Improving the Accuracy and the Efficiency of Geo-Processing through a Combinative Geo-Computation Approach

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Declaration

I, Zhiwei Cao confirm that the work presented in this thesis is my own. Where information has been derived from other sources, I confirm that this has been indicated in the thesis.

Abstract

Geographical Information Systems (GIS) have become widely used for applications ranging from web mapping services to environmental modelling, as they provide a rich set of functions to solve different types of spatial problems. In the meantime, implementing GIS functions in an accurate and efficient manner has received attention, throughout the development of GIS technologies. This thesis describes the development and implementation of a novel geo-processing approach, namely Combinative Geo-processing (CG), which is used to address data processing problems in GIS.

The main purpose of the CG approach is to improve the data quality and efficiency of processing complex geo-processing models. Inspired by the concept of Map Calculus (Haklay, 2004), in the CG approach GIS layers are stored as functions and new layers are created through a combination of existing functions. The functional programming environment (Scheme programming language) is used in this research to implement the function-based layers in the CG approach. Furthermore, a set of computation rules is introduced in the new approach to enhance the performance of the function-based layers, such as the CG computation priority, which provides a way to improve the overall computation time of geo-processing.

Three case studies, which involve different sizes of spatial data and different types of functions are investigated in this research in order to develop and implement the CG approach. The first case study compares Map Algebra and our approach for manipulating two different raster layers. The second case study focuses on the investigation of a combinative function through the implementation of the IDW and Slope functions. The final case is a study of computational efficiency using a complex chain processing model.

Through designing the conceptual model of the CG approach and implementing the CG approach in the number of case studies, it was shown that the new approach provides many advantages for improving the data quality of geo-processing. Furthermore, the overall computation time of geo-processing could be reduced by using the CG approach as it provides a way to use computer resources efficiently and avoid redundant computations. Last but not least, this thesis identifies a new research direction for GIS computations and GIS software development, such as how a robust geo-processing tool

with higher performance (i.e. data quality and efficiency) could be created using the CG approach.

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List of Acronyms

CG: Combinative Geo-processing

DEM: Digital Elevation Model

DTM: Digital Terrain Model

GIS: Geographical Information Systems

GRASS: Geographic Resources Analysis Support System

GUI: Graphical User Interface

IDW: Inverse Distance Weighting

INSIDE: Interactive Numeric and Spatial Information Data Engine

IRL: Integrated Reference Layer

ISL: Integrated Sample Layer

LiDAR: Light Detection And Ranging

NDVI: Normalised Difference Vegetation Model

RAM: Random Access Memory

ROI: Region of Interest

RS: Remote Sensing

SQL: Structured Query Language

SYMAP: Synteny Mapping and Analysis Program

TIN: Triangulated Irregular Networks

1. Introduction

1.1 Background

Geographical information systems (GIS) form a powerful set of spatial analysis tools, where spatial data processing contributes significantly to the quality of the information and critically affects a GIS user's ability to carry out reliable and valid analysis. In principle, spatial data processing provides a comprehensive computation progress, including input data, functions operating on the input data, and the output or visualisation of the results. Spatial data processing components can be linked together in order to build different types of geo-processing models, which can then be used for more advanced spatial analyses within various contexts, such as urban planning, climate modelling, utility network management and transport network analysis.

Due to the rapid development of GIS technologies, various implementation approaches and tools for spatial data processing are already available within GIS software, with one of the most common approaches being geo-processing. This is based upon a framework of data transformation, which allows users to interpret data and functions obtained from different resources (Krivoruchko and Gotway-Crawford, 2003). Geo-processing tools were first developed and applied in the UK and US in the 1950s in order to reduce map production and maintenance costs (Vulera, 2011). Currently, geo-processing is a popular approach within GIS for decision-making and risk assessment purposes due to the large number of functions provided, such as the integration of geographical features, features selection and analysis, topology processing, raster processing, and spatial data conversion (Sommer and Wade, 2006).

A common characteristic of the traditional geo-processing approach is the sequential computation for implementing a set of functions or a geo-processing model, and Figure 1-1 displays a sequential computation in a simple chain processing model. The system initially loads 'Input Data1' into the function 'Funtion1', which yields the output 'Output1'; 'Output1' is then used as input data for the next function 'Function2', which returns the final result 'Ouput2'. This sequential computation strategy is applied in the traditional geo-processing approach for the implementation of various geo-processing models mainly due to the fact that many GIS software packages have been developed using imperative programming languages (e.g. Java and C++), where a function must be completed and return a value before it can be used by the next function and so on.

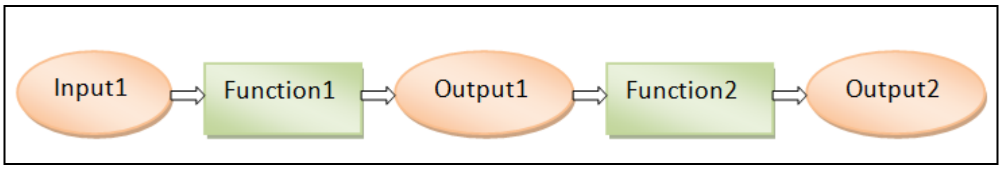


Figure 1-1 An example of the simple chain process.

A sequential computation may introduce uncertainties and errors into the traditional geo-processing approach. For example, the conversion of spatial data is one of the primary areas where different types of results need to be transferred and converted into a specific data format. The influence of data uncertainty is potentially increased when spatial data are converted from 'one system to another', 'one data format to another' or 'one resolution to another'. Furthermore, round-off errors during numerical computations, re-sampling operations, and error propagation can also affect the quality of geo-processing results, and these will be discussed in more detail in Section 2.3.3.

Given the aforementioned problems, this research investigates a number of methodologies for improving the performance of processing GIS data and functions, especially with respect to data quality and computational efficiency. The next section commences with a brief discussion on geo-processing models in order to explain the major functionalities.

1.2 Geo-Processing Models

A geo-processing model aims to help individuals to understand a problem and study the effects of different factors in the real world in order to identify solutions and make predictions (Longley et al., 2005). The major functionalities of a geo-processing model include:

a) ***A simplified way to describe a relationship amongst various spatial problems***
   The primary target of a geo-processing model is to use suitable tools to understand the relationships between the factors for a specific problem. For example, when users want to evaluate site suitability there are several factors that may need to be considered, such as land cost, elevation and slope, the transport network, and residential distributions. Overlaying the data for the same area helps users to understand the relationships between them.

b) ***To solve problems, find potential patterns, and support decision-making***

A geo-processing model provides a powerful tool for manipulating different types of GIS data and functions in order to answer questions such as ‘where is the best location?’ Consequently, the results will help users to understand different types of problems in the real world.

c) ***To provide an assumption or prediction***

Many successful applications have been created for modelling environmental problems and for making predictions. For example, when predicting areas where flooding may be an issue, users need to assess the amount of rainfall, acquire information about river discharges, and utilise a terrain model.

A geo-processing model may involve different types of GIS data and functions in order to solve complex spatial problems, and a geo-processing tool provides a useful way to implement and manipulate various geo-processing models. Consequently, different spatial questions can be answered using geo-processing tools, such as ‘Where is the best location to live?’ or ‘What spatial features does this region include?’

An example of a geo-processing model is how a site for a new school in Stowe, Vermont, USA was identified (ESRI, 2011). The model included four steps: (a) define input datasets, which include land use, elevation, recreation site locations, and existing schools; (b) calculate the slope and distance data from the inputs; (c) reclassify the new datasets; and (d) weight datasets and combine them in order to identify suitable locations. The resultant map displays suitable locations for the new school, and is an integrated map of the four different classification layers (Figure 1-2).

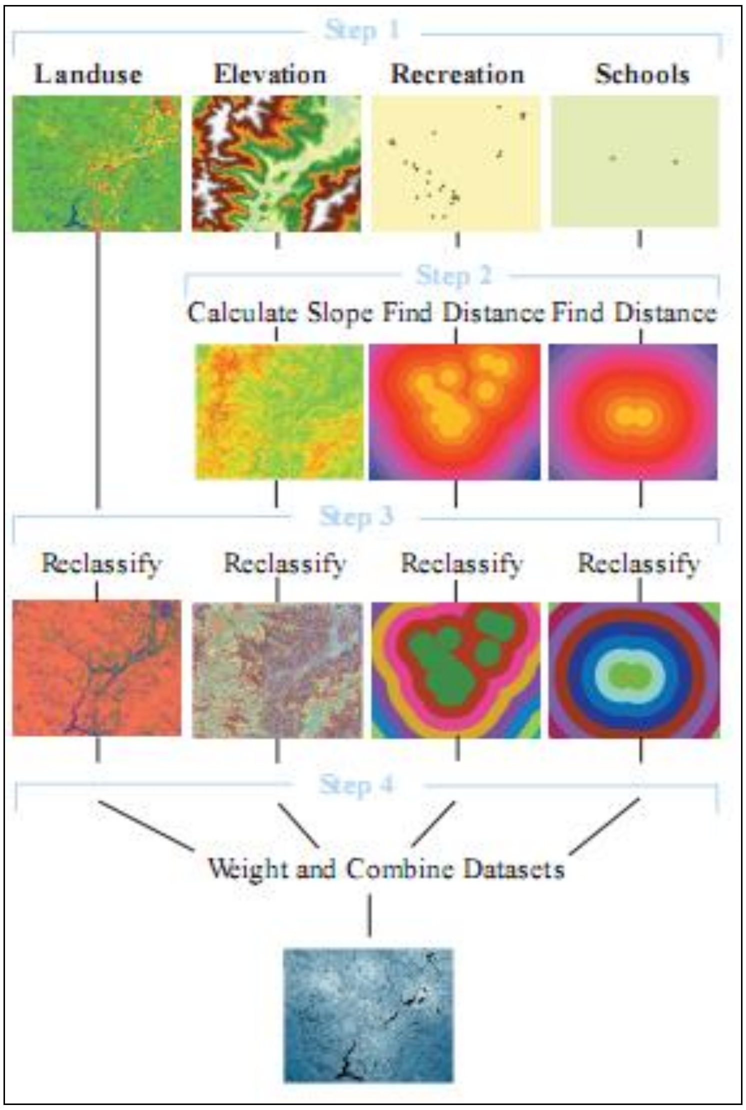


Figure 1-2 The site selection model for identifying a potential school location (Source: ESRI 2011).

1.3 Research Motivation

Although the traditional geo-processing approach offers a convenient means for dealing with different types of GIS data and functions within a geo-processing model, GIS experts have already identified many limitations. For example, Box argues that '.. all models are wrong. We make tentative assumptions about the real world which we know are false but we believe may be useful' (1979, pp.201-236). It should be noted that the assumptions and predictions of GIS models may introduce various data uncertainties and errors, which are discussed later in this thesis.

In this research the term 'data uncertainty' refers to the lack of certainty with regards to spatial data processing, such as assumption values, raster data re-sampling, error propagation and round-off errors during numerical computations (Devillers and Jeansoulin, 2010). The influence of data uncertainty issues are very difficult to manage within the traditional geo-processing approach, as most geo-processing models are calculated straightforwardly and without the progress of data quality control. Therefore, many GIS users apply spatial data analysis using the traditional geo-processing approach under the assumption that data processing is entirely error free (Burrough and McDonnell, 1998). However, to further clarify the importance of errors in this context, consider the following geo-processing scenarios and their associated data quality problems:

- Geo-processing operations often produce results that are generated by aggregating or disaggregating form input datasets. A common example is the application of Digital Elevation Model (DEM) data. With the aim of integrating geographical information, DEM data are often upscaled or downscaled to provide estimated elevation values for a particular scale, and during this process spatial interpolation methods, such as Kriging and inverse distance weight (IDW), are frequently employed for re-sampling raster data. However, the interpolation methods provide only estimated values for attributes associated with the newly created features, not the real values. Therefore, how to control data quality and the impact of estimated values during geo-processing should be considered.
- Vectorisation is a geo-processing function for converting a raster image to vector data. In common GIS tools, such as ArcGIS, the vectorisation function includes two different algorithms: (a) to generate vector lines along the centre of the raster linear elements; and (b) to generate vector lines at the border of the connected cells. However, which algorithm represents more closely the true features and what is the impact of these algorithms on subsequent computations?
- Raster data provide a simple data structure for representing spatial information. However, the resolution of the raster significantly affects the data quality. In a raster image with a resolution of five metres, any points located within the same grid will be represented as the same value even they are five meters apart. What will happen if users apply this image as the input dataset to generate a new output and how are errors propagated in this context?

These scenarios indicate that data quality problems influence different types of geo-processing models. Moreover, there are a number of existing problems in spatial data processing:

- Data conversion: The main characteristic of geo-processing is to link various functions into an integrated model, whereby data conversion is a basic process to transfer the results from different type of functions. When spatial data are converted, there is the potential of increasing the error in the resulting data (Devillers and Jeansoulin, 2006).

- Numerical computation: This is widely used by current GIS software packages, such as ArcGIS, MapInfo, GRASS, and Manifold, for data processing. This method uses numerical approximation algorithms to represent mathematical equations, and it is worth noting that there is an error between approximated values and true values. The accumulated errors in traditional geo-processing may directly affect the quality of the final result (Hildebrand, 1987).

- Error propagation: One of the most important functionalities of geo-processing is to derive new attributes from attributes already held within a GIS database. However, no data stored in a GIS database are truly error-free and no GIS tools exist that can mitigate the effect of error propagation in a reliable manner (Heuvelink, 2006).

- Cost of large computation resources: In addition to data quality, the computational efficiency when processing a large spatial dataset has also attracted attention in recent years. There are many potential issues concerning current geo-processing tools with respect to computational efficiency, for example, spatial data always needs to be processed by entire region, not by the specific request.

Finally, the influence of data uncertainties and computational efficiency during data processing may cause additional and more critical problems (e.g. system damage) when such geo-processing models are used to solve spatial problems in the real world. For example, the interpolation method (e.g. IDW) in GIS is commonly used to produce DEM data in order to describe land surface features (i.e. elevation values), and many engineering applications rely on DEM data (e.g. hydrological system, infrastructure network, property construction, and utility services). Therefore, if DEM data produced by a geo-processing model includes a significant level of data uncertainties or errors, then there is the potential for many issues to occur following the application of such data, e.g. flooding, infrastructure system failures, transport network system failures, or water supply system damage.

1.4 Research Aims and Objectives

A number of existing problems concerning the traditional geo-processing approach have been briefly discussed in the previous section. Further details on the causes of these problems and their effects on spatial data processing will be discussed in Sections 2.3 and 2.4. Based on their influences on spatial data processing, the current issues concerning geo-processing can be classified into two categories: data quality and computational efficiency. Table 1-1 provides a summary of the problems with the traditional geo-processing approach and their categories. It should be noted that this thesis focuses on the computation method, and applying how GIS data and functions are processed, and not on the technical issues of data acquisition and measurement.

Table 1-1 Brief summary of the existing issues concerning the traditional geo-processing approach.

Issues	Problem Category
Spatial data conversion	Data Quality
Numerical computation	
Error propagation	
Large computation resources cost	Computational efficiency (Overall computation time)

This thesis proposes the combinative geo-processing (CG) approach in order to improve the traditional geo-processing approach. Specifically, this thesis aims to improve data quality and reduce the overall computation time of geo-processing using the CG approach. The two main research objectives of this thesis are outlined below.

As shown in Table 1-1, the first category of geo-processing issues is data quality, which is an important research topic in GIS because it heavily affects the quality of the information generated. This topic has been actively pursued since the 1980s, and previous researchers have shown that errors cannot be avoided but can be managed (Heuvelink, 2006; Krivoruchko and Gotway-Crawford, 2003; Devillers and Jeansoulin, 2006). In order to provide accurate outcomes in geo-processing, the first objective of this thesis is to improve the quality of the data using the CG approach and to validate the results by comparing them with the traditional geo-processing approach. This objective leads to the following research questions:

- How can the data quality be improved in the CG approach?
  This requires an exploration of the methods that can be applied in the CG approach to improve data quality and also how these methods can be implemented in the CG approach.
- How can the results of the CG approach be validated?

The second category of the problems illustrated in the Table 1-1 is the computational efficiency of geo-processing. GIS is widely used in various fields, such as transportation, environmental modelling, asset management, and citizen science. Nevertheless, computational efficiency is a major concern for the development of GIS tools as the size of spatial datasets and the complexity of spatial problems are dramatically increasing (Brown and Coenen, 2000). Moreover, the CG approach is employed to process large geographical data and complex GIS functions then there is the potential risk of heavy computation time costs, as many computation rules (e.g. symbolic computation) will be used to improve the data quality and may potentially extend the overall computation time. Therefore, the second objective of this thesis is to improve the overall computation time of geo-processing using the CG approach and to validate the results by comparing them with the traditional geo-processing approach. To address this objective the following research questions should be explored:

- What methods can be applied to reduce the overall computation time in geo-processing?
- How can computer resources (e.g. computer memory and CPU) be efficiently used for the geo-processing computations?
- How can redundant computations be avoided in a geo-processing model?
- How can the results from the CG approach be validated?

1.5 The Structure of Thesis

The CG approach is a multidisciplinary concept and consequently this research includes many important topics, such as functional programming, data quality, computational efficiency, and so on. Therefore, it is necessary at this stage to provide a brief overview of the thesis outline.

The research is organised into four steps for the development of the CG approach:

Step 1: ***An extensive review of the traditional processing of GIS data and functions, and potential methods that can be applied in the CG approach (Chapter 2).***

The major characteristics of the traditional geo-processing approach and their limitations are investigated in this step in order to identify the major problems. A preparation phase has been previously undertaken, which involved a study of the basic methods related to the CG approach in order to improve the traditional geo-processing approach.

Step 2: ***Design of a framework for the CG approach and the basic methodologies for the implementation of the CG approach (Chapters 3 and 4).***

A conceptual framework for the CG approach is required in order to answer the research questions. This research needs to build a set of formulae to create the CG functions and function-based layers, before establishing a set of computation rules to manipulate the CG functions and function-based layers.

Step 3: ***Design of a set of case studies to demonstrate how the CG approach can be implemented and the evaluation of the results (Chapter 4).***

A set of scenarios is designed for the development of the CG approach. These scenarios are focused on the basic questions of geo-processing, such as how to generate spatial information from functional layers.

Step 4: ***Implementations and analysis of the results (Chapters 5 to 7).***

The case studies are implemented and a comprehensive comparison of the results is performed as the last step of this research. The investigation attempts to answer the research questions by discussing how the influence of data uncertainties is reduced in the CG approach and how the computational efficiency is improved.

Table 1-2 illustrates the structure of the thesis in relation to the research steps and objectives in a diagrammatic form.

Table 1-2 The structure of the thesis.

Introduction	Literature Review	Methods	Implementation				Conclusions
Introduction and Research Framework	Processing GIS Data and Functions	The Conceptual Framework of the CG Approach	The Implementation Tools and Case Studies Design	Case Study 1: A Map Overlay Operation	Case Study 2: Implementing a Simple Chain Processing	Case Study 3: Implementing a Complex Chain Processing	Research Discussion, Summary, and Further Work
Chapter 1	**Chapter 2**	**Chapter 3**	**Chapter 4**	**Chapter 5**	**Chapter 6**	**Chapter 7**	**Chapter 8**

Chapter 2 presents the literature review in relation to the fundamental elements of geo-processing, such as the spatial data model, data processing functions, computational strategies, and existing problems. Section 2.2 begins with an overview of data processing within GIS, such as the computation strategy of the traditional geo-processing approach, and the challenges for the current approach. Section 2.3 is a discussion on the data quality of geo-processing and provides suggestions for improving the quality of the data. Section 2.4 discusses the computational efficiency of geo-processing, such as the problems of sequential computation and how the overall computation time of a geo-processing model could be improved. Finally, Section 2.5 concludes this chapter with a summary of the major findings of the literature review.

Chapter 3 provides the conceptual model for the CG approach. Section 3.2 commences with a discussion of the basic characteristics of the CG approach in order to understand the differences compared to the traditional geo-processing approach. Section 3.3 proposes a conceptual model for the CG approach and discusses in detail implementation issues, which mainly refer to: how spatial objects are represented; how different types of GIS functions are applied in the CG approach; how the GIS functions and spatial data are further evaluated; and how the CG outputs are produced. Section 3.4 discusses the strengths and limitations of the proposed CG approach.

Chapter 4 provides an overview of the main methodological framework of this thesis. Section 4.2 begins with a discussion of a set of case studies, which gradually increase in complexity, and which were carried out in order to implement and also evaluate the CG functions and the results obtained. Section 4.3 illustrates CG computations in the three case studies for the development of the CG approach, e.g. building up function-based layers and dealing with a group of function-based layers. Section 4.4 describes how the CG approach can be implemented in a digital computer environment, while Section 4.5

describes the selected data that are used in the case studies. Finally, Section 4.6 summarises the main issues that are discussed in this chapter.

A set of experiments was designed for this research through a series of case studies. The first case study is explained in Chapter 5, and investigates a multi-layer overlay operation using the CG approach and map algebra. Section 5.2 discusses the 'Raster Overlay with Raster' function. Section 5.3 explains how the 'Raster Overlay with Raster' function is implemented using map algebra, which is commonly used within the context of the traditional geo-processing approach in order to overlay more than one raster data layers. Section 5.4 presents the datasets and more specifically the reference and sample data that are used in the case study. Section 5.5 describes the implementation strategy for the 'Raster Overlay with Raster' function and Section 5.6 presents the results. Section 5.7 provides a more detailed comparison of the map algebra and the CG approach results, and Section 5.8 discusses the differences. Finally, Section 5.9 discusses the main issues and problems that are revealed in the first case study.

Chapter 6 validates the quality of a simple chain processing model. Section 6.2 starts with a discussion of a primitive simple chain processing model and describes the geo-processing model that it is used in this case study. Section 6.3 introduces the two different approaches that can be used for the implementation of any simple chain processing models: the traditional geo-processing approach using the ModelBuilder tool in ArcGIS and the CG approach. Section 6.4 presents the datasets that are used in this second case study. Section 6.5 discusses the implementation strategy for executing the simple chain processing model and Section 6.6 presents the results. In Section 6.7 the Monte Carlo simulation is used to compare the influences of data uncertainties in both simple chain processing model implementations. Section 6.8 discusses the differences between the various Monte Carlo simulation outcomes and Section 6.9 summarises the main issues that are discussed in the second case study.

Chapter 7 discusses how the computational efficiency of geo-processing can be improved in the CG approach. Section 7.2 reviews the implications of an inefficient computation strategy in geo-processing and discusses the concepts of computation flexibility and computation sequence. Section 7.3 introduces the concept of CG computation priority, which aims to reduce the overall computation time of geo-processing through the use of an improved computation strategy. Section 7.4 discusses the complex chain processing model that is applied in the third case study and Section 7.5 describes how the model is implemented in the traditional geo-processing and the

CG approaches using computation priority. Section 7.6 presents the datasets that are used in the third case study. Section 7.7 discusses in detail the implementation and strategy for executing the complex chain processing model using the two different geo-processing approaches and Section 7.8 presents the results. Section 7.9 compares the implementation results on overall computation time using the Monte Carlo simulation method. Finally, Section 7.10 concludes with a summary of the main issues and findings discussed in this third case study.

Chapter 8 concludes the thesis by discussing and summarising the research undertaken. Section 8.1 presents a brief overview and Section 8.2 discusses the major research findings. Section 8.3 discusses the contribution of this thesis, whilst Section 8.4 reviews the limitations of the CG approach development, and Section 8.5 proposes the direction of future research.

2 Processing GIS Data and Functions

2.1 Introduction

Data processing involves extracting meaningful information from raw data, which is then used for data analysis and decision-making (French 1996). Data processing has been a topic of research in various applications, such as commercial data processing and data analysis, and is widely accepted as a critical part of addressing complex problems. In GIS, spatial data processing, known as 'geo-processing', includes various computational tasks, such as spatial analysis, GIS visualisation and geostatistics (Karimi et al. 2011). The aim of geo-processing is the collection and manipulation of spatial data to produce useful information and solve complex spatial problems (Niu et al. 2013).

Geo-processing relies on a computational framework consisting of spatial functions and models, which traditionally are applied in sequence. Such a framework usually lacks mechanisms for data quality control and effective management of computation time. Moreover, some basic methods involved in geo-processing (e.g. spatial data representation and basic computation) may introduce uncertainties and errors through approximations and error propagation. This thesis addresses the implications of this framework, which we call the 'traditional geo-processing approach', and proposes a new approach – the 'Combinative Geo-processing (CG) approach' – aimed at improving the data quality and computational efficiency of geo-processing.

The proposed CG approach is realised using a point-based spatial data model, symbolic computation, and functional layers in order to improve data quality. By describing features of both discrete objects and continuous fields, the point-based spatial data model aims to reduce the complexity of GIS representations and avoid problems with data quality that can arise from raster resolution and spatial data conversion. Symbolic computation and functional layers minimise the effects of data uncertainty and error propagation on geo-processing results. Additionally, the proposed CG approach employs a priority-based computation strategy that reduces the entire time-cost of a geo-processing model and thereby improves computational efficiency.

This chapter reviews problems with data quality and computational efficiency that arise from the traditional geo-processing approach, and discusses how these problems can be improved. First, basic concepts of spatial data processing are introduced; these then enable an exploration of traditional geo-processing problems which influence data quality and computational efficiency. Lastly, potential ways to improve the traditional geo-processing approach are discussed.

Section 2.2 discusses the major characteristics and implications of the traditional geo-processing approach. Section 2.2.1 reviews the concept of data processing and enables us to understand its fundamental elements. In Section 2.2.2 the discussion narrows down to spatial data processing and describes how a geo-processing model is built and executed. Section 2.2.3 summarises and concludes with the major characteristics of the traditional geo-processing approach and its challenges.

Section 2.3 discusses major data-quality problems that arise in traditional geo-processing and provides evidence of scope for improvement. Section 2.3.1 defines common data-quality terms that are used in this thesis. Section 2.3.2 reviews common errors in GIS, and Section 2.3.3 discusses the specific data-quality problems seen in geo-processing, including with spatial data representation and geo-processing computation. These two methods are singled out because they have many existing data-quality problems affecting on the traditional geo-processing approach, such as data uncertainty and error propagation. Section 2.3.4 discusses methods that are applicable to the CG approach for improving geo-processing, particularly by reducing the influence of data-quality problems.

Section 2.4 discusses another issue – computational efficiency – with the traditional geo-processing approach, as this provides further evidence for the necessity of improving the traditional geo-processing approach. Section 2.4.1 reviews common computational efficiency definitions that are used in this research. Then, Section 2.4.2 discusses existing problems with computational efficiency in a complex geo-processing, including 'waiting' functions and unnecessary computations. These two problems are selected because they can extend the entire computation time of a geo-processing model. Section 2.4.3 concludes by contrasting the traditional geo-processing approach with improvements in computational efficiency achieved by the CG approach.

Section 2.5 summarises the main points discussed and concludes with suggestions for improving the data quality and computational efficiency of geo-processing.

