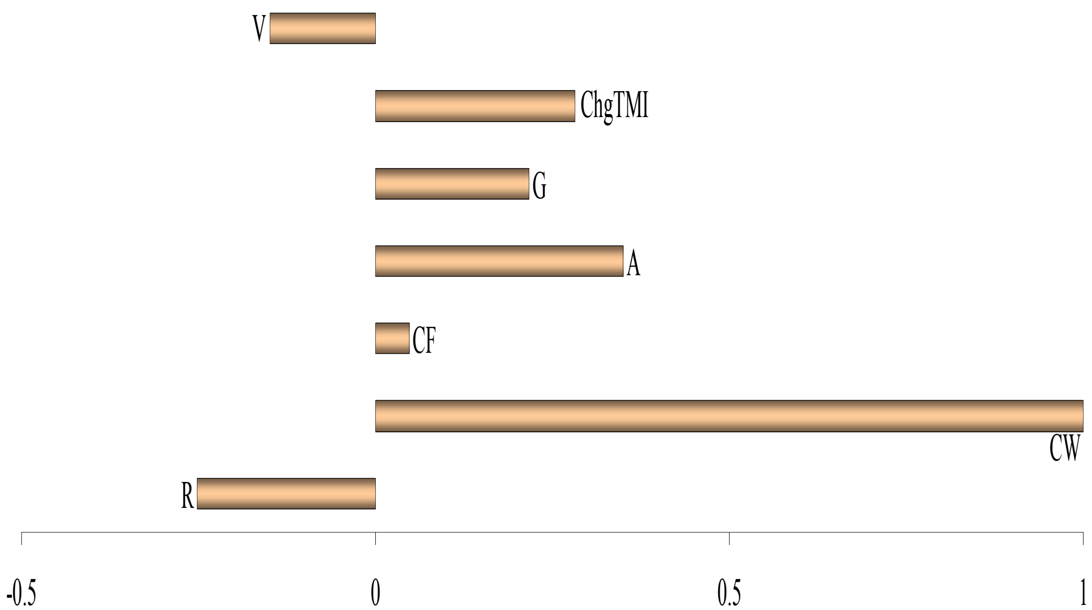


Figure 32: Correlation with *Construction Wall*

- *Construction Footing*

Figure 33 shows the correlation between *construction footing* with all other parameters. It seemed that *construction footing* has the weakest correlation with all other parameters with most of the values falling below ±0.3. This showed that the *construction footing* did not need the other parameters to influence damage. It was mentioned that *construction footing* was the most susceptible to damage due to movement. However, it still needed other parameter to trigger the movement. For example, change in climate. Since this result was ambiguous, another method would be used to prove the accuracy.

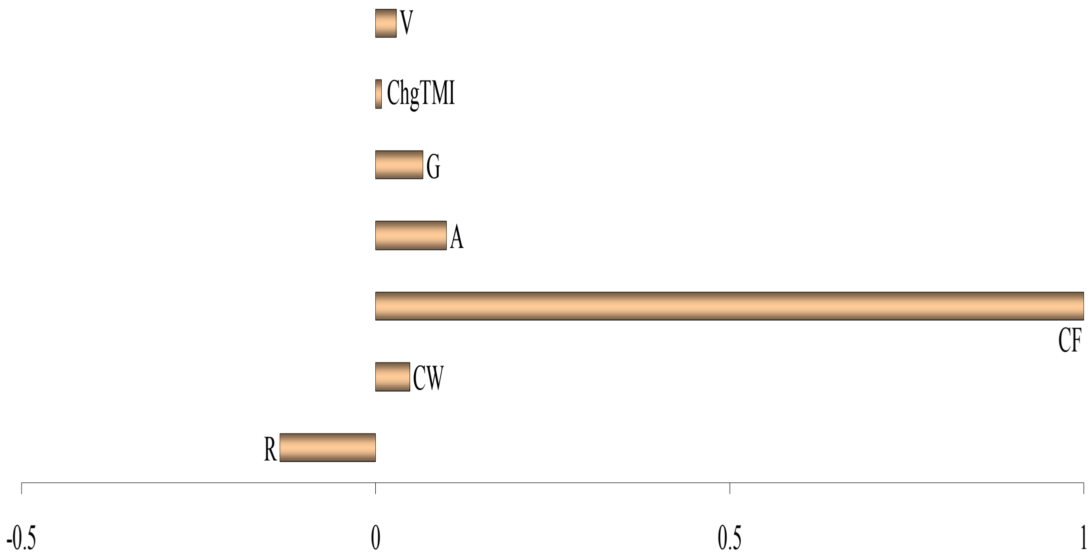


Figure 33: Correlation with *Construction Footing*

- *Age*

Age has a strong correlation with most of the parameters but not so with *construction footing* and *vegetation* as shown in Figure 34. This showed that together with other parameters, age could influence damage to light structures. On its on, age, was the lowest ranked in terms of influencing damage.

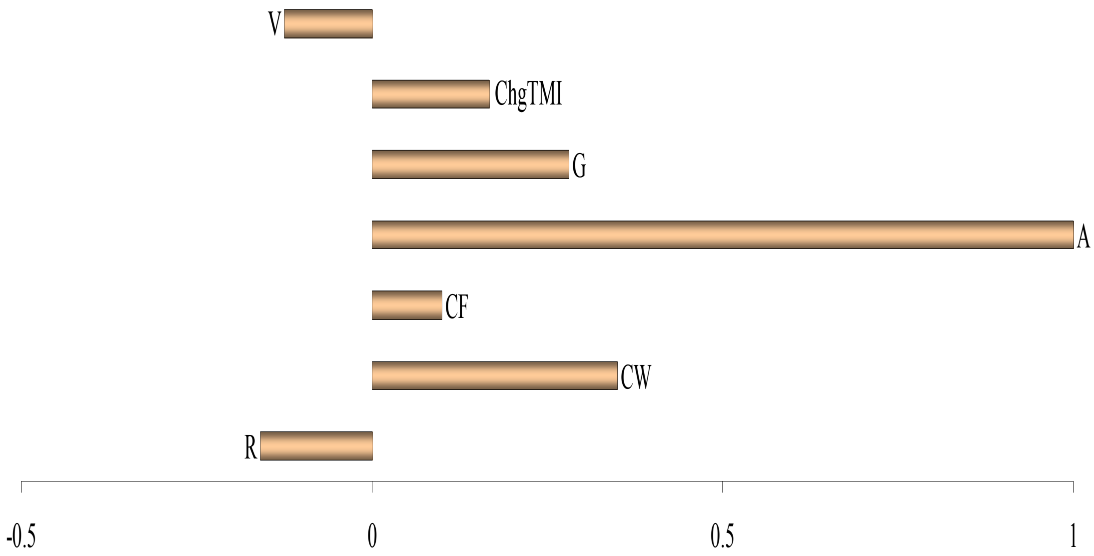


Figure 34: Correlation with Age

- *Geology*

Geology as shown in Figure 35 had strong correlation with all parameters except for *Construction footing*. It had the strongest correlation especially with *region* and change in Thornthwaite Moisture Index. This was probably due to the fact that *geology* type depended on its location (*region*) and the change in climate. The type of *geology* may change over the years depending on the environment. Thus, change in climate was one of the factors influencing *geology* type.

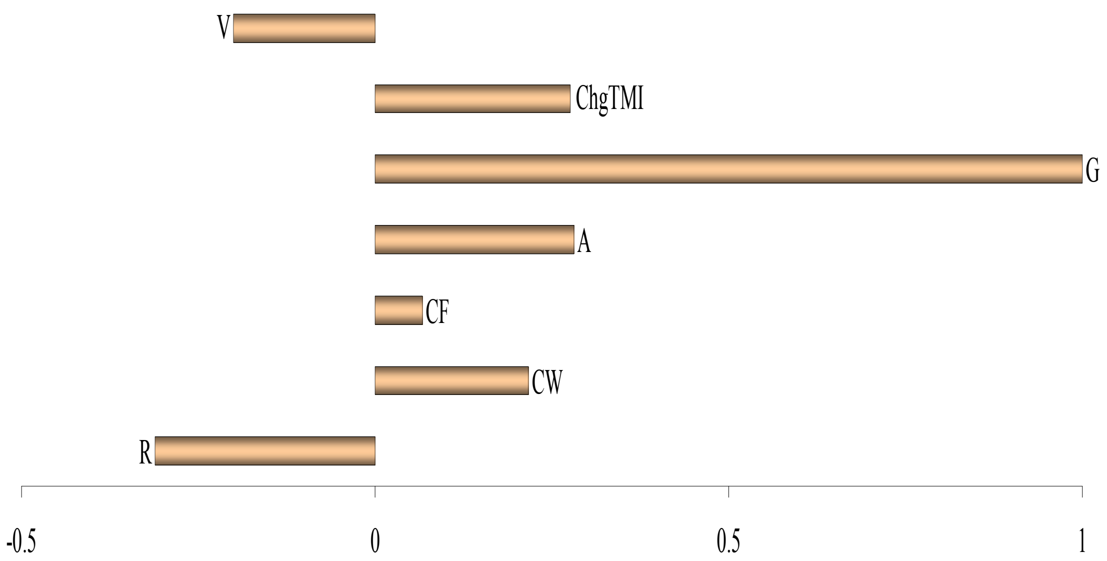


Figure 35: Correlation with *Geology*

- *Vegetation*

Figure 36 shows the correlation between *vegetation* and other parameters. It showed that *vegetation* has strong correlation with all parameters except *Age* and *construction footing*. Again, it showed that *construction footing* was independent with other parameter. *Vegetation* had the strongest correlation with *region* and change in Thornthwaite Moisture Index. This indicated that the type of *vegetation* depended on these two parameters. The type of *vegetation* may be different from one *region* to another for example.

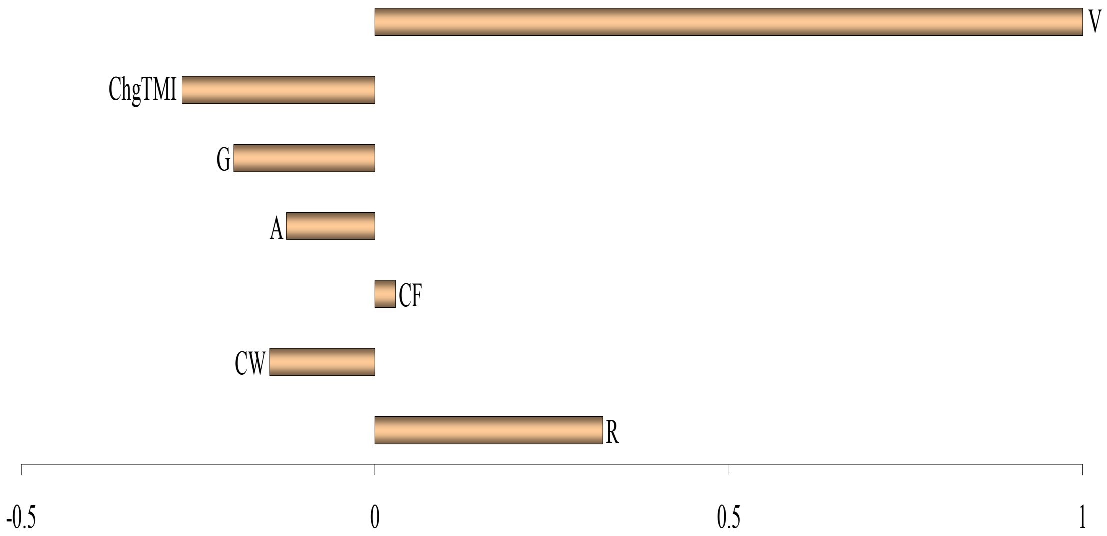


Figure 36: Correlation with *Vegetation*

- *Change in Thornthwaite Moisture Index*

Change in Thornthwaite Moisture Index as shown in Figure 37 had a fairly strong correlation with all the parameters except *Construction footing* with values above 0.300. The strongest correlation was with *region*. This was probably due to the fact that every *region* has different Thornthwaite Moisture Index and this was reflected in the figure.

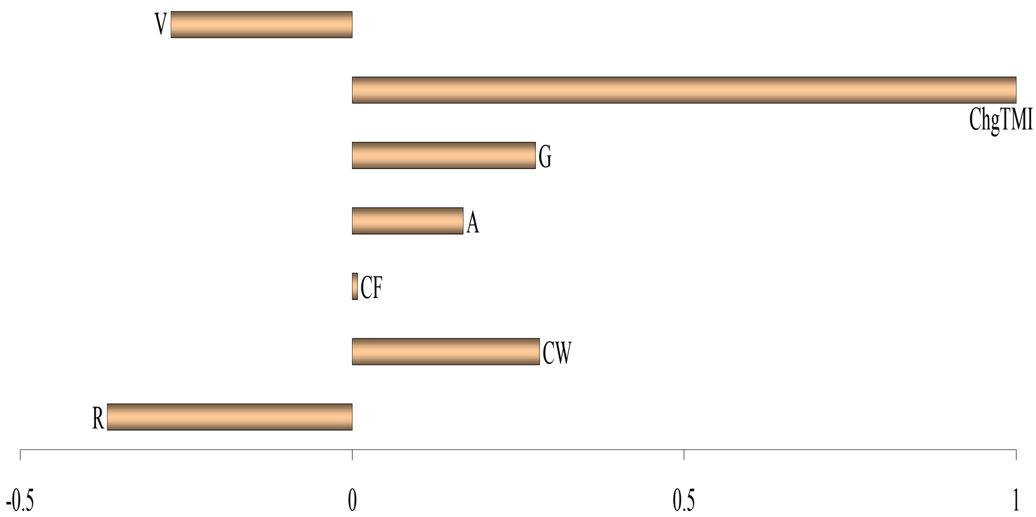


Figure 37: Correlation with Change in Thornthwaite Moisture Index

5.1.7.2 Connection Weights Analysis and Garson's Algorithm

For the investigation of the correlation of input parameters, seven data marts were created that were listed in Table 27. Each set contained data with combined input parameters. Table 27 shows how the input parameters were correlated with each other.

	Correlated with						
Dataset/Parameter	***R***	***CW***	***CF***	***G***	***V***	***A***	***ChgTMI***
R		✓	✓	✓	✓	✓	✓
CW	✓		✓	✓	✓	✓	✓
CF	✓	✓		✓	✓	✓	✓
G	✓	✓	✓		✓	✓	✓
V	✓	✓	✓	✓		✓	✓
A	✓	✓	✓	✓	✓		✓
ChgTMI	✓	✓	✓	✓	✓	✓	

Table 27: Correlated Datasets

All the data marts were trained using the proposed model. Connection Weights Analysis and Garson's Algorithm were used to calculate the weights obtained from the training of the networks. The results of the weights calculated using Connection Weights Analysis and Garson's Algorithm were converted into percentage values. The average values of the two methods were used in the ranking of the importance of the input parameters when correlated.

The larger the percentages the more influential the input parameters were. From the training process, the performances of the dama marts are shown in Table 28. The performance of the correlated networks was in the range of 40 to 55 percent accuracy. This meant that only 40 to 55 percent of the output was predicted correctly. Recall that the *change in Thornthwaite Moisture Index* network/dataset had 58 percent success rate. It could be said that *change in Thornthwaite Moisture Index* network was approximately 25 percent more accurate in predicting the damage condition. The purpose of this section however was not to compare the performances of the network but to verify whether there was any correlation between parameters that influences the prediction of the damage condition.

Dataset/Network	**Performance (%)**
Correlated *Region*	52.54
Correlated Construction Wall	50.85
Correlated *Construction footing*	54.24
Correlated Age	54.24
Correlated Geology	54.24
Correlated Vegetation	40.68
Correlated ChgTMI	45.76

Table 28: Performance of the Correlated Datasets

The following were the results for the correlated input parameters in terms of their relation with the other parameters.

- *Region*

Figure 38 shows the correlation between the *Region* and other input parameters. The results showed an agreement with Spearman's Rank Correlation method. *Region* had a fairly strong correlation with all the input parameters. This was especially for the parameters *change in Thornthwaite Moisture Index, geology* and *Construction footing*. This was obvious as different region had different geological condition and climate zone. The influence of *region* with *construction wall*, age and *vegetation* was not as strong. This meant region had not much influence on these three parameters. For instance, the presence of *vegetation* did not necessarily rely on *region*

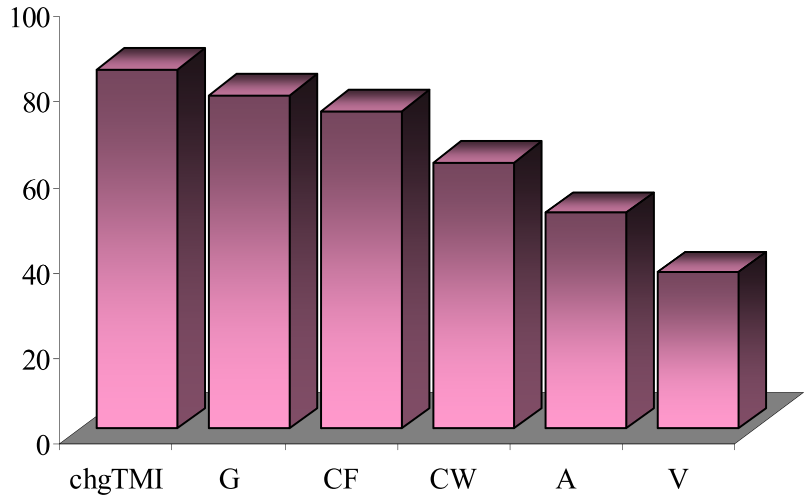


Figure 38: Correlation of *Region*

- *Construction Wall*

Figure 39 shows that *construction wall* was most influenced by *change in Thornthwaite Moisture Index.* This meant that the type of wall chosen for a light structure depended considerably on change in climate. *Construction wall* correlated fairly well with the other parameters though not as strong as *change in Thornthwaite Moisture Index.* This again was in agreement with the results obtained in Spearman's Rank Correlation except *construction footing*. When using the Spearman's Rank Correlation method, *construction wall* was not correlating well with *construction footing*. Here it did.