2.2 Data Processing In GIS

To understand the fundamental methods and basic characteristics of data processing, this chapter presents a historical review of the development of data processing, focusing on both manual and automatic processing. Then the research narrows down to spatial data processing, i.e. geo-processing, and its major functionalities, in order to explain how spatial data and functions are manipulated in GIS. Furthermore, the traditional geo-processing approach and its challenges are discussed in this section.

2.2.1 Data Processing Overview

As the real world becomes more complex, various questions need to be investigated. For example, global networked risks (e.g. economic, environmental, health, and food) are extremely complicated, as they are globally connected and influence each other (Helbing 2013). In order to address complicated problems and support useful information for decision making, there is a need to organize, manipulate, and analyse large amounts of data using different data-processing tools (French 1996). Consequently, this section discusses the basic concept of data processing.

Most data processing tools include *"a group of interrelated components that seek the attainment of a common goal by accepting inputs and producing outputs in an organised process"* (O'Brien 1986, p. 66). In principle, a data processing system has three components. The first component is the ***data input***. Some popular functions of ***data input*** include data capture and collection in preparation for processing. The second component is the ***data processing***, which includes functions such as data sorting, classification, interpolation, assumptions, and valuation. Sorting and classification arrange items or data in a specific order or in different sets for processing; interpolation and assumptions provide a way to calculate unknown information from captured data; evaluation tries to ensure the manipulated data is correct, reliable, and useful. The third component is the ***output of information***, and common processing functions here include data aggregation, presentation, summarization, and reportation. Data aggregation integrates different outputs into a comprehensive result, for example by combining different data layers into a final single layer. Data validation ensures that the manipulated data are correct, reliable, and useful for problem-solving. Data presentation is used to illustrate the results of the data processing. Summarisation and reportation capture the main features of the datasets and results. Taken together, the three components provide the basic structure of the data processing framework and can help users to build their own data-processing system, such as the conceptual framework for the CG approach, discussed in Chapter 3.

Data processing developed in three stages (Bohme and Wyatt 1991). The first stage was ***manual data processing***, which was costly and required intensive resources to implement. For example, data processing functions were performed manually in the 1880 US census survey, for which the Census Bureau employed a tallying system to mutually record and classify information. It took over seven years to publish the results of this census (Bohme and Wyatt 1991). The second stage was ***automatic data processing***, which was less costly than ***manual data processing***. Automatic data processing operated functions by using unit record equipment, which allowed large-volume, sophisticated data-processing tasks to be accomplished before electronic computers were invented. For example, the Census Office completed most of the 1890 census data in two to three years using automatic data processing, compared with seven to eight years for the 1880 census survey (Bohme and Wyatt 1991). The third – and current – stage is ***digital data processing***, which enables users to process computational tasks more efficiently by exploiting modern computers and the latest computational methods. Cloud computing, for example, enables the production of computational results in real time (Mathew 2014).

Digital data processing with modern computational techniques is a main direction for future development. Many commercial companies rely on data-processing techniques to provide their services. A successful example is the Amazon Web Service, which provides a web cloud sever to handle major functions including data sharing, storage, analysis, summarization, and reportation (Shao et al. 2012). Many data-processing tools are also developed commercially. Bu et al. (2010) proposed an efficient open-source tool for digital data processing, named HaLoop, to enable large-scale data mining and data analysis applications, and this tool has been applied at Yahoo!, Facebook, and other companies. These examples indicate that ***digital data processing*** is a promising avenue for providing useful information and efficient computational performance.

This section has reviewed the basic concept of data processing and discussed how current data-processing techniques could be applied for commercial purposes. Data processing is also an essential tool in GIS for producing useful information for spatial analysis. The next section (2.2.2) narrows the discussion to spatial data processing in order to understand its major characteristics and limitations.

2.2.2 Spatial Data Processing: Geo-processing

Spatial data processing, or geo-processing, is a core part of GIS. It not only embodies a large number of functions for processing, querying, and analysing spatial data, but also provides a way to organise and integrate GIS functions and processes into a sophisticated system for modelling and solving complex spatial problems (Almeida et al. 2011; Sun and Yue, 2010).

Four concepts related to geo-processing are discussed in the next Section (2.2.2.1).

2.2.2.1 Geo-processing Concepts

Before geo-processing is further discussed in this chapter, it is essential to define basic geo-processing concepts and corresponding terminology.

1. **Geo-processing:** Krivoruchko and Gotway-Crawford (2003) explain that geo-processing is actually a data transformation framework, which is implemented using various computational algorithms and functions in GIS computation. Therefore, in this thesis, geo-processing represents a data transformation framework that it is used to produce useful information from various data inputs.
2. **Geo-processing model:** A geo-processing model is a representation of reality (Longley et al. 2005). The aims of a geo-processing model are to help people understand a spatial problem, study the effects of different factors in the real world, and identify a solution or make a prediction (Cao and Ames 2012; Lv et al. 2011).
3. **Geo-processing tool:** Geo-processing tools are used in order to build geo-processing models. Modelbuilder is an example of a powerful geo-processing tool, which is incorporated in the ArcGIS software package, because Modelbuilder can be used to connect existing functions, components, and scripts together to create a new model with the aim of improving the efficiency of computations. The components of ModelBuilder are illustrated by Figure 2-1.

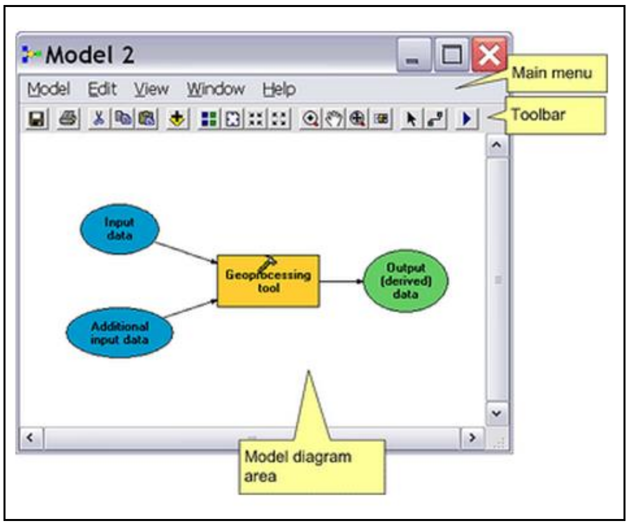


Figure 2-1 An example of a geo-processing model in ModelBuilder.

4. **Traditional geo-processing approach:** As the term ‘traditional geo-processing approach’ is very frequently used in this thesis, it should be clarified that it refers to the current digital data-processing method for a geo-processing model implementation, which is applied in different geo-processing tools.

The basic geo-processing concepts and corresponding terminology enable us to describe geo-processing in detail. Section (2.2.2.2) discusses the major characteristics of a geo-processing model, emphasising mainly how a basic geo-processing model can be built using the traditional geo-processing approach.

2.2.2.2 Characteristics of a Geo-processing Model

This section discusses the major characteristics of a geo-processing model. For example, how can a geo-processing be built using the traditional approach? What is the computation strategy to calculate a complex geo-processing model? These characteristics are essential for this research because they will help us to explore the potential challenges of the traditional geo-processing approach.

2.2.2.2.1Creating a Geo-processing model

Although most geo-processing models differ in their functionalities and applications, there is a basic way to create and calculate geo-processing models. The following paragraphs discuss how a geo-processing model can be built using the traditional geo-processing approach.

There are three basic steps to build a geo-processing model with the traditional geo-processing approach. First, the most basic element of a geo-processing model comprises three components: the input data, the GIS function itself, and the output (Figure 2-2).

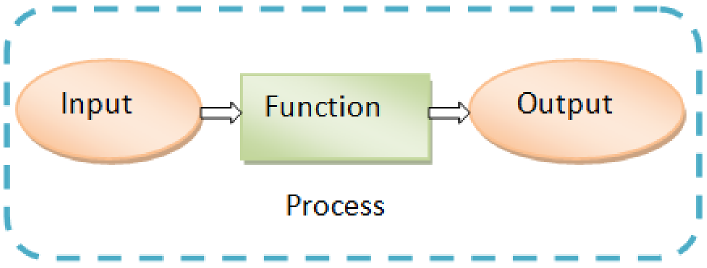


Figure 2-2 The basic components of a simple geo-processing model.

Second, this simple geo-processing model could be used to build more complicated geo-processing models, such as simple and parallel chain models. Figure 2-3 illustrates a simple chain model, in which the output of one model becomes the input of the resulting model. As it can be seen by Figure 2-3 the first model applies an inverse distance weighting (IDW) function to produce a continuous elevation surface (i.e. 'Output1') from the input of 'Raw LiDAR Points'. The derived raster layer becomes the input data for the next model, which classifies the input data based on a set of conditions.

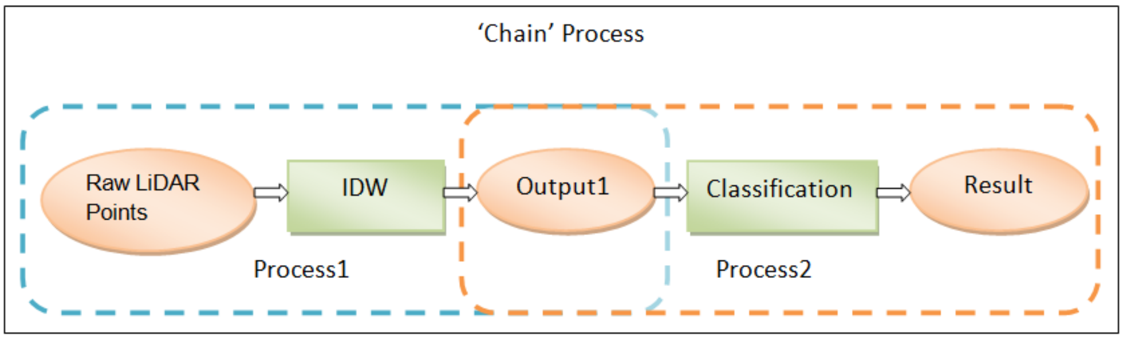


Figure 2-3 Geo-processing example of a simple chain model.

Figure 2-4 illustrates a parallel chain model that has the same input data (i.e. 'Continuous Elevation Surface') and produces two outputs, the 'Slope Map' and 'Classified Map'. It should be noted that the direction of the parallel chain model could be reversed, which means it could produce a single output from many functions and input datasets.

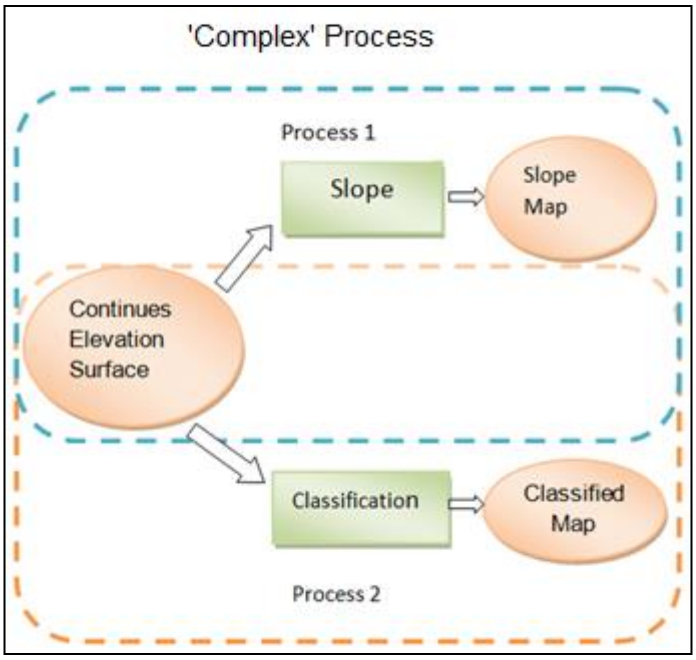


Figure 2-4 Geo-processing example of a parallel chain model.

Third, based on the simple and parallel chain models, different types of GIS functions, tools, and scripts could be graphically linked to solve real spatial problems (Bruns and Egenhofer 1997). For instance, Figure 2-5 demonstrates a complex geo-processing model that was developed for the identification of a new location for building a school. As noted previously, this specific example involves several stages.

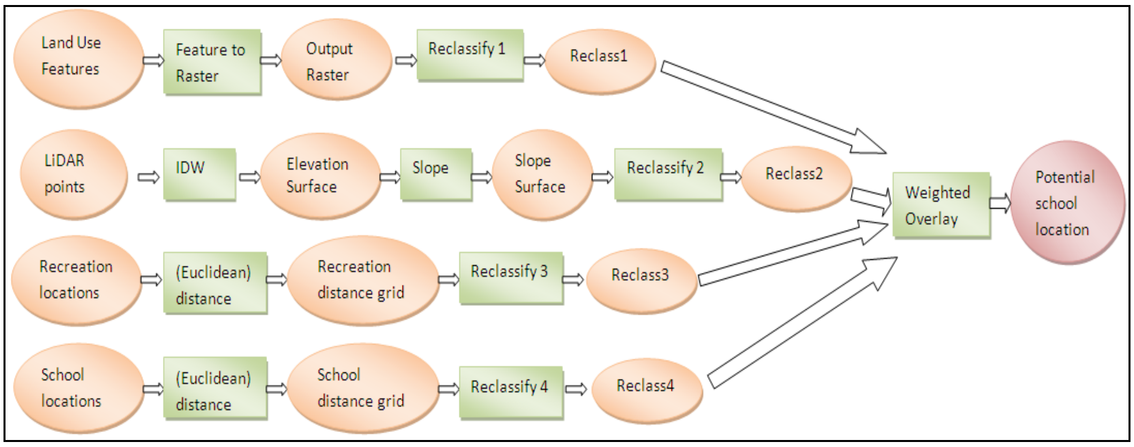


Figure 2-5 The geo-processing model for location analysis.

The geo-processing model of location analysis illustrates two characteristics: (a) the complex geo-processing model is implemented using many sub-models; and (b) these sub-models are sequentially linked together. These characteristics indicate that a computation strategy is required to manage and calculate the sub-models in a complex geo-processing model. The next Section (2.2.2.2.2) discusses the computation strategy of the traditional geo-processing approach.

2.2.2.2.2 Computation strategy of the Traditional Geo-processing Approach

This section discusses the computation strategy of the traditional geo-processing approach in order to understand how different spatial data and functions are executed in a geo-processing model. A computation strategy is a plan to achieve one or more computational tasks (Ansola et al. 2006).

Existing geo-processing tools (e.g. ArcGIS's ModelBuilder) employ a simple computation strategy to calculate spatial data and functions. In particular, these geo-processing tools graphically link spatial data and functions based on a specific workflow, which is then implemented in a sequential strategy (ESRI, 2011). Figure 2-6 shows how this sequential strategy is currently implemented using the traditional geo-processing approach. The geo-processing model illustrated by Figure 2-6 includes three GIS functions, with each function evaluated one after another until the final result ('Output3') is produced. This model also produces two intermediary results, 'Output1' and 'Output2'. It should be noted that the spatial data and functions involved in a simple chain, parallel chain, and complex model are also implemented individually and sequentially from the first to the last function.

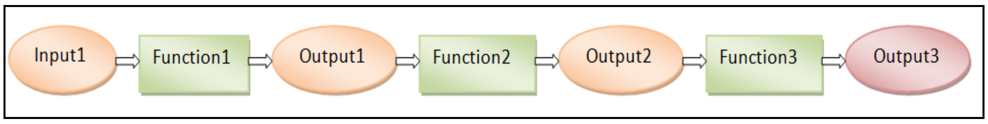


Figure 2-6 The basic strategy of sequential computation.

The major characteristics of this sequential sequence are visualised in Figure 2-6. First, the input and output of a function must always involve a value. These values are processed using specific GIS functions, in a similar way that 'Input1' is used by 'Function1', to produce a result which will be used by subsequent functions (e.g. As 'Ouput1' is used by 'Function2'). Second, sequential programming involves a consecutive and ordered execution of these functions, which are implemented one after another, in a similar way that 'Function1' to 'Function3' are executed. The programme will execute a function that will initially wait for user input or for output from the previous function.

Although sequential computation provides a simple way to implement a geo-processing model, many potential challenges may influence its data quality and computational efficiency, such as data uncertainty and error propagation. Section (2.2.2.3) discusses these challenges in detail.

2.2.2.3 Identifying the Challenges in the Traditional Geo-processing Approach

While the traditional geo-processing approach with sequential computation is used to process spatial data and functions, it incorporates many challenges, which are discussed here to illustrate that there is a need to improve the traditional geo-processing approach

2.2.2.3.1 Data Quality

Data quality is a major challenge for the development of the traditional geo-processing approach as different data-quality issues can cause many problems in data processing.

Spatial representation is a fundamental issue in geo-processing, as spatial features must be correctly represented in a digital environment to produce meaningful information (Komarkova et al. 2011, Komarkova et al. 2012). However, many data-quality issues arise in spatial representation methods that are applied in the traditional geo-processing approach, especially in relation to raster data. Braunisch and Suchant (2010) state that there is a trade-off between the size of raster data and the precision with which spatial features can be represented, so spatial data quality can be reduced due to limited computer memory. Haklay (2004) observes that because spatial attributes are represented as raster layers with an arbitrary resolution, many potential data uncertainties exist in raster data. Kienzle (2004) claims that many types of raster data, such as DEM or DTM, have data quality problems because they are created using interpolation methods (e.g. IDW) and there is a trade-off between data accuracy and computational efficiency. Furthermore, when raster and vector data are converted, there is potential for adding further problems to the resulting data. Liao et al. (2012) explain that vector-to-raster conversion is accompanied by errors because there is a loss of information with regard to spatial accuracy. These errors vary with grid size, data sources, and computational algorithms (Burrough 1986, Shortridge 2004).

A second data quality issue lies with the basic computation method applied in the traditional geo-processing approach. Numerical computation is applied in current GIS software packages (e.g. ArcGIS, MapInfo, GRASS, and Manifold) to implement a geo-processing model, and this uses numerical approximation algorithms to represent mathematical equations. Hildebrand (1987) claims that approximated values in numerical computations always come with with errors. Specifically, two types of errors in a numerical computation are truncation error and round-off error (Vandergraft and Rheinboldt 2014). Truncation error is the difference between an infinite value and its approximation by a finite value (Fraysse et al. 2012). Round-off error is the difference between the calculated approximation of a number and its exact mathematical value (Spada 2013). Additional common errors in geo-processing include data entry errors (Irizarry et al. 2013), data generalization errors (Zhao et al 2012), and error propagations (Bingham and Karssenberg 2014). Therefore, it is necessary to manage the data errors and data uncertainties of the traditional geo-processing approach.

Lastly, error propagation is a data quality issue in the traditional geo-processing approach because any errors and uncertainties in the input data will propagate to the output of the function (Lemmens 2011, Bingham and Karssenberg 2014). Biljecki et al. (2014) claim that error propagation in geo-processing is an unavoidable fact, and errors propagate differently depending on the applied GIS operations. Heuvelink (2006) concludes that the main research question for error propagation is quantifying the influence of input data errors on the output data of a geo-processing model. Hence, understanding and managing the propagation of errors in geo-processing is important.

2.2.2.3.2 Computational efficiency

Computational efficiency has long been a challenge in the development of the traditional geo-processing approach. Sequential programming involves consecutive execution of a geo-processing model, whereby the computer programme will execute a function that will initially wait for user input or for output from a previous function. Mitchell et al. (2001) observed that these wait functions in sequential programming allow a thread to block its own execution. Moreover, a geo-processing model potentially carries out unnecessary computations, because it always produces data on the entire extent of the study area, rather than only for a Region Of Interest (ROI). These issues are important for the traditional geo-processing approach because they can extend the overall computation time of a geo-processing model.

Challenges of the traditional geo–processing approach relate mainly to data quality and computational efficiency. These will be further discussed in the following sections (Section 2.3 and 2.4) in order to provide a suggestion for development of a new CG approach.

To sum up, this section reviewed the basic idea of data processing. A historical review of data processing development facilitated an understanding of the methods of data processing, which indicate that digital data processing with modern computational techniques is a main direction for future development. As data processing is an essential tool in spatial data analysis, the major functionalities of geo-processing were reviewed in the second part of this section, with particular focus on the computation strategy of the traditional geo-processing approach. Although the traditional geo-processing approach provides a simple computation strategy to implement a complex geo-processing model, it comes with difficulties in managing data quality and computational cost. Therefore, an improvement to the traditional geo-processing approach is required, especially with respect to data quality and computational efficiency.

2.3 Geo-Processing Data Quality

Although the traditional geo-processing approach can be used for GIS modelling and decision-making purposes, it has been repeatedly acknowledged in the literature that many data-quality problems are associated with this approach, such as spatial representation (Komarkova et al. 2011, Komarkova et al. 2012), numerical computation errors (Hildebrand 1987, Vandergraft and Rheinboldt 2014), and error propagation (Heuvelink 2006, Leibovici et al 2013). In the interest of reducing the impact of these problems, this section reviews existing data-quality problems of geo-processing and explains how potential improvements can be applied.

Section 2.3.1 reviews the definition of data quality. Section 2.3.2 provides an overview of data quality problems in GIS, and Section 2.3.3 narrows the discussion to the specific data quality problems of geo-processing to understand their major characteristics, causes, and influences. Section 2.3.4 discusses potential improvements that can minimise these problems.

2.3.1 Defining Data Quality Concepts

Data quality is a major concern in data processing because it can cause a variety of problems. For example, Strong et al. (1997) observed that around 50% to 80% of the computerized criminal data in U.S. organizational databases were identified as having data quality issues, which may influence the accuracy of criminal data analysis results. Arts et al. (2002) discussed data quality issues in medical registries; these records depend on the quality of the data contained in the registry, so there is a potential risk for health data analysis and decision making. Chiu et al. (2012) discovered a data completeness problem in the Health-Related Quality Of Life (HRQOL) database arising from the fact that psychometric properties of HRQOL were largely missing for people who abuse heroin.

Many terms have been used to describe the different problems related to data quality. Weidem and Wesnæs (1996) describe data quality as a specific characteristic expressed through information about the data, and it includes many common attributes, such as uncertainty, accuracy, and reliability. Furthermore, Wang and Strong (1996) view data quality as a major dimension for evaluating the success of an information system. This dimension includes some attributes, such as error, uncertainty, reliability, accuracy, and precision.

Four common terms pertaining to data quality are applied in this thesis to build up the research framework: ***error***, ***uncertainty***, ***accuracy*** and ***precision***. The next paragraphs define and discuss each of these attributes in more detail.

Error is the most common data quality problem in geo-processing. In principle, an ***error*** has different meanings in various contexts. In science and engineering, an error represents a difference between a computed, estimated, or measured value and the true value (Parodi et al. 2014, Kolokoltsov and Tomasz 2015). In numerical computation, errors arise from a trade-off between efficiency (space and computation time) and accuracy, as only a limited amount of numbers can be stored exactly in a digital computer (Standage et al. 2014).

Figure 2-7 illustrates a conceptual model of different types of ***uncertainty*** in spatial data (Devillers and Jeansoulin, 2010). This figure shows that the central issue for uncertainty is defining the class of objects or features to be manipulated (e.g. a set of critical infrastructure network data). If these objects or features are well-defined, uncertainty is caused by errors and probabilities; that is, input errors in critical infrastructure network data may cause uncertainty. Otherwise, if the objects or features are poorly defined, many additional types of uncertainty may be identified in the dataset, including vagueness and ambiguity. Vagueness means that items are not explained or expressed clearly (for example, if there is a ‘significant’ influence on a water main pipe burst, how should ‘significant’ be quantified?). Ambiguity means that a concept can be understood in more than one way (for example, if the material of a water pipe is defined as ‘metal’, this can be either iron or copper).

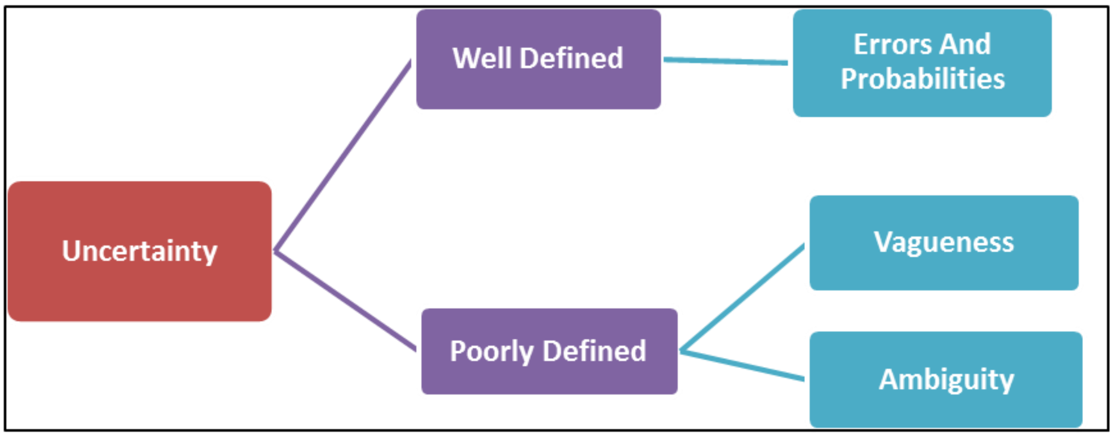


Figure 2-7 A conceptual model of uncertainty (after Devillers and Jeansoulin, 2010).

Accuracy and ***precision*** are two common terms aiming to quantify the quality of spatial data produced from a measurement system, such as a GPS receiver (Lee et al. 2015). Theoretically, accuracy and precision have a fundamental difference (Brown 2012). ***Accuracy*** indicates the degree of closeness between a measurement of a quantity and its actual value (the centre point of the cross in Figure 2-8). In contrast, ***precision*** indicates the resolution to which repeated measurements under unchanged conditions show the same results, and the ability to reproduce the same target using a given measurement. ***Accuracy*** and ***precision*** can be influenced by many issues, such as measurement errors, systematic methodological problems, data capture, and processing problems (Komarkova et al. 2011). As illustrated in Figure 2-8, a set of spatial data can be accurate but not precise, precise but not accurate, neither, or both.

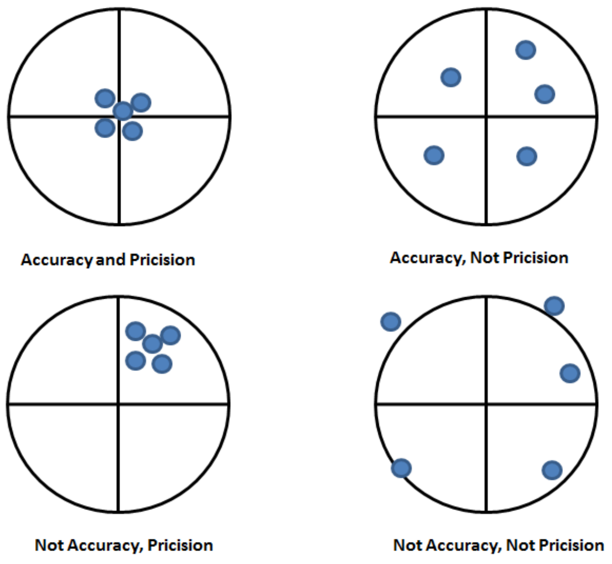


Figure 2-8 A comparison between accuracy and precision (after Lee et al 2015).

Common terms related to data quality can avoid ambiguity in this thesis and enable us to describe the corresponding data quality problems in detail. Section 2.3.2 provides an overview of the data quality problems in GIS to help us explore typical data quality problems in geo-processing.

2.3.2 Overview of Data Quality Problems in GIS

Data quality is a key issue in data processing, as it frequently influences operations, decision making, and planning. In GIS, the term ***spatial data quality*** refers to the degree of spatial data excellency that satisfies the given conditions and objectives, such as positional and attribute accuracy (Li et al. 2012). Komarkova et al. (2012) claim that a higher quality of data and/or information provided by information systems could support better decision making. However, as spatial data are mainly produced from models which are simplified from a complex reality, these data have different levels of imprecise, inaccurate, incomplete, and outdated problems (Devillers and Jeansoulin, 2010).

In order to understand the problems of ***spatial data quality***, Figure 2-9 summarises typical errors in GIS, including three levels (Beard 1989). The first and most basic level is the so-called ***source of errors*** (Figure 2-9, bottom of the pyramid), which involves problems that are mainly observed at the stages of data collection, data processing, and data usage. Data collection errors include errors from field surveys and measurements, inaccurate equipment and devices, and fuzzy input data. Data processing can lead to digitising errors, inaccurate prediction and assumption, errors in re-sampling, and error propagation. Data usage can produce errors due to the misunderstanding of spatial information.

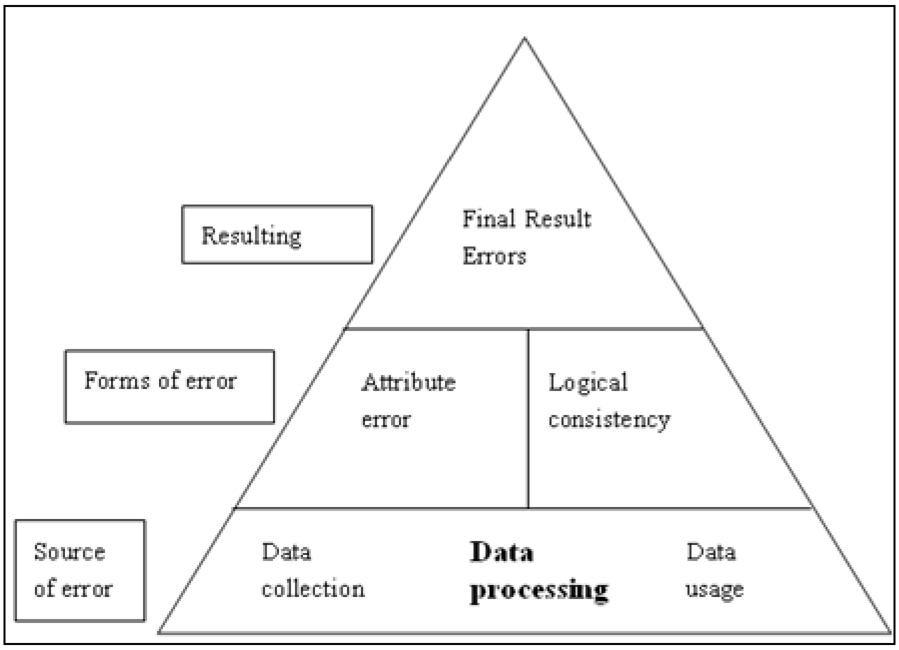


Figure 2-9 A review of errors in GIS (after Hunter and Beard 1992).

The second level of GIS errors is called ***forms of error***, and includes such errors as attributed errors and logical consistency (Hunter and Beard 1992). Finally, the top level of the pyramid consists of errors in the final result (***Resulting***), which are mainly caused due to errors in the two lower levels (Devillers and Jeansoulin, 2010).

Figure 2-9 indicates that most errors are produced from the basic level (***source of errors***), and these errors can propagate to the upper levels and influence the final result and decision-making. Table 2-1 summarises the specific causes of ***source of errors*** in GIS, including measurement, assignment, class generalization, spatial generalization, entry, temporal, and data processing (Fisher 1999). The summary of common errors in GIS and their causes indicates that ***spatial data quality*** is a broad topic, with many error sources that can influence the final results of a geo-processing model. Thus, it should be clarified that this thesis focuses only on data-processing problems.

Table 2- 1 Cause of spatial data errors (Fisher 1999).

Type of error	Cause of error
Measurement	A mistake in measurement of a property.
Assignment	The object is assigned to the wrong class because of measurement error.
Class generalization	Following observation in the field, and for reasons of simplicity, the object is grouped with objects processing somewhat dissimilar properties.
Spatial generalization	Generalization of the cartographic representation of the object before digitising, including displacement, simplification, etc..
Entry	Data are miscoded or misdigitized during entry in a GIS.
Temporal	The object changes character between the time of data collection and the time of database use.
Data processing	**In the course of data transformations an error arises because of computation, rounding, re-sampling, algorithm, error propagation, etc.**

After reviewing generic data-quality problems in a GIS, Section (2.3.3) discusses specific problems in a geo-processing model, such as data representation and basic computation methods.

2.3.3 Data Quality Problems of Geo-processing

This section narrows down the data-quality discussion to typical problems in geo-processing. These are spatial representation and basic computation methods. Whether spatial data correctly represent real features can impact the quality of spatial data and processing results (Sadeghi-Niaraki et al. 2011). Furthermore, the current computation method has many potential data-quality problems due to approximated value

(Hildebrand 1987) and error propagation (Rasouli and Timmermans 2013). Hence, this section discusses spatial representation and basic computation methods in detail.

2.3.3.1 Spatial Representation

A fundamental issue in geo-processing is how spatial features can be represented in a digital environment to produce meaningful information (Komarkova et al. 2011, Komarkova et al. 2012). Many spatial data models are used for storing geographical data digitally, while others have been proposed for different purposes, such as describing discrete objects and continuous field features.

Vector data comprise the most common spatial data model for describing discrete objects, and can be used to store linear features, such as city locations, popular places, road networks, and national boundaries, on a digital computer (Worboys and Duckham, 2004). There are three main advantages of vector data. First, vector data offer an accurate spatial representation of spatial objects at all levels (Worboys and Duckham, 2004). For example, spatial objects may be represented at their original resolution, without map generalisation, and maintained by location. Secondly, vector data provide an easy way to retrieve, update, and generalise spatial attributes. For instance, the attributes of a point, including its coordinate value and location name, can be directly modified or updated by users. Lastly, more complicated spatial features, such as topological networks, can be represented and described explicitly and efficiently using vector data (Dowers et al. 2000).

Compared with vector data, raster data can be used to effectively describe continuous field features. In principle, raster data divide the real-world surface into an array or matrix of pixels in a continuous field, and each pixel represents its position and attribute in a raster layer (Worboys and Duckham, 2004). In fact, raster data provide an easier and faster way to describe continuous surfaces. There are three advantages of raster data for representing continuous fields. First, raster data have a simplified data structure (e.g. a matrix of cell values) and thus can be more easily processed by computer programming tools (Worboys and Duckham, 2004). Secondly, raster data provide an efficient way to model continuous data and perform surface analysis. Thirdly, raster data are ideally suited for GIS functions such as query and overlay, as a pixel size can be converted to a specific dimension using interpolation methods (Arbia et al.1998).

2.3.3.1.1 Spatial Data Model Problems

Although vector and raster are the most commonly used data models for storing and representing discrete object features and continuous field features, respectively, their major characteristics may cause different data quality problems in a geo-processing model.

There is a trade-off between the size of raster data and the precision with which spatial features can be represented (Braunisch and Suchant 2010). For example, a very fine raster grid will represent sufficient detail (e.g. high-resolution satellite images) but will require a large amount of disk space. A point object (e.g. elevation value) must occupy a full cell in raster, which may create problems for processing (e.g. data uncertainty and error propagations).

Haklay (2004) claims that spatial attributes are represented as raster layers with an arbitrary resolution. For example, Figure 2-10 shows how to treat slopes in a raster-based layer, where each grid is assigned a value that represents the slope from the centre of the pixel. Any irregular points, such as the sample locations illustrated by Figure 2-10 (green circles), must represent the same value as the centre of the pixel (red cross). This generates a problem that directly affects the accuracy of the results and may introduce additional errors when the output is used as input for other GIS functions.

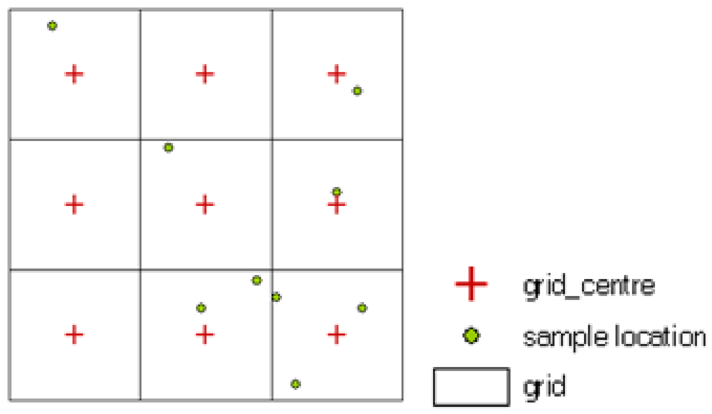


Figure 2-10 Slopes in a raster-based layer.

When raster and vector data are converted, further problems can be added to the resulting data, such as data errors and uncertainties (Devillers and Jeansoulin, 2010). Spatial data conversion refers to either rasterisation and/or vectorisation. Rasterisation is the conversion of vector data into a raster form, while vectorisation is the conversion of raster data into a vector form (Worboys and Duckham, 2004). There are many spatial data-quality problems associated with rasterisation and vectorisation functions. Rasterisation involves a loss of information, such as topological relationships, which may lead to missing data and produce data uncertainties in the spatial analysis (Dendoncker et al. 2008). In vectorisation, two choices are possible for converting the raster into a vector data model: either no more information is added, and the result may have significant pixel edges, or additional data are needed to smooth pixel borders, but no accurate information is available (Kovalerchuk and Perlovsky 2011).

This section discusses the major GIS representation problems in the traditional geo-processing approach. Section (2.3.3.2) discusses the computation method for geo-processing to understand how errors and data uncertainties are produced and propagated in the traditional geo-processing approach.

2.3.3.2 Geo-processing Computation

A computation is a process that manipulates one or more input in order to produce one or more results. In GIS, computations are used to interpret spatial characteristics, explain geographical phenomena, and solve spatial problems (Couclelis 1998; Cheng et al. 2012). This section discusses the drawbacks of computation methods in the traditional geo-processing approach.

2.3.3.2.1 Numerical Computation Problems

Numerical computation is widely used by current GIS software packages (e.g. ArcGIS, MapInfo, GRASS, and Manifold) for data recording and storage purposes. Numerical computation uses numerical approximation algorithms to represent mathematical equations, which are usually expressed using algebra, differentiation, integration, or other types of equations. The problem with numerical computation is that, because digital computers cannot accurately express real numbers, all results obtained using numerical calculations approximate the true value (Hoffmann 1989).

Hildebrand (1987) defined the relationship between an approximation and its true value using Formula 2.1, in which the true value is the real value without any distortions and errors, and the approximation is the result of numerical computations. This equation indicates that errors always accompany approximated values.

True value = approximation + error **(Formula 2.1)**

To understand the influence of errors on approximated results, it is necessary to discuss the potential drawbacks of numerical computations. One problem is round-off error, which represents the difference between the approximated value of a number and its exact value (Murat et al. 2004). Widrow and Kollár (2008) demonstrated that round-off errors occur whenever physical quantities are represented numerically. Examples include the time displayed by a digital watch, and the temperature indicated by a digital thermometer. Table 2-2 gives an example of a round-off error introduced by an attempt to represent the approximated value of the number π. If three digits for π are used, the error could be 0.15% below the exact value.

Table 2- 2 Errors due to π values with different accuracies.

π	**Error (30 decimal digits)**
3.14159265358979323846264338327 (round to 30 digits)	Ignore (very small)
3.141592653 (round to 10 digits)	0.00000000058979323846264338327
3.1415 (round to five digits)	0.00009265358979323846264338327
3.14 (round to three digits)	0.00159265358979323846264338327

In the traditional geo-processing approach, when round-off errors are produced in a sequence of GIS functions, initial errors will accumulate in subsequent intermediary steps, and this will eventually lead to serious round-off errors in the final result (Chapman 2012). Moreover, round-off error is a major resource of quantization noise, which may accumulate, sometimes dominating the calculation results (Widrow and Kollár 2008). For example, distances given on a map have round-off errors, which can be magnified as any initial errors are carried through one or more intermediate steps in a geo-processing model. Therefore, the numerical computation applied in the traditional geo-processing approach needs improvement.

2.3.3.2.2 Data Uncertainty and Error Propagation

All data carry a level of inherent uncertainty associated with their truth and correctness. Identifying potential sources of uncertainty can help to distinguish between reliable and unreliable data. Most data uncertainty is associated with errors in direct measurements of a quantity (Morgan et al. 1990).

Within a GIS, no spatial data are truly error-free, because much of the data are produced by assumption, interpolation, and prediction methods (Devillers and Jeansoulin 2010). An assumption is a major resource of data uncertainty because it provides something that users assume to be true or assume will happen, often without proof. As Shahriar et al. (2012) discuss, it is a challenge to characterise model uncertainty that arises from an assumption of independence among different risk events. Interpolation is another major resource of data uncertainty, as it produces data based on a assumed value. Brodlie et al. (2012) claim that uncertainty is introduced in an interpolation step by guessing the output data. Additionally, a prediction or forecast could increase the chances of data uncertainties because it deals with the future. For example, a weather forecast is an application of science and technology to predict information (e.g. temperature, wind speed) about the atmosphere in a specific location, but these data have multiple uncertainties due to interpolations (Hu et al. 2010).

When users select spatial data from a GIS database to use as input datasets for a geo-processing process, errors and uncertainties that exist in the input data will propagate to the output of the function (Bingham and Karssenberg 2014). Error propagation becomes more complicated when the output from one function or a sub-model is used as the input for a subsequent function or sub-model (Rasouli and Timmermans 2013). For example, re-sampling is an important function in image processing, as it can be used for the integration of different raster layers (Skifi and Bosner 2014); however, the re-sampling process complicates the raster overlay function and introduces uncertainties into the computations, and is a major source of error propagation (Haklay, 2004). Moreover, inaccuracies (e.g. data errors and data uncertainties) may be introduced during this calculation step, which will also affect any subsequent computations due to error propagation.

This section discussed the major data quality problems of geo-processing. The drawbacks of spatial representation and computation methods applied in the traditional geo-processing approach can cause many data quality problems and influence the final results. The next section discusses how these data-quality problems could be improved using the new CG approach.

2.3.4 Data Quality Improvement

The problems discussed in Section 2.3.3 lead us to the conclusion that we need to address data-quality concerns in traditional geo-processing. Nevertheless, it is widely accepted that data uncertainty and its related implications cannot be avoided, but rather can be managed (He et al. 2004, Heuvelink 2006).

The CG approach is proposed in this thesis with the aim to improve the data quality and computational efficiency of geo-processing. Specifically, a set of methods comprising the CG approach, including a point-based spatial data model, symbolic computation, and functional layers, is introduced to address the previously discussed problems.

2.3.4.1 Spatial Data Model Improvement

It was noted that raster and vector data are popular spatial data models to represent the real world features. However, these two spatial data models introduce data quality problems into geo-processing, such as the resolution of raster data and conversion between raster data and vector data. This section reviews other spatial data representation method in order to provide a suggestion for reducing the influence of raster and vector data in the traditional geo-processing approach.

2.3.4.1.1 Spatial Data Models Review

This section discusses how spatial features can be described using different representation methods. These is a Triangulated Irregular Network (TIN).

A TIN is a vector-based spatial data model used to represent elevation in a 3D surface (Worboys and Duckham, 2004), and is comprised of triangles which are constructed from a set of points with ‘X and Y’ coordinate values and ‘Z’ elevation values. Moreover, each triangle apart from the coordinates is further associated with topological information. As Longley et al. (2005) explain, the key benefit of a TIN is that the density of sampled points, and consequently the size of triangles, can be adjusted to better reflect the relief of the surface that it is being modelled. In contrast to raster data (e.g. DEM), an advantage of TINs is that points are distributed based on the complexity of an area (De Smith et al. 2007). Therefore, TIN data are flexible and require less storage space, especially when compared with raster data models. However, a disadvantage of TIN data is that they can be hard or extremely complex to integrate with other spatial data models.

2.3.4.1.2 Point-based Spatial Data Model

Point data play an important role in spatial representation, as the majority of spatial data models are based on, or consist of, points. For example, as Table 2-3 demonstrates, a polygon (vector data) is composed of a group of points, and a raster image (raster data) is constructed from a matrix of values or centroids with grid size. Additionally, a 3D object can be represented using point data (e.g. X, Y coordinates and Z elevation value) (Chen and Schneider 2009). Table 2-3 illustrates that the point-based spatial model has more flexibility for representing various spatial objects. For example, when point-based spatial data are processed in a model, the outputs can take any form of spatial data model (e.g. raster or vector) according to the user’s request.

Table 2- 3 A summary of major spatial data models and their relationships with points.

Spatial Data Type	**Description**	**Relationship with points**
Polyline (Vector)	Representing linear objects, such as road networks, rivers.	A polyline is constructed by a straight line joining two or more points (vertex).
Polygon (Vector)	Representing area objects.	A polygon is constructed by a close path joining a group of points (vertex).
Triangular Irregular Network (TINs)	A TIN is a vector-based representation of the physical land surface.	This is constructed by irregularly distributed points (nodes) and lines with three dimensional coordinates (X, Y, and Z) that are arranged in a network with no overlapping triangles (Worboys and Duckham, 2004).
Grid cells (Raster)	Representing land surface by a grid of small units (pixels) that are widely applied in satellite images and digital elevation models.	A raster image is constructed from a matrix of representative values. In addition, the location of each pixel is recorded by its centre point coordinate values.
3D data	Representing three-dimensional features or surfaces.	A 3D model is created from a basic set of points with coordinate and height values (X, Y, and Z) (Chen and Schneider 2009).

The point-based data model does not require rasterisation and vectorisation processes, because it describes both discrete objects and continuous field features. As a result, any data-quality problems and concerns that arise from rasterisation and vectorisation can be avoided using the point-based spatial data model.

Additionally, the point-based spatial data model provides a way to reduce the complexity of spatial data models (Jjumba and Dragicevic 2014, Camara et al. 2014). Although many types of spatial models have been created to model spatial features, such as vector, raster, TIN, and 3D data, these structures directly increase the complexity of a GIS database, and this complexity may potentially increase the difficulty of maintaining the realism and clarity of the system content (Goodchild et al. 2007).

For these reasons, the point-based spatial data model is introduced in the CG approach to improve its spatial representation.

2.3.4.2 Geo-processing Computation Improvement

It was discussed that numerical computation and sequential computation are applied in the traditional geo-processing approach for spatial data calculation. However, there are some data quality problems in these methods, such as approximate values and error propagation. This section explains the reasoning behind using symbolic computation and function-based layers in the CG approach to improve the data quality of geo-processing.

2.3.4.2.1 Symbolic Computation and Function-Based Layer

An alternative to the numerical computation applied in the traditional geo-processing approach is symbolic computation. Symbolic computation provides an exact method of mathematical calculation, such as differentiation and integration, linear algebra and matrix calculus, and the simplification of algebraic equations (Grossman 1989). A significant characteristic of symbolic computation is that mathematical formulas are manipulated in a symbolic form. Heck (2003) noted that symbols can represent numbers such as integers, rational numbers, real numbers and complex numbers, but they may also be used to represent mathematical operations.

Symbolic calculation provides greater flexibility for users to define the quality of a result (Carminati and Vu 2000). Software applications that perform symbolic calculations are called computer algebra systems (Cafuta et al. 2011). Such systems have been widely used in various applications, such as high energy physics, chemical engineering, mechanics, cybernetics, and computer science.

Symbolic computation has two main advantages for mathematical computations in a geo-processing model (Hoffmann 1989). First, it could avoid a large number of complicated operations, such as simplification of algebraic equations, which helps to improve the efficiency of geo-computations. Table 2-4 provides two examples of simplification, which illustrates how the complited algebraic equations could be simplified by the simplification rules.

Table 2- 4 The examples of simplification.

Equation NO	Equation	Simplification
1	$5x^2 +3x(-9x+5)$	
	$=5x^2 +3x(-9x)+ 3x (5)$	Use distributive property.
	$=5x^2 -27x^2+ 15x$	Clear parenthess.
	$= -22x^2+ 15x$	Combine like terms by adding coefficients.
2	$6m^2n^3- (6mn - 4m^2n^3 + 3) + 6$	
	$=6m^2n^3- 6mn + 4m^2n^3-3 + 6$	Use distributive property.
	$=(6 + 4) m^2n^3 - 6mn -3 + 6$	Combine like terms.
	$=10m^2n^3 - 6mn +(-3 + 6)$	Combine constants.
	$=10m^2n^3 - 6mn -3$	

Secondly, more calculation methods are provided, such as approximate calculation and exact calculation. This allows users, depending on project requirements, to choose between numerical calculations and symbolic calculations as needed to improve data quality. A typical example of a computer algebra software is Maple, which was first developed in 1980 by the Symbolic Computation Group at the University of Waterloo and ETH Zurich (Heck, 2003). Table 2-5 provides two examples of symbolic computation in Maple. In this table, ‘Rational Number’ keeps the dynamic function for the result because users can define the accuracy of the final output. ‘Flexible Accuracy’ shows that the quality of a result can be defined by users with a greater flexibility.

Table 2- 5 Examples of functional programming: Maple.

	Input	**Output**
Rational Number	>41! / (2^32-1)	(1311863788751521847379218119742774575104000000000) / (16843009)
Flexible Accuracy	>evalf (a, 20)	7.39562677840266521267

To support both numerical calculations (i.e. approximate values) and symbolic calculations (i.e. exact values) in a geo-processing model, the CG approach introduces a completely different way to create and process GIS functions, called function-based layers. The theory of function-based layers is inspired by the idea of Map Calculus (Haklay 2004), which provides an approach for spatial representation. The key idea behind the function-based layer is integrating functional programming and symbolic computations to calculate spatial data and perform GIS functions.

The function-based layer attempts to support the following functionalities in a geo-processing model: (a) it supports both numerical and symbolic computations in order to reduce the influence of approximation; (b) it can apply a function or functions as input or output to minimise the influence of error propagation; (c) computations can be suspended or reordered to increase efficiency, and (d) it can produce results directly from a combination of functions. Function-based layers are discussed in more detail in Chapter 4.

In summary, data quality is an essential issue for geo-processing as it influences model outputs and decision-making results. The traditional geo-processing approach is subject to a variety of data-quality problems. Specifically, the spatial representation method applied in the traditional geo-processing approach can cause data-quality problems because there are several drawbacks to raster and vector data and conversion between them. The basic computation methods applied in the traditional geo-processing approach cause additional data errors and uncertainty problems. To address these problems, a set of methods comprising the CG approach is proposed. The new approach includes a point-based spatial data model, a symbolic computation, and a function-based layer. The point-based spatial data model minimises spatial representation problems, while symbolic computation and function-based layers reduce data error and uncertainty when users apply numerical computation in a geo-processing model.

2.4 Computational Efficiency of Geo-Processing

The sequential computation strategy applied in the traditional geo-processing approach not only has data-quality problems, but also causes computational efficiency problems such as extra computation time costs. Consequently, problems related to computational efficiency need to be further considered in this thesis.

This section continues to discuss the problems of the traditional geo-processing approach, toward the aim of improving the computational efficiency of geo-processing. Section 2.4.1 reviews computational efficiency concepts and Section 2.4.2 discusses computational efficiency problems associated with the traditional geo-processing approach. Section 2.4.3 discusses how computational efficiency in geo-processing can be improved using the CG approach.

2.4.1 Defining the Computational Efficiency Concept

Computational efficiency is a common term used in digital computation to quantify the performance of a digital device. For example, computational efficiency can refer to the resources (e.g. computer memory and computation time) used by an algorithm (Liu and Wang 2012). 'Big **O**' notation is used to quantify the performance of algorithms (e.g. processing time or working space requirements) when they have different input data (Cormen et al. 2001; De Smith et al. 2007). As illustrated in Figure 2-11, $\boldsymbol{O}\ (\mathbf{1})$ denotes processing time or memory space that is constant (a flat line) regardless of the size of the dataset; $\boldsymbol{O}\ (\boldsymbol{n})$ indicates linear growth in direct proportion to the size of the input dataset, that means the performance is directly dependent on the size of the input data; $\boldsymbol{O}\ (\boldsymbol{n}^{\boldsymbol{n}}), \boldsymbol{O}\ (\boldsymbol{n}^{\mathbf{2}}),$ and $\boldsymbol{O}\ (\boldsymbol{n}^{\mathbf{3}}),$ indicate the performance will be directly proportional to a power of the input data size; and $\boldsymbol{O}\ (\sqrt{\boldsymbol{n}})$ and $\boldsymbol{O}\ (\mathbf{log}\ \boldsymbol{n}),$ denote growth curves that rise sharply at the beginning of the execution and then increase more slowly as the size of the dataset grows.

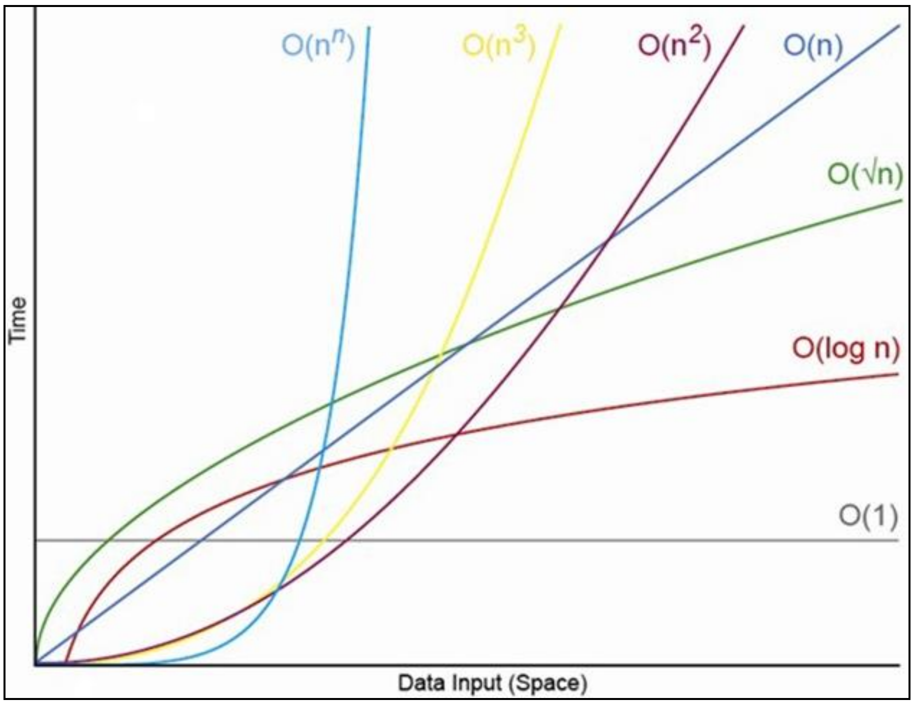


Figure 2-11 The performance of various algorithms (after Apelbaum 2011).