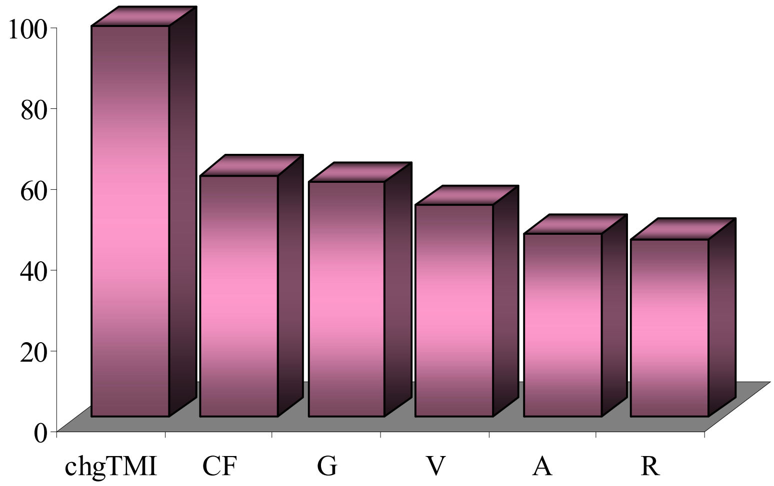


Figure 39: Correlation of *Construction Wall*

- *Construction Footing*

The results obtained in Spearman's Rank Correlation stated that *construction footing* had the weakest correlation with all the parameters. It did not seem to be the case when using Connection Weights Analysis and Garson's Algorithm. *Construction wall* correlated strongly with all the other parameters. *Change in Thornthwaite Moisture Index* has the most influence in *construction footing* as shown in Figure 40. In accordance with the Australian Standard 2870, the design of *construction footing* was influenced by both *change in Thornthwaite Moisture Index* and *geology*. *Construction footing* had fairly strong correlation with *vegetation* and *region*. This could be that ground movement depended both on the type of *vegetation* and the footing.

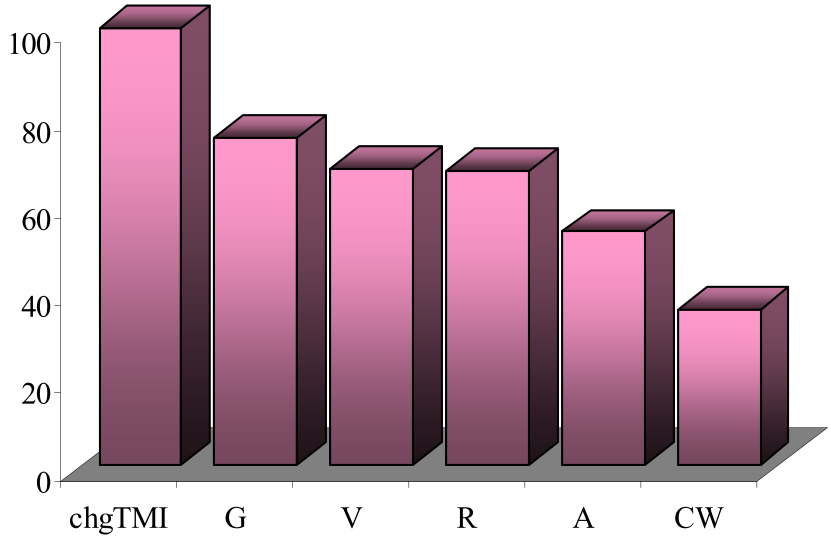


Figure 40: Correlation of *Construction Footing*

- *Age*

Figure 41 shows that Age had a strong correlation with all the parameters especially *change in Thornthwaite Moisture Index.* The relationships with other parameters were also equally strong. This indicated that the age of light structure was influencing all the other parameters. This was in agreement with Spearman's Rank Correlation except for *construction footing*. For example, the older the light structure was, the more vulnerable it was to damage caused by these parameters.

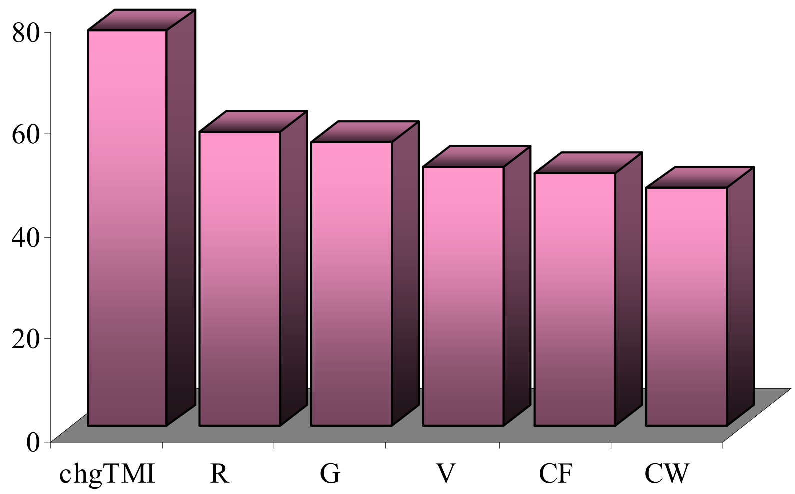


Figure 41: Correlation of Age

- *Geology*

Geology influenced all the parameters equally as can be seen in Figure 42. *Region* and *construction wall* were the most affected by *geology*. This result was in agreement with Spearman's Rank Correlation. This could mean that *geology* varied in different region. The type of *construction wall* depended on the geological site. The design of *construction wall* was another parameter that relied on *geology* as one of the design factors.

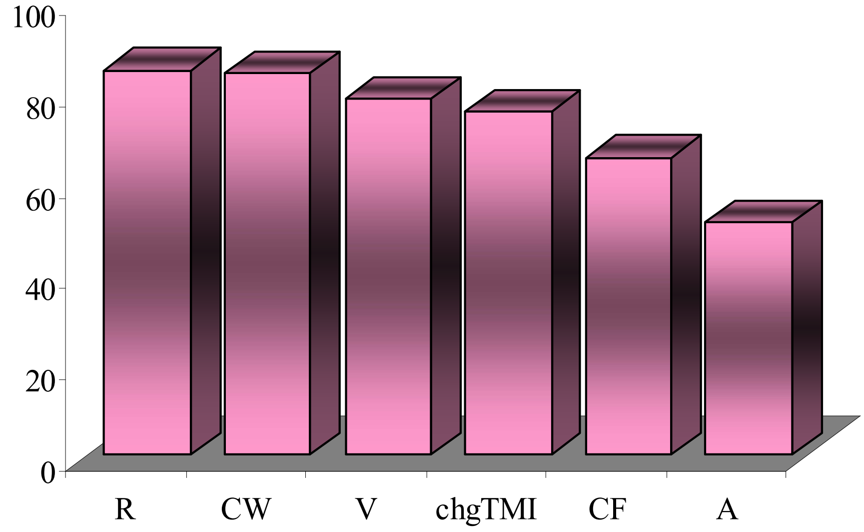


Figure 42: Correlation of *Geology*

- *Vegetation*

Figure 43 show that *vegetation* influenced *construction wall* and *construction footing* the most. The presence of *vegetation* may be the cause of the movement of foundation and wall. *Vegetation* had the least influenced on *geology* and *region*. This could be that the presence of *vegetation* did not rely on the *geology* type or the *region*.

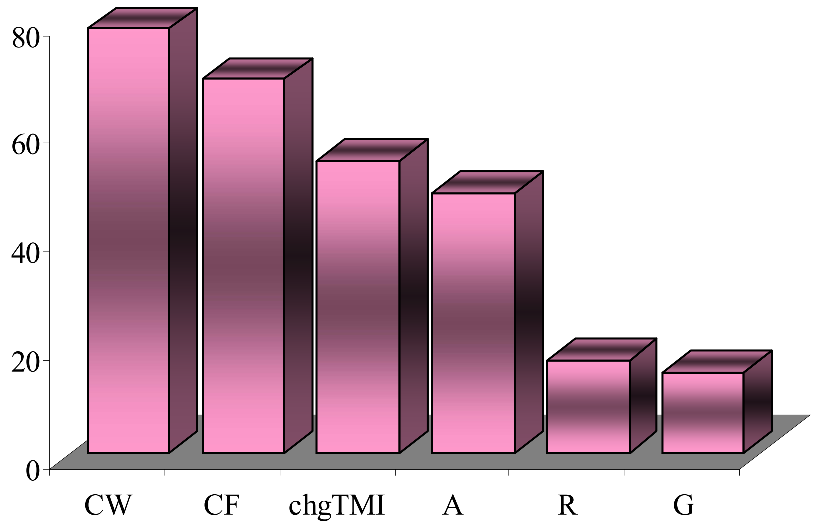


Figure 43: Correlation of *Vegetation*

- *Change in Thornthwaite Moisture Index*

As indicated in Figure 44 and Spearman's Rank Correlation, it was clear that *change in Thornthwaite Moisture Index* had strong correlation with all the parameter. However, unlike Spearman's Rank Correlation method, *change in Thornthwaite Moisture Index* had the strongest correlation with *construction footing*. It had also a strong bond with *construction wall* compared to the other input parameters. The type of both these parameters in accordance with Australian Standard depended on the climatic zone as one of the design factor. The *change in Thornthwaite Moisture Index* influenced *vegetation* and *region*. The type of *vegetation* depended on the climate. Some *vegetation* was more tolerant to dry or wet climate. *Region* depended on climate since some of the *regions* were dry and some were wet.

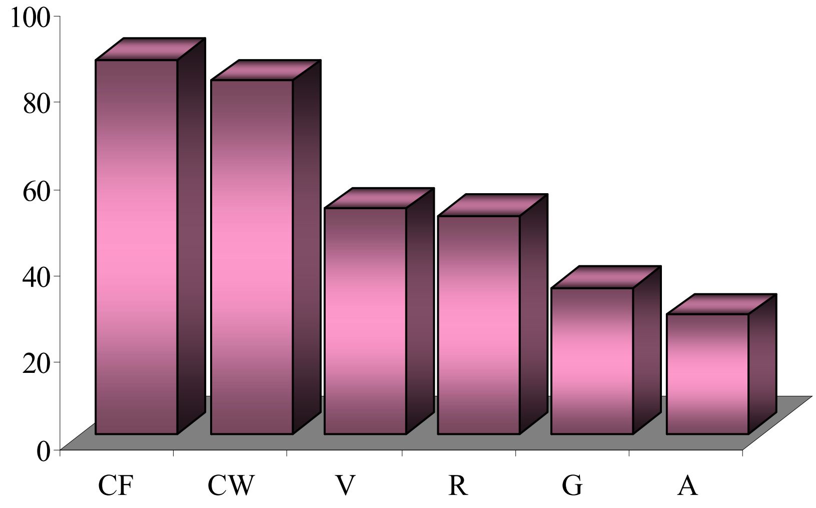


Figure 44: Correlation of *Change in Thornthwaite Moisture Index w*ith other Input Parameters

5.1.7.3 Ranking of Correlated Input Parameters

From the results obtained from the three methods, it could be concluded that the strongest correlation was observed in change in Thornthwaite Moisture Index. Figure 45 shows the ranks of importance of input parameters in terms of their relationship with other parameter. The ranking were based on the average percentage of each parameter using Connection Weights Analysis and Garson's Algorithm. The ranking were evaluated in descending orders according to their importance.

The results obtained from Spearman's Rank Correlation were just to compare the accuracy. Since the results from this method were unclear and not very consistent with the other two methods. Therefore, only the averages of the other two methods were taken into account where they showed more consistency.

Since *change in Thornthwaite Moisture Index* influenced most of the other parameters, it was obvious that it was ranked first. This was followed by *construction footing* which was ranked first in the ranking of individual parameter. This showed that *change in Thornthwaite Moisture Index* and *construction footing* were important in terms of predicting damage condition.

Construction wall and *geology* shared the third rank. This indicated that they were equally important in influencing the other factors. *Region*, *vegetation* and *Age* were ranked fourth, fifth and sixth respectively. This however, did not mean that they do not influence the other parameters.

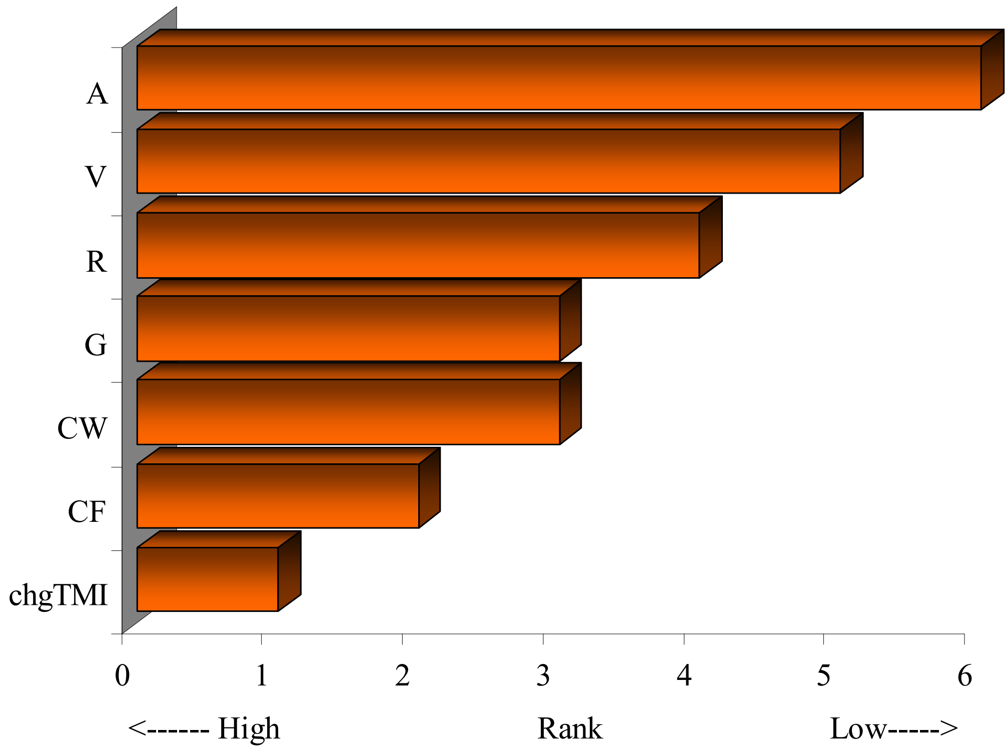


Figure 45: Ranking of Correlated Input Parameters

5.2 The Prediction of Damage Condition of Light Structures

The hybrid Artificial Intelligence model was tested for its ability to predict the damage class of a structure. This was done using the available real life parameters using a simulation function as shown in Figure 22 in the previous chapter. The damage class was based on Table 21and Figure 23. Due to the possibility of various different scenarios, only eight scenarios were predicted. The first scenario (Scenario 1) acted as "guidance" when the variables for each input parameters were changed (Scenarios 2 to 8). The eight scenarios are shown in Table 29. The selection of the eight scenarios was based on typical combination of parameters in real life. Scenarios 2 to 8 were used to compare other variables with scenario 1 which was considered to have "extreme" variables except *geology*. The variables for the parameters used in scenario 1 have been shown to influence damage to light structures. For example, West Melbourne showed the most reported damage. On top of that, it was assumed that old buildings were more prone to damage.

Scenario 5 was developed to compare the significance of different geological condition. The output values or the damage class for Scenario 5 should be more than Scenario 1. This was because 50% of damage occurred in Quaternary condition with moderate to highly expansive soils while 40% occurred in Tertiary condition with low to moderately expansive soils (Holland 1981). Raft slabs on the other hand, were usually preferred on a highly reactive site as strip footings were vulnerable to sideways and twisting movements (Standards Australia 1996b). Hence, Scenario 3 was developed. Scenario 8 indicated the change in climate. Since climate was one of the most important parameters that influenced damage to light structure, it was essential to have a scenario that could show this outcome. The predictions for these scenarios were compared with scenario 1. Scenario 4 was to determine the effect of construction wall when different type was used. Since there were few instances where damage was reported in the inner Melbourne (Scenario 2), it was used to compare the most "extreme" case (West Melbourne).

The output values for the damage condition for scenarios 1 to 8 after simulation are shown in Table 29. In comparison to scenario 1, the values of the scenario 2 to 8 after simulation indicated that there were not much different in using different variables for the different input parameters. With the exception of *change in Thornthwaite Moisture Index*, the rest of the different variables gave the same class of damage as scenario 1 which was damage class 2. When the scenario changed to a wet climate, the output values decreased to 0.461. This indicated that there was significance when the scenarios experience different climate. This proved the importance of the change in climate in terms of influencing damage to light structures on expansive soils (where it was ranked second in the previous section).

It was also proven that the output value for scenario 5 (0.543) with Quaternary condition is higher than scenario 1 (0.539) with Tertiary condition accordingly even though the damage classes for both scenarios fell in the same class which is class 2. Scenario 2 which had inner Melbourne instead of West Melbourne indicated almost similar output values. The difference between the two output values were merely 0.001. This indicated region was not the most significance in predicting damage to light structures where it was ranked last as shown in the previous section,

However, the results were not yet conclusive. Thus to confirm the findings, further tests were conducted using a new set of data from a different organisation.

Scenario	Region	Footing	Wall	Geology	Age	Vegetation	Chg TMI
1	WM	RS	BV	Tertiary	41-50	Built Up	Dry
2	IM	RS	BV	Tertiary	41-50	Built Up	Dry
3	WM	SF	BV	Tertiary	41-50	Built Up	Dry
4	WM	RS	DB	Tertiary	41-50	Built Up	Dry
5	WM	RS	BV	Quaternary	41-50	Built Up	Dry
6	WM	RS	BV	Tertiary	1-10	Built Up	Dry
7	WM	RS	BV	Tertiary	41-50	Annual Crop	Dry
8	WM	RS	BV	Tertiary	41-50	Built Up	Wet

Table 29: Scenarios

Scenario	Output Value	Damage Class	Description
1	0.539	2	Distinct crack. Change in level
2 (Different region)	0.538	2	Distinct crack. Change in level
3 (Different Footing)	0.529	2	Distinct crack. Change in level
4 (Different Wall)	0.542	2	Distinct crack. Change in level
5 (Different Geology)	0.543	2	Distinct crack. Change in level
6 (Different Age)	0.547	2	Distinct crack. Change in level
7 (Different Vegetation)	0.553	2	Distinct crack. Change in level
8 (Different ChgTMI)	0.461	2	Distinct crack. Change in level

Table 30: Damage Class for Various Scenarios

5.3 Conclusion of the Analysis of Predictive Damage Condition Model

This chapter described the uses of the model in terms of analysing Building Housing Commission Datamart. The importance of all input parameters was determined followed by an investigation of the correlation between all input parameters. The relative importance of individual input parameters was determined using Clamping and Pruning method as well as connection weights and Garson's Algorithm. The average values for all the methods were used to finalise the results. The results for the individual parameters showed that *construction footing* and *vegetation* were the most important parameters that influence the damage to light structures on expansive soils. This was followed by *change in Thornthwaite Moisture Index*, construction *wall* and *age*. It was not surprising to see *construction footing* and *vegetation* as ranked first. It was said that *construction footing* was the most susceptible to damage to light structure. *Vegetation* was another factor that can influence ground movement followed by the change in climate. *Region* and *geology* seemed to be the least important of all the parameters, which implied that these parameters were not reliable to predict the damage of a light structure. Nevertheless it was vital to include the parameters. This was because the more precise the input parameter for a light structure was, the higher the chance of predicting damage accurately.