In addition, Thakur et al. (2013) state that computational efficiency represents the performance or speed of the Central Processing Unit (CPU), a core part within a computer that carries out the instructions of computer programs.

Computational efficiency is a wide topic and has been investigated in many different contexts. In this research, the computational efficiency of geo-processing focuses only on the resources required for spatial data and function processing, such as the total computation time cost of a geo-processing model implementation.

2.4.2 Computational Efficiency Problems of Geo-processing

The total computation time cost of a geo-processing model implementation can be influenced by several factors, such as a computation strategy (Stallings 2004), computational algorithms (Gao et al. 2012), and complicated system structure (Chiang et al. 2013). This section focuses on computation strategy because it is an important problem for the traditional geo-processing approach that has not yet been fully investigated.

Over the last 30 years, computational strategies have been developed using different applications in order to implement complex computations (Jones et al. 1997). For example, Ladevèze et al. (2001) demonstrate a micro-macro computation strategy to analyse highly heterogeneous structures with a large number of degrees of freedom. Helton et al. (2007) present a sampling-based computation strategy for representing epistemic uncertainty in model predictions for evidence theory. These examples indicate that strategy is an essential element of computation.

However, the current computation strategy applied in traditional geo-processing has some problems of computational efficiency, due to 'waiting' functions and unnecessary computations. An example of complex geo-processing is given in Figure 2-12 to illustrate such problems in a geo-processing model, which involves three main steps. The first step involves input of the original spatial data, which includes LiDAR points, property locations, and road network data (shown by the blue circles in Figure 2-12). LiDAR points are used to produce elevation and slope values. Property locations and road networks are applied to understand additional features such as local noise levels. The second step refers to data processing and consists of five main types of computational tasks for this geo-processing model, which are shown by the orange circles in Figure 2-12.

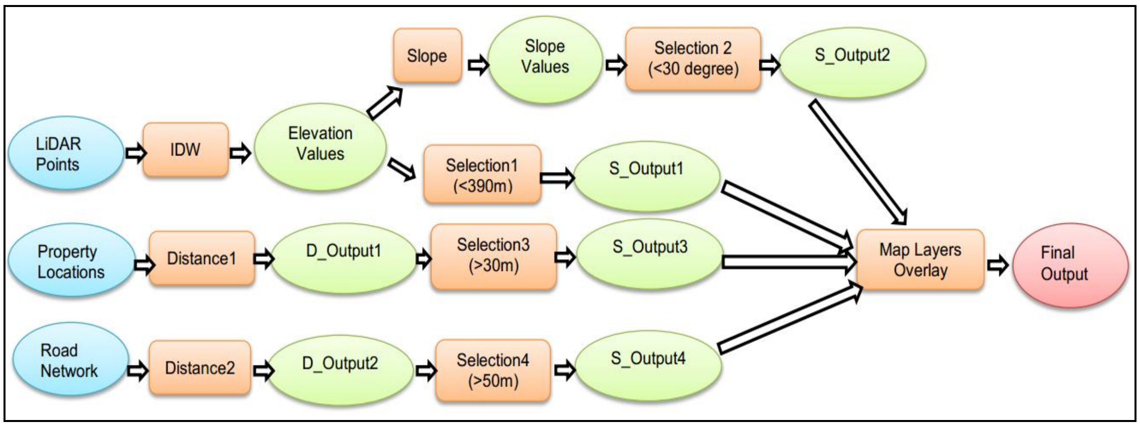


Figure 2-12 An example of a complex geo-processing model.

In the traditional geo-processing approach, the functions in Figure 2-12 model are processed one by one in sequence (i.e. starting with the first computational task and moving to the next one). Therefore, all functions should follow the sequence for implementation of a geo-processing model, which means a function needs input data from its previous function. For example, in Figure 2-12, '***Slope'*** needs the output from '***IDW',*** and '***Map Layers Overlay'*** must wait for results from the four previous functions ***'S_Output1', 'S_Output 2', 'S_Output 3',*** and ***'S_Output 4'***. This example indicates that if early functions deal with intensive datasets, later functions have to be suspended while they wait for the results. However, wait functions in sequential programming allow a thread to delay its own execution (Mitchell et al. 2001).

Figure 2-13 illustrates unnecessary computations in a complex geo-processing model. This figure shows an example of the Region of Interest (ROI) in ***'Land Use'*** (grey colour), which occupies approximately 20% of the region. The ROI, a popular approach in image processing which involves a selected subset of samples within a dataset identified for a particular purpose, may only use a portion of the whole area (Bendell and Wan 2011). For example, if users need to produce DEM or DTM data, computations in the traditional geo-processing approach always produce the data on the entire extent of the study area, while only the ROI area is needed. In the example in Figure 2-13 it is unnecessary to calculate the data located outside the ROI (80% of the entire region) because it may not be considered in the final result.

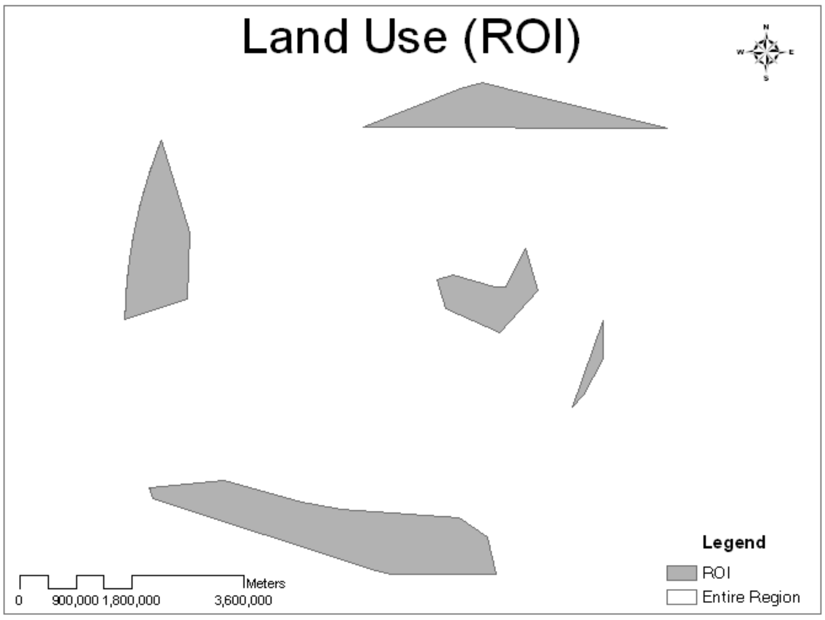


Figure 2-13 Region of Interest (ROI) in Land Use.

This section discusses existing problems with geo-processing models, especially in relation to a computation strategy and its efficiency. Sequential computation causes two computational efficiency problems in traditional geo-processing. First, all functions need to await input data from previous functions; and secondly, unnecessary computations may occur in a complex geo-processing model. These two problems can potentially increase the computational cost (e.g. computation time) of a geo-processing model. Addressing these implications will support the more efficient processing of spatial data and functions.

Section (2.4.3) reviews current methods that may be used to improve computational efficiency and suggests improvements to the traditional geo-processing approach.

2.4.3 Computational Efficiency Improvement

In geo-processing, issues related to computational efficiency have received increasing attention due to the number and complexity of spatial problems, which have both increased dramatically in recent years. This section reviews recent computational methods to facilitate a later demonstration of how computational efficiency problems in traditional geo-processing can be addressed.

2.4.3.1 Modern Computation Methods Review

In recent years, many high performance computational techniques have been applied in GIS to improve computational efficiency, including parallel computation and spatial data query methods. Parallel computation has been widely used in GIS as it enables the implementation of multiple instructions by using multi-core processors (Grama 2003). Spatial query is a fundamental function which supports various spatial analyses and data processing applications (Zhong et al. 2012). These two methods are discussed in the next Sections (2.4.3.1.1 and 2.4.3.1.2).

2.4.3.1.1 Parallel Computation

Before 2005, most CPUs had only one core for processing all instructions, which frequently influenced the computational efficiency as the instructions had to be implemented one by one. Then, the multi-core processor (including more than one core in a single computing component) was introduced in 2009. The multi-core processor supported a way to run multiple instructions at the same time and increase overall speed for programs amenable to parallel computation.

In traditional computing, a problem is divided into a discrete series of instructions which are executed sequentially on a single processor. In contrast, parallel computation breaks a problem into discrete parts, with each part further divided into a series of instructions. Final instructions for each part execute concurrently on a multi-core processor or different processors (Megiddo 1983).

Currently, parallel computation is widely used in GIS in order to improve computational efficiency, especially in relation to large data sharing, dynamic data processing, and web-GIS. Jiang et al. (2012) proposed a parallel computation approach of spatial vector data conversion based on a common interface, which provides an efficient way to share large geospatial data from a variety of data resources. Kremmydas et al. (2011) developed a parallel computation approach to reduce the data processing time of a web based Spatial Decision Support System (web SDSS), which was implemented in Thessaly to evaluate the supply of selected energy crops. These studies showed that total solution time drops significantly under the parallel computational approach.

Although parallel computation can improve the computational efficiency of traditional geo-processing by using a multi-core processor, it does not change the sequential computation strategy. Consequently, the problems discussed in Section 2.4.2 still exist in parallel computation.

2.4.3.1.2 Spatial Data Query

In addition to parallel computation, many other methods can be used to improve computational efficiency and performance in geo-processing. For example, spatial data query methods support a way to access and search larger spatial databases more efficiently to reduce the entire computation time of a geo-processing model.

Guttman (1984) describes the so-called R tree, a spatial data access method used to store, search, and query spatial information. The R-tree method is an efficient way to query a spatial database as it reduces computer memory and temporary database usage. R-tree has been widely used in different applications of spatial data management. For example, R-tree is commonly used to store spatial data, such road networks and city locations, and then to query the data quickly and efficiently; for example, to ‘Find a shortest distance from city A to city B’ or ‘Find a nearest motorway access point around city C’. Spatial data query methods are widely used in GIS to improve the computational speed of access, query, and storage of large spatial databases (Luo et al. 2012, Aji et al. 2012).

Kriegel et al. (1993) discuss a method which combines spatial access and computational geometry concepts to improve the performance of GIS operations. The method can be used in different applications or algorithms, such as map overlay and map merge. However, the current method needs further investigation into the design of efficient algorithms based on spatial access methods and computational geometry for all retrieval operations.

To sum up, spatial data query methods contribute to geo-processing, especially with respect to accessing and querying large spatial datasets. Nevertheless, these methods do not improve the computational efficiency of executing a large group of computation tasks in a geo-processing model.

2.4.3.2 Computation strategy

Although computational efficiency of geo-processing could be improved using parallel computational and spatial data query, these methods do not address the sequential computation problem in the traditional geo-processing approach. This means that spatial data and functions are still evaluated one by one until the final result is computed in parallel.

In order to address the sequential computation problem in the traditional geo-processing approach, this section discusses how a different computation strategy, ***priority-based computation***, can be used for geo-processing.

Computational priority, or scheduling, is a method that optimizes use of computation resources and improves computation performance (Jones et al. 1997). In computer science, priority (or scheduling) is used for implementing multiple computation tasks. For example, scheduling could be used to suspend a heavy computation task in order to free up the main computing memory for other computation tasks which have less computational cost (e.g. time and memory) (Stallings 2004). Moreover, priority (or scheduling) has also been widely applied in GIS, mainly for the purposes of determining least-cost paths across a continuous surface (De Smith et al. 2007) or reducing delay due to an unexpected event in a complex railway network (Pellegrini et al. 2014)

Similar to the priority rule used in computer science or in spatial problems of path selection, the ***priority-based computation strategy*** provides a new computation strategy in geo-processing to implement various computation tasks more efficiently, especially by lowering computation time and use of costly computer resources. In the ***priority-based computation strategy***, priority (or scheduling) can be used to suspend a computation task that has a low priority, or a computation task which allocates a large amount of memory, in order to free up main memory for other computation tasks, implementing the computation task later when more computer memory is available (Stallings 2004). More details of ***priority-based computation strategy*** will be discussed in Chapter 7.

In summary, computational efficiency is an important concern in geo-processing, as it can influence computation performance and delay decision-making. In particular, the current computation strategy (sequential computation) applied in traditional geo-processing can cost extra computation time and computer memory because it involves 'waiting' functions and unnecessary computations. In view of our study of computational efficiency methods, we propose a priority-based computation strategy for the CG approach in order to improve the computation time of a complex geo-processing model.

2.5 Conclusion

Geo-processing is used to solve complex spatial problems. The traditional geo-processing approach has been widely applied in tools for spatial modelling, spatial analysis, and decision-making systems. Although the traditional geo-processing approach provides a simplified computation strategy for implementing a complex spatial model, the trade-off between simplification and complexity shows that data quality and computational cost have yet to be fully understood in the traditional geo-processing approach.

Data quality is a key concern in a geo-processing model because it influences the final geo-processing outputs and decision support system. Our review of data quality under the traditional geo-processing approach (Section 2.3.3) shows that the current approach is influenced by several data-quality problems. The first problem is the current spatial data representation, which may cause problems due to the limitations of raster and vector data formats. The second problem involves basic computation methods, which also can cause data error and uncertainty problems due to numeric computation and error propagation.

Computational efficiency is another important concern for geo-processing, as it can influence computation performance. Our review of computational efficiency in traditional geo-processing (Section 2.4.2) suggests that the current computation strategy (sequential computation) costs extra computation time and computer memory because it employs inefficient processes (i.e. waiting functions) and unnecessary computations.

This thesis introduces the CG approach in order to address these problems related to data quality and computational efficiency. A set of methods is proposed for the CG approach, including a point-based spatial data model, a symbolic computation, a function-based layer, and a priority-based computation strategy. The point-based spatial data model is used to minimise spatial data representation problems such as data conversion. The symbolic computation method and function-based layers are applied to reduce the data error and uncertainty associated with numerical computation in a geo-processing model. The priority-based computation strategy is used to reduce computation time by re-ordering the computational sequence.

This chapter has reviewed the current data quality and computational efficiency problems that arise under the traditional geo-processing approach, and has discussed the methods that we apply in the CG approach for improvement of these issues. The next chapter discusses the conceptual model of the CG approach, which provides a basic element for the development of the new approach.

3 Conceptual Model of Combinative Geo-processing (CG) Approach

3.1 Introduction

One of the important characteristics of the traditional geo-processing approach is that a geo-processing model is composed of one or more processes, which are implemented individually and in a sequence. As was explained in the previous chapter, this influences the data quality and computational efficiency. In an attempt to overcome these problems, Chapter 3 introduces the CG approach. The major characteristics of the CG approach are presented together with a conceptual model, as well as the limitations and strengths of this approach.

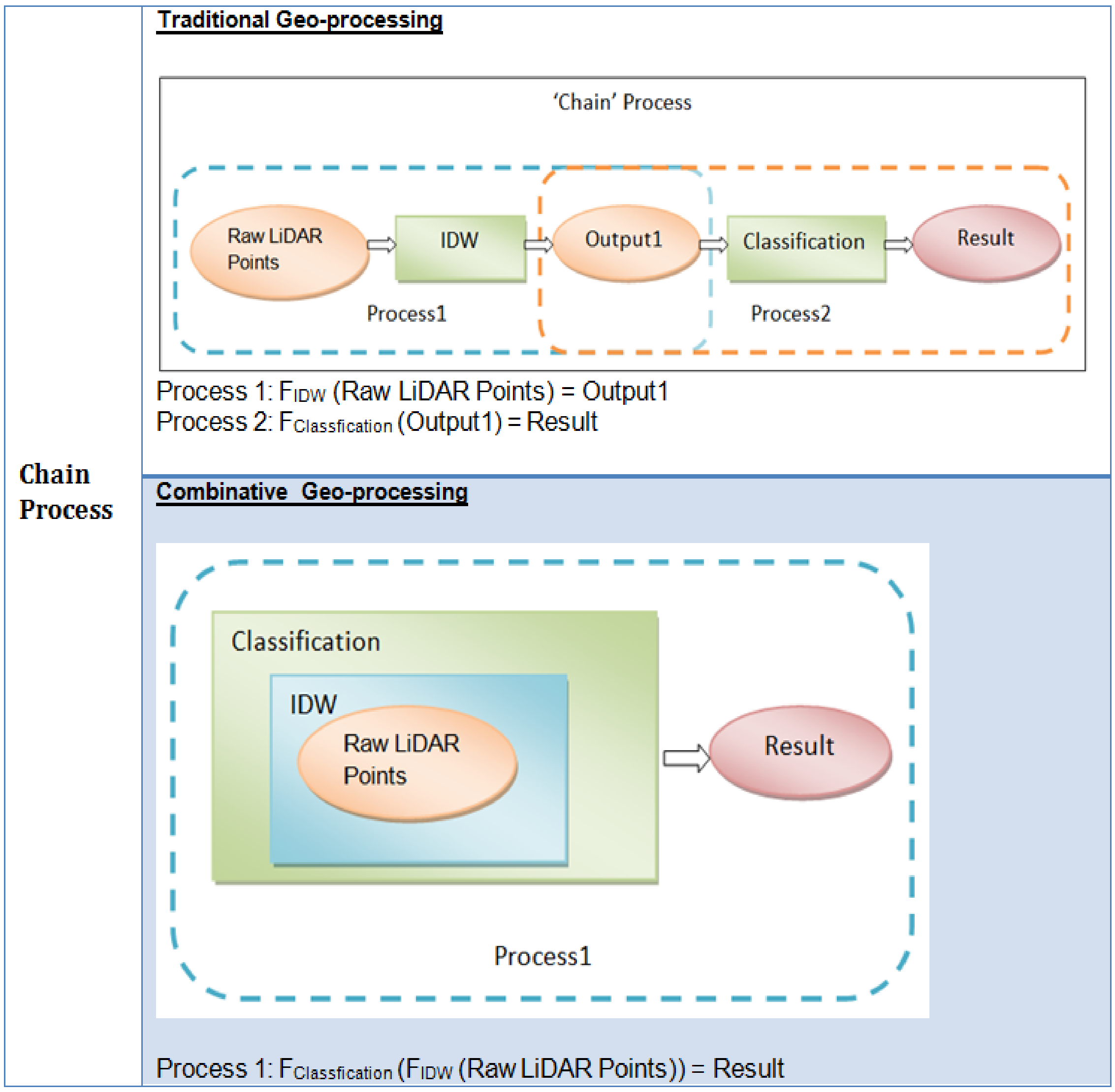
More specifically, Section 3.2 discusses the basic characteristics of the CG approach, with the aim of understanding the differences compared to the traditional geo-processing approach, which was reviewed in the previous chapter. Section 3.3 introduces a conceptual model for the CG approach and discusses in detail the implementation issues, which mainly refer to how spatial objects are represented and how different types of GIS functions are applied in the CG context, together with how the GIS functions and spatial data are further evaluated. A set of CG computational rules are introduced and how the CG output is produced in order to solve spatial problems is described. Section 3.4 discusses the strengths and limitations of the proposed approach, and finally, Section 3.5 concludes with a summary of the main issues discussed in this chapter.

3.2 Basic Characteristics of the Combinative Geo-Processing Approach

A major characteristic of the CG approach is that there is only one CG function for the entire geo-processing model. In other words, a complex geo-processing model, which in the traditional geo-processing approach is normally implemented using a sequence of different processes, is integrated into only one CG function. To further clarify what a CG function involves, Figures 3-1 and 3-2, which are discussed in Sections 3.2.1 and 3.2.2, respectively, demonstrate two examples; a ‘simple chain’ and a ‘complex chain’ process which focus on the computation steps that are needed to execute them using the traditional geo-processing approach and the CG approach.

3.2.1 Simple Chain Process

The upper workflow chart in Figure 3-1 illustrates an example of a simple chain process in the traditional geo-processing approach, while the lower workflow chart shows the same example but within the context of the CG approach.



Chain Process
Traditional Geo-processing
'Chain' Process
Raw LiDAR Points
IDW
Output1
Classification
Result
Process1
Process2
Process 1: F_IDW (Raw LiDAR Points) = Output1
Process 2: F_Classification (Output1) = Result
Combinative Geo-processing
Classification
IDW
Raw LiDAR Points
Result
Process1
Process 1: F_Classfication (F_IDW (Raw LiDAR Points)) = Result

Figure 3-1 A comparison of a 'simple chain' process using the traditional geo-processing and CG approaches.

The simple chain process for the traditional geo-processing approach incorporates two continuous processes: the first uses the '*IDW* function' to produce '*Output1*' from '*Raw LiDAR points*'; and the second applies the '*Classification* function' to calculate the result from '*Output1*'. In the workflow for the CG approach it can be seen that these two processes are now combined into one process, i.e. {Classification (IDW CG dataset)}. In addition, in the CG approach the final result is produced without any intermediary outputs (i.e. '*Output1*'), as in the traditional geo-processing approach.

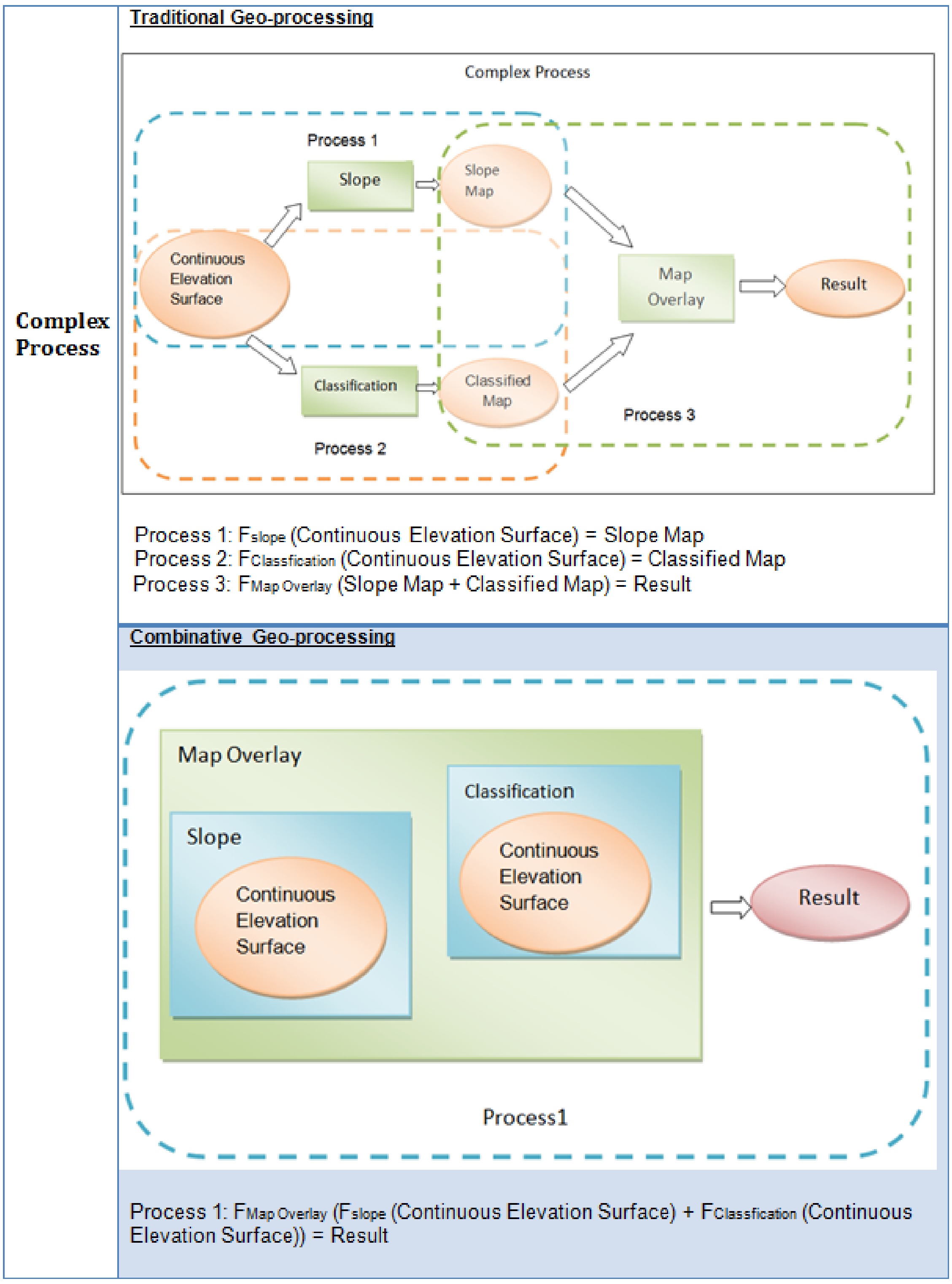
3.2.2 Complex Chain Process

An example of a complex chain process is demonstrated in Figure 3-2. The upper workflow describes how a complex chain process is executed using the traditional geo-processing approach, while the lower workflow illustrates how a complex chain process is executed using the CG approach.

Using the traditional geo-processing approach to execute the complex chain function illustrated involves three processes: first, the '*Slope* function' is used to produce a '*Slope Map*' from the '*Continuous Elevation Surface*'; second, the '*Classification* function' is applied to produce a *'Classified Map'* from the *'Continuous Elevation Surface'*; and finally, the *'Map Overlay* function' is used to integrate the two previous outputs and produce the final '*Result output'*. The lower workflow chart clearly demonstrates that these three processes are integrated into one CG function. The '*Slope'* and '*Classification'* functions are loaded into the '*Map Overlay'* function as two parameters, and then the result is directly produced from the CG function, i.e. {Map Overlay (Slope + Classification)}.

Both examples demonstrated by Figures 3-1 and 3-2 show that the CG approach provides a different way to deal with the simple and complex chain processes, as all the necessary GIS functions are combined into one CG function. Thus, it may be suggested that the proposed CG approach provides an entirely new way of dealing with different types of geographical information and GIS functions in geo-processing.

After detailing the major characteristics of the CG approach, in which all geo-processing tasks can be integrated into one CG function, the next section introduces the conceptual model for the CG approach.



Process 1: F_{slope} (Continuous Elevation Surface) = Slope Map
Process 2: $F_{Classification}$ (Continuous Elevation Surface) = Classified Map
Process 3: $F_{Map\ Overlay}$ (Slope Map + Classified Map) = Result

Process 1: $F_{Map\ Overlay}$ (F_{slope} (Continuous Elevation Surface) + $F_{Classification}$ (Continuous Elevation Surface)) = Result

Figure 3-2 A comparison of a 'complex chain' process using the traditional geo-processing and CG approaches.

3.3 The Combinative Geo-Processing Conceptual Model

The CG conceptual model introduces the major components of the CG approach and the relationships between them. It should be noted that the elements that were reviewed in the previous chapter are also integrated into the following conceptual model, which is shown in Figure 3-3. For example, one of the fundamental elements of the CG conceptual model is the CG function library, which should include all types of GIS functions that are needed during processing.

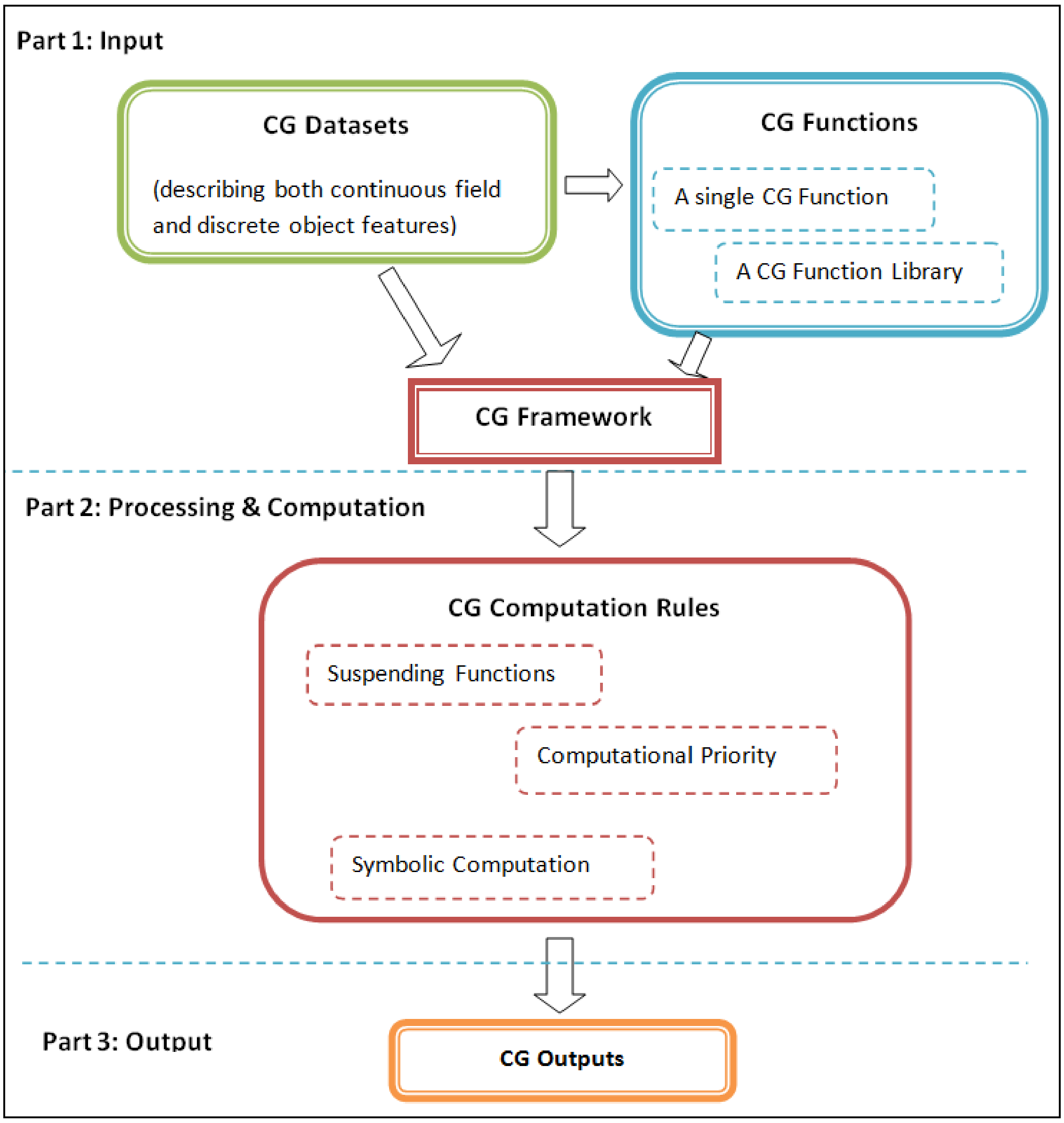


Figure 3-3 Conceptual model of the CG approach.

The CG conceptual model consists of three parts which are discussed separately in Sections 3.3.1-3.3.3. Section 3.3.1 describes the first part of the CG conceptual model, which focuses on the input level of the CG approach, such as the basic data model, functions, and computation framework. Section 3.3.2 discusses the second part of the CG conceptual model, which focuses on the processing and computation rules employed in the CG approach. Finally, Section 3.3.3 describes the major characteristics of the output or results of the proposed CG approach.

3.3.1 Input Level

There are three basic elements that a GIS user needs to consider before designing a geo-processing model using the CG approach. The first element refers to the primary spatial data model, as this influences many fundamental elements related to geo-processing, e.g. data quality and computational efficiency. The second element refers to the CG functions, as these are key components for building complex geo-processing models using the CG approach. Finally, the third element is the CG framework, which illustrates how to process CG datasets and CG functions using the proposed approach.

1) Combinative Geo-processing Dataset

An important concern of the proposed CG approach is the storage and representation of spatial objects. In the previous chapter two main data types were discussed (i.e. vector and raster data), and it was explained that vector data provides a popular way to represent discrete objects, such as city boundaries and road networks, while raster data can be used to show continuous fields, such as elevation models and land surface. At the same time, it was also noted that both vector data and raster data representations have limitations, such as for vector data a massive data storage space is required and the algorithms for processing spatial analysis functions are complex, while for raster data a very fine raster grid will represent sufficient detail but will require a large amount of disk space.

As discussed in Section 2.3.4.1, the CG approach uses the point-based model concept to represent spatial entities. In other words, the CG approach uses point data to represent geographical features that include both discrete objects and continuous field features. Point data plays an important role in GIS representations, as the majority of spatial data are based on, or consist of, points.

The primary spatial data model in the CG approach involves points and the mathematical model shown in Formula 3.1 is used to define a CG Dataset.

$$\textbf{CG Dataset} \in ((X_1, Y_1, (Z_1))\ldots(X_n, Y_n, (Z_n))) \qquad \textbf{[3.1]}$$

Where, 'CG Dataset' is a single dataset, which could include a single point (X_1, Y_1, (Z_1) or a series of points from 1 to n ((X_1, Y_1, (Z_1))… (X_n, Y_n, (Z_n))). X_1 and Y_1 refer to the coordinate value, and Z_1 is the optional elevation value.

2) Combinative Geo-processing Functions

A CG function also consists of a fundamental component of the CG approach. In contrast to the traditional geo-processing approach, the CG approach proposes the use of function-based layers for the creation of a CG function. In the CG approach a function-based layer includes the following functionality: it can store a single function or a set of functions (e.g. a function to calculate distance or a geo-processing model to analyse complicated objects); the input for a function-based layer can be a dataset or a function(s) (e.g. an IDW function can be the direct input to a SLOPE function to produce a function-based layer); and the output of a function-based layer can be a dataset or a function(s).

The four mathematical forms of a CG function, based on CG datasets and function-based layers, are illustrated in the following formula (3.2).

$$\textbf{CG Function} \in \begin{cases} FL\ (null)\ | \\ FL\ (CG\ dataset)\ | \\ (FLn\ldots\ldots(FL2\ (\ FL1\ (null))))\ | \\ (FLn\ldots\ldots(FL2\ (\ FL1\ (CG\ dataset)))) \end{cases} \qquad \textbf{[3.2]}$$

Where the 'CG function' represents a function in the CG approach, 'FL' is a function-based layer, and n is an integer.

(a) FL (null) is a single, temporary, and generic function-based layer without any datasets, such as an IDW function: IDW (null);

(b) FL (CG dataset) is a single function-based layer linked to a CG dataset, such as loading a set of LiDAR points into an IDW function: IDW (LiDAR);

(c) (FLn….. (FL_2 (FL_1 (null)))) is a group of function-based layers (FL_2 (FL_1 (null))) is loaded into another function-based layer FL_n, such as loading (Slope (IDW (null))) into a Combination function: (Combination… (Slope (IDW (null)))).

(d) (FLn….. (FL_2 (FL_1 (CG dataset)))) is different to (c) as F_1 is linked to a CG dataset, such as: (Combination… (Slope (IDW (LiDAR)))).

This method for creating a generic function in the CG approach can be used to further incorporate in the CG approach various GIS functions, which were reviewed in the previous chapter. Thus, it is essential that the proposed CG approach provides a CG function library to effectively store and manage different CG functions. In principle, a function library is a collection of ready-to-use segments of code that can be used for development purposes. It has been widely accepted that an optimum function library can save development costs and reduce errors because the library's codes can be reused, and this means that they only have to be debugged once (Drepper, 2011). Therefore, a CG function library was created at this early development stage of the CG approach.

Figure 3-4 provides an overview of the CG function library, which is composed of eight function classes. It is common practice for a function class to include a group of functions that have similar functionality. Thus, the eight function classes shown in Figure 3-4 are grouped according to basic GIS functionality; six (orange boxes) are common GIS functions, while the other two function classes (blue boxes) involve additional functions that can be used to store and query geographical data.

It should be noted that the proposed CG function library currently includes only thirty core GIS functions, which were developed and can be directly cited and frequently re-used. The proposed CG function library may significantly help to improve development time.

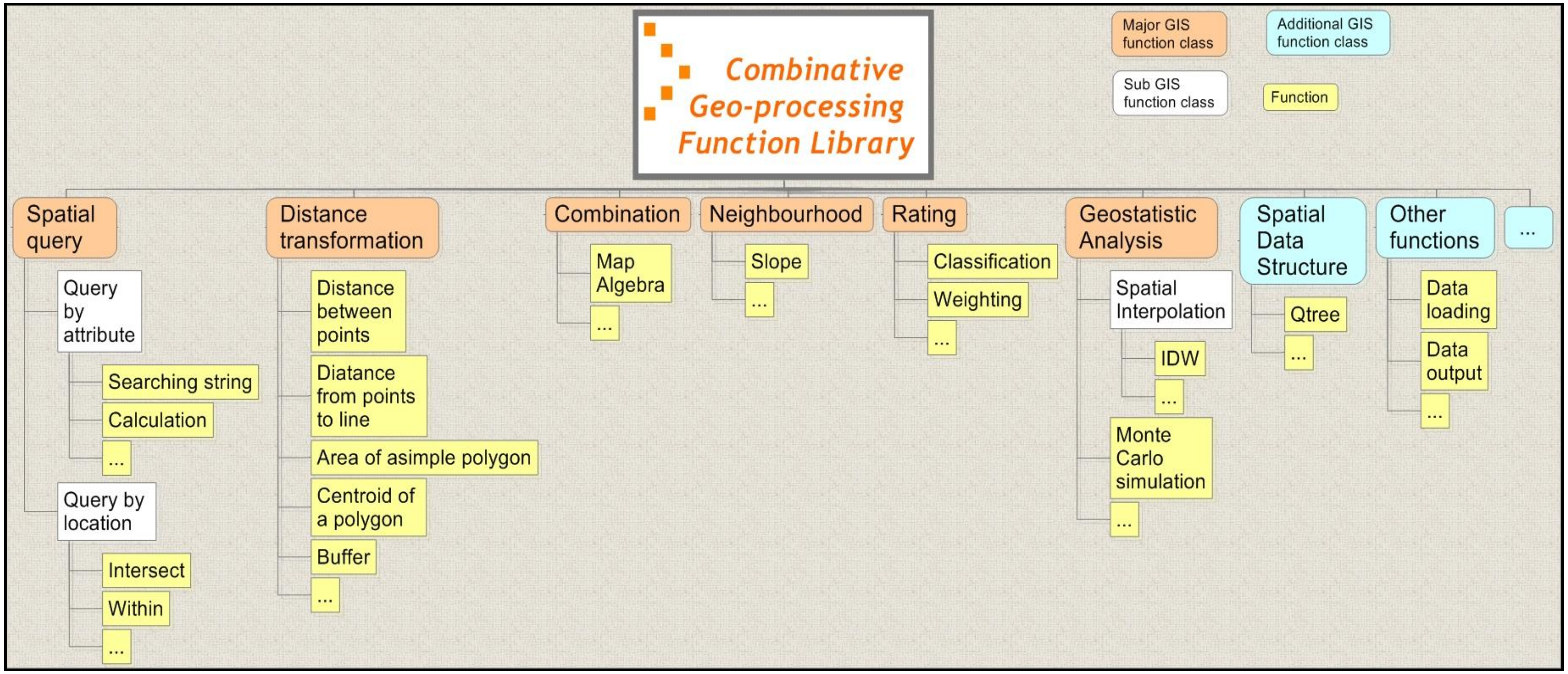


Figure 3-4 Basic GIS functions included in the CG function library.

3) The Combinative Geo-processing Framework

The CG framework provides a means of integrating the CG datasets and CG functions together in order to solve complex spatial problems. Figure 3-5 illustrates the generic frameworks of the traditional geo-processing and CG approaches. The upper flow chart shows the traditional geo-processing framework, where the initial step loads the '*Input*' into a function '*Fun1*', and then this yields an output '*Out1*'. '*Out1*' is re-used as an '*Input*' for function '*Fun2*' and returns the result '*Out2*'. This sequential computation strategy is used until the model produces the final result. In contrast, the lower flowchart illustrates the CG framework, where a function can take other functions as parameters and return functions as results.

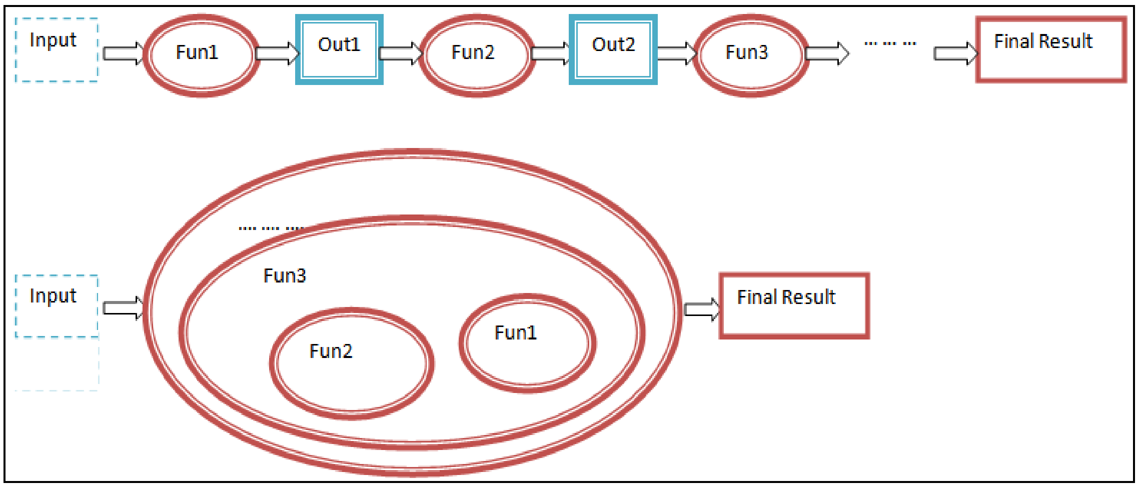


Figure 3-5 The generic frameworks of the traditional geo-processing and CG approaches.

The corresponding generic mathematical models for the traditional geo-processing and CG frameworks are described respectively by formulas 3.3 and 3.4. In formula 3.3 the various functions are performed sequentially until the model reaches the final function. In contrast, formula 3.4 shows that the final result is produced directly from the CG function. It is essential to note that the parameters $E_{tradition}$ and E_{CG} are incorporated into these formulas in order to compare data quality between the traditional geo-processing approach and the proposed CG approach.

$$\textbf{Traditional Geoprocessing Framework}(\text{dataset}) \xrightarrow{\text{yields}} F_1(\text{dataset}) = O_1 + E_1 \xrightarrow{\text{Next Stage}} F_2(O_1 + E_1) = O_2 + E_2 \xrightarrow{\text{Next Stage}} F_3(O_2 + E_2) = O_3 + E_3 \xrightarrow{\text{Next Stage}} F_i\,(O_i + E_i) \xrightarrow{\text{final step}} \text{Result} + E_{\text{tradition}} \qquad [3.3]$$

In formula 3.3, the ‘dataset’ is the input, which can be raster or vector data, and ‘F_1, F_2, F_3, …, F_i’ represent different types of GIS functions, such as data interpolation, map algebra, vectorisation and network analysis. ‘O_1, O_2, O_3, …, O_i’ are the various outputs based on the numerical computations and approximated value, while ‘E_1, E_2, E_3, …, E_i’ represent the potential errors accompanying each single stage of the sequential computation. ‘$E_{\text{tradition}}$’ represents the potential errors in the traditional geo-processing approach. Finally, $\xrightarrow{\text{yields}}$ represents the computation progress, $\xrightarrow{\text{Next Stage}}$ represents the ‘stage by stage’ computation strategy, and $\xrightarrow{\text{final step}}$ describes the last step in the entire framework.

$$\textbf{CG Framework}\,(\text{CG dataset}) \xrightarrow{\text{yields}} (FL_i \ldots\ldots(FL_3\,(FL_2(FL_1(\text{CG dataset}))))) = \text{CG Function}(\text{CG dataset}) \xrightarrow{\text{final step}} \text{Result} + E_{CG} \qquad [3.4]$$

In formula 3.4, ‘CG dataset’ is the input, and ‘FL_1, FL_2, FL_3, …, FL_i’ represent the different types of function-based layers in the CG approach. The ‘CG function’ represents a combinative function which includes all function-based layers (i.e. FL_1, FL_2, FL_3, …, FL_i). 'E_{CG}' represents the potential error in the CG approach. Moreover, a recursive algorithm will be applied in this formula to execute the functions from FL_1 to FL_i.

It should be noted that this thesis attempts to compare the difference between '$E_{tradition}$' and 'E_{CG}', something which is discussed further in Chapters 5 and 6, where different case studies are presented with the aim of investigating the data quality of the CG implementations.

3.3.2 Processing and Computation

Following the discussion on the fundamental components of the CG approach, this section discusses the processing and computational issues, and explains how the CG framework can be evaluated in the proposed approach.

An ideal CG framework needs a reliable way to operate and evaluate various CG datasets and CG functions, thus a set of CG computational rules is introduced, which include 'suspending', 'computation priority', and 'symbolic computation'. Notably, these computation rules essentially constitute the key difference between the CG approach and the traditional geo-processing approach.

'Suspending' is a method which can help manage a CG function. All CG functions in a geo-processing model can be suspended until a GIS needs them for producing the results. Suspending can further help to understand a basic difference between the traditional geo-processing and CG approaches. As illustrated in Figures 3-1 and 3-2, the traditional geo-processing approach uses a sequential computation strategy, with each function returning a specific result; therefore the final result will only be calculated when all the functions have been executed. In contrast, using the CG approach the input datasets are temporarily stored in the function-based layers and calculations are suspended until the user defines the parameters of the final result or requests the value of a function at a specific location. Thus, computations will only commence when requested by the end user, and this is when the final result will be calculated.

It should be noted that there are two main advantages to suspended functions. First, the CG-enabled GIS does not need to use extra memory space to store intermediary results during the computation processes. Second, functions are only executed when users require the final results, which may reduce the total computational period and introduce fewer errors, especially when compared with the errors that can be generated when there are several intermediary steps involved (Haklay, 2004). These aspects are explored in later in this thesis.

The second rule refers to ‘computation priority’, and it is similar to the priority rule used in mathematics. When functions are suspended in a geo-processing model the CG approach needs to decide which spatial function will be executed first. The aim is to provide an optimum computational sequence for implementing a set of spatial functions at a lower computational cost. A typical example of a priority-based computation is that of algorithm scheduling, which is concerned with the optimal allocation of scarce resources to activities over time. When there are many spatial functions that need to be executed (e.g. in Figure 3-2 the functions ‘Slope’, ‘Classification’ and ‘Map Overlay’ all needed to be executed), the computational priority should make a judgment concerning which function should be performed first. Computational priority helps to further define in what order the functions will be executed until the entire set of functions is finally executed as efficiently as possible.

The third rule refers to symbolic computation. In contrast to the traditional geo-processing approach, where functions are evaluated using numerical calculations and approximate values, the CG approach uses symbolic computation to calculate the CG functions. As discussed in Section 2.3.4.2, symbolic computation provides an exact method for mathematical calculation.

3.3.3 Outputs and Results

The last part of the proposed CG conceptual model is concerned with the production of the final result. There are two alternative formats in the CG approach for producing a final output and which further differentiate it from the traditional geo-processing approach.

The first format of the final result is points, which is due to the fact that the primary spatial data model of the CG approach involves the use of points. GIS users can process these points straightforwardly or transform them into other spatial data models, such as raster and vector data, for further computations.

The second format of the final result is functions, because the way CG functions are operated by higher-order functions could produce new functions from existing functions. In other words a CG function can produce a function or a set of functions as the final outcome. Consequently, the functions can be reused or can be used as the input for other geo-processing models for advanced spatial analysis.

Formula 3.5 defines the CG output in two different forms.

$$\textbf{CG Output} \in \left(\{(X_1, Y_1, (A_1, \ldots, A_m)) \ldots (X_n, Y_n, (A_n, \ldots, A_m))\} \mid \{CG\ functions\} \right) \qquad \textbf{[3.5]}$$

Where '$(X_1, Y_1, (A_1, \ldots, A_m)$' represents an output point location (X_1, Y_1) with a single or several attributes '$(A_1, \ldots, A_m)$'. n and m are both integers.

The major components of the conceptual model of the CG approach have now been described and the next section discusses the strengths and also potential limitations of the CG approach.

3.4 Potential Advantages and Disadvantages of the Combinative Geo-Processing Approach

The previous sections have explained some of the advantages of the proposed CG approach over the traditional geo-processing approach, which include the final output being directly produced from a CG function. One of the benefits of this is that the CG-enabled GIS does not need to produce any intermediary results. In addition, in CG-enabled GIS there is no need to convert geographical data in different spatial data models, such raster and vector data, because all the CG datasets are stored as points and all the computations and manipulations use points. For example, in the traditional geo-processing approach two conversion steps are needed to convert LiDAR to a DEM image, and convert a DEM image to a contour map in order to implement this task, while the CG approach can produce a contour map using LiDAR points directly.

The CG approach provides more flexibility in terms of producing a final result. For example, in existing GIS tools the resolution and extent (or study area) of the final results are the default values and are defined by the system when users run a layer combination operation. However, the CG approach can provide a flexibility in the final result creation. For instance, the resolution can be defined by the user and the extent can be based on a five metre buffer of residential area.

Finally, when users calculate different CG functions in a CG-enabled GIS, all the computations run on computer random access memory (RAM) are faster, while the traditional approach may take longer. This is because the traditional geo-processing approach needs to access, query, and save multi-step results on locally available storage.

Although the proposed CG approach has the potential to significantly improve the performance of geo-processing, there are still two significant concerns that should be noted and the remainder of this thesis aims to address these specific concerns.

The first concern refers to the development period. The fact that geo-processing is an integrated platform means that the tasks include not only the GIS functions, but also various functionalities which can be used to capture, store, and visualise spatial data. Therefore, the more CG functions developed, the more effective the development of the proposed CG approach will be. However, it should be clarified that due to time restrictions this research will only consider the most popular GIS functions, such as interpolation methods, map algebra, and slope.

The second issue refers to the efficiency of functional programming. Functional programming (i.e. Scheme, the functional programming language that is used in this research) was selected as the basic programming tool for developing the CG functions as it provides full support for high-order functions and symbolic computation. However, in general functional programming languages are typically less efficient in their use of the CPU and memory than imperative languages such as C and Pascal. This means that the use of a functional programming language for the development of the proposed CG approach may reduce efficiency with respect to the CPU and computer memory. Taking this limitation into account a case study is discussed in Chapter 8, where computational priority is used as a way to improve computational efficiency and possibly counterbalance the negative effects of functional programming.

3.5 Summary

This chapter has introduced the conceptual model of the CG approach, which used three levels to illustrate the differences between the new approach, the traditional geo-processing approach and the computation progress in the new approach. The conceptual model showed that the CG approach provides a completely different way of processing geographical data and GIS functions. Additionally, a number of the strengths and limitations of the CG approach have been briefly discussed, as these help in the organisation of the development process.

To implement the proposed CG conceptual model, the next chapter will address the development design of the CG approach and discuss the appropriate methodologies.

4 Case Study Design and Combinative Geo-Processing Implementation Methods

4.1 Introduction

This chapter provides an overview of the main methodological framework of this thesis. Section 4.2 introduces a set of case studies, which gradually increase in complexity, and which were carried out in order to implement and also evaluate the CG functions and the results obtained. Section 4.3 explores the manipulation and execution of CG computations in the three case studies for the development of the CG approach, e.g. building up function-based layers and dealing with a group of function-based layers. Section 4.4 describes how the CG approach can be implemented in a digital computer environment, while Section 4.5 describes the selected data that are used in the case studies. Finally, Section 4.6 summarises the main issues that are discussed in this chapter.

4.2 Experimental Design

Three case studies were designed which try to demonstrate how function-based layers, i.e. CG functions, and a priority-based computation strategy are used in the CG approach. These also support the investigation into understanding whether the CG approach improves data quality and computational efficiency, which are aims of this thesis.

4.2.1 Case Study Selection

In the early stages of case study design it is worth explaining the reasons for selecting the case studies and their specific research questions. As discussed in Figure 4-1, Sections 2.3.3 and 2.4.2 provides an overview of the common issues within a complex geo-processing model, which is a popular geo-processing model used to select potential locations for a new property development. There are three typical issues illustrated in this model: (1) the multiple map layers overlay function, which could cause data uncertainty and error problems due to re-sampling and data conversion operations; (2) simple chain processing, which may cause data uncertainty and error propagation problems due to approximated values and round-off errors; and (3) overall computation time cost, which could cause extra computation time due to the ‘wait’ functions and unnecessary computations.