In comparison with the above ranking of individual input parameters, the ranking for the correlated input parameters were totally different. This was expected as the analysis for the individual parameter was based only on the relationship of individual parameters with damage condition. It was in contrast with correlated parameter where it was based on the relationship of the parameters with other parameters with damage condition. It was found that some input parameters correlated strongly with other input parameters. *Change in Thornthwaite Moisture Index* for instance had the strongest correlation with all parameters except *geology* and *vegetation*. *Geology* had strong correlation with *region* and *construction footing*. From the analysis; it could be concluded that *change in Thornthwaite Moisture Index*, *construction footing* and c*onstruction wall* had the strongest correlation with the other input parameters. This means that most of the input parameters rely on these parameters. For instance, the parameters that influence damage to light structure could be *construction footing* but it needed other parameters to trigger the movement such as the presence of *vegetation* or *geology* type for example.

This chapter also covered the method for the prediction of the damage class. This was done with life scenarios using the simulation function in Neural Network Toolbox for MALTLAB. The results have been promising but further testing was needed to check how precise the results were. Therefore, few tests were performed using a new data set to check the accuracy of the Predictive Damage Condition model. These included; testing of the precisions of rankings (individual) and the accuracy of the Predictive Damage Condition model. These were done in the next chapter.

Chapter 6

TESTING OF THE PREDICTIVE DAMAGE CONDITION MODEL

The challenging task for the model was the correct prediction of the damage class of a building that was never used to train or validate the model. The Predictive Damage Condition model was tested for its accuracy and reliability using another data mart that has never been used to develop the model. The new data mart that was used was based on reports obtained from the USL Group Pty Ltd. USL Group Pty Ltd is a private geo-technical company that investigates and reports on distressed residential building independently. Their reports included the extent of damage findings, causes of distress and possible remedial measures.

There were approximately 250 lines of data in the database which consisted of information on the property such as regions, types of construction, presence of vegetation, change in climate, soil type and type of movements. There was more information gathered (such as size and depth of footings, liquid limit etc.) which was also more consistent compared to the Building Housing Commission reports. This was because they have used well designed uniform reports where the investigation was done by only one engineering firm. However, for the purpose of testing the Predictive Damage Condition model, the same information of the seven parameters (*construction wall, construction footing, vegetation, age, change in Thornthwaite Moisture Index, region*) as from Building Housing Commission were implemented. The "extra" information from USL Group Pty Ltd could be used for further studies.

In this chapter, USL Group Pty Ltd. data mart was used as validation and testing sets for the Predictive Damage Condition model. This was to evaluate whether the model was precise in predicting damage class and/or ranking the input parameters. Here the data mart was divided into 70% validation set and 30% test set before training the model.

Three tests were performed. Firstly, the generalisation performance of the Neural Network was tested for its reliability using a different data mart that was not taken into account in developing the model. Secondly, the data mart was used to check whether the selected input parameters chosen during the development of the model were accurate and consistent. The last step was to test the model for its capability of predicting damage condition or class. The same scenarios as Building Housing Commission were used to compare the findings. An outcome of the Predictive Damage Condition model which was the development of on an integrated web- based map was also shown.

6.1 Testing the Model

The performances of the model using two different data marts were based on mean squared error. The performances were consistent for both the data mart. Table 31 shows the performance values of the model. The goal was to have a mean squared error equals to zero. However, this was impossible unless the data used was complete and clean without “noise”.

From Table 31, the performance value for USL Group Pty Ltd data mart was slightly better compared to the Building Housing Commission data mart performance since it was approximately 15% less. This could be due to the well designed reports where there was more information on the parameters compared to Building Housing Commission reports. This proved that the model was consistent and could be applied with data from different organisations for a fairly accurate damage prediction. The performance of the model was further tested and the results were reported on in the next two sections. These tests were to validate the accuracy of the ranking of the importance of the input parameters as well as the precision in predicting the damage condition.

Datamart	**Performance (MSE)**
Building Housing Commission	0.058
USL Group Pty Ltd	0.051

Table 31: Performance of the Model Using Different Data Marts

6.2 Testing of the Accuracy of the Ranking of Input Parameter

The same principals and procedures as the Building Housing Commission data marts were used to perform the tests. The connection weights of the trained Neural Network were calculated using Connection Weights Analysis and Garson's Algorithm and were averaged.

Figure 46 shows the comparison of the ranking of input parameters for the Building Housing Commission and the USL Group Pty Ltd data marts. The ranking for both organisations were fairly consistent. The major difference was in the ranking of *geology*, *vegetation* and *construction wall*. The *change in Thornthwaite Moisture Index* using the USL Group Pty Ltd data was ranked first before *construction footing* while in the Building Housing Commission; it was ranked second after *construction footing* and *vegetation*. Nevertheless, *change in Thornthwaite Moisture Index* and *construction footing* seemed to be the two most important parameters in regards to damage to light structures for both organisations.

Vegetation however, in the USL Group Pty Ltd data mart was ranked fifth together with *construction wall*. *Vegetation* was ranked first in the Building Housing Commission data mart. The different sources and accuracies of information of the vegetation data used in both the data marts might be the main concern. In USL Group Pty Ltd data mart, the *vegetation* was dictated only as (i) present, (ii) removed, (iii) adjacent or (iv) no vegetation at the site. While in the Building Housing Commission data mart, it was more specific. A vegetation map (Bureau of Rural Sciences 2003), was used to select which type of vegetation is "common" to the particular area. Therefore, it could be argued that the data was more precise. Hence *vegetation* was ranked first instead of fifth in the Building Housing Commission data mart.

Geology was ranked third for the USL group Pty Ltd data mart. It was ranked last together with *region* in the Building Housing Commission data mart. This was probably due to the fact that USL group Pty Ltd is a geological company where their main emphasise was on soil. Therefore, their reports were more focused on what type of soil or geology the particular property had. It could be argued that the information on soil or geology was more accurate in the USL group Pty Ltd reports than Building Housing

Commission reports. In the Building Housing Commission reports, there was no geology information for the area and only some of the reports had soil classification. This information had to be extracted from the geology map of Victoria (Mc Andrew 1965) and hence the data extracted would not be precise as the same site did not necessarily have the same geological condition.

The other parameter that had a different rank as the Building Housing Commission was the *construction wall*. In USL Pty Ltd group; the *construction wall* was ranked fifth together with *vegetation*. In Building Housing Commission it was ranked third. This was probably due to the various types of construction walls for the properties in the data mart. Most of the properties in the USL Group Pty Ltd Datamart, 70% of the properties were constructed with brick veneer. 20% with double brick and the rest was timber or the construction type was unknown. In the Building Housing Commission data mart it was more diverse. 66% of the structures were constructed with brick veneer, 12% with concrete. Properties constructed with double brick were 18% and the rest was built with weatherboard.

Both data marts had *region* and *age* as the last and fourth ranked accordingly. This meant that *region* was not the most important parameter in terms of its influence on damage of light structures. Therefore, it could mean that *region* may be eliminated from the input parameters if necessary. However, at the moment it would be retained. *Age* on the other hand was still crucial in predicting damage condition unlike the results obtained using statistical method. The older the property, the more vulnerable it was to ground movement or damage. An old property may experience prolonged changes in climate for instance. Therefore, it was more susceptible to ground movement due to seasonal changes in climate.

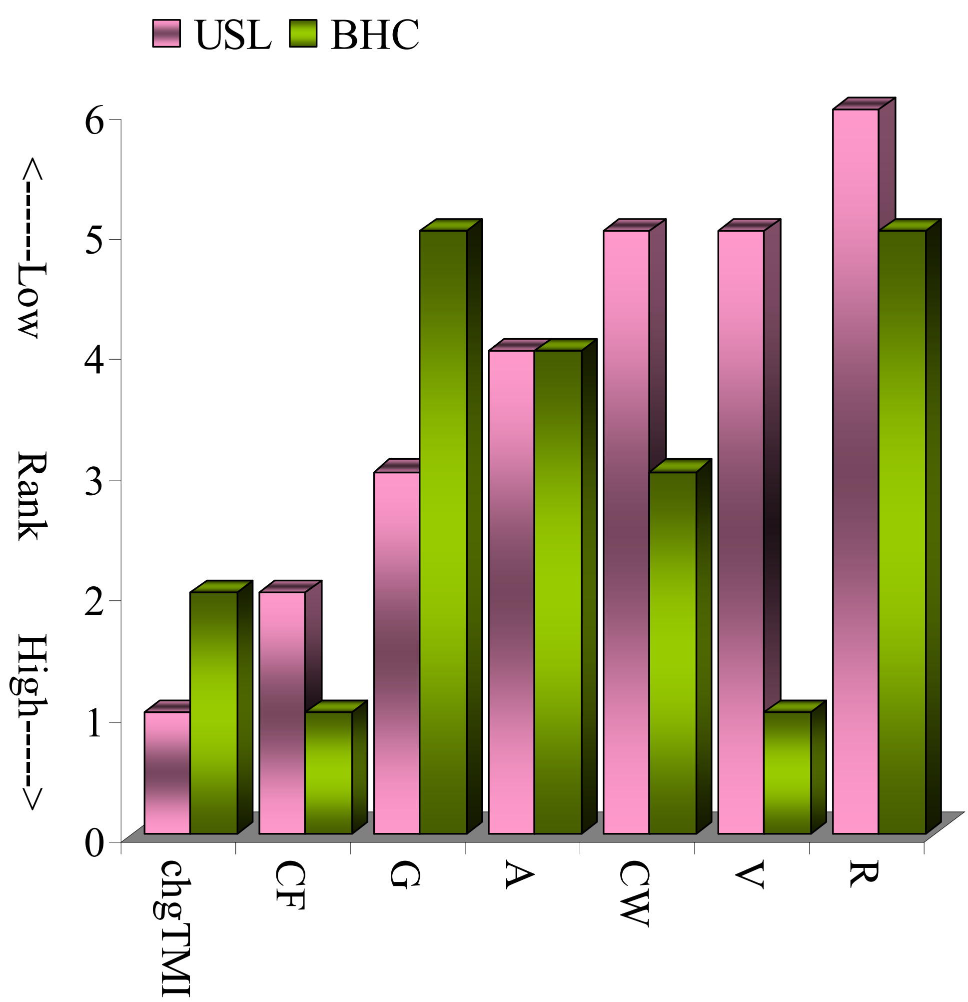


Figure 46: Comparison of Ranking of Input Parameters for USL and Building Housing Commission

6.3 Prediction of Damage Condition

The same methodology was used to predict the damage condition using the USL Group Pty Ltd data mart. The same scenarios and reason for choosing the scenarios as Building Housing Commission were adopted and compared. Scenario 1 was the "guidance" scenario. Using neural network toolbox for MATLAB version 7.1, the model was simulated using the scenarios shown in Table 32 to predict damage condition. The damage class was based on Table 21 and Figure 23. Two ways were adopted to interpret the results; firstly the scenarios for USL Group Pty Ltd were compared to the scenarios for Building Housing Commission data mart. Secondly, the scenarios for USL Group Pty Ltd were compared to scenario 1 for USL Group Pty Ltd.

a) Comparing USL Group Pty Ltd with Building Housing Commission

From Table 33, all scenarios except scenario 8 for USL Group Pty Ltd were the same the damage class as Building Housing Commission data mart. Most of the damage class for USL Group Pty Ltd fell in class 2 ($0.375 < PDC \leq 0.625$). This class has distinct cracks and change in level. In USL Group Pty Ltd, scenario 1 showed a lower output value than Building Housing Commission data mart. The only difference for the damage class in both the data marts was scenario 8. Scenario 8 increased to class 3. Most of the scenarios in USL Group Pty Ltd have lower output values compared to Building Housing Commission data mart. This is with the exception of scenarios 7 and 8 which have higher values than Building Housing Commission data mart.

As mentioned in the previous section, vegetation information was described differently in both the data marts. In Building Housing Commission, a specific vegetation cover was used in scenario 7 which was “annual crop”. In USL Group Pty Ltd., Scenario 7, had vegetation as “adjacent”. This meant that there was vegetation presence in the area which was adjacent to the property. The higher output value for USL Group indicated that there was significance when vegetation was adjacent to a property. This showed that nearby vegetation could influence the damage potential to light structures.

Scenario 8 increased to damage class 3 in the USL Group Pty Ltd. which indicated that the change in climate was crucial in influencing damage to light structures. The higher output value compared to Building Housing Commission data mart could mean that the USL Group Pty Ltd was more affected by change in climate. This could be the influence of not only the change in climate but also the other factors or parameters such as vegetation. As mentioned earlier, the vegetation information for both the data marts were recorded differently. In USL Group Pty Ltd. the vegetation was indicated as “presence”. “Presence” could mean that the vegetation was presence any where within the property. Therefore, the combination of all the parameters would have much influence when different climate condition was used in scenario 8.

From both the data marts, the damage class fall in the same class which was damage class 2 except for scenario 8. This indicated that the results were fairly accurate and consistent.

b) Comparing Scenario 1 of USL Group Pty Ltd with other Scenarios

Most of the damage class with the exception of scenario 8 had the same class which was damage class 2. Most of the output values in all the scenarios were higher than scenario 1. Scenario 8 which had different climate condition gave the highest output value of 0.746 which fell in damage class 3. As in Building Housing Commission, this parameter was the most significant in predicting damage condition. This meant that the recordings of change in climate were crucial to determine the damage class of a property.

In Table 33, when double brick was used in the scenario in USL Group Pty Ltd, the output value was higher compared to when brick veneer was used. This was somehow not surprising as houses constructed with brick veneer were not as prone to cracking as solid brick (double brick) houses in reactive soil areas. Due to its brittleness, double brick houses were prone to cracking even when the walls have undergone only small distortion.

When different variables were used for different parameters, there was an increase in the output values. This showed that all these parameters were significant in predicting damage. The presence of *vegetation* in predicting damage condition influences the damage class. Even though, vegetation was ranked fifth in USL Group Pty Ltd. data mart, it was ranked first in Building Housing Commission data mart. Therefore, it was crucial to keep vegetation as one of the most important parameters. As for geology, the scenario with Quaternary clays gave a higher output value compared to scenario 1 with Tertiary clays. This proved, Holland's (1981) finding that housing failures in Victoria occurred more in Quaternary clays than Tertiary clays.

The output value for scenario 6 which used a "younger" (1 to 10 years old) house was higher than scenario 1 with older (41-50 years old) house. This indicated that old houses were not necessarily being prone to damage. "Younger" houses were as prone to damage as older houses due to factors such as climate, type of wall etc. On the other hand, even though, construction footing was ranked first in USL Group Pty Ltd, there was not much different when using different construction footing system. This was because the design standard (AS2870) did not take into account factors such as the change in climate. Therefore, it was not surprising that the output values were the same.

Scenario	**Region**	**Footing**	**Wall**	**Geology**	**Age**	**Vegetation**	**Chg TMI**
1	WM	RS	BV	Tertiary	41-50	Presence	Dry
2	IM	RS	BV	Tertiary	41-50	Presence	Dry
3	WM	SF	BV	Tertiary	41-50	Presence	Dry
4	WM	RS	DB	Tertiary	41-50	Presence	Dry
5	WM	RS	BV	Quaternary	41-50	Presence	Dry
6	WM	RS	BV	Tertiary	1-10	Presence	Dry
7	WM	RS	BV	Tertiary	41-50	Adjacent	Dry
8	WM	RS	BV	Tertiary	41-50	Presence	Wet

Table 32: Scenarios

Scenario	Output Value		Damage Class	
	BHC	USL	BHC	USL
1	0.539	0.470	2	2
2(Different region)	0.538	0.512	2	2
3(Different Footing)	0.529	0.481	2	2
4(Different Wall)	0.542	0.506	2	2
5(Different Geology)	0.543	0.524	2	2
6(Different Age)	0.547	0.507	2	2
7(Different Vegetation)	0.553	0.580	2	2
8(Different ChgTMI)	0.461	0.746	2	3

Table 33: Comparison of Damage Class for Building Housing Commission and USL Group Pty Ltd.

Summary

The trend of the results from both the data marts can be seen in Table 34. Even though, the trend for Building Housing Commission for damage condition showed that damage class 1 and 2 were the most observed, the predicted damage from the simulation process showed mostly damage class 2. Damage class 3 and 4 were the most observed in USL Group Pty Ltd data mart. However, the damage class for this data mart fell mostly in damage class 2 and one in damage class 3. From this, it was obvious that the model did not rely on statistics or historical data. It could be implied that the Predictive Damage Condition model using a hybrid Artificial Intelligence techniques worked fairly well and consistent. This was evident from the predictions that were made using various scenarios. Further tests should be conducted with more data from different sources to assess that the predictive damage model will work in other real-life scenarios. This could be the work for further studies.

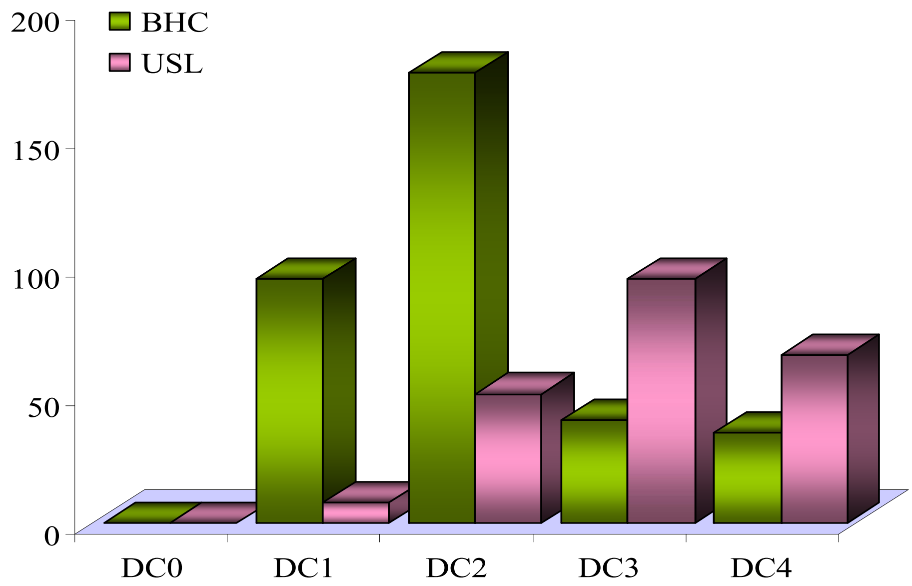


Table 34: Frequency for Damage Classes for Building Housing Commission and USL Group Pty Ltd

6.4 Outcome of the Predictive Damage Condition Model

Besides being able to rank the input parameters according to their importance and predict the damage condition, the Predictive Damage Condition model could also be used for other useful application. As part of this research project, a web-based map was developed to show a more realistic and interactive outcome of the Predictive Damage Condition model to light structures on expansive soils in Victoria. This map was a preliminary introduction of the proposed model to interested parties.

The advantage of this web-based map was that it was interactive and easy-to-use where it could be used and viewed at a click of a button. The map could be installed on a server where it could be accessed from any computer that has a web browser installed. New information could be added to the web-based map whenever it was available. This new information was instantly available the next time the map was accessed.

It could be used by parties such as the government, civil and geotechnical engineers and also home owners to explore and understand the factors that caused damage to light structures. They could also explore and have an idea on which region in Victoria was the most problematic site.

The drawback for this web-based map was that it was not available online as yet due to restrictions of fund. It was hoped that one day the web-based map could be published online and could be used by interested parties. It was also hoped that once it was up and running, the web-based map could be linked with any kind of software that could measure things like liquid limit, damage classification and many more. Users of the map could also add more up-to-date and precise data for analysis. This would also further improve the accuracy of the damage prediction. The integrated web-based map can be viewed in more detail in Appendix 8.

6.5 Conclusions of the Testing of Predictive Damage Condition Model

Three tests to determine the accuracy of the Predictive Damage Condition model were performed in this chapter. The first test used the developed methodology to train the proposed hybrid system consisting of a Neural Network and a Genetic Algorithm with a completely new data mart. The model was tested firstly for its performance which was based on mean squared error. The performances of the model using two different data marts were consistent with each other. This was a good indication. Since the model was based on Artificial Intelligence methods, it was not very surprising. This was because; Artificial Intelligence was able to train a network or a database it had never seen before.

An Artificial Neural Network was able to adapt to changes in the dataset as it could always be updated to obtain better results by preventing new training examples as new data becomes available (Osman and McManus 2005). A Genetic Algorithm was very useful in improving the learning process of Neural Network by initialising the connection weights with already good values to prevent the Neural Network to get stuck in a local minima (Osman et al. 2006b). The advantage of this was that any data mart can be used with the developed methodology which meant that any interested party would be able to perform a data analysis.

The second test that was done using a new data mart for validating the accuracy of the ranking of input parameters according to their importance in predicting the damage condition. The result was that the ranking obtained from the analysis of the two data marts were fairly consistent. The parameters *construction wall* and *change in Thornthwaite Moisture Index* were the two most important parameters in influencing damage to light structures in both cases. The parameters *age* and *region* showed the least importance. The major difference was found in importance of the input parameters *geology* and *vegetation*. The *geology* as an input parameter was more important in USL Group Pty Ltd. The main reason was probably due to the better accuracy of the provided data in order to give better results. The different rank of *vegetation* found in both analyses was because of the different way of providing the vegetation information. In USL Group Pty Ltd, the *vegetation* was only dictated as existent at the site or not while the integrated vegetation map was used in determining the vegetation in the Building Housing Commission data mart. A combination of the existence information and the vegetation map in the case of the data from the USL Group Pty Ltd. could give better results and may require further investigation.

The last important test was to verify the model's ability to predict the damage class/condition of a structure. It was demonstrated that the developed model was able to predict consistent results when tested with the same scenarios but using different data marts. The predicted values showed only a slight difference that fell in the same damage condition class. However, it could not be concluded that the model will work in all cases. More tests with additional data would be required to demonstrate the applicability for companies and government organisations. Further studies need to be done in order to continue the research.

A web-based integrated map was also developed as an outcome of the Predictive Damage Condition model. The advantages of this map included the user interaction where users can understand or visualise damage condition of a particular region and so on. The map was also able to incorporate new data when available. However, the drawback was that the map was currently not available online.

The next chapter covered the conclusion and recommendation.

Chapter 7

CONCLUSIONS AND RECOMMENDATIONS

7.1 Conclusion

The geotechnical characteristics of the soils in Victoria as seen from the geological map signified that they have a high shrink and swell potential. Expansive soils could cause damage to light structures due to movement of soil. The prediction of damage to light structures founded on expansive soils was investigated in this research project. Based on collected data on damage to light structures in Victoria, Artificial Intelligence and statistical methods were adopted to analyse different factors and to rank according to their importance in characterising the caused of damage. Based on the results of this analysis, a Predictive Damage Condition model was developed. The performance of the model was also investigated in order to check the reliability of the prediction ability.

A novel approach in engineering research was adopted for the development of the Predictive Damage Condition model. A hybrid Artificial Intelligence technique that consisted of Neural Network trained with Genetic Algorithm was adopted and compared with a conventional approach such as statistical method. A hybrid Artificial Intelligence technique was more reliable than a conventional method. On top of that, the performance of the model in terms of the accuracy of the prediction was better compared to the performance of an individual Artificial Intelligence technique. The results indicated that a hybrid Neural Network and Genetic Algorithm had the ability to predict the potential damage to light structure on expansive soils when trained with any kind of data set be it with missing or with complete parameters. There was no doubt that Neural Network can adapt to changes in the data set as it could always be updated to obtain better results as new data became available. Genetic Algorithm on the other hand was very useful in improving the learning process of Neural Network.

All the objectives and questions in the research project had been addressed. The study of the behaviour of the expansive soils including their mineralogy and their volume change properties have been done in Chapter 2: Literature review. Chapter 3 dealt with the data mining process. This process was necessary to extract data Building Housing Commission for further analysis. The development of the Predictive Damage Condition model was performed in Chapter 4. The analysis of the model in terms of its performance, ability to rank input parameters, relationship of input parameters with other parameters as predicting damage conditions was done in chapter 5. The parameters c*hange in climate* and *construction footing* were found to be the parameters that influenced the soils movement most followed by structural systems which were the type of construction footings and walls. The performance of the proposed model together with the testing of the accuracy of the model in terms of analysing the ranking of the input parameters; and predicting damage condition was also evaluated by testing the model with a new data mart which was done in Chapter 6. Chapter 6 also emphasised on the outcome of the model. Here a web-based map was developed and presented. The web-based integrated map of the Predictive Damage Condition model was essential to have in order to gain a better understanding on the condition of damage in Victoria. However, further work was needed to be done to update the map and also to make it available online.

The motivation of the research project was the lack of a Predictive Damage Condition model in Victoria, Australia. Before the thesis was completed, there was no model available that could predict damage condition of light structures. The only available method for the classification of the damage was that in the Australian Standards (AS2870). However, this method could only be used when damage had already occurred. Then the damage class could be identified using AS2870. The difference between the classification method and the proposed model was that the proposed model could predict damage before the damage occurred provided that all the parameters needed to use the model were at hand. Then a damage class prediction could be made according to the variables as demonstrated in Chapters 5 and 6.

The importance of the Predictive Damage Condition model was that it could help practitioners or engineers to design light structures according to the combination of variables. Of course it was impossible to have a “damage free” structure. Thus, to maintain or minimise a certain damage class over a period of time, a practitioner had to consider which type of construction systems to use, the presence of vegetation and where the dwelling is going to be built and so on. This was where the Predictive Damage Condition model became useful with a software program that could predict the damage to a light structure depending on the magnitude of the influencing factors.

On top of the actual damage class prediction, the model served as an essential tool for a better understanding of the parameters that influenced the damage to light structure founded on expansive soils and a practical way of dealing with the problem. The main challenge for any inspector was to investigate technically, which one of these parameters were predominant in any particular case. Hence in this research project, the challenge was answered by developing a Predictive Damage Condition model. This research project had helped identify the parameters that influence damage to light structures on expansive soils using the proposed model. It was found that the parameter which influenced the damage to light structures most was the *change in climate* followed by the structural systems; *footing* and *walls* then *geology.* These parameters were the most common parameters that were said to be causing damage to light structures on expansive soils. Therefore, practitioners had to consider these parameters when designing light structures in order to minimise damage.

Even though there were shortcomings in the Building Housing Commission reports, a database called data mart was able to be developed. Alternative ways of gaining additional information such as extracting data from a geology, a vegetation and two Thornthwaite Moisture Index maps which were done in this research project were adopted. The availability of these maps were also a problem as they were not easily accessible especially vegetation and geology maps. Therefore, a readily available map such as Geology of Victoria (Mc Andrew 1965) and Integrated vegetation map online (Bureau of Rural Sciences 2003) had to be used.

The positive outcome of the thesis was the ability of the model to predict the classification of the damage to light structures on expansive soils as shown in Chapter 5 and 6. This could be beneficial to the government, building inspectors and the homeowners to enable them to understand and to decide when the properties need urgent attention and taking necessary measures. With this knowledge, the resilience of the properties to movements could hopefully be guaranteed. The more positive outcome of this research project was that it had the potential to improve the design and the standards of the light structures.

7.2 Recommendations For Further Research

The recommendations summarised below were based on the research project and the findings from the analysis of the Predictive Damage Condition model.

- *Availability of Data*

The main problem encountered in this research project was the lack of available data or reports. Not many organisations were willing to “share” their data. If only there were more data available for the use of university research, it would be an advantage as the results in this research project would be more precise. More data meant there was more diverse information available. It was also an opportunity to train and test the proposed model with more data, which in turn would produce more stable results.

- *Quality of reports*

Another problem encountered was having non-uniform reports. Thus guess work or other alternatives had to be undertaken in order to cover the missing information in the report. The future reports should be uniform so that everyone can benefit. It is recommended that all the parties involved in reporting damage to light structure on expansive soils should use one template for all reports on damage to light structures as the one developed in Appendix 9.

- *Database*

Another solution to maximise the quality of the report was to develop a uniform database. There was a need to develop a uniform database similar to the proposed database in this research project in order to manage reports from different organisations.

This database should have defined requirement of what information needed to be reported on. All important parameters should be included in the database. It is recommended to use a central database which was also uniform. A sample of a template can be seen in Appendix 9.

- *Scientific Diagnostic*

There was a need for scientific diagnosis in order to report on damage to light structures on expansive soils. This could be done by investigating one or a row of structures that suffers damage from soil movements and observing any changes that occur over a period of time. This was intended to single out buildings in dire need of remedy. In other words, a regular measure of the condition of the asset was reccomended.

- *Output*

The output in the proposed model was based on the likely future damage condition. This indicated the severity or the class of damage to the light structures on expansive soils. Other output parameter such as cracks, heave or settlement could be used to predict other type of damage. This would give different outcomes of the proposed model which may be useful for specifying a specific type of damage of light structures on expansive soils.

- *Extra input parameters*

So far, the research was based on the availability of the existing input parameters, which were regarded by practitioners as the most influential parameters. Extra input parameters (such as shown in Appendix 9) could influence the results of the findings. However, it was essential to include all the possible input parameters that could have an influence to light structures. Parameters such as regulations, footing depth and size and liquid limit to name a few were possible input parameters that should be included in the report. Therefore, further research with more data could be performed for this task.

- *Web-Based Integrated map*

Though much work had been done in the integrated map, further work was still required. The map needed to be updated with more data or information in order to maximise its use. It would be an advantage if most or all of the organisations that dealt with damage to light structures have a uniform interactive database. On top of this, it would be useful if the map was available online so that it could be access by interested parties. The integrated web-based map could also be linked to other softwares such as MATLAB toolboxes. This would enable the users to predict damage condition using the Predictive Damage Condition model.

There were many fertile research areas that could be pursued as a result of this work. As a first step, addressing all of the limitations noted in the prior section could solidify and validate the proposed Predictive Damage Condition model. The model could be validated with a larger sample size and every available parameter. This was essential to firmly establish the research findings of this study. The model could be extended and tested on more real life scenarios. Further work could be done to explore the reasons behind the significance of other input parameters. It was hoped that the model could assist the government in finding a solution on how to identify and avoid the most influential parameters on damage to light structures when designing a property for social housing. On top of that, it was hoped that the developed integrated web-based map could assist interested parties to gain knowledge of a site or property.

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APPENDICES (REFER CD ROM)

Appendix 1

Soil Legend

Appendix 2

Melbourne Soil Classification (Table D1) (Standards Australia 1996a)

Appendix 3

Classification of Damage with Reference to Wall (Table C1) (Standards Australia 1996a)

Appendix 4

Classification of Damage with Reference to Concrete Floors (Table C2) (Standards Australia 1996a)

Appendix 5

Vegetation Map

Appendix 6

The data and variables of the data warehouse

Appendix 7

Default Values for Genetic Algorithm

Appendix 8

Integrated Web-Based Map

Appendix 9

Example of Uniform Database Template

City

Regional Centre

Geological Polygons 4M

Qa Unnamed alluvium

Qdl Unnamed coastal dune deposits

Na Unnamed incised alluvium

Qrw Woorinen Formation

Qn Newer Volcanic Group

Nx Undifferentiated sedimentary rocks and laterite

Nh Heytesbury Group

-Pn Nirranda Group

-Pa Unnamed alluvium

-Po Older Volcanic Group

-Pxh White Hills Gravel

-Pw Wangerrip Group

Ko Otway Group

Jc Coleraine Volcanic Group

TRl Mount Leinster Igneous Complex

Pxb Bacchus Marsh Formation

Dgl Late Devonian granitic rocks

Dul Mansfield, Avon River, Merrimbula Groups and equivalents

Da Avon Supergroup

Dxk Upper Devonian subaerial caldera volcanics

Dgm Undifferentiated Middle Devonian granitic rocks

Dc Cathedral Group

Appendix 2: Melbourne Soil Classification (Standards Australia 1996)

Soil profiles	**Climatic zone**			
	1 (Alpine/Wet Coastal)	**2 (Wet Temperate)**	**3 (Temperate)**	**4 to 5 (Dry temperate to Semi Arid)**
BASALTIC CLAYS				
(Including pyroclastics and residual and alluvial clays derived from basaltic and similar volcanic rocks)				
≤0.6 m depth of clay	S to M	S to M	M	M
>0.6 ≤1.8 m depth of clay	M	H	H	H-D to E
>1.8 m depth of clay	M	H	H to E	E
Predominantly gravelly clay (Lateritic)	M	M	M to H	M-D to H-D
NON-BASALTIC RESIDUAL CLAYS				
(Including residual clays derived from sedimentary, metamorphic and granitic rocks)				
≤0.6 m depth of clay	S	S	S	S
>0.6 m depth of clay	M	M	M to H	M-D to H-D
LIMESTONE CLAYS				
(Including clays derived from marls and other highly calcareous sediments)				
≤0.6 m depth of clay	M	M	M	M

>0.6 m ≤1 m depth of clay	M	M to H	H	H-D
>1.0 m depth of clay H-H, H-D to E-E	H	H	H-D to E	E
QUATERNARY ALLUVIALS AND TERTIARY SEDIMENTS				
(Including delta, dune, lake, stream, colluvial and wind-laid deposits)				
Where predominantly silts or sands overlie clays				
≤0.6 m silts or sands overlying clays	S to M	M	M to H	M-D to E
>0.6 ≤1 m silts or sands overlying clays	A to S	S to M	M	M-D to H-D
>1 m silts or sands overlying clays	A	A to S	S	S to M-D
Interbedded silts, sands and clay mixtures				
(Assess on the basis of total depth of clay over Hs)				
≤0.6 m total depth of clay	A to S	S	S to M	M
>0.6 ≤1 m total depth of clay	S	M	M	M-D to H-D
>1 m total depth of clay	S	M	M to H	M-D to E

Appendix 3: Classification of damage with reference to walls (Table C1 in Standards Australia 1996)

Description of typical damage and required repair	Approximate crack width limit	Damage category
Hairline cracks	< 0.1 mm	0
Fine cracks which do not need repair	< 1 mm	1
Cracks noticeable but easily filled. Doors and windows stick slightly	< 5 mm	2
Cracks can be repaired and possibly a small amount of wall will need to be replaced. Doors and windows stick. Service pipes can fracture. Weather tightness often impaired	5 mm to 15 mm (or a number of cracks 3 mm or more in one group)	3
Extensive repair work involving breaking-out and replacing sections of walls, especially over doors and windows. Window and door frames distort. Walls lean or bulge noticeably, some loss of bearing in beams. Service pipes disrupted	15 mm to 25 mm but also depends on number of cracks	4

Appendix 4: Classification of damage with reference to concrete flooring (Table C2 in Standards Australia 1996)

Description of typical damage and required repair	Approximate crack width limit in floor	Change in offset a 3 m straight edge centered over defect	Damage category
Hairline cracks, insignificant movement of slab from level	< 0.3 mm	< 8 mm	0
Fine but noticeable cracks. Slab reasonably level	< 1 mm	< 10 mm	1
Distinct cracks. Slab noticeably curved or changes in level	< 2 mm	< 15 mm	2
Wide cracks. Obvious curvature or change in level	2 mm to 4 mm	5 mm to 25 mm	3
Gaps in slab. Disturbing curvature or change in level	4 mm to 10 mm	> 25	4

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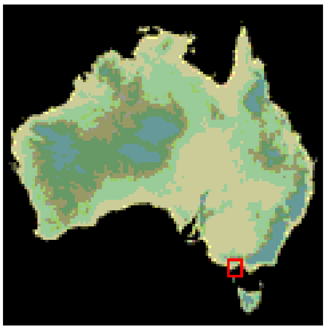
Integrated Vegetation Online
Corangamite Region

Summary Area Data

Vegetation Cover	Area (km sq)	Area percent
Native forests and woodlands	2,750	20.6
Native shrublands and heathlands	42	0.3
Native grasslands and minimally modified pastures	4,556	34.1
Horticultural trees and shrubs	2	0.0
Annual crops and highly modified pastures	4,424	33.1
Plantation (hardwood)	42	0.3
Plantation (softwood/mixed)	202	1.5
Ephemeral and Permanent Water	475	3.6
Built-up	126	0.9
Unknown/not reportable	728	5.5
Total native	**7,348**	**55.1**
Total woody	**3,037**	**22.8**
Total perennial	**7,593**	**56.9**
Total vegetated	**12,017**	**90.0**
Total area of region	**13,347**	**100.0**



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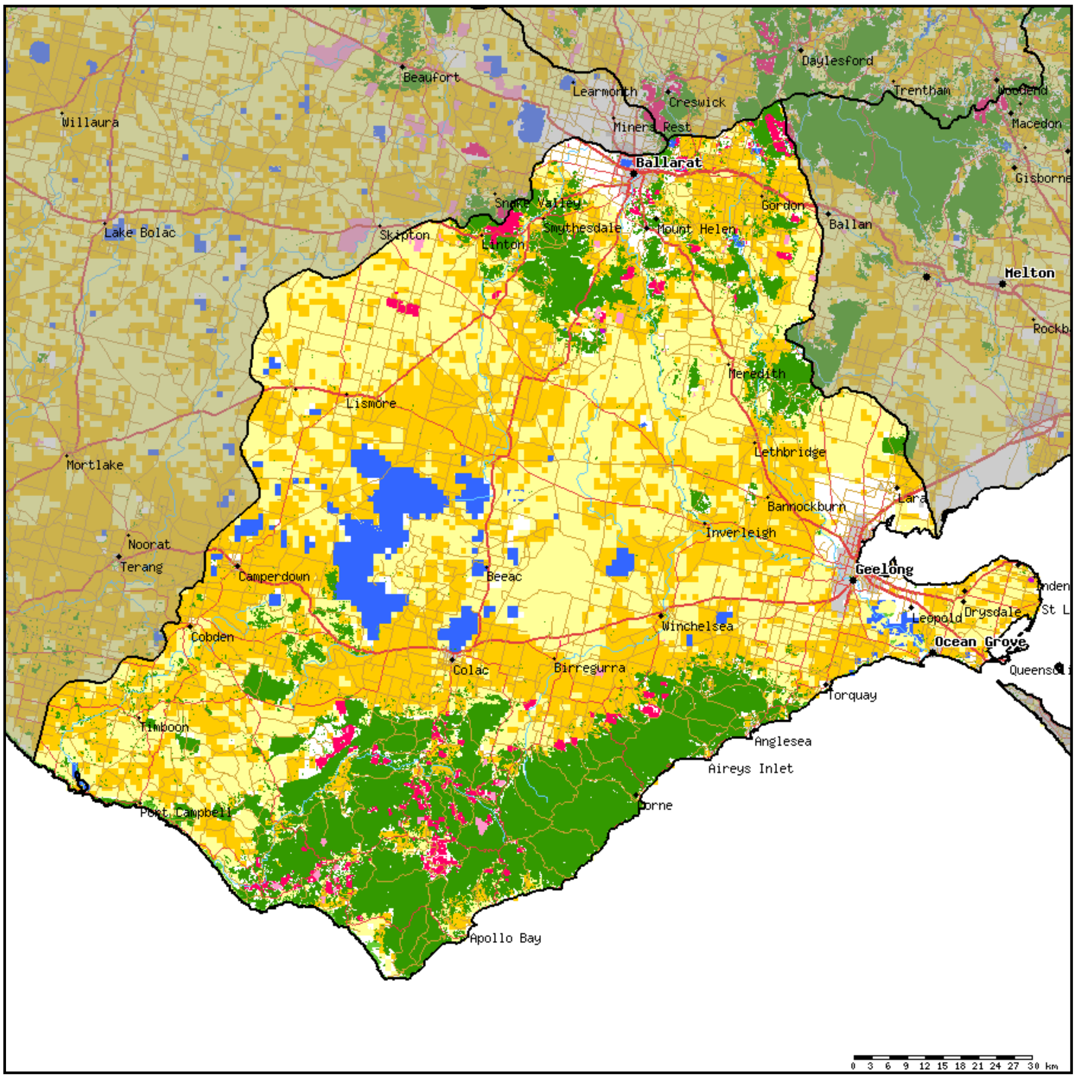

- Native forests and woodlands
- Native shrublands and heathlands
- Native grasslands and minimally modified pastures
- Horticultural trees and shrubs
- Perennial crops
- Annual crops and highly modified pastures
- Plantation (hardwood)
- Plantation (softwood/mixed)
- Bare
- Ephemeral and Permanent Water
- Unknown/not reportable

Refer to the Introduction for more information.
Regions from National Heritage Trust Interim Boundaries, July 2003, Department of Environment and Heritage. Boundaries may change under State/Territory legislation.