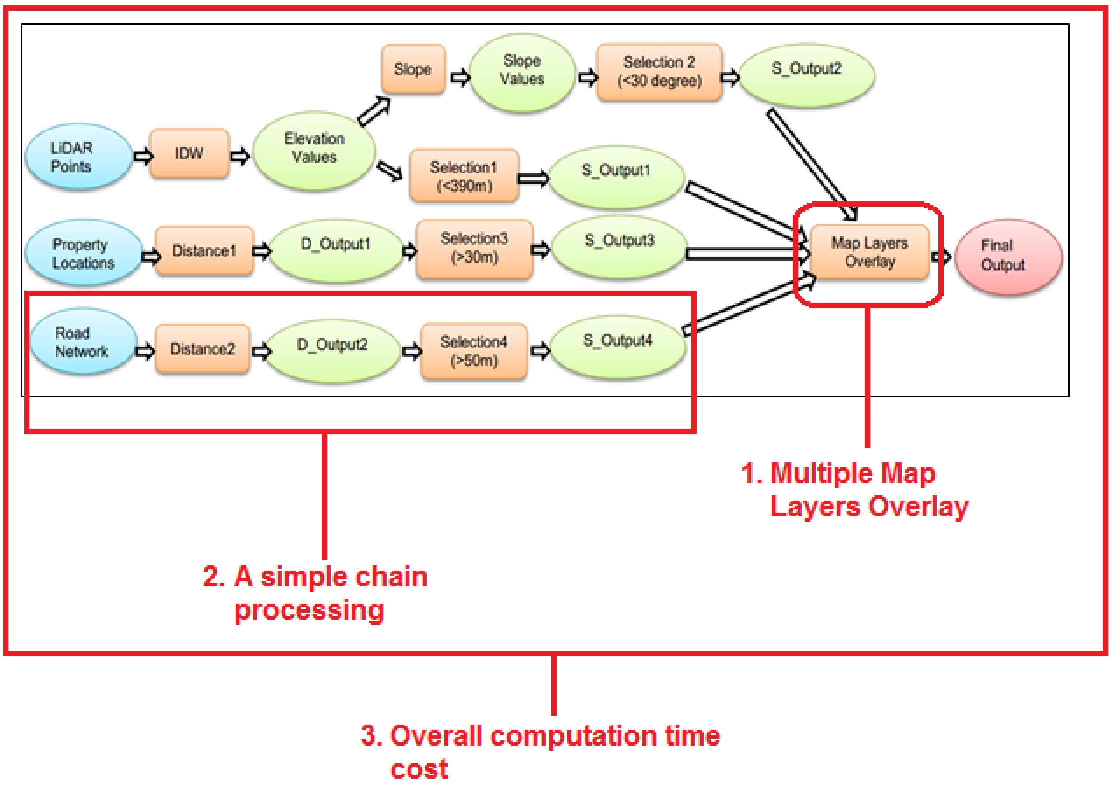


Figure 4- 1 Overview of three typical issues in a complex geo-processing model.

The three case studies have been designed in order to investigate these three typical issues in a complex geo-processing model (Figure 4-2). The first two case studies focus on the evaluation of data quality problems, such as re-sampling, data conversion, data uncertainty and error propagation, while the third case study focuses on the evaluation of computational efficiency problems, such as ‘wait’ function and unnecessary computations. During the case study development, the output of the previous case study will be used in the next case study as a benchmark for further investigation. For example, the CG functions developed in the case studies 1 and 2 will be applied in case study 3 to build up a complex geo-processing model. The three case studies are discussed separately in the following paragraphs.

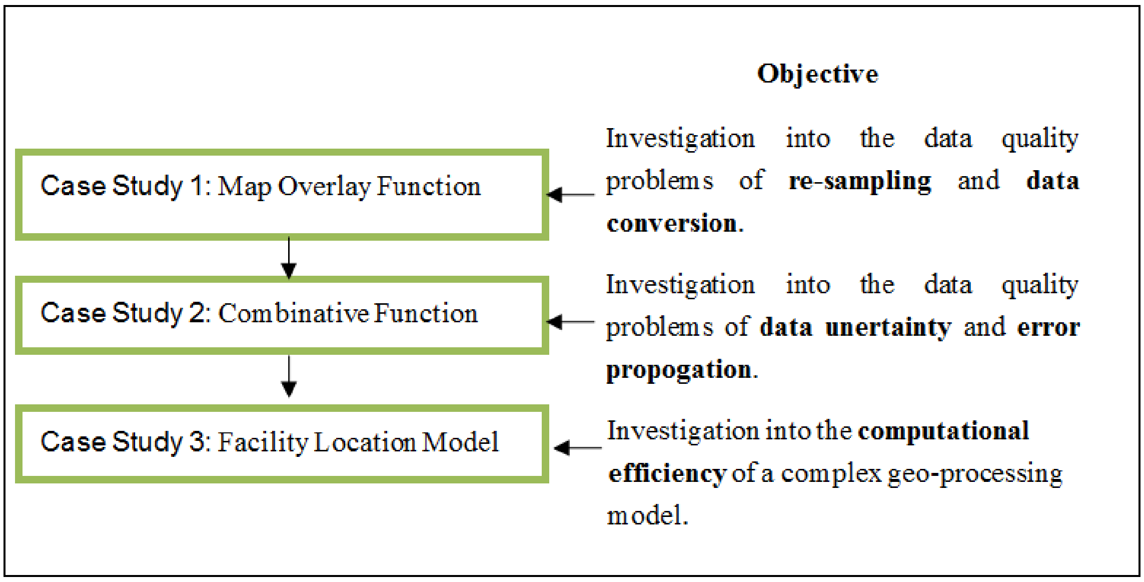

Objective
Case Study 1: Map Overlay Function
Case Study 2: Combinative Function
Case Study 3: Facility Location Model
Investigation into the data quality problems of **re-sampling** and **data conversion**.
Investigation into the data quality problems of **data uertainty** and **error propogation**.
Investigation into the **computational efficiency** of a complex geo-processing model.

Figure 4- 2 Summary of the experimental case studies used for the development of the CG approach.

4.2.1.1 Case Study 1: Map Overlay Function

The purpose of this case study is to investigate the influence of re-sampling and data conversion issues in the traditional geo-processing approach, and how these influences can be reduced using the CG approach.

The Map Overlay function is a basic GIS function used in spatial analysis as it enables a way to integrate different types of information or map layers. Map Algebra is traditionally used for Map Overlay operations and was originally introduced by Tomlin (1990). It involves the process of re-sampling and data conversion in order to combine co-registered map layers, which are raster-based and which have the same size and resolution. In this case study the implementation of the same process is explored using the CG approach.

Figure 4-3 illustrates this case study's model, which requires the overlay of two different outputs (from IDW1 and IDW2). This is a simplified geo-processing model and the purpose is to test the data quality of the results obtained when combining two different layers which have different grid sizes, as the IDW1 layer has a 1 metre pixel size, while the IDW2 layer has a 1.5 metre grid size. It should be noted that data uncertainties and errors may be introduced when two raster layers with different pixel sizes are converted into the same pixel size for implementing Map Layers Overlay operations. This case study is discussed in Chapter 5.

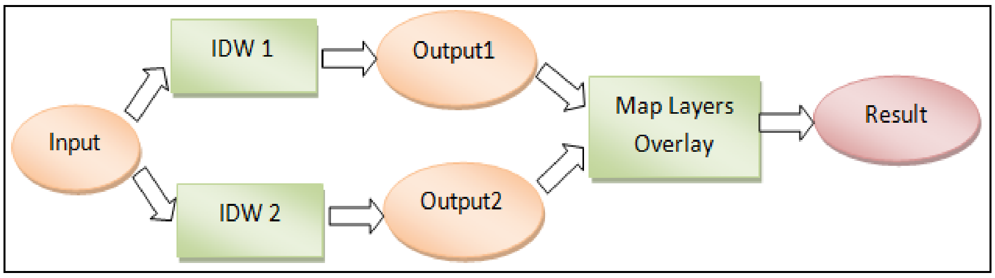


Figure 4- 3 Map Overlay function used in the second case study.

4.2.1.2 Case Study 2: A Combinative Function

This case study aims to investigate the influences of data uncertainty and error propagation issues in the traditional geo-processing approach and how these influences can be reduced using the CG approach. Furthermore, this case study also focuses on the implementation of a CG function, which is composed of functions-based layers, using the CG approach.

Figure 4-4 demonstrates the CG function (shown in the red dashed box), which consists of an IDW function layer and a Slope function layer. In traditional geo-processing this process would involve: (a) the IDW function producing the DEM surface, and (b) the DEM data being re-used as the input for the Slope function in order to derive the new slope surface. This sequential computation may introduce data uncertainties and errors due to approximated values and error propagation. However, in the CG approach this geo-processing model is applied using a single computation step and the results are directly produced from the CG function without any intermediate outputs. A Monte Carlo simulation is also used here to validate and compare the data quality of the results from traditional geo-processing (using ModelBuilder in ArcGIS) and those obtained from the CG approach. This case study is discussed in Chapter 6.

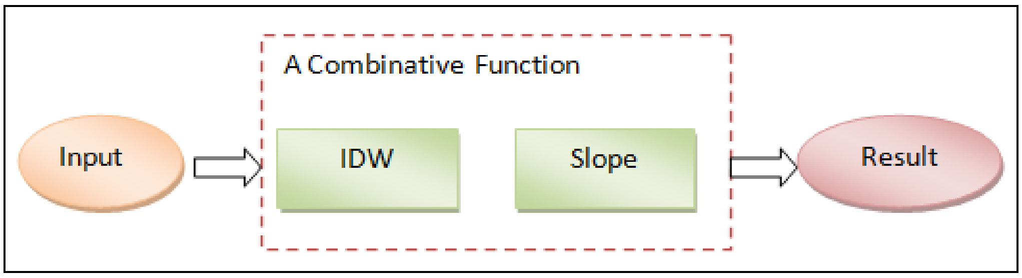


Figure 4- 4 A CG function used in the second case study.

As previously noted, in the first two case studies the focus of the evaluations is on data quality issues and on demonstrating how data uncertainties and errors in the traditional geo-processing can be reduced using the CG approach. In the third case study, the focus of the evaluation is on the computational efficiency of the CG approach.

4.2.1.3 Case Study 3: Facility Location Model

This case study attempts to investigate computational efficiency problems in the traditional geo-processing approach, e.g. the 'wait' function and unnecessary computations, and how the influence of these problems can be reduced using the CG approach.

This case study demonstrates the implementation of a complex geo-processing model using the CG approach, and also provides the basis to further investigate the issue of computational efficiency by reducing the time cost of geo-processing. Thus, in this case study the concept of CG computation priority for processing spatial data and functions is introduced. The goal of CG computation priority is to improve the performance of GIS computations using an optimum evaluation and manipulation sequence. In contrast to the sequential computation of a traditional geo-processing model, a more sophisticated variant of this method is that each spatial function is given a priority value derived from the particular computation cost, and then the available functions with the highest priority are evaluated.

The third case study involves a complex geo-processing model for the identification of potential locations for building new properties. This model uses LiDAR points, transport networks, and existing residential locations as the input data, as well as various GIS functions (Figure 4-5).

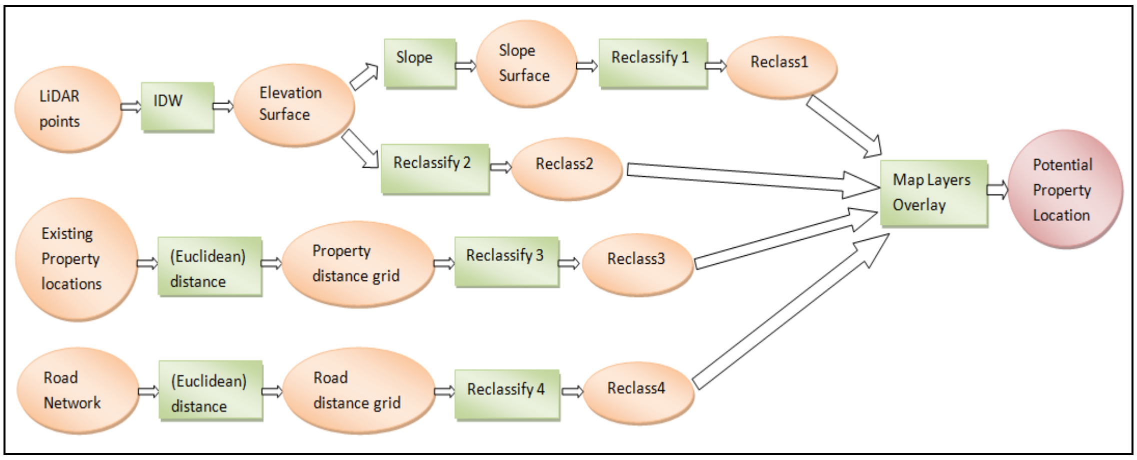


Figure 4- 5 Property Location Planning Model used in the third case study.

The proposed Facility Location Planning Model is executed using both the CG approach and the traditional geo-processing approach (using ModelBuilder in ArcGIS) in order to compare the computational efficiency, especially with respect to the time cost of implementation. This case study is discussed in Chapter 7.

This section has introduced the three case studies in this thesis and the next section pre-defines the parameters for the functions applied in the three case studies.

4.2.2 Parameter and Function Declaration

Different types of parameters and functions will be used in this research to implement the three case studies and compare their outputs. In order to illustrate the basis for comparison is identical across software platforms, this section pre-defines the parameters and the selected functions for each case study.

4.2.2.1 Case Study 1

The first case study aims to investigate a GIS overlay function for the integration of two raster layers with different grid sizes. There are two types of GIS functions, including IDW and raster overlay functions, which will be applied in this case study (Table 4-1). IDW is used to produce two different raster layers, then raster overlay function enables us to combine the two raster layers. The algorithm and calculation strategy of these two functions are illustrated in Appendix D and Section 5.2. It should be noted that these algorithms are not only applied in the CG approach to develop the GIS functions, but also used in the commercial GIS tools.

Furthermore, the online help documents for IDW and raster overlay functions are given in Appendix E (E.1 and E.2). These documents are cited from ArcGIS (Esri) website and help us to identify the conceptual formulae for the GIS functions.

Table 4- 1 GIS functions and software platforms in Case Study 1.

Function Name	GIS software platform	Functionally
IDW	MapInfo	Produce the sample layers
IDW	ArcGIS	Produce the sample layers
IDW	The CG Approach	Produce the sample layers
IDW	R	Produce the reference layers
Raster Overlay	MapInfo	Produce the sample layers
Raster Overlay	ArcGIS	Produce the sample layers
Raster Overlay	The CG Approach	Produce the sample layers
Raster Overlay	R	Produce the reference layers

Parameters (Case Study 1)

The parameters for IDW and raster overlay functions are given in the Table 4-2. These parameters will be used in the selected GIS software platforms repeatedly.

Table 4- 2 Parameters of GIS functions in Case Study 1.

Function Name	Parameter Name	Description
IDW	Spatial Reference	British National Grid
	Grid Size	1 meter and 1.5 meters grid size
	Input (for reference data)	Reference Dataset
	Input (for sample data)	Sample Dataset 1; Sample Dataset 2
Raster Overlay	Spatial Reference	British National Grid
	Input Raster (reference data)	Outputs of IDW function
	Input Raster (sample data)	Outputs of IDW function

Input Dataset (Case Study 1)

The attribute of input dataset for Case Study 1 is illustrated in Table 4-3. These data will be used as the input data for the IDW functions in the selected GIS software platforms. More details about the input data are discussed in Section 5.4.

Table 4- 3 Input dataset for Case Study 1.

Input Name	Description	Value
Reference Dataset	Number of sample points	1010 points
	Spatial Reference	British National Grid
	Data Resource	See Appendix A
	Attributes	X, Y Coordinate Location; Z Elevation Value
Sample Dataset 1	Number of sample points	819 points
	Spatial Reference	British National Grid
	Data Resource	80% of Reference Dataset
	Attributes	X, Y Coordinate Location; Z Elevation Value
Sample Dataset 2	Number of sample points	70 % of Reference Dataset

	Spatial Reference	British National Grid
	Data Resource	See Appendix A
	Attributes	X, Y Coordinate Location; Z Elevation Value

Comparison Method (Case Study 1)

The map algebra and statistical analysis are used in this case study to exam the outputs. Produced from the GIS software platforms. Raster Algebra's minus function subtracts the value of the second input raster from the value of the first input raster on a cell-by-cell basis and supports investigating the difference of grid cells between the actual, observed values that are stored in the Integrated Reference Layers (IRLs) and the derived values that are stored in Integrated Sample Layers (ISLs). Furthermore, statistical analysis was also undertaken in order to compare the Raster Algebra (Minus) results in more detail. For the purposes of this comparison, the Maximum (Max), Minimum (Min), and the Standard Deviation values are used. The results of comparison, such as the key discrepancies of outputs, are discussed in Section 5.7.

4.2.2.2 Case Study 2

The second case study focuses on a simple chain processing, which includes two GIS functions: IDW and slope (Table 4-4). IDW is used to produce elevation value from point data, and slope is applied to produce a surface model from the elevation value. In addition to IDW, the algorithm and calculation strategy of slope function is discussed in Section 6.2.1 and Appendix E (E.3). It should be noted that this algorithm is not only applied in the commercial GIS software platforms (e.g. ArcGIS), also used in the CG approach to develop the slope function.

Table 4- 4 GIS functions and software platforms in Case Study 2.

Function Name	GIS software platform	Functionally
IDW	ArcGIS	Produce the sample layers
IDW	The CG Approach	Produce the sample layers
Slope	ArcGIS	Produce the sample layers
Slope	The CG Approach	Produce the sample layers

Parameters (Case Study 2)

The parameters for IDW and slope functions are given in the Table 4-5. These parameters will be used in the ArcGIS and the CG approach repeatedly.

Table 4- 5 Parameters of GIS functions in Case Study 2.

Function Name	Parameter Name	Description
IDW	Spatial Reference	British National Grid
	Grid Size	1 Meter
	Input data	Input Dataset
Slope	Spatial Reference	British National Grid
	Input (elevation value)	Output from the IDW function
	Grid Size	Depends on the input data

The Input Dataset (Case Study 2)

The attribute of input dataset for Case Study 2 is illustrated in Table 4-6. More details about the input data are discussed in Section 6.4.

Table 4- 6 Input dataset for Case Study 2.

Input Name	Description	Value
Input Dataset	Number of sample points	26499 points
	Spatial Reference	British National Grid
	Data Resource	See Appendix A
	Attribute	X, Y Coordinate Location; Z Elevation Value

The Comparison Method (Case Study 2)

In this case study, Monte Carlo simulation is used to calculate the results' mean and variance in order to investigate the impact of data uncertainties on data quality in both simple chain processing model implementations, including ArcGIS and the CG approach. Table 4-7 illustrates the primary parameters of Monte Carlo simulation. The details about the computation strategy and comparison results are discussed in Section 6.7.

Table 4- 7 Primary parameters for Monte Carlo simulation in Case Study 2.

Parameter Name	Description
Input data	Randomly select 60% of raw LiDAR points (Input Dataset)
Output data	Slope values
Iterations	50 times

4.2.2.3 Case Study 3

The third case study focuses on a complex chain processing, which includes five types of GIS functions: IDW, slope, selection, distance, and map layer overlay (Raster) (Table 4-8). In addition to IDW, slope, and map layer overlay (Raster), the computation algorithms of selection and distance are illustrated in the Appendix E (E.4 and E.5). These algorithms are used in both GIS software platforms (ArcGIS and the CG approach) in the third case study.

Table 4- 8 GIS functions and software platforms in Case Study 3.

Function Name	GIS software platform	Functionally
IDW	ArcGIS	Produce elevation value
IDW	The CG Approach	Produce elevation value
Slope	ArcGIS	Produce slope value
Slope	The CG Approach	Produce slope value
Selection 1	ArcGIS	Select the suitable location based on the elevation condition (< 390m)
Selection 1	The CG Approach	Select the suitable location based on the elevation condition (< 390m)
Selection 2	ArcGIS	Select the suitable location based on the slope condition (< 30 degree)
Selection 2	The CG Approach	Select the suitable location based on the slope condition (< 30 degree)
Selection 3	ArcGIS	Select the suitable location based on the distance between properties (> 30 m)
Selection 3	The CG Approach	Select the suitable location based on the distance between properties (> 30 m)
Selection 4	ArcGIS	Select the suitable location based on the distance between property and main road (> 50 m)
Selection 4	The CG Approach	Select the suitable location based on the distance between property and main road (> 50 m)
Distance 1	ArcGIS	Calculate the distance between properties

Distance 2	The CG Approach	Calculate the distance between properties
Map layer overlay (raster)	ArcGIS	Combine the outputs from Selection 1 - 4
Map layer overlay (raster)	The CG Approach	Combine the outputs from Selection 1 - 4

Parameters (Case Study 3)

The parameters for IDW, Slope, Selection, Distance, and Map layer overlay are given in the Table 4-9. These parameters will be applied in ArcGIS and the CG approach repeatedly.

Table 4- 9 Parameters of GIS functions in Case Study 3.

Function Name	Parameter Name	Description
IDW	Spatial Reference	British National Grid
	Grid Size	1 Meter
	Input data	Input Dataset
Slope	Spatial Reference	British National Grid
	Grid Size	Depend on input value
	Input data	Output from IDW
Selection 1	Spatial Reference	British National Grid
	Grid Size	Depend on input value
	Input data	Output from IDW
	Condition	Pixel Value < 390m
Selection 2	Spatial Reference	British National Grid
	Grid Size	Depend on input value
	Input data	Output from Slope
	Condition	Pixel Value < 30 degree
Selection 3	Spatial Reference	British National Grid
	Grid Size	Depend on input value
	Input data	Output from Distance 1
	Condition	Pixel Value > 30 m
Selection 4	Spatial Reference	British National Grid

	Grid Size	Depend on input value
	Input data	Output from Distance 2
	Condition	Pixel Value > 50 m
Distance 1	Spatial Reference	British National Grid
	Grid Size	1 Meter
	Input data	Property Location
Distance 2	Spatial Reference	British National Grid
	Grid Size	1 Meter
	Input data	Road Network
Map layer overlay (raster)	Spatial Reference	British National Grid
	Grid Size	Depend on input value
	Input data	Outputs from Selection 1 - 4

The Input Dataset (Case Study 3)

The attribute of input dataset for Case Study 3 is illustrated in Table 4-10. More details about the input data are discussed in Section 7.6.

Table 4- 10 Input dataset for Case Study 3.

Input Name	Description	Value
Input Dataset	Number of sample points	1000000 Points
	Spatial Reference	British National Grid
	Data Resource	See Appendix A
	Attribute	X, Y Coordinate Location; Z Elevation Value
Property Location	Number of sample points	145 Points
	Spatial Reference	British National Grid
	Data Resource	Digitised from the Bing Maps satellite image.
	Attribute	X, Y Coordinate Location; Z Elevation Value
Road Network	Number of sample points	170 Points

	Spatial Reference	British National Grid
	Data Resource	Digitised from the Bing Maps satellite image.
	Attribute	X, Y Coordinate Location; Z Elevation Value

The Comparison Method (Case Study 3)

Monte Carlo simulation is continuously applied in this case study to trace the average computation time (i.e. mean value) of both GIS tools, including ArcGIS and the CG approach. Based on the output of Monte Carlo simulation, we can investigate the two different implementations of the complex chain processing model with respect to their overall computation time. Table 4-11 illustrates the key parameters of Monte Carlo. The details about the computation strategy and comparison results are discussed in Section 7.9.

Table 4- 11 Primary parameters for Monte Carlo simulation in Case Study 3.

Parameter Name	Description
Input data	90% of the raw LiDAR points (Input Dataset)
Output data	Average computation time by using ArcGIS and the CG approach
Iterations	100 times

The next section presents the computation methods which are used in order to implement the major functionalities in the three case studies, such as a combinative geo-processing model and a priority-based computation strategy.

4.3 Methods Used in Combinative Geo-processing Function Execution

The three case studies implementation requests a set of methods in the CG approach to manipulate and execute the CG functions. The basic methods applied in the CG approach were introduced in Chapter 3, such as symbolic computation. Therefore, this section focuses on the computation methods applied in the CG approach practically, with respect to the development of the 'CG function' and a 'priority-based computation strategy'. The CG function enables a basic way to implement the function-based layer together with an attempt to improve data quality, while the priority-based computation strategy is a key method for computational efficiency improvement.

It was also noted in Sections 3.2 and 3.3 that there are two main characteristics of the proposed CG approach that differentiate it from traditional geo-processing: first, a CG function is used to implement the entire geo-processing model; and second, a priority sequence is used for the execution of the CG functions. To achieve these two characteristics the CG approach uses the concepts and functionality of 'Higher-Order Function', 'Recursive Algorithms' and 'Lazy Evaluation', which are discussed in the following sections.

4.3.1 Higher-Order Function

A Higher-Order Function is a function which takes functions as parameters and returns functions as results (Dybvig, 2002). A pseudo-code to demonstrate how Higher-Order Functions are executed is provided below:

Step1: define the first Higher-Order 'Function$_1$' $\boldsymbol{Function_1(x) = x + 9}$;

Step2: define the second Higher-Order 'Function$_2$' $\boldsymbol{Function_2\ (fun, x) = fun\ (x) * fun\ (x)}$

Where the input is 'fun' (i.e. function) and a value 'x' and output is 'fun (x) * fun (x)'

After defining Higher-Order Functions, i.e. Function$_1$ and Function$_2$, users can run a calculation similar to the example below:

$$\boldsymbol{Function_2\ (Function_1, 7) \rightarrow ((7 + 9)*(7 + 9)) \rightarrow 256}$$

Where 'Function1' is loaded into 'Function2' as a parameter.

This algorithm demonstrates that the Higher-Order Function has the ability to take a pre-defined function and pass it as a parameter to other functions. This functionality is used for the development and implementation of the CG function, which can accept other function-based layers as parameters and then process them using other functions. This was discussed in detail in Section 3.3.1.

CG functions, which are implemented using Higher-Order Functions, have three main advantages in geo-processing. A CG function can directly produce the final result of a mathematical computation or a geo-processing model; hence the impact of intermediary-step outputs, such as round-off errors, data conversion, and error propagation, can be reduced in a CG computation. Both symbolic computation and numerical computation can be applied in CG functions in order to improve data quality. Finally, computer memory, which is used to store and process intermediary-step results, can be also saved using CG functions.

4.3.2 Recursive Algorithms

The concept of 'Recursive Algorithms' is also used in the CG approach, as these algorithms further enable the implementation of Higher-Order Functions. In principle, a Recursive Algorithm calls itself repeatedly until a certain condition is met. Compared to other algorithms, e.g. Iterative Algorithms, Recursive Algorithms are simpler to apply as they provide a natural way of thinking about the problem. Niklaus (1976) noted that the power of recursion lies in the possibility of defining an infinite set of objects by using a finite statement. Thus, an infinite number of computations can be defined by a finite recursive program, even if it contains no explicit repetitions.

In data processing users can use a Recursive Algorithm to implement a recursive function or a data structure. One popular example of such a recursive function is the algorithm for calculating the 'nth' Fibonacci number for a given number 'n'. Fibonacci numbers include an infinite sequence of integers, whereby each new number is the sum of the two previous numbers (e.g. 0, 1, 1, 2, 3, 5, 8, 13, 21,…). Recursive Algorithms are also widely used in geometric analysis and an example of this context is given in Figure 4-6, which illustrates the Sierpinski triangle, a confined recursion of triangles that form a geometric lattice. The first Sierpinski triangle was described by the Polish mathematician Waclaw Sierpinski in 1915 and the entire Sierpinski triangle is characterised by its fractal or self-similar character. Rothemund introduced a basic principle for constructing a Sierpinski triangle, with a large triangle consisting of three smaller triangles, and each of them consisting of a further three smaller and black triangles. This process is repeated recursively until the final Sierpinski triangle is built.