Source of topographic features:
Geoscience Australia, Division of National Mapping, GEODATA TOPO-250K.

Projection: Albers conic equal-area
Datum: Geocentric Datum of Australia, 1994

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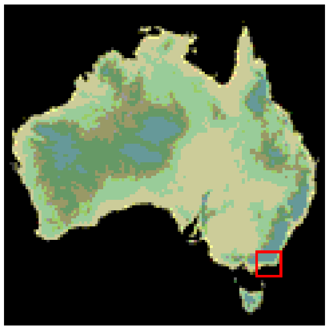
Integrated Vegetation Online
East Gippsland Region

Summary Area Data

Vegetation Cover	Area (km sq)	Area percent
Native forests and woodlands	18,027	82.0
Native shrublands and heathlands	196	0.9
Native grasslands and minimally modified pastures	590	2.7
Annual crops and highly modified pastures	2,284	10.4
Plantation (hardwood)	13	0.1
Plantation (softwood/mixed)	30	0.1
Bare	2	0.0
Ephemeral and Permanent Water	246	1.1
Built-up	79	0.4
Unknown/not reportable	514	2.3
Total native	**18,812**	**85.6**
Total woody	**18,265**	**83.1**
Total perennial	**18,855**	**85.8**
Total vegetated	**21,139**	**96.2**
Total area of region	**21,980**	**100.0**



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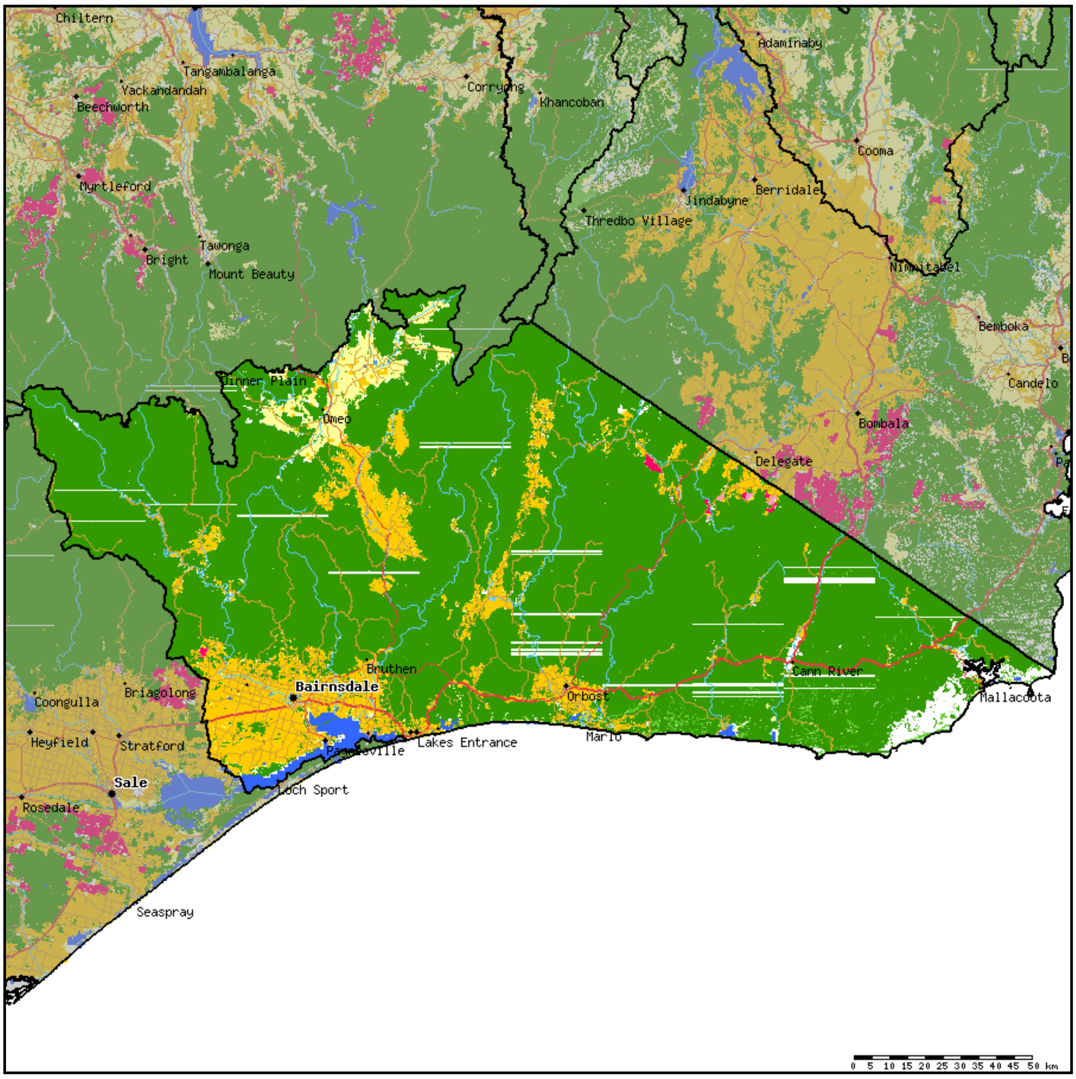

Native forests and woodlands
Native shrublands and heathlands
Native grasslands and minimally modified pastures
Horticultural trees and shrubs
Perennial crops
Annual crops and highly modified pastures
Plantation (hardwood)
Plantation (softwood/mixed)
Bare
Ephemeral and Permanent Water
Unknown/not reportable

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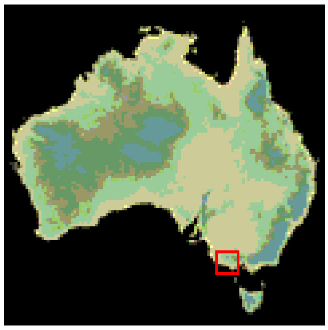
Integrated Vegetation Online
Glenelg Region

Summary Area Data

Vegetation Cover	Area (km sq)	Area percent
Native forests and woodlands	4,531	16.9
Native shrublands and heathlands	99	0.4
Native grasslands and minimally modified pastures	9,705	36.2
Horticultural trees and shrubs	2	0.0
Annual crops and highly modified pastures	10,125	37.8
Plantation (hardwood)	606	2.3
Plantation (softwood/mixed)	641	2.4
Ephemeral and Permanent Water	257	1.0
Built-up	53	0.2
Unknown/not reportable	758	2.8
Total native	**14,335**	**53.5**
Total woody	**5,879**	**22.0**
Total perennial	**15,584**	**58.2**
Total vegetated	**25,709**	**96.0**
Total area of region	**26,777**	**100.0**



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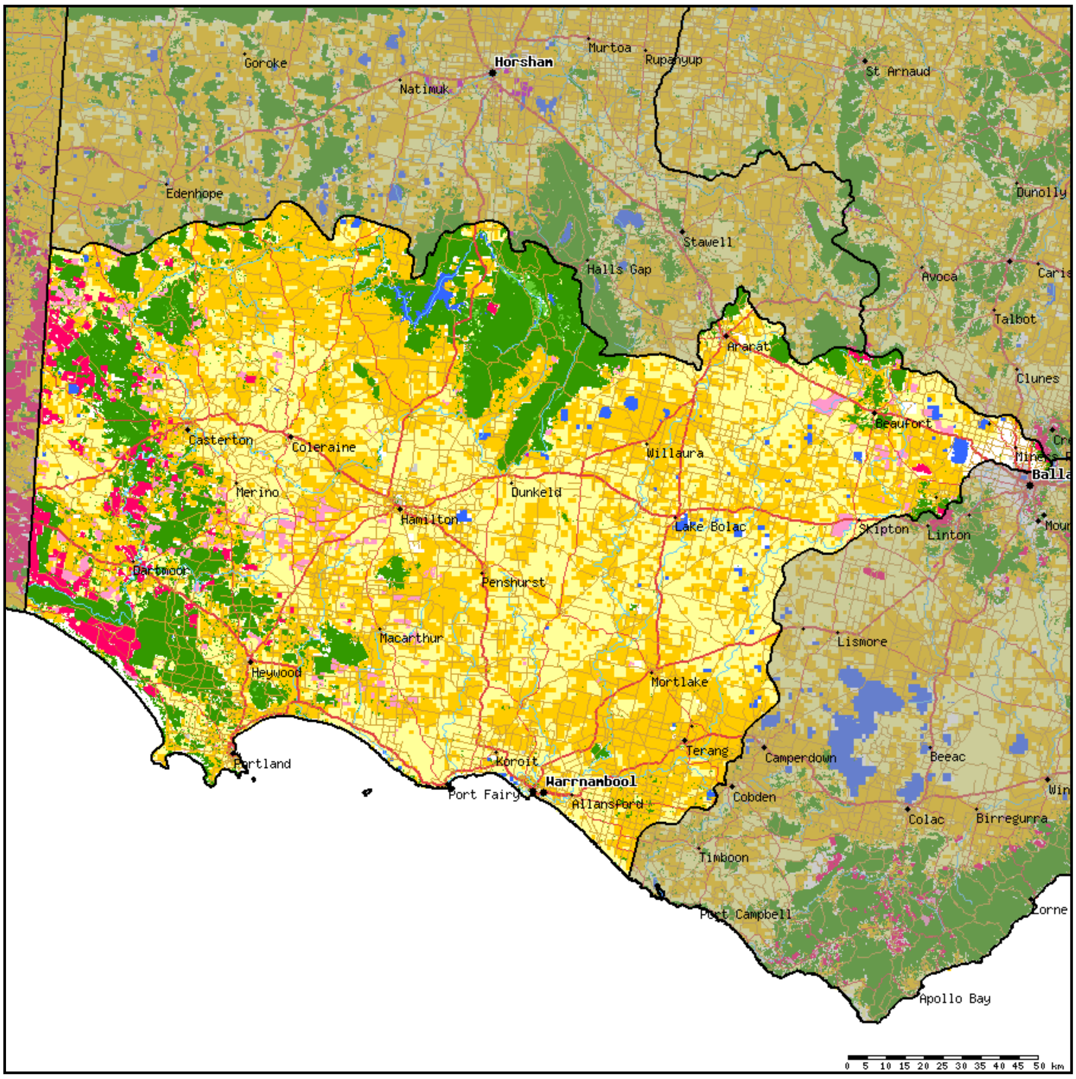

- Native forests and woodlands
- Native shrublands and heathlands
- Native grasslands and minimally modified pastures
- Horticultural trees and shrubs
- Perennial crops
- Annual crops and highly modified pastures
- Plantation (hardwood)
- Plantation (softwood/mixed)
- Bare
- Ephemeral and Permanent Water
- Unknown/not reportable

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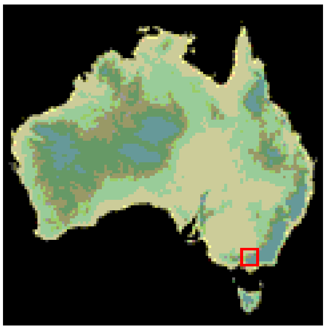
Integrated Vegetation Online
Goulburn Region

Summary Area Data

Vegetation Cover	Area (km sq)	Area percent
Native forests and woodlands	7,463	31.0
Native shrublands and heathlands	80	0.3
Native grasslands and minimally modified pastures	3,192	13.3
Horticultural trees and shrubs	216	0.9
Perennial crops	1	0.0
Annual crops and highly modified pastures	11,708	48.6
Plantation (hardwood)	1	0.0
Plantation (softwood/mixed)	201	0.8
Bare	2	0.0
Ephemeral and Permanent Water	439	1.8
Built-up	208	0.9
Unknown/not reportable	562	2.3
Total native	**10,735**	**44.6**
Total woody	**7,962**	**33.1**
Total perennial	**11,155**	**46.3**
Total vegetated	**22,863**	**95.0**
Total area of region	**24,074**	**100.0**



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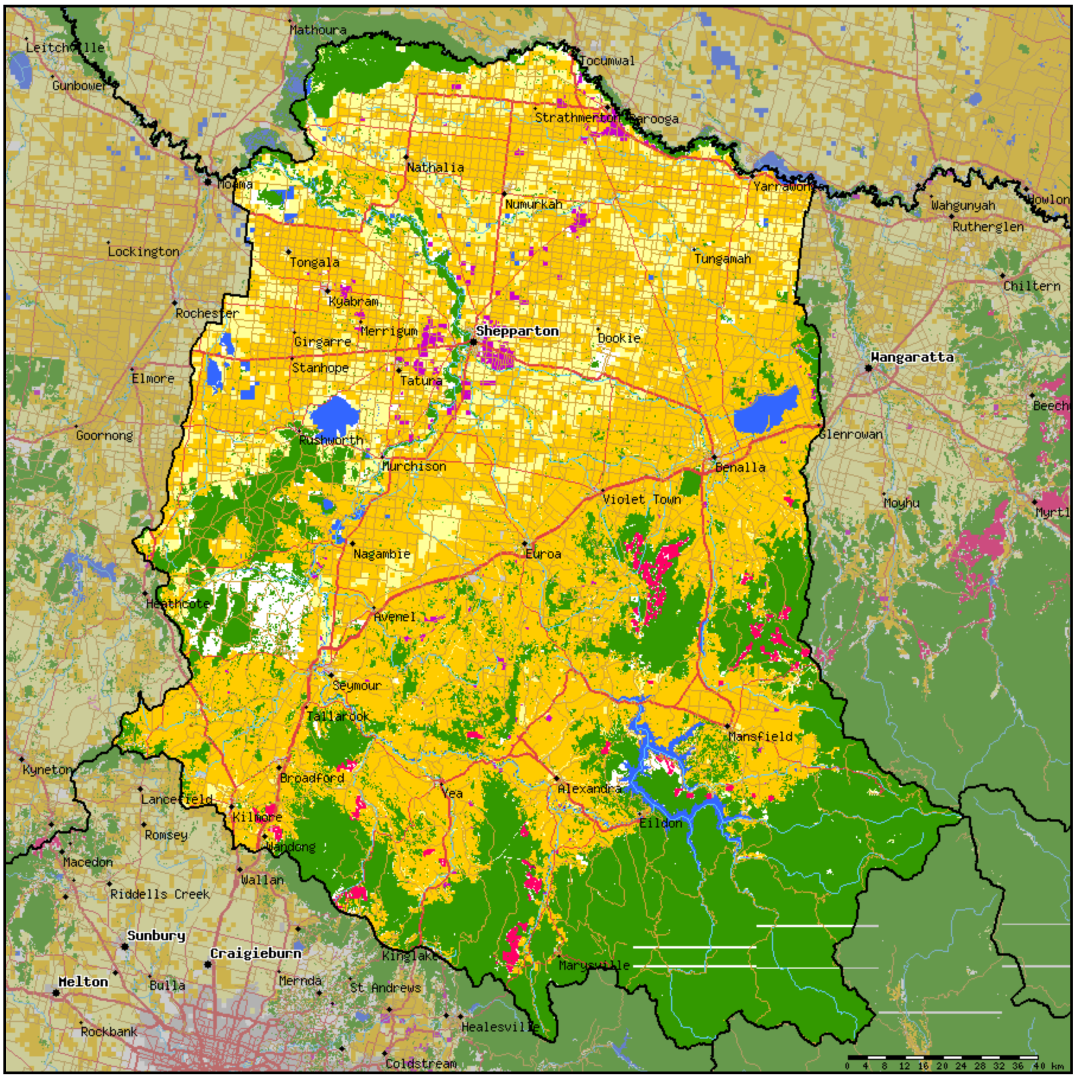

- Native forests and woodlands
- Native shrublands and heathlands
- Native grasslands and minimally modified pastures
- Horticultural trees and shrubs
- Perennial crops
- Annual crops and highly modified pastures
- Plantation (hardwood)
- Plantation (softwood/mixed)
- Bare
- Ephemeral and Permanent Water
- Unknown/not reportable

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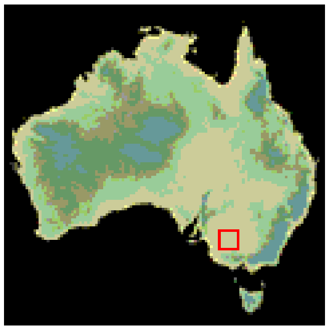
Integrated Vegetation Online

Mallee Region

Summary Area Data

Vegetation Cover	Area (km sq)	Area percent
Native forests and woodlands	12,669	32.2
Native shrublands and heathlands	1,060	2.7
Native grasslands and minimally modified pastures	10,596	27.0
Horticultural trees and shrubs	473	1.2
Annual crops and highly modified pastures	11,003	28.0
Ephemeral and Permanent Water	411	1.0
Built-up	20	0.1
Unknown/not reportable	3,061	7.8
Total native	**24,326**	**61.9**
Total woody	**14,203**	**36.1**
Total perennial	**24,800**	**63.1**
Total vegetated	**35,803**	**91.1**
Total area of region	**39,296**	**100.0**



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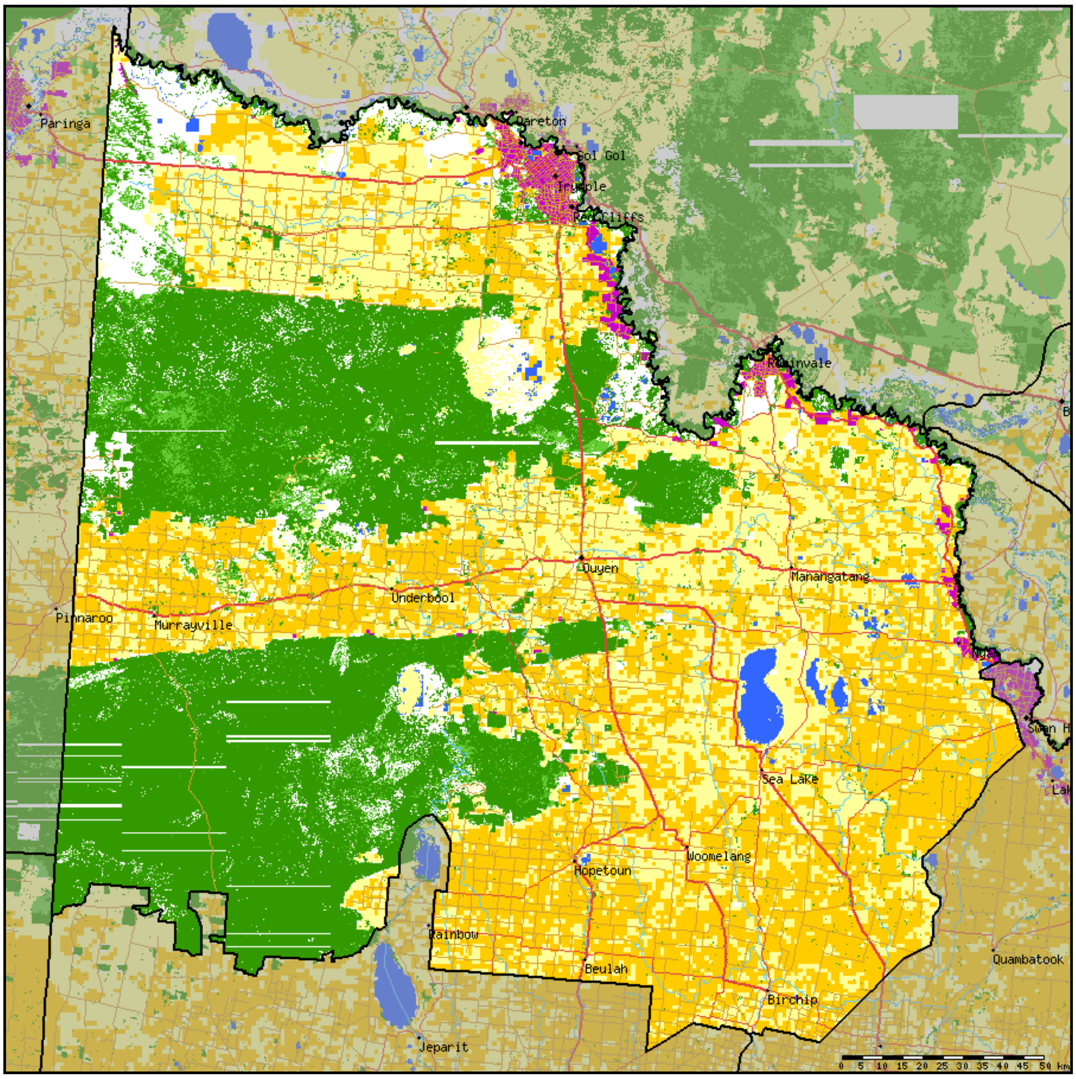

- Native forests and woodlands
- Native shrublands and heathlands
- Native grasslands and minimally modified pastures
- Horticultural trees and shrubs
- Perennial crops
- Annual crops and highly modified pastures
- Plantation (hardwood)
- Plantation (softwood/mixed)
- Bare
- Ephemeral and Permenant Water
- Unknown/not reportable

Refer to the Introduction for more information.
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Integrated Vegetation Online

- Native forests and woodlands
- Native shrublands and heathlands
- Native grasslands and minimally modified pastures
- Horticultural trees and shrubs
- Perennial crops
- Annual crops and highly modified pastures
- Plantation (hardwood)
- Plantation (softwood/mixed)
- Bare
- Ephemeral and Permenant Water
- Unknown/not reportable

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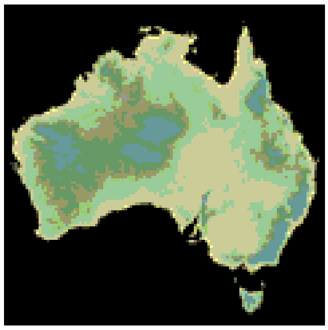

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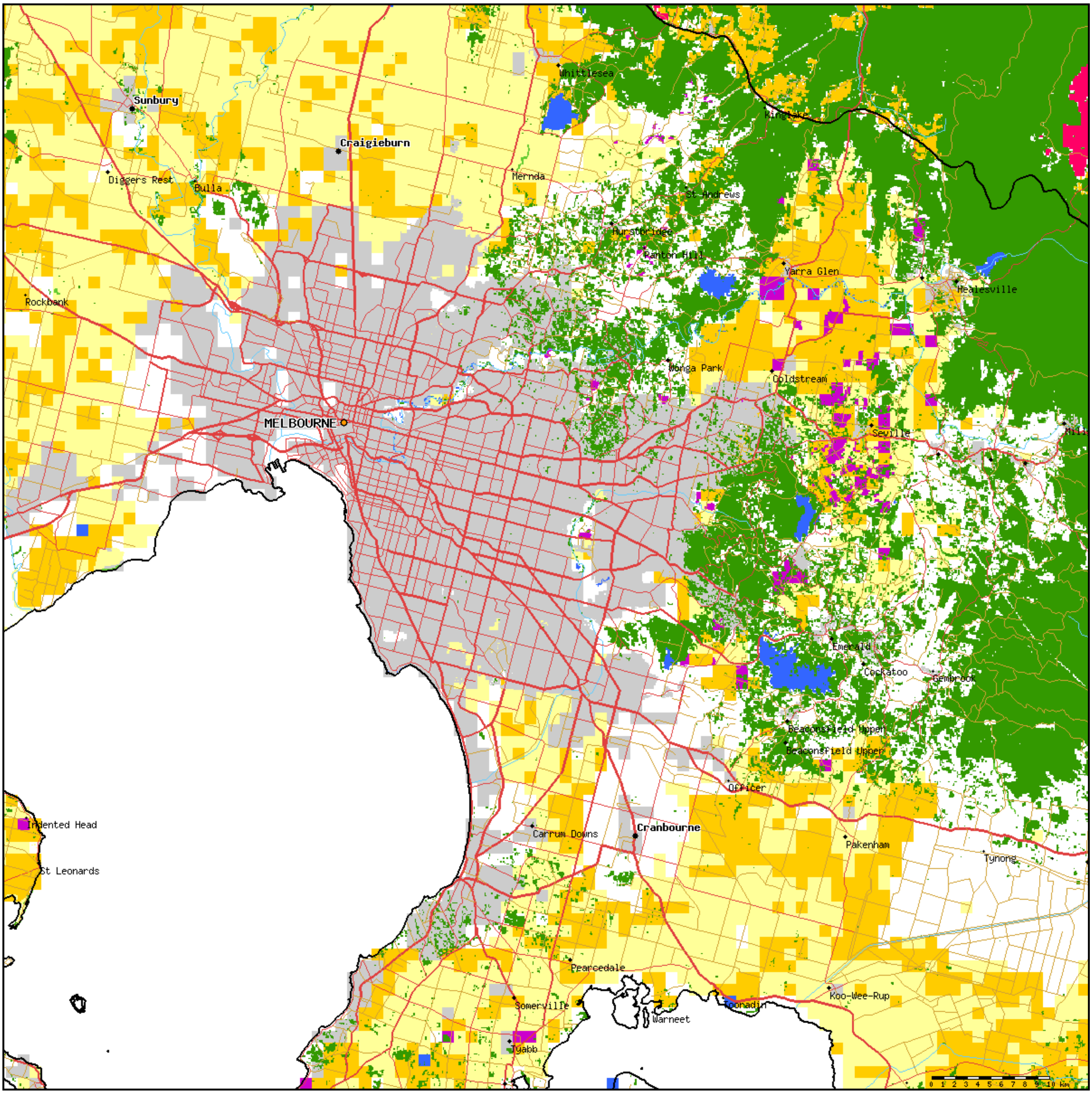

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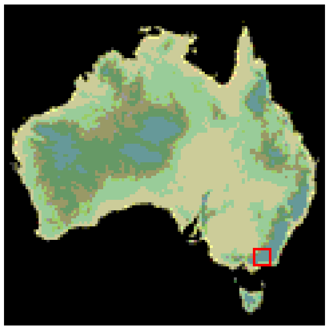
Integrated Vegetation Online

North East (VIC) Region

Summary Area Data

Vegetation Cover	Area (km sq)	Area percent
Native forests and woodlands	12,165	64.6
Native shrublands and heathlands	50	0.3
Native grasslands and minimally modified pastures	3,555	18.9
Horticultural trees and shrubs	15	0.1
Annual crops and highly modified pastures	1,678	8.9
Plantation (hardwood)	0	0.0
Plantation (softwood/mixed)	400	2.1
Ephemeral and Permanent Water	231	1.2
Built-up	45	0.2
Unknown/not reportable	696	3.7
Total native	**15,769**	**83.7**
Total woody	**12,629**	**67.1**
Total perennial	**16,184**	**85.9**
Total vegetated	**17,863**	**94.8**
Total area of region	**18,835**	**100.0**



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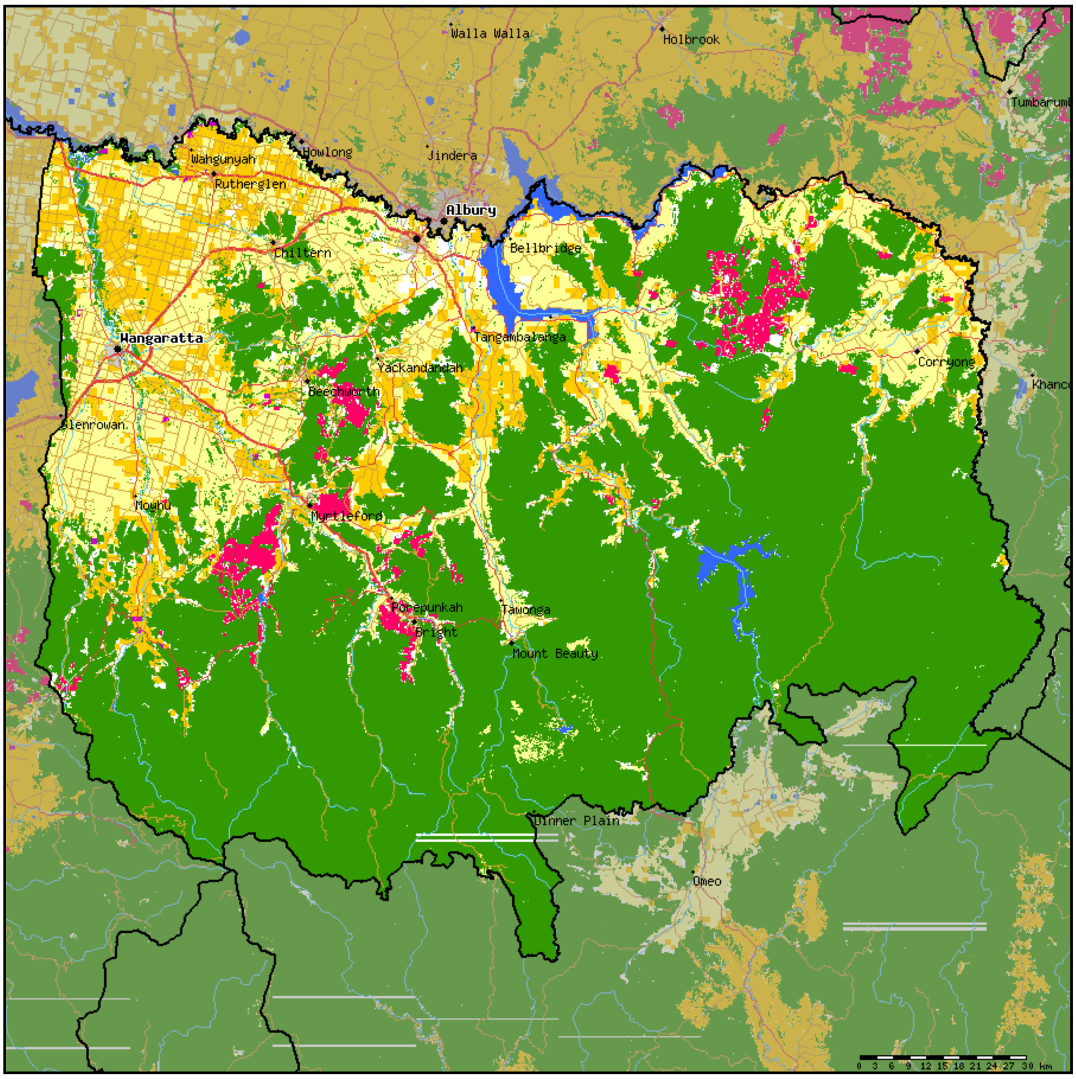

Native forests and woodlands

Native shrublands and heathlands

Native grasslands and minimally modified pastures

Horticultural trees and shrubs

Perennial crops

Annual crops and highly modified pastures

Plantation (hardwood)

Plantation (softwood/mixed)

Bare

Ephemeral and Permanent Water

Unknown/not reportable

Refer to the Introduction for more information.
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Datum: Geocentric Datum of Australia, 1994

Data compilation and cartography:
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Australian Government
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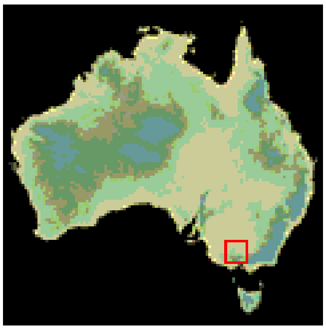
Integrated Vegetation Online
North Central Region

Summary Area Data

Vegetation Cover	Area (km sq)	Area percent
Native forests and woodlands	4,084	13.8
Native shrublands and heathlands	77	0.3
Native grasslands and minimally modified pastures	10,184	34.3
Horticultural trees and shrubs	155	0.5
Annual crops and highly modified pastures	13,777	46.5
Plantation (hardwood)	12	0.0
Plantation (softwood/mixed)	47	0.2
Ephemeral and Permanent Water	370	1.2
Built-up	114	0.4
Unknown/not reportable	831	2.8
Total native	**14,345**	**48.4**
Total woody	**4,375**	**14.8**
Total perennial	**14,559**	**49.1**
Total vegetated	**28,336**	**95.6**
Total area of region	**29,651**	**100.0**



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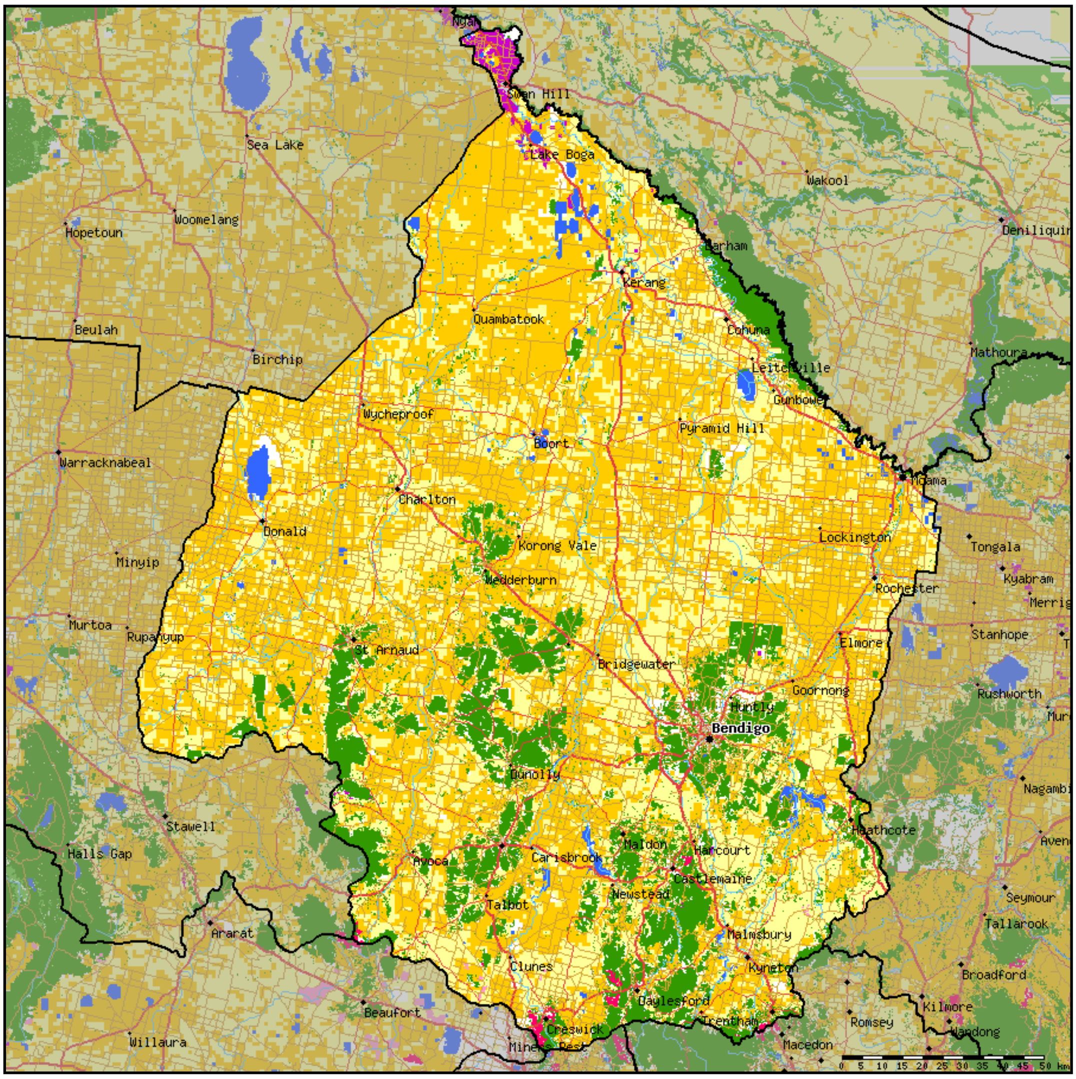

Native forests and woodlands

Native shrublands and heathlands

Native grasslands and minimally modified pastures

Horticultural trees and shrubs

Perennial crops

Annual crops and highly modified pastures

Plantation (hardwood)

Plantation (softwood/mixed)

Bare

Ephemeral and Permanent Water

Unknown/not reportable

Refer to the Introduction for more information.
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Source of topographic features:
Geoscience Australia, Division of National Mapping, GEODATA TOPO-250K.