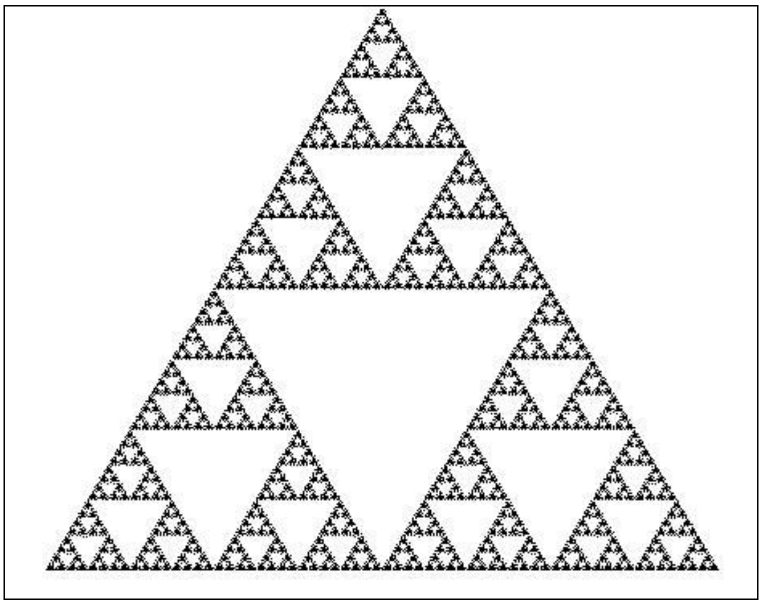


Figure 4- 6 The Sierpinski triangle (after Weisstein, 2013).

In the next section the concept of Lazy Evaluation is discussed, which is used in this research thesis in order to run CG functions using a specific sequence of execution, i.e. the priority-based computation strategy.

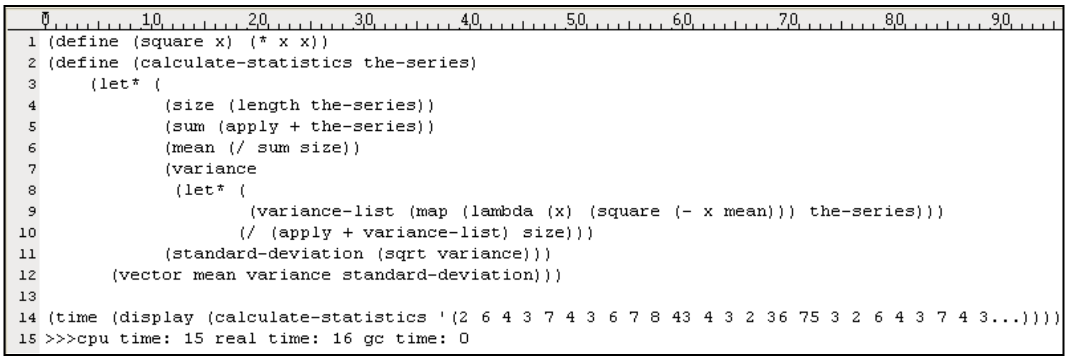
4.3.3 Lazy Evaluation

In computer science, there are two common strategies that can be used in order to execute functions; the Eager Evaluation and Lazy Evaluation strategies. Eager Evaluation is the most commonly used strategy and is applied by various popular programming languages, such as C and Java. In this evaluation strategy a function is executed once it bonds to a variable, while a Lazy Evaluation offers an alternative way that can be used for the calculation of functions. In the Lazy Evaluation strategy functions are only executed when the calculation needs them. As memory and time efficiency issues are considered in the CG approach, the Lazy Evaluation strategy is used. Lazy Evaluation enables the suspending of function-based layers and calculating them via a specific sequence.

The use of Lazy Evaluation for the manipulation and execution of function-based layers in the CG approach has two main advantages: Lazy Evaluation executes a function only when it is necessary and it never performs the same step twice. To illustrate these advantages two examples are provided below, which compare calculating the mean, variance and standard deviation of a list of numbers, using the Eager and Lazy

Evaluation strategies. The algorithms are shown in Figure 4-7 and Figure 4-8, are in Scheme and furthermore, they implement the Higher-Order Function concept.

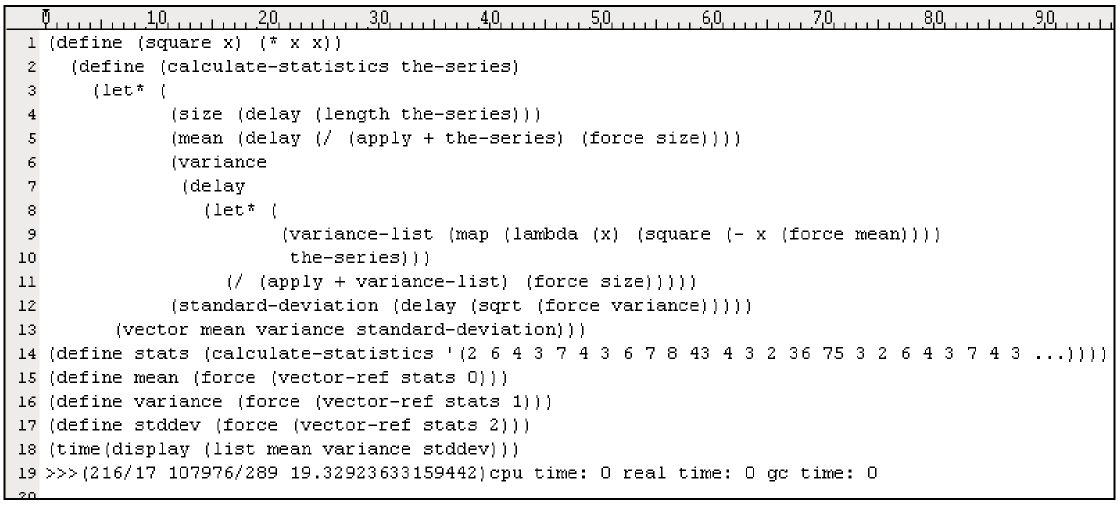
Figure 4-7 demonstrates the Eager Evaluation strategy algorithm. In this example, calculating the standard deviation involves calculating the mean three times and the variance twice, before the actual value for the standard deviation can be calculated to give the final result. It should be obvious that this strategy involves considerably more, and possibly useless, computations as opposed to the Lazy Evaluation example illustrated in Figure 4-8.



```
(define (square x) (* x x))
(define (calculate-statistics the-series)
    (let* (
           (size (length the-series))
           (sum (apply + the-series))
           (mean (/ sum size))
           (variance
            (let* (
                   (variance-list (map (lambda (x) (square (- x mean))) the-series)))
                  (/ (apply + variance-list) size)))
           (standard-deviation (sqrt variance)))
        (vector mean variance standard-deviation)))

(time (display (calculate-statistics '(2 6 4 3 7 4 3 6 7 8 43 4 3 2 36 75 3 2 6 4 3 7 4 3...))))
>>>cpu time: 15 real time: 16 gc time: 0
```

Figure 4- 7 Eager Evaluation algorithm for calculating the mean, variance and standard deviation for a set of numbers.

Figure 4-8 provides the Lazy Evaluation algorithm for the same task. As can be seen from Figure 4-8, Lazy Evaluation uses the keyword 'delay', which allows users to delay the evaluation of code until they need a specific value.



```
(define (square x) (* x x))
  (define (calculate-statistics the-series)
    (let* (
           (size (delay (length the-series)))
           (mean (delay (/ (apply + the-series) (force size))))
           (variance
            (delay
              (let* (
                     (variance-list (map (lambda (x) (square (- x (force mean))))
                      the-series)))
                (/ (apply + variance-list) (force size)))))
           (standard-deviation (delay (sqrt (force variance)))))
      (vector mean variance standard-deviation)))
(define stats (calculate-statistics '(2 6 4 3 7 4 3 6 7 8 43 4 3 2 36 75 3 2 6 4 3 7 4 3 ...))))
(define mean (force (vector-ref stats 0)))
(define variance (force (vector-ref stats 1)))
(define stddev (force (vector-ref stats 2)))
(time(display (list mean variance stddev)))
>>>(216/17 107976/289 19.32923633159442)cpu time: 0 real time: 0 gc time: 0
```

Figure 4- 8 Lazy Evaluation algorithm for calculating the mean, variance and standard deviation for a set of numbers.

Figure 4-8 also shows that there are two basic rules in the Lazy Evaluation strategy. First, computation flow is managed in a way that 'nothing happens until it is needed'.

For example, if users request the variance first then this will lead to running and saving the mean value before calculating and saving the variance value. The second rule is that Lazy Evaluation does not duplicate computations. For example, if a user asks for the standard deviation, then the program will use the saved value for the variance to calculate the standard deviation. As a result, these rules may provide an efficient means of data processing.

Mainly due to the previously discussed advantages of Lazy Evaluation, this strategy is used in the CG approach for the development of the CG computation rules, e.g. the CG priority-based computation strategy. For example, a CG function with a higher cost (computation time and computer memory) could be re-ordered in a Lazy Evaluation until to the computation system requires them, thereby improving the computational efficiency.

This section has discussed the major methods applied in the CG approach to implement the CG function and priority-based computation strategy. The next section discusses how these methods can be achieved in a digital computer.

4.4 Implementation Tool and Computational Environment

This section introduces the implementation tools that support the development of the CG approach. Section 4.3.1 discusses the major types of computer programming languages, i.e. imperative and functional programming, which could be potentially used for the development of the CG function-based layers and it is explained why a functional programming language is used herein. Section 4.3.2 introduces Scheme, the programming language that is used here for the development of the CG functions and finally, Section 4.3.3 describes the computational environment for implementing the three case studies.

4.4.1 Programming Paradigms

In this research a computer programming language is needed in order to develop the CG function-based layers and also in order to implement a set of CG computational rules. It should be noted that there are two types of computer programming languages that may be used for this purpose, the so-called imperative and functional programming languages.

Imperative programming uses a programming pattern that executes commands following a specific sequence, e.g. 'First do A, next do B'. Typical examples of imperative programming languages include FORTRAN, Algol, Pascal, Basic, Java, and C. In contrast, functional programming languages are a class of languages that are mainly designed to reflect the mathematical thinking of people rather than following a specific sequence (Goldberg, 1994). Typical examples of functional programming computer languages include Erlang, Haskell, Lisp, ML, Miranda, and Scheme.

There are two main differences between imperative and functional programming languages. First, basic imperative language constructs are imperative statements which are applied in order to change existing values, e.g. x = x + 3; while basic functional language constructs are declarative statements which are used to declare new values, e.g. (function f (int x) {return x + 3}).

Before the second key difference is described, it is necessary to explain the side effects which influence the predictability of the behaviour of a computer programming language. By definition, any function or expression which modifies the state of a computer or which interacts with the outside world is said to have a side effect (Hughes, 1989). Consequently, the execution of a function which is built using an imperative programming language can have side effects, which will affect any future executions of that function or other functions. Functional programming languages avoid these side-effects and make it much easier to understand and predict the behaviour of a program, which is apparently one of the key motivations that led to the development of functional programming languages in the first place (Hudak, 1989).

With the need to utilise High-Order Functions, Recursive Algorithms, and Lazy Evaluation, a functional programming language is more suitable as a basic programming tool for the development of the CG implementation framework and for the development and implementation of the function-based layers and the CG functions which are utilised in the CG approach. Hughes (1989) claimed that two important features of functional languages, including Higher-Order Function and Lazy Evaluation, can contribute significantly to functional modularity, while Fokker (1995) noted that High-Order Functions and Lazy Evaluation are built-in features of functional programming languages, and these features can be flexibly manipulated by users.

The first functional programming language, LISP, was created as a mathematical notation for the IBM 704 computer by the Artificial Intelligence group at the Massachusetts Institute of Technology (Steele, 1990). As one of the earliest high-level programming languages, LISP was designed for symbolic calculations in various domains, e.g. differential and integral calculus, electrical circuit theory, mathematical logic, game playing, and artificial intelligence. Today, the Scheme programming language is one of the most widely known LISP dialects and the next section discusses the Scheme programming language in more detail.

4.4.2 The Scheme Programming Language

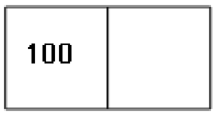
The Scheme programming language has been applied in this research as it provides full functionality to support the execution of Higher-Order Functions and has other capabilities required in this research. Scheme was designed by Guy L. Steele and Gerald J. Sussman in the 1970s and was one of the first programming languages to incorporate first class procedures, as in Lambda Calculus, thereby proving the usefulness of static scope rules and block structure in a dynamically typed language (Dybvig, 2002).

Scheme handles data values quite differently compared to other programming languages. The basic objects manipulated in Scheme are called atoms or objects, and can represent numbers, strings, symbols, and lists, as illustrated in Table 4-12.

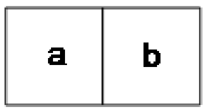
Table 4- 12 Basic objects in the Scheme programming language.

Number	100
String	AAAAA
Symbol	$$$
List (at least two parameters)	(a b)

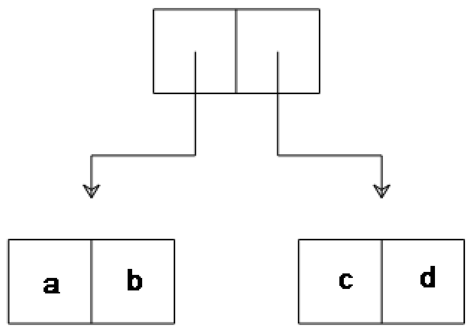
The fundamental data structure in the Scheme programming language is a ‘pair’, which is a special data type which is used to record a pair of attributes, such as (a b) or (x y). For example, ‘*100*’ is represented as:



‘(a b)’ is represented as:



‘((a b) (c d))’ is represented as:



In addition, '(cons)', '(car)', and '(cdr)' are common Scheme operations, which are explained in more detail in Table 4-13.

Table 4- 13 Common operations in Scheme.

Operation Name	**Functionality**	**Example**
(cons)	a pair constructor procedure	Two individual objects a, b can construct a pair (a b)
(car)	returns the first object of a list	(car (a b)) => (a)
(cdr)	returns the second object of a list	(cdr (a b)) => (b)

The Scheme programming language was applied as the main computer programming tool to develop the various CG functions in this research and the next section discusses the benchmark to exam the performance of the exsiting GIS tools.

4.4.3 Benchmark

In order to select the GIS tools that will be used in this thesis to implement the case studies, a benchmark process is designed in this section. Due to the rapid development of computing technology, many GIS tools have been developed, such as ArcGIS, MapInfo and Manifold. However, it was difficult to compare the performance of these GIS tools simply by looking at their specifications; therefore, the benchmark is provided so that this research can evaluate the existing GIS tools for geo-computation.

The comparison process of the benchmark includes four steps. First of all, a set of specific GIS tools is identified for comparison. Second, the implementation strategy and comparison methods are designed in order to evaluate the performance of the selected GIS tools, especially as regards data quality. Third, the initial data are gathered for implementation of the benchmark. Finally, we discuss the result of the benchmark process and provide a guide for the CG development approach.

4.4.3.1 Scope of benchmark

This section discusses the GIS tools and function which are used for the benchmark. Four GIS tools are used (Table 4-14). ArcGIS, MapInfo and Manifold are used for this purpose, as they are commercial GIS software packages, which are widely used by various private and public companies for spatial analysis purposes. R, which is an open-source statistical package with spatial analysis capabilities, is also used to validate the computation performance in the benchmark.

The computer programmer language Python is applied in this section to produce the reference data. The reference layer plays an important role in the benchmark, as the various results are compared with the reference layer in order to validate the data quality obtained using the four GIS tools.

Table 4- 14 GIS tools used for evaluating findings.

GIS tools	Description
ArcGIS	A desktop GIS software developed by ESRI. There are three product levels in ArcGIS's licences, which include ArcReader (basic level), ArcView (middle level), and ArcInfo (top level). ArcGIS was developed using an object-orientation approach for storing and operating spatial features and basic information. Currently, ArcGIS includes several integrated applications, such as ArcMap, ArcCatalog, ArcToolbox, ArcSence, and ArcGlobe.
MapInfo	MapInfo was the first desktop GIS, developed in 1986 with the initial aim of creating an easy-to-use GIS software. Its major characteristics include: (a) good support for the Microsoft operating system – Microsoft Excel®, Microsoft Access® or database data which can be directly opened in MapInfo; (b) MapInfo collaborated with Oracle Corporation to develop the original spatial database, therefore, Oracle® data can be easily accessed and viewed in MapInfo.
Manifold	A low-cost GIS commercial software product.
R (R Project for	R provides an open-source environment for implementing

Statistical Computing)	many spatial analysis functions and it is assumed that more care was paid to its implementation to ensure that it resembles the basic equation.

The IDW function is selected in the benchmark to test the performance of the GIS tools. This function is a commonly used spatial interpolation method, and it can be used to assign values to unknown points by using values from a scattered set of known points (Hengl 2009). However, the assumed value has data uncertainties which could impact on the data quality of outputs. Therefore, the IDW function is selected in the benchmark to compare the data quality of outputs which are produced from the selected GIS tools.

The IDW algorithm is displayed in Appendix D, which is used in Python and CG approach to implement the IDW function. The next section introduces the implementation strategy and the comparison methods used.

4.4.3.2 Implementation Strategy and Comparison Methods

In the benchmark process, the IDW function was implemented using the CG approach, as well as the traditional geo-processing approach, by using the following GIS tools and computer programming language: ArcGIS, MapInfo, Manifold, R, and Python.

Figure 4-9 illustrates the three major steps that were undertaken for the IDW implementation. As can be seen from Figure 4-9, in the first step the points are selected from the raw LiDAR data, and then the selected points are used to produce a sample dataset, which includes 80% of the selected data. This sample dataset is to be used as input data for the IDW function implementation to examine the impact of data quality issues.

The second step mainly focuses on the generation of the sample layer by using ArcGIS, MapInfo, Manifold, R, and the CG approach. The sample layer is the layer that is produced after the IDW implementation and includes the interpolated values. Since five GIS tools are used to apply the various IDW functions, the interpolated values in IDW outputs may differ, and thus, as explained in the following sections, the results of the various IDW implementations are further validated.

Python is used to create a reference layer for comparison. Specifically, Python is applied to implement the same IDW algorithm, which is displayed in Appendix D, to produce the reference layer. The reference layer plays an important role in the third step of the proposed implementation strategy, as the various IDW results are compared with the reference layer in order to validate the data quality of the various IDW implementations. It should be noted that all the IDW results use a one-metre grid size to generate the various interpolated surfaces.

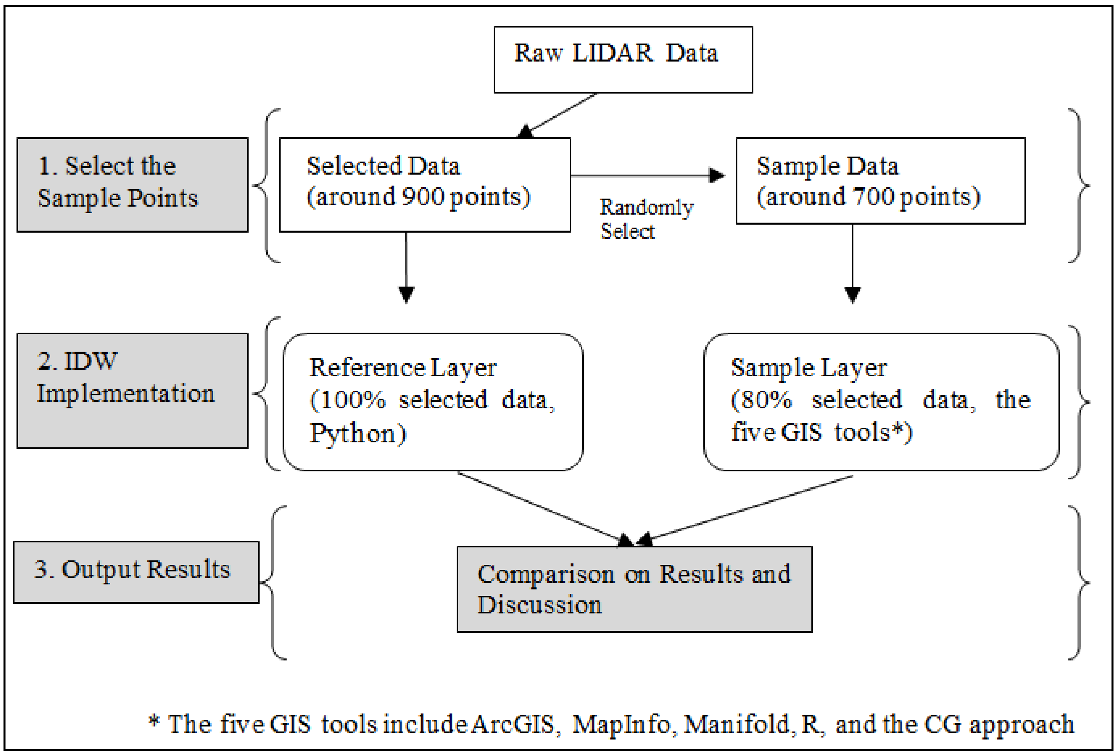

Raw LIDAR Data
1. Select the Sample Points
Selected Data (around 900 points)
Randomly Select
Sample Data (around 700 points)
2. IDW Implementation
Reference Layer (100% selected data, Python)
Sample Layer (80% selected data, the five GIS tools*)
3. Output Results
Comparison on Results and Discussion
* The five GIS tools include ArcGIS, MapInfo, Manifold, R, and the CG approach

Figure 4- 9 IDW implementation steps.

Finally, in order to validate the data quality of GIS tools and the CG approach, two methods are used here to validate the IDW outputs; the ‘Raster Algebra (subtract)’ and ‘Statistical Analysis’ methods. Although these methods and the results are extensively discussed in the next sections, it should be briefly noted that the ‘Raster Algebra’ method can be used to compare the difference of input rasters based on a mathematical function. Subsequently, statistical analysis further enables the validation of the IDW results using their actual numerical values and statistical methods.

The next section introduces the initial data for the benchmark.

4.4.3.3 The Initial Data

Input data for the implementation of the IDW function are the elevation values of point data (i.e. Z value). In the benchmark process, the initial data are manipulated using two different datasets, selected data and sample data.

Selected Data

The primary dataset of this research involves raw LiDAR points, which include a group of points with X, Y, and Z values. Figure 4-10 illustrates that a total of 910 LiDAR points were selected from the dataset of raw LiDAR points, as well as the geographical location (i.e. around 2,000 square metres) and the topographical features within the study area (shown by the yellow rectangle in the Bing Maps satellite image in Figure 4-10). The selected dataset includes 910 points which were selected from the original raw LiDAR dataset (i.e. the first group of the LiDAR dataset[1]), and which are used as reference data in the benchmark process to represent the actual observed values. It should be noted that 910 is a smaller amount of points and it used as the start level (i.e. minimum number) of sample points in order to test the accuracy of the new CG function (i.e. IDW function) in this research.

Moreover, the purpose of the selected data is to produce the reference layers, which include the actual observed values and are later used to validate the CG approach and the other GIS tools results.

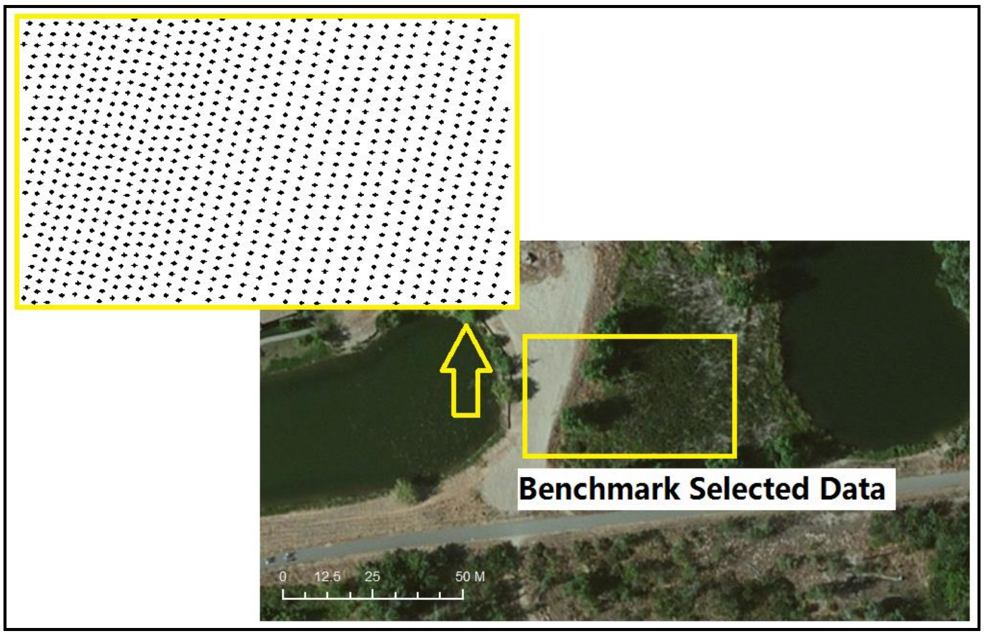


Figure 4- 10 The Selected data for the benchmark process.

[1] Technical information on the first group of raw LiDAR dataset is provided in the Appendix A (Table A.1).

Sample Dataset

In order to examine the IDW functions provided by different GIS software packages, and especially in order to examine the quality of the interpolated values for the areas with unknown elevation values (i.e. the areas where there is no LiDAR point coverage), 80% of the selected points (910 X 0.8 = 722 points) were randomly selected from the selected data.

The next section shows the result of the benchmarking based on the two comparison methods: raster algebra and statistical analysis.

4.4.3.4 Benchmark results and discussion

4.4.3.4.1Raster Algebra

The raster algebra (using the Minus function) method subtracts the value of the second input raster from the value of the first input raster on a cell-by-cell basis. Figure 4-11 illustrates this process. After inputting the 'sample layer' and 'reference layer', the generated 'difference of values' layer shows the change in values in a single grid cell. This method is applied here to understand the difference in grid cells between the actual, observed values (stored in the reference layer) and the interpolated values (stored in the sample layer). Figure 4-12 shows the strategy to compare the various GIS tools and CG results of the raster algebra function (minus) amongst the reference layer and the five sample layers.