Projection: Albers conic equal-area
Datum: Geocentric Datum of Australia, 1994

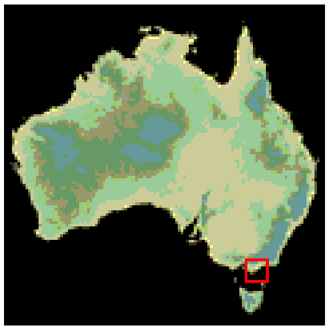
Data compilation and cartography:
Bureau of Rural Sciences
http://adl.brs.gov.au

Australian Government
Bureau of Rural Sciences

Integrated Vegetation Online
West Gippsland Region

Summary Area Data

Vegetation Cover	Area (km sq)	Area percent
Native forests and woodlands	7,825	45.2
Native shrublands and heathlands	124	0.7
Native grasslands and minimally modified pastures	297	1.7
Annual crops and highly modified pastures	6,892	39.8
Plantation (hardwood)	266	1.5
Plantation (softwood/mixed)	595	3.4
Bare	123	0.7
Ephemeral and Permanent Water	374	2.2
Built-up	297	1.7
Unknown/not reportable	510	2.9
Total native	**8,246**	**47.7**
Total woody	**8,811**	**50.9**
Total perennial	**9,108**	**52.6**
Total vegetated	**16,000**	**92.5**
Total area of region	**17,304**	**100.0**



Created: 02-Apr-2005

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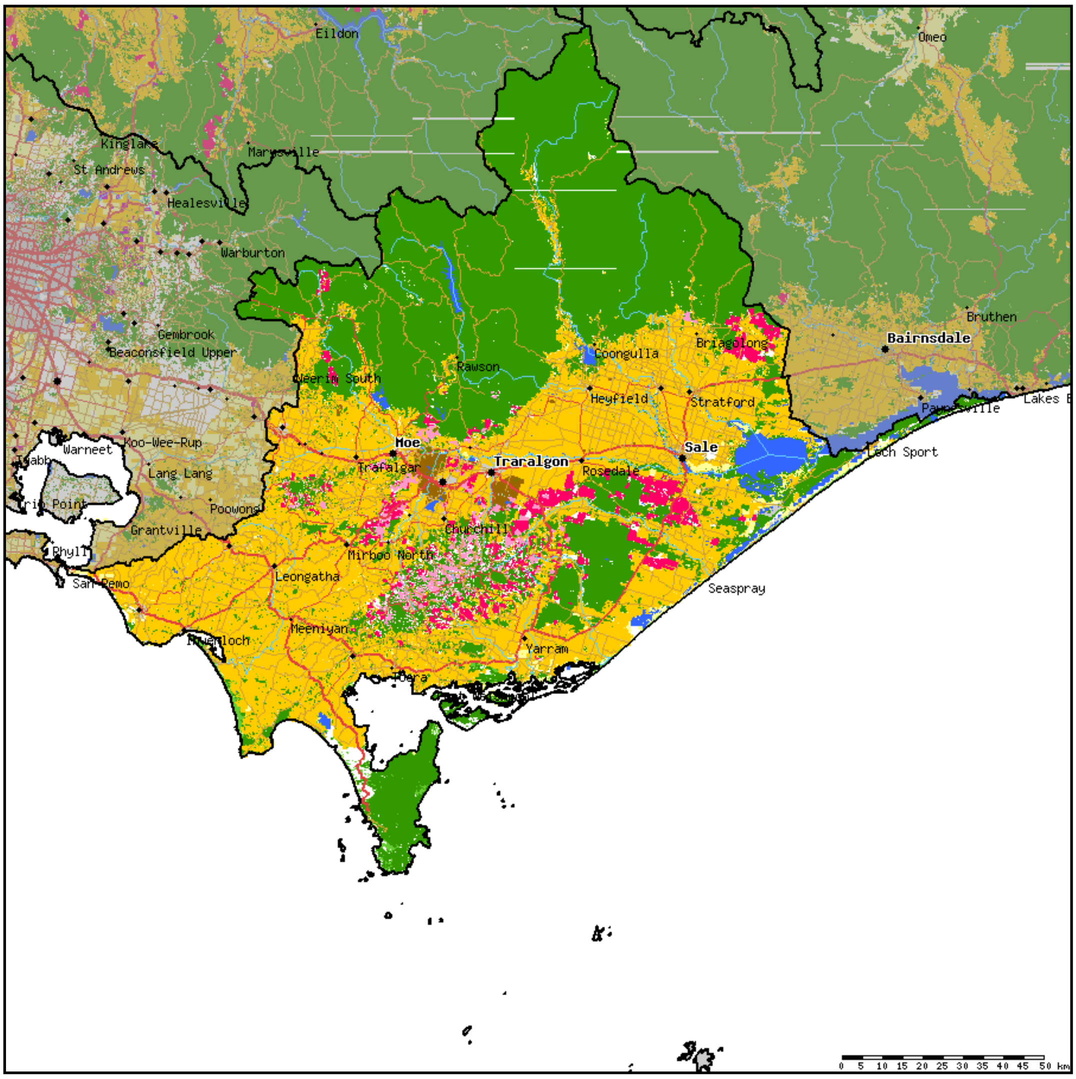


Native forests and woodlands
Native shrublands and heathlands
Native grasslands and minimally modified pastures
Horticultural trees and shrubs
Perennial crops
Annual crops and highly modified pastures
Plantation (hardwood)
Plantation (softwood/mixed)
Bare
Ephemeral and Permanent Water
Unknown/not reportable

Refer to the Introduction for more information.
Regions from National Heritage Trust Interim Boundaries, July 2003, Department of Environment and Heritage.
Boundaries may change under State/Territory legislation.

Source of topographic features:
Geoscience Australia, Division of National Mapping, GEODATA TOPO-250K.

Projection: Albers conic equal-area
Datum: Geocentric Datum of Australia, 1994

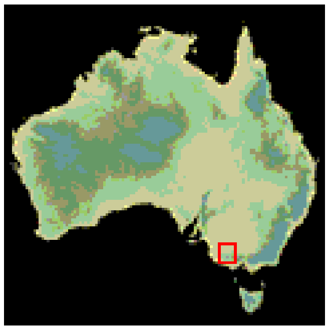
Data compilation and cartography:
Bureau of Rural Sciences
http://adl.brs.gov.au

Australian Government
Bureau of Rural Sciences

Integrated Vegetation Online
Wimmera Region

Summary Area Data

Vegetation Cover	Area (km sq)	Area percent
Native forests and woodlands	4,126	17.6
Native shrublands and heathlands	15	0.1
Native grasslands and minimally modified pastures	6,331	26.9
Horticultural trees and shrubs	54	0.2
Annual crops and highly modified pastures	12,107	51.5
Plantation (hardwood)	12	0.1
Plantation (softwood/mixed)	4	0.0
Ephemeral and Permanent Water	415	1.8
Built-up	39	0.2
Unknown/not reportable	390	1.7
Total native	**10,471**	**44.6**
Total woody	**4,211**	**17.9**
Total perennial	**10,542**	**44.9**
Total vegetated	**22,648**	**96.4**
Total area of region	**23,493**	**100.0**



Created: 02-Apr-2005

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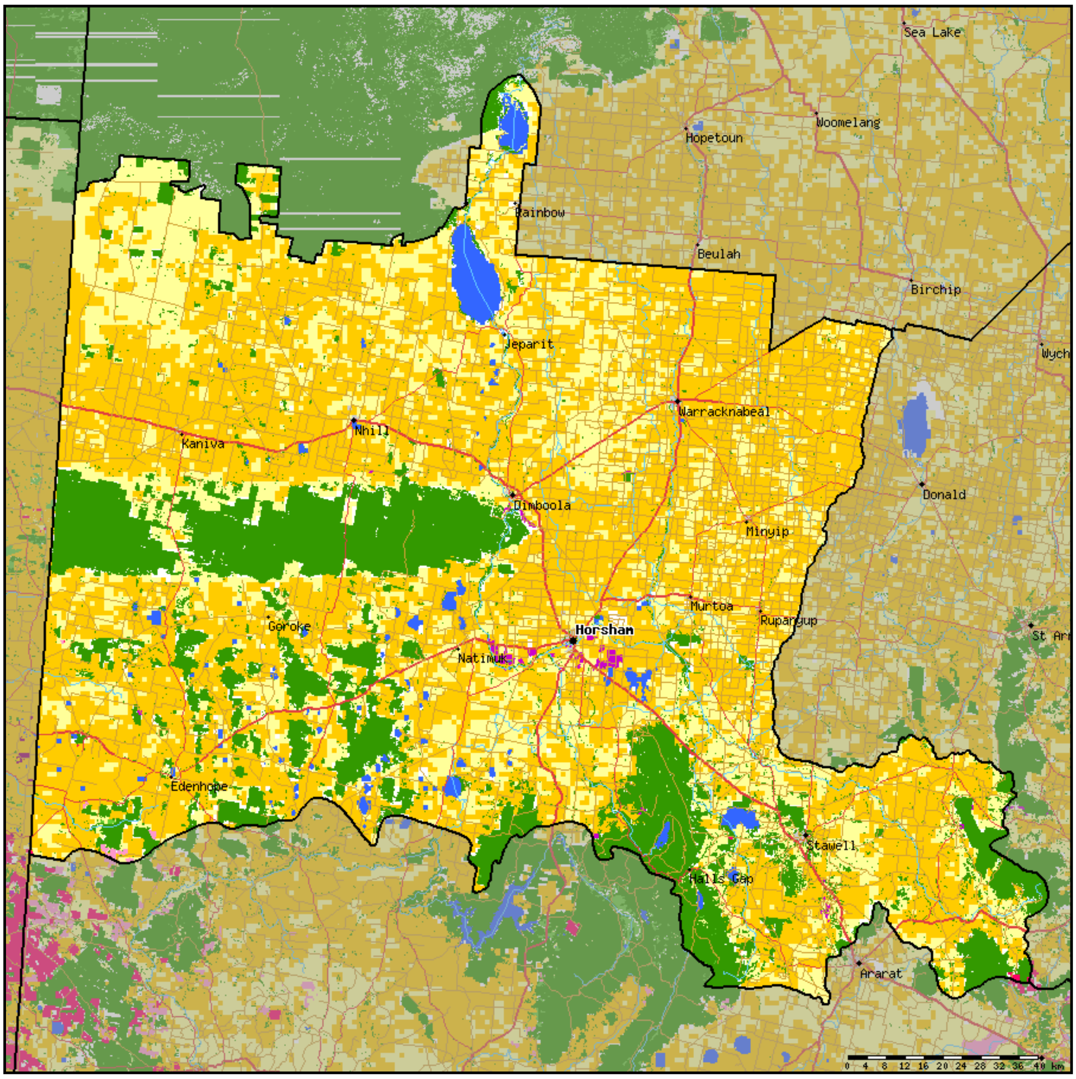


- Native forests and woodlands
- Native shrublands and heathlands
- Native grasslands and minimally modified pastures
- Horticultural trees and shrubs
- Perennial crops
- Annual crops and highly modified pastures
- Plantation (hardwood)
- Plantation (softwood/mixed)
- Bare
- Ephemeral and Permanent Water
- Unknown/not reportable

Refer to the Introduction for more information.
Regions from National Heritage Trust Interim Boundaries, July 2003, Department of Environment and Heritage. Boundaries may change under State/Territory legislation.

Source of topographic features:
Geoscience Australia, Division of National Mapping, GEODATA TOPO-250K.

Projection: Albers conic equal-area
Datum: Geocentric Datum of Australia, 1994

Data compilation and cartography:
Bureau of Rural Sciences
http://adl.brs.gov.au

Appendix 6: Data Warehouse Categories and Variables

Category	Variable	
Property Information	LGA ID Suburb Unit Number Street Number	Street Name Postcode CD/HC References •Electronic copy •Hard Copy
Building Information	Type Building Description Construction Wall Floor/Slab	Roof Footings Articulation joint (AJ) Year Built Age at 1st Inspection
Site Information	Site Classification (AS2870) Climate •Climatic Zone (AS2870) •New Climatic Zone (McManus et al. 2003)	Vegetation •Location from dwelling •Distance from dwelling •Type •Height
Consultant's Diagnosis	Type of damage Crack Settlement Movement Soil heave	Floor hump Rotation Other (e.g. Site leakages etc) Classification of damage Damage Category (AS2870)
Schedule of works	Repairs Footings Wall Articulation Joints Floor/Slab Brickwork Cladding Retaining Wall Windows/Doors Balconies/handrails/Steps Chimneys Cosmetic repairs Cosmetic Paint Balconies/handrails/Steps Chimneys	Cosmetic repairs Cosmetic Paint Patch Soil Moisture Stabilisation Gardens Landscaping Site regrading Trees Removal Root Barrier Drainage/pipes/pits/plumbing Install/relay perimeter concrete path Other perimeter installation Vertical Moisture Barrier
Estimated cost of repairs	Estimated Cost (AU$)	

Appendix 7: Default Values for the Operator's Options in MATLAB® Genetic Algorithm Toolbox

Operator	Option
Population	
Type	Double vector
Size	51
Creation Function	Uniform
Initial Range	(0;1)
Fitness scaling	
Scaling Function	Rank
Selection	
Selection Function	Stochastic uniform
Reproduction	
Elite Count	2
Crossover Fraction	0.8
Mutation	
Function	Gaussian
Crossover	
Function	Scattered
Migration	
Direction	Forward
Fraction	0.2
Interval	20
Stopping Criteria	
Generations	100
Time Limit	Infinity
Fitness Limit	Minus Infinity
Stall Generation Limit	50
Stall Time Limit	20

Appendix 8: Preview of the Integrated Web-based Map

Figure 1 to Figure 9 present the overall views of the web based map. The information on the damage to light structures in this map is based on two data marts. These are data marts from the Building Housing Commission and the USL Group Pty Ltd respectively. The main page of the web is the overview page of Victoria with a navigation or menu tool that can be used to switch between different settings of the map and navigation. Figure 1 shows the overview of the sites in Victoria with currently available information where the damage to light structures on expansive soils occur. As in the model, Victoria is divided into six regions; *North West*, *West*, *South West*, *North East*, *South East* and *Melbourne* regions. Melbourne region is divided into nine sub-regions; *Inner*, *Inner Eastern*, *Outer Eastern*, *Western*, *South*, *South East*, *North* and *North East Melbourne* and *Mornington*.

Figure 1: Overview of Damage of Light structure in Victoria

The map has different layers that can be activated and deactivated with the navigation tool – *Geology*, *climate* and *Melbourne information*. By clicking an option on the layer navigation tool, the selected information will be displayed for a particular region. For example, by selecting the climate information; TMI 1960-1990 and TMI 1940-1960 for

Melbourne region, a close up of the map such as Figure 2 will be displayed. Figure 3 shows the map with the geology layer activated for the Melbourne region only. Selecting the appropriate options will reveal or hide other regions and information respectively. A colour coded map of the Melbourne region with more detailed information as shown in Figure 4 will be displayed when the Melbourne Region option in the layer navigator is selected.

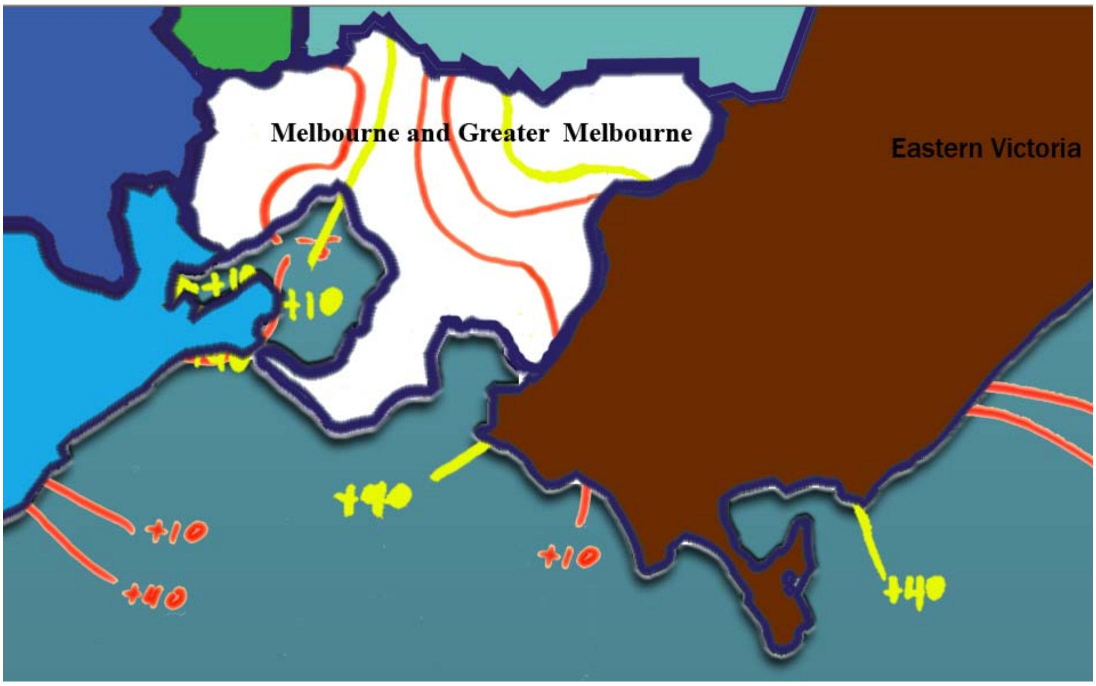


Figure 2: Climate information–TMIO(Yellow) and TMI New(Orange) of Melbourne

Figure 3: Geology information for Melbourne and Greater Melbourne

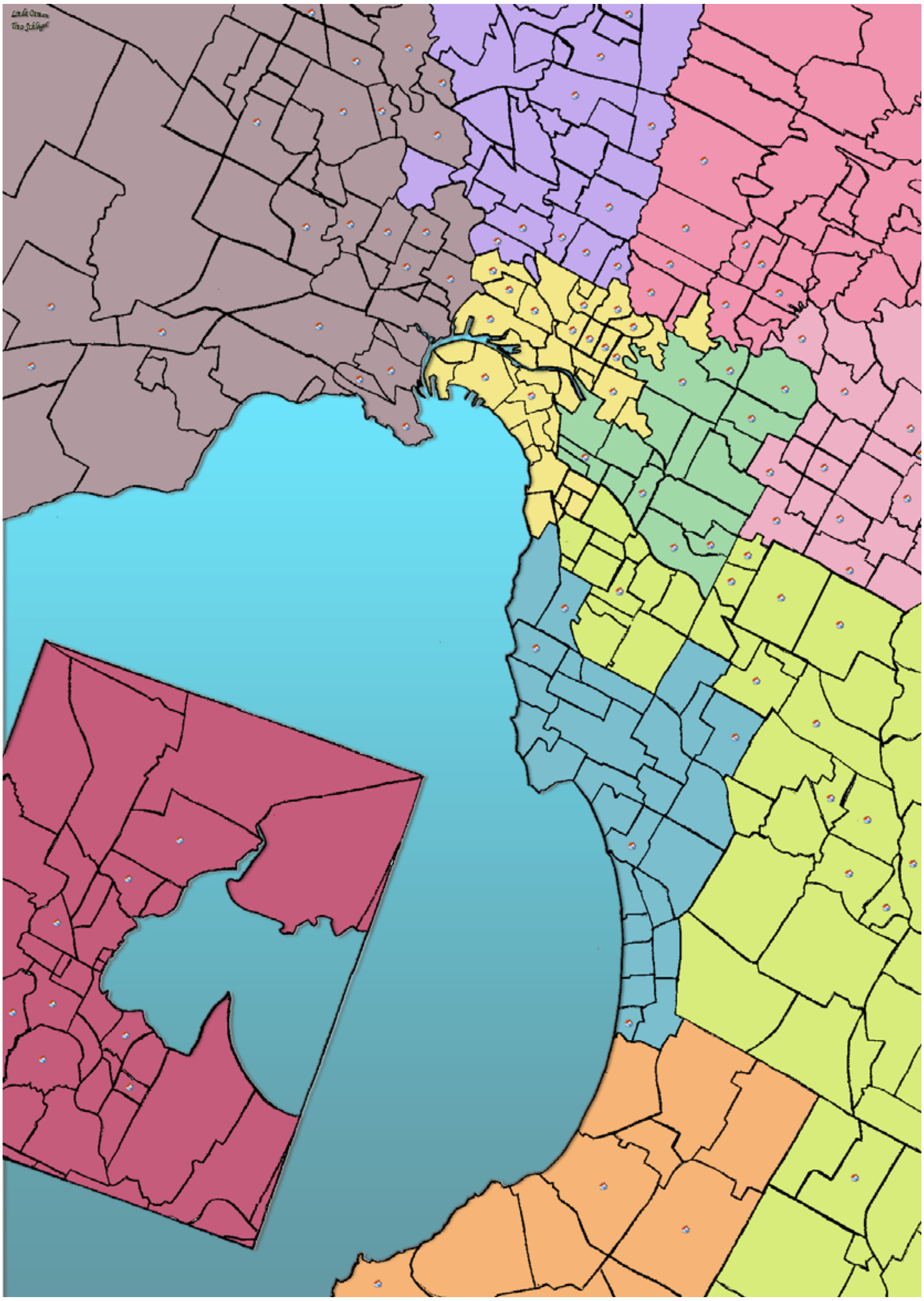
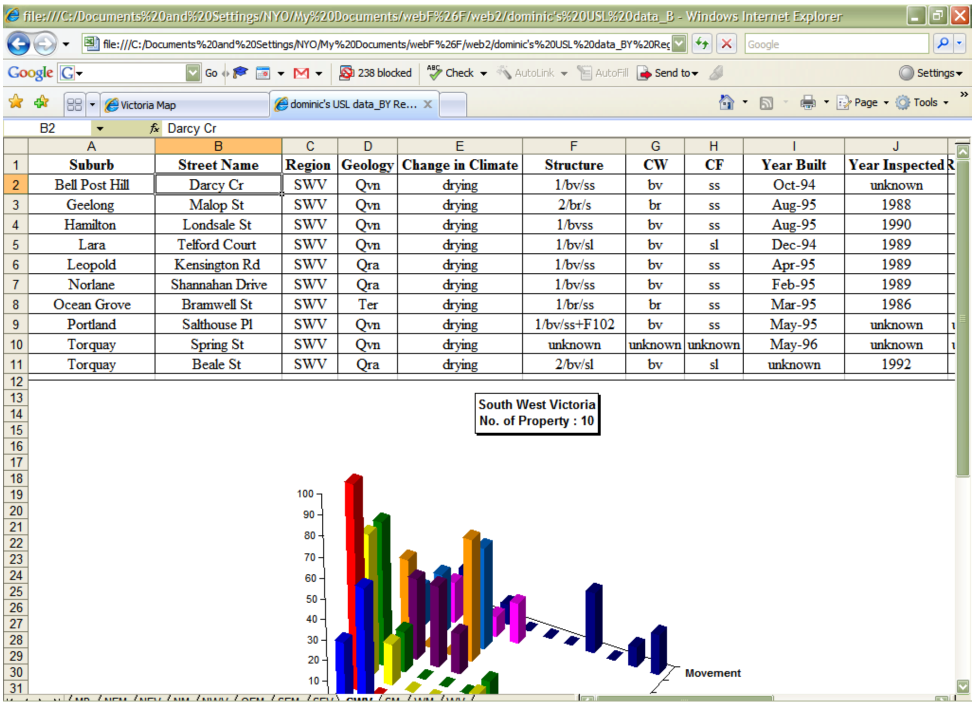


Figure 4: Properties of Damage Light Structures in Melbourne and Greater Melbourne

Clicking a house icon displays the available information about the properties located in that region. For example, a click on the house icon located in the South West Victoria region on the overview map of Victoria will display the damage properties in that region in excel format as shown in Figure 5. The information contains all relevant information from the suburbs in that region for the classification and the cause of the damage. It also contains a graph that shows the percentage of the properties stating their geology, change in climate, structural system, regulations, vegetation, damage condition and its causes.

Figure 6 shows an example of the available information about the suburbs in the Melbourne region that is available by clicking on one of the house icons in the Melbourne Region map (ref. Figure 4). Available information such as the postcode, geology, climate and number of properties in the selected sub-region will appear in a popup window. The popup window will also provide links to the available property information for the Building Housing Commission data (▬) and USL data (USL) as displayed in Figure 8 and Figure 9 respectively. The information about the ranking of the input parameters regarding their importance to classify the damage to light structure on expansive soils is available by clicking the chart icon (▬) as shown in Figure 9.



Suburb	Street Name	Region	Geology	Change in Climate	Structure	CW	CF	Year Built	Year Inspected
Bell Post Hill	Darcy Cr	SWV	Qvn	drying	1/bv/ss	bv	ss	Oct-94	unknown
Geelong	Malop St	SWV	Qvn	drying	2/br/s	br	ss	Aug-95	1988
Hamilton	Londsale St	SWV	Qvn	drying	1/bvss	bv	ss	Aug-95	1990
Lara	Telford Court	SWV	Qvn	drying	1/bv/sl	bv	sl	Dec-94	1989
Leopold	Kensington Rd	SWV	Qra	drying	1/bv/ss	bv	ss	Apr-95	1989
Norlane	Shannahan Drive	SWV	Qra	drying	1/bv/ss	bv	ss	Feb-95	1989
Ocean Grove	Bramwell St	SWV	Ter	drying	1/br/ss	br	ss	Mar-95	1986
Portland	Salthouse Pl	SWV	Qvn	drying	1/bv/ss+F102	bv	ss	May-95	unknown
Torquay	Spring St	SWV	Qvn	drying	unknown	unknown	unknown	May-96	unknown
Torquay	Beale St	SWV	Qra	drying	2/bv/sl	bv	sl	unknown	1992

Figure 5: Property Information for USL group for South West Victoria Region

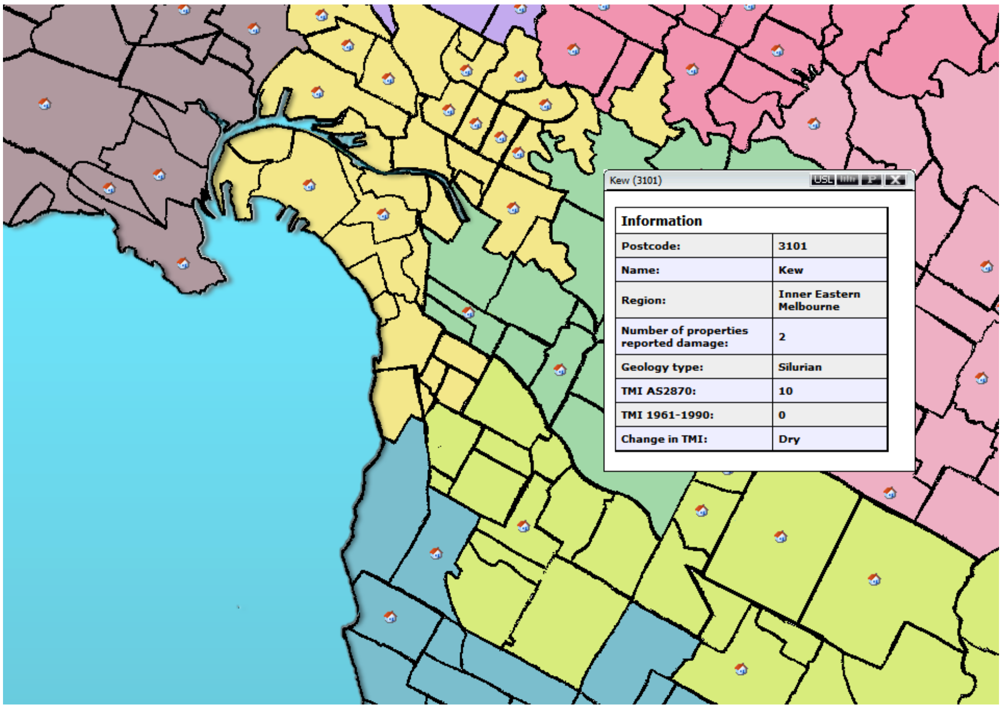
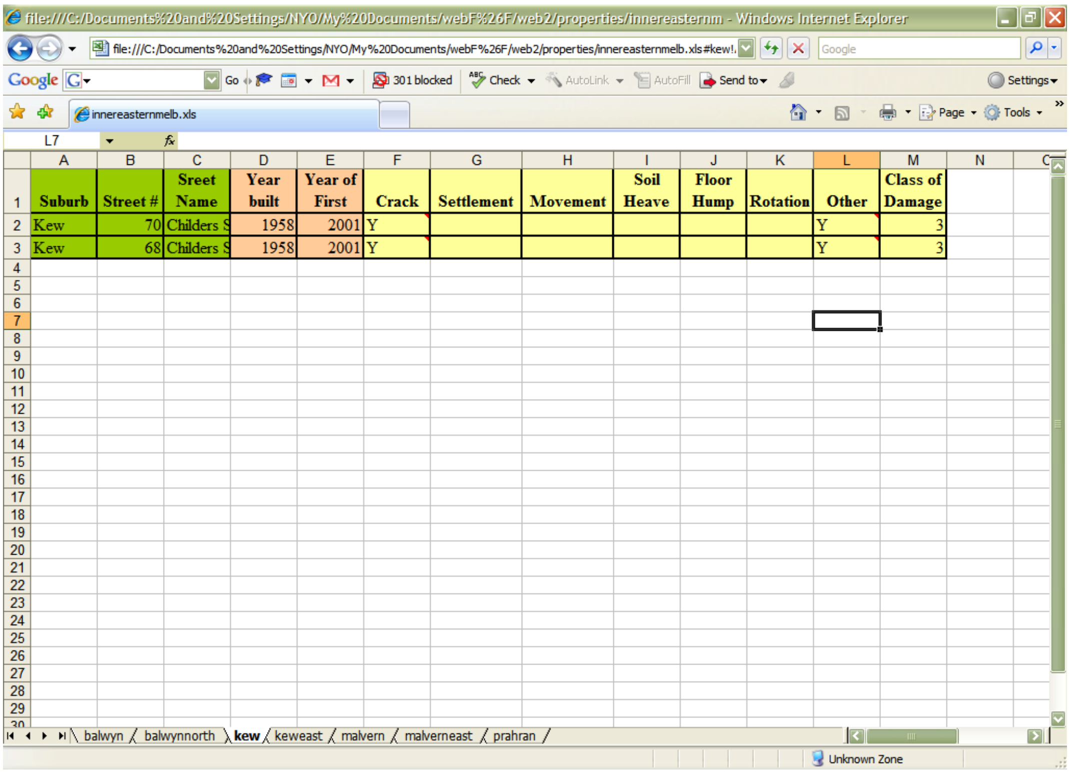


Figure 6: Example of Site Information



Suburb	Street #	Sreet Name	Year built	Year of First	Crack	Settlement	Movement	Soil Heave	Floor Hump	Rotation	Other	Class of Damage
Kew	70	Childers S	1958	2001	Y						Y	3
Kew	68	Childers S	1958	2001	Y						Y	3

Figure 7: Property Information for Building Housing Commission

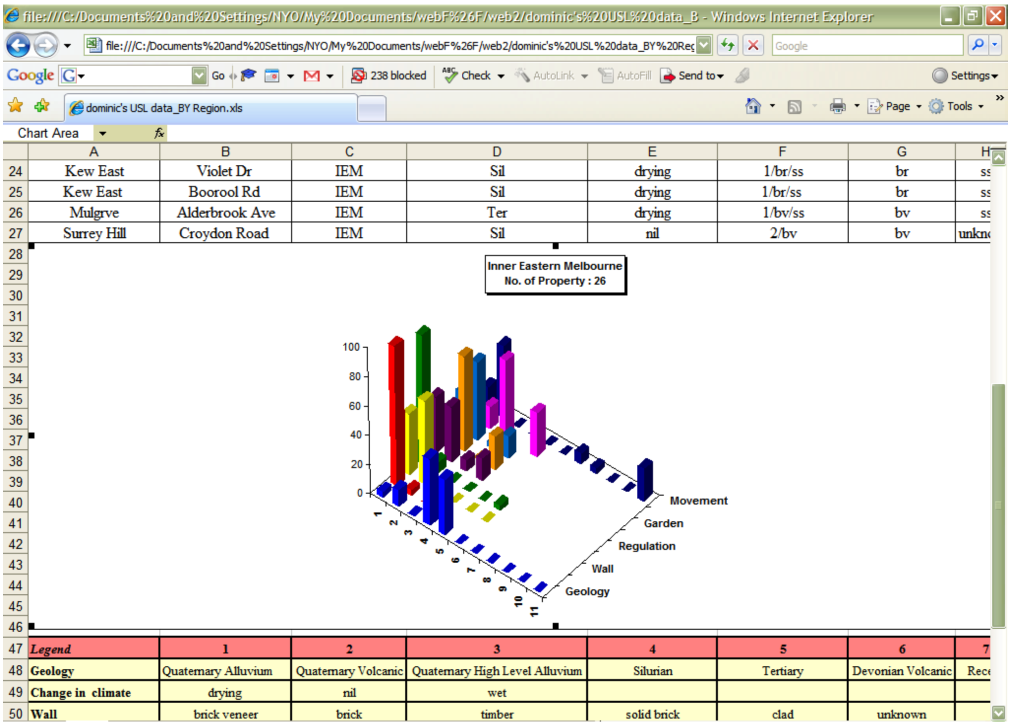


Figure 8: Property information for USL Group

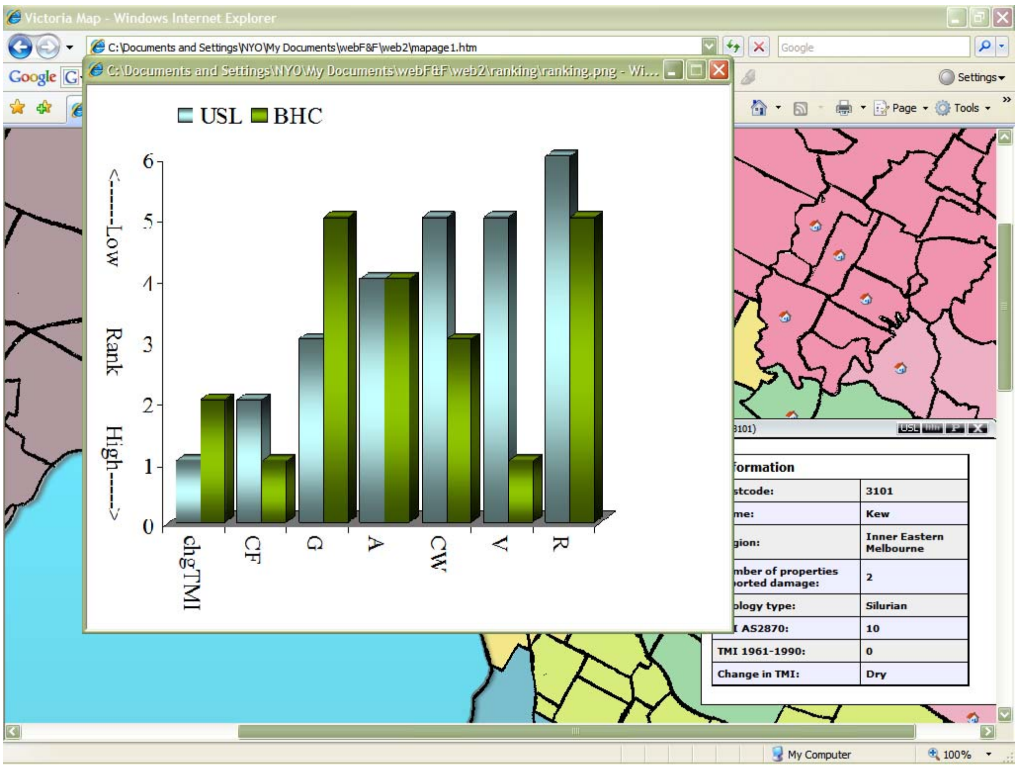


Figure 9: Ranking of important parameters

Parameters	Region	Change of Climate	Construction Type			Vegetation/Trees
			Structural System	Foundation and Footing	Renovation	
Variables		Dry/Wet Drought/Flood (Year ?)	Type of wall (interior/exterior) Type of frame	Type Depth Size Material	Extension	Type Distance Height Removed Age Watering Frequency Soil Suction value

Garden	Soil Information	Pipes	Damage	Cost
Watering Frequency Distance from Dwelling	Class (AS2870) Type Liquid Limit Soil Suction value	Leak Age	Type (Cracks etc) Class Size	Damage Repair