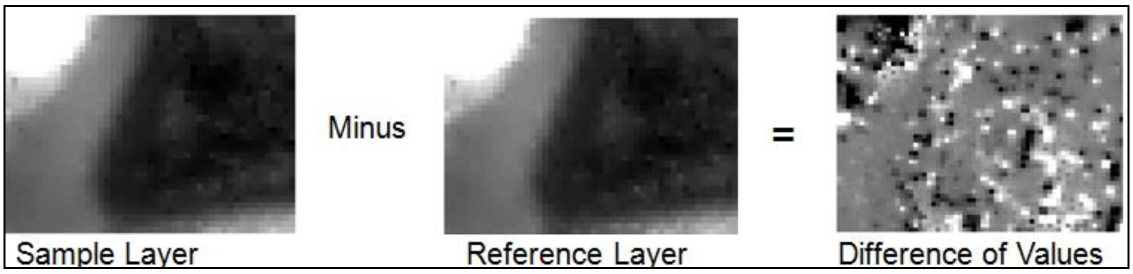


Figure 4- 11 An example of raster math.

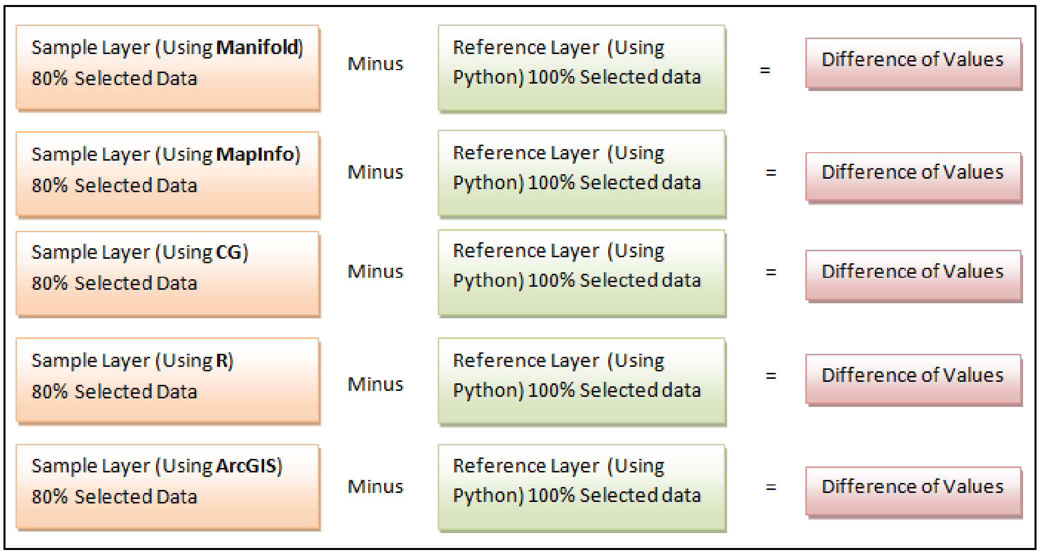

Sample Layer (Using Manifold) 80% Selected Data
Minus
Reference Layer (Using Python) 100% Selected data
=
Difference of Values
Sample Layer (Using MapInfo) 80% Selected Data
Minus
Reference Layer (Using Python) 100% Selected data
=
Difference of Values
Sample Layer (Using CG) 80% Selected Data
Minus
Reference Layer (Using Python) 100% Selected data
=
Difference of Values
Sample Layer (Using R) 80% Selected Data
Minus
Reference Layer (Using Python) 100% Selected data
=
Difference of Values
Sample Layer (Using ArcGIS) 80% Selected Data
Minus
Reference Layer (Using Python) 100% Selected data
=
Difference of Values

Figure 4- 12 The strategy to compare the various GIS tools and CG results.

Based on the comparison strategy, Figure 4-13 illustrates the results from raster algebra. In Figure 4-13, the grid values are classified using the ‘natural break’ option, which can be used to classify unevenly distributed data and which divides the data into different groups according to value gaps. For example, the ‘black’ grid cells, where the grid value ranges from -1 to -0.1 and from 0.1 to 1, are defined by the gaps of the classified data, representing the groups with a higher ‘difference of values’.

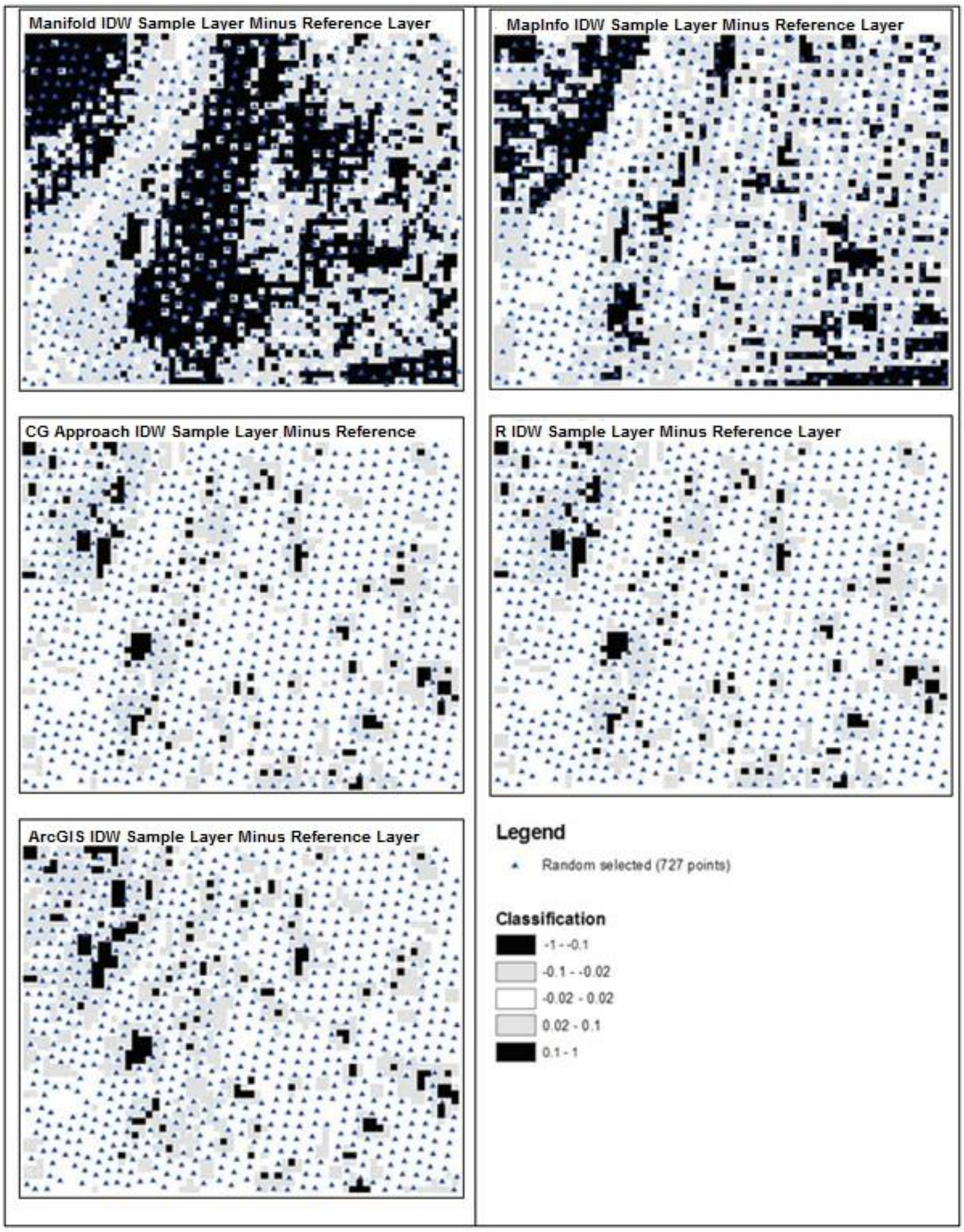

Manifold IDW Sample Layer Minus Reference Layer
MapInfo IDW Sample Layer Minus Reference Layer
CG Approach IDW Sample Layer Minus Reference
R IDW Sample Layer Minus Reference Layer
ArcGIS IDW Sample Layer Minus Reference Layer
Legend
Random selected (727 points)
Classification
-1 - -0.1
-0.1 - -0.02
-0.02 - 0.02
0.02 - 0.1
0.1 - 1

Figure 4- 13 Raster algebra: Comparison of IDW outcomes.

The results of the 'raster algebra (minus)' operation are illustrated in Figure 4-13, and it is noteworthy that the results generated using Manifold and MapInfo have many differences with respect to the reference layer. At the same time the ArcGIS, R and CG results are very similar. Therefore, a mainly descriptive-based statistical analysis was further undertaken in order to compare the ‘raster algebra (minus)’ results in more detail.

4.4.3.4.2 Statistical Analysis

For the purposes of comparison of the differences of ‘reference layer’ and ‘sample layer’, the maximum (max) and minimum (min) and the standard deviation values are used. The maximum and minimum values show the range of significant differences between the sample layer and reference layer, and standard deviation shows the variability or dispersion of the data.

The results are summarised in Table 4-15. In this table, the highest standard deviation value is observed when the Manifold results are compared with the reference layer (StDev=0.182194), while the lowest standard deviation value (StDev=0.046599) is observed in the CG approach and R comparisons with the reference layer. Similarly, the highest differences in the maximum and minimum values are observed in the Manifold comparison with the reference layer (Max=0.4904, Min=-0.4718). These values further confirm that the interpolated values using the CG approach and R have higher precision and less differences with the observed data.

Table 4- 15 Comparison on statistical analysis.

	Standard Deviation	Max	Min
Manifold Sample layer MINUS Reference layer	0.182194	0.4901	-1.5995
MapInfo Sample layer MINUS Reference layer	0.102878	0.8275	-0.6692
CG approach Sample layer MINUS Reference layer	0.046599	0.4896	-0.4471
R Sample layer MINUS Reference layer	0.046599	0.4896	-0.4471
ArcGIS Sample layer MINUS Reference layer	0.05114	0.4904	-0.4718

The next section provides a discussion of the various IDW findings.

4.4.3.4.3 Discussion

Based on the previous analysis, it is clear that the IDW results (i.e. sample layers) of the CG approach and R are exactly the same and are closer to the reference layer. This similarity can be explained on the basis that the same IDW algorithm and parameters were used for both R and CG implementations. However, the identical results improve confidence about the accuracy and correct implementation of the new CG IDW function, which is important for the next steps of the development of the thesis.

Moreover, it is clear that there was variation in the IDW results (sample layers) that were produced using different GIS tools. This is clear from the comparisons of the various sample layers with the reference layer and despite the fact that the same input dataset (sample data) was used for all the IDW implementations. Manifold's IDW function, which is called 'Gravity', generated the most different results, compared to the rest, and possibly the least accurate output. This conclusion is mainly based on Figure 4-13 (top left corner layer), where it can be clearly seen that the black grid cells, which represent the differences between the interpolated and the observed values, cover almost 60% of the study area. Finally, the statistical analysis in Table 4-15 confirms this conclusion, as the Standard Deviation value when Manifold results are compared with the reference layer (StDev = 0.182194) is four times larger than the standard deviation value of the CG results when these are also compared with the reference layer (StDev =0.046599).

MapInfo's IDW function also generated results that were different from the rest of the IDW implementations. This conclusion is based on Figure 4-13 (top right corner layer), where it can be clearly seen that the difference of the 'MapInfo IDW Sample Layer Minus Reference Layer' (black grids) covers almost 30% of the study area. Furthermore, the statistical analysis in Table 4-15 confirms this conclusion, as the standard deviation value when we compare MapInfo's result with the reference layer (StDev = 0.102878) is twice as large as the CG approach's results when also compared with the reference layer (StDev = 0.046599).

MapInfo's results can be explained on the basis of its algorithm for interpolating sample points. This specific feature is explained in Figure 4-14, which is composed of two elements: 'Black Dot' and 'Regular Grid Net'. The 'Black Dot' represents the centroid of the interpolated grid created by the interpolation function, (e.g. IDW). The 'Regular

Grid Net' is a virtual regular vector net generated by using the geographical extent (bounding rectangle of study area) and resolution of the interpolation, (e.g. 1 metre grid size). Figure 4-14 (a) shows that the interpolated grid (illustrated by the 'Black Dot') is located within each grid of 'Regular Grid Net' in ArcGIS, while in Figure 4-14 (b), it can be seen that the interpolated grid is located at the cross point of 'Regular Grid Net' in MapInfo.

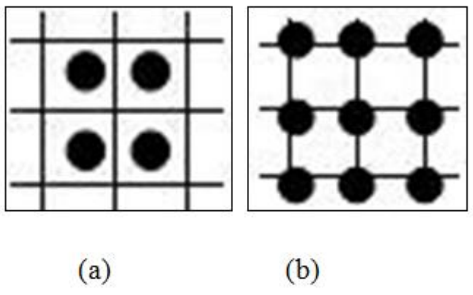


Figure 4- 14 The geometry (centroid) of the interpolated grid (a. in ArcGIS; b. in MapInfo).

Figure 4-15 shows how this strategy works on the same sample data using ArcGIS and MapInfo: the same sample points result in different IDW output images. We also note that because commercial GIS tools are provided as a 'black box' to their users, it is very hard to identify these differences, and thus investigative work is required in order to infer what their algorithm has implemented.

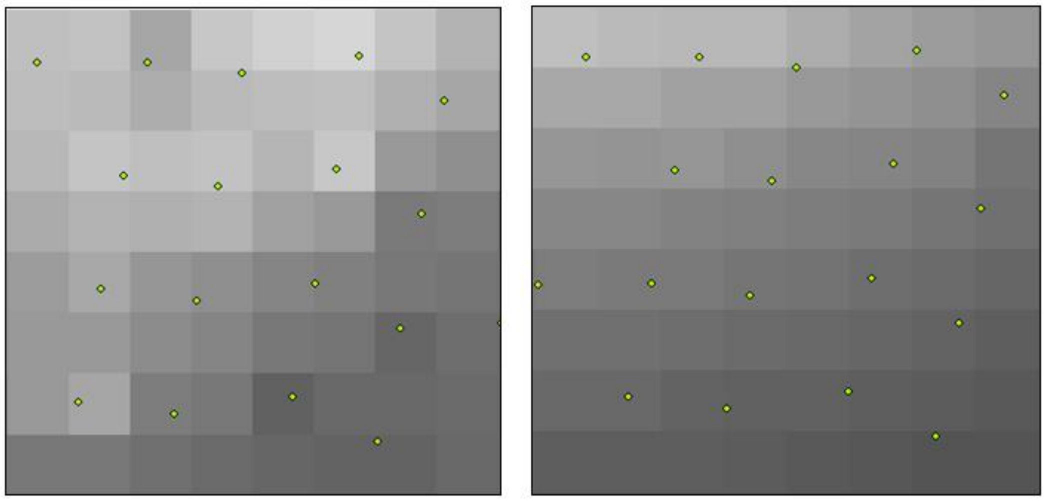


Figure 4- 15 Examples of interpolating sample points in ArcGIS and MapInfo.

Compared with Manifold and MapInfo, ArcGIS, the CG approach and R provided the most accurate results. In Figure 4-13, it is difficult to identify the differences between the results between these three GIS tools. However, based on the statistical analysis, we observe that the CG approach and R are slightly more accurate than ArcGIS. For instance, Table 4-15 reveals that the Standard Deviation value from the comparison of the CG approach and R results and the reference layer (StDev = 0.046599) is 20% better than the comparison of the ArcGIS result and the reference layer (StDev = 0.05114).

In conclusion, this benchmark process has demonstrated the performance of the selected GIS tools. Specifically, the results of the different IDW implementations were compared and it was found that the CG IDW implementation results were very similar to the IDW implementation results using R, while the interpolated results using the CG approach and R had the smallest standard deviation value. Thus, the CG approach has many potential advantages, especially when dealing with simple raster data (e.g. the interpolated values using the CG IDW function are closer to the observed values). Moreover, ArcGIS provides a better performance than other commercial GIS tools (e.g. MapInfo and Manifold) based on the 'raster algebra (subtract)' and 'statistical analysis' comparison results. Therefore, the CG approach and ArcGIS are used as the two major GIS tools in the following case studies.

Moreover, it should be noted that R will be not used in the case studies, although it produced the same output with the CG approach in the benchmark. That is because R provides fewer spatial analysis functions, compared with ArcGIS and MapInfo.

The next section discusses the computational environment for the case studies.

4.4.4 Computational Environment

This section introduces the computational environment for the three case studies, including both the traditional geo-processing approach (Section 4.4.3.1) and the CG approach (Section 4.4.3.2). The computational environment is defined as a summary of the features of the software packages and the computer for implementing the three case studies in this thesis.

4.4.4.1 The Traditional Geo-processing Approach

There are two GIS tools that were used in this thesis to implement the case studies using the traditional geo-processing approach: ArcGIS Version 9.2 (Figure 4-16) and MapInfo

Version 8.5.1 (Figure 4-17). ArcGIS and MapInfo are common commercial GIS software packages, which are widely used for spatial analysis purposes.

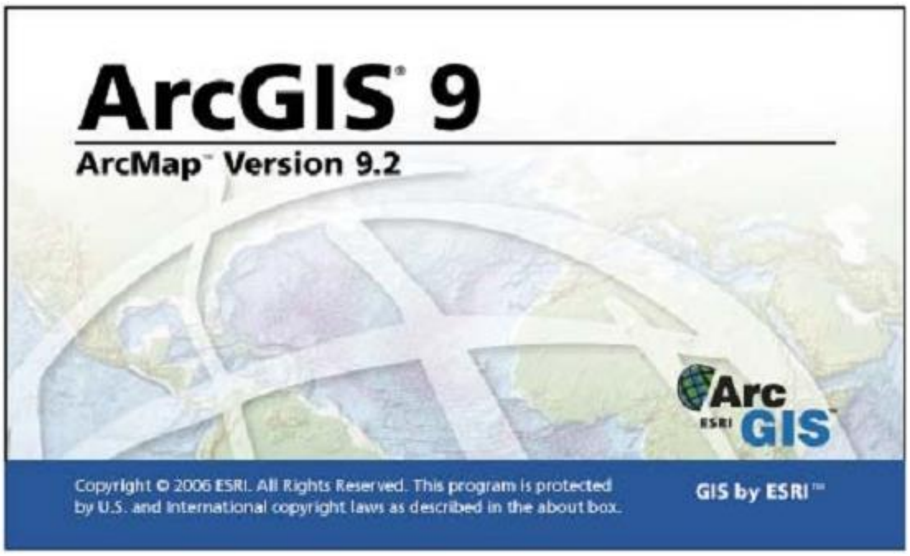
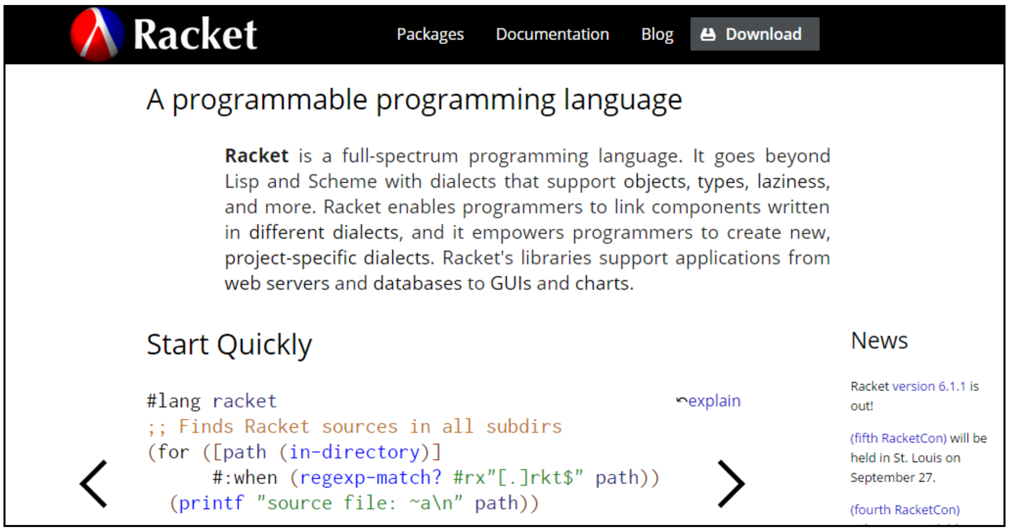

ArcGIS® 9
ArcMap™ Version 9.2
Arc GIS
ESRI
Copyright © 2006 ESRI. All Rights Reserved. This program is protected by U.S. and International copyright laws as described in the about box.
GIS by ESRI™

Figure 4- 16 ArcGIS 9.2 software.

Figure 4- 17 MapInfo 8.5.1 software.

4.4.4.2 The CG Approach

As described in the previous section, the Scheme programming language was used to create the computer programs that perform the computations in the CG approach. In this research, the Scheme programming language was implemented using a software tool, named Racket Version 6.1.0 (Figure 4-18). Racket, formerly named PLT Scheme, is a full-spectrum programming language in the Lisp/Scheme family. In fact, it goes beyond the computer programming of Lisp and Scheme, through dialects that support objects, types, laziness, and more. One of Racket’s design goals is to serve as a platform for language creation, design, and implementation (Figure 4-19).



A programmable programming language

Racket is a full-spectrum programming language. It goes beyond Lisp and Scheme with dialects that support objects, types, laziness, and more. Racket enables programmers to link components written in different dialects, and it empowers programmers to create new, project-specific dialects. Racket's libraries support applications from web servers and databases to GUIs and charts.

Start Quickly

```
#lang racket
;; Finds Racket sources in all subdirs
(for ([path (in-directory)]
        #:when (regexp-match? #rx"[.]rkt$" path))
  (printf "source file: ~a\n" path))
```

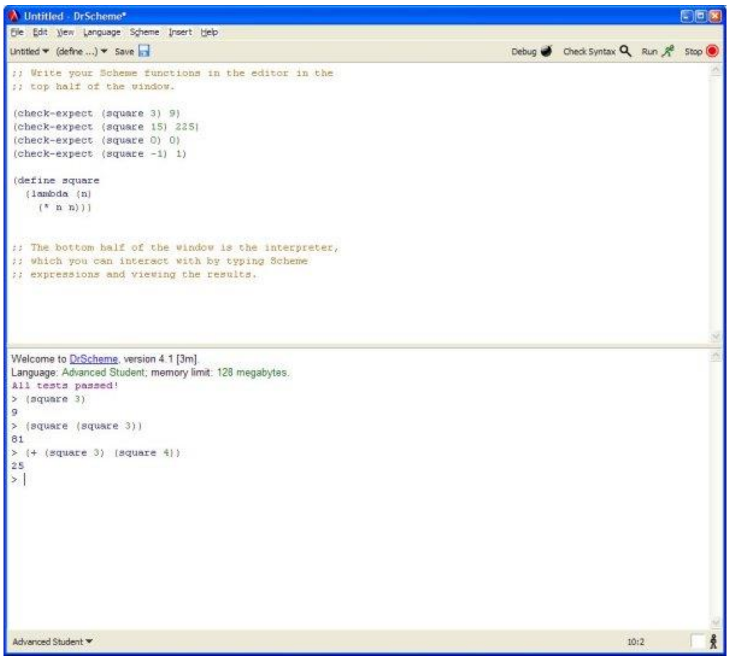
News

Racket version 6.1.1 is out!

(fifth RacketCon) will be held in St. Louis on September 27.

(fourth RacketCon)

Figure 4- 18 Racket main webpage.

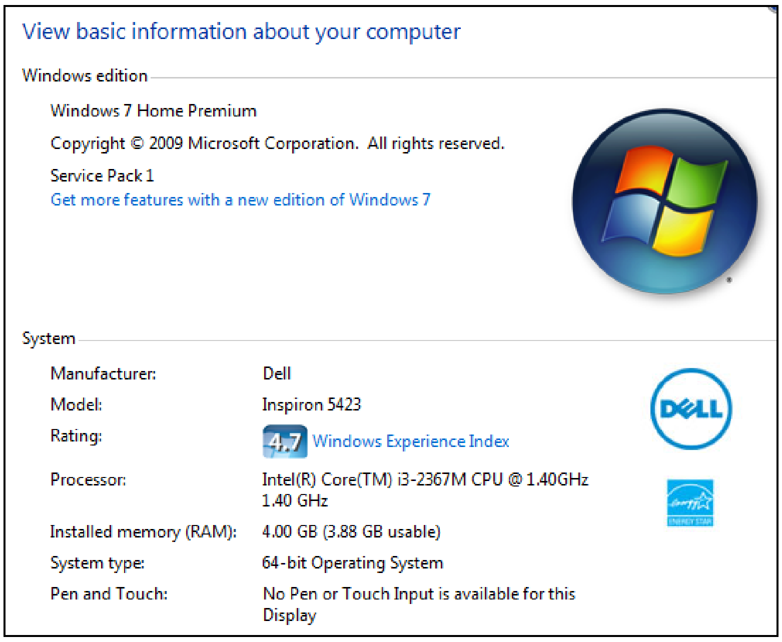

Untitled - DrScheme*
File Edit View Language Scheme Insert Help
Untitled (define ...) Save
Debug
Check Syntax
Run
Stop
Advanced Student
10:2

```
;; Write your Scheme functions in the editor in the
;; top half of the window.

(check-expect (square 3) 9)
(check-expect (square 15) 225)
(check-expect (square 0) 0)
(check-expect (square -1) 1)

(define square
  (lambda (n)
    (* n n)))


;; The bottom half of the window is the interpreter,
;; which you can interact with by typing Scheme
;; expressions and viewing the results.
```

```
Welcome to DrScheme, version 4.1 [3m].
Language: Advanced Student; memory limit: 128 megabytes.
All tests passed!
> (square 3)
9
> (square (square 3))
81
> (+ (square 3) (square 4))
25
> |
```

Figure 4- 19 The Racket interface.

Finally, it should be noted that all three computer programming tools, including ArcGIS, MapInfo, and Racket, were run on the same computer. A full description of the computer is provided in Figure 4-20. In brief, it is equipped with an i3-2367M @ 1.40 GHz CPU and Windows 7 operating system.


View basic information about your computer

Windows edition

Windows 7 Home Premium

Copyright © 2009 Microsoft Corporation. All rights reserved.

Service Pack 1

Get more features with a new edition of Windows 7

System

Manufacturer:	Dell
Model:	Inspiron 5423
Rating:	4.7 Windows Experience Index
Processor:	Intel(R) Core(TM) i3-2367M CPU @ 1.40GHz 1.40 GHz
Installed memory (RAM):	4.00 GB (3.88 GB usable)
System type:	64-bit Operating System
Pen and Touch:	No Pen or Touch Input is available for this Display

Figure 4- 20 Description of the testing computer.

The next section presents and discusses the selected data for the case studies.

4.5 Case Study Data Selection

In all three case studies and their subsequent models, raw LiDAR points were used as the primary input data type in order to produce new elevation or slope data. Two groups of LiDAR datasets were downloaded from the INSIDE IDAHO (Interactive Numeric and Spatial Information Data Engine) website (http://inside.uidaho.edu/popular_data.html) and these were separately captured in 2007 and 2008.[2] The webpage interface used to access the data is illustrated in Figure 4-21, where the LiDAR data access is highlighted by a red box. The Projected Coordinate System of the selected LiDAR data is NAD_1983_NSRS2007_UTM_Zone_11N.

2 Full details of the downloaded LiDAR datasets are provided in Appendix A.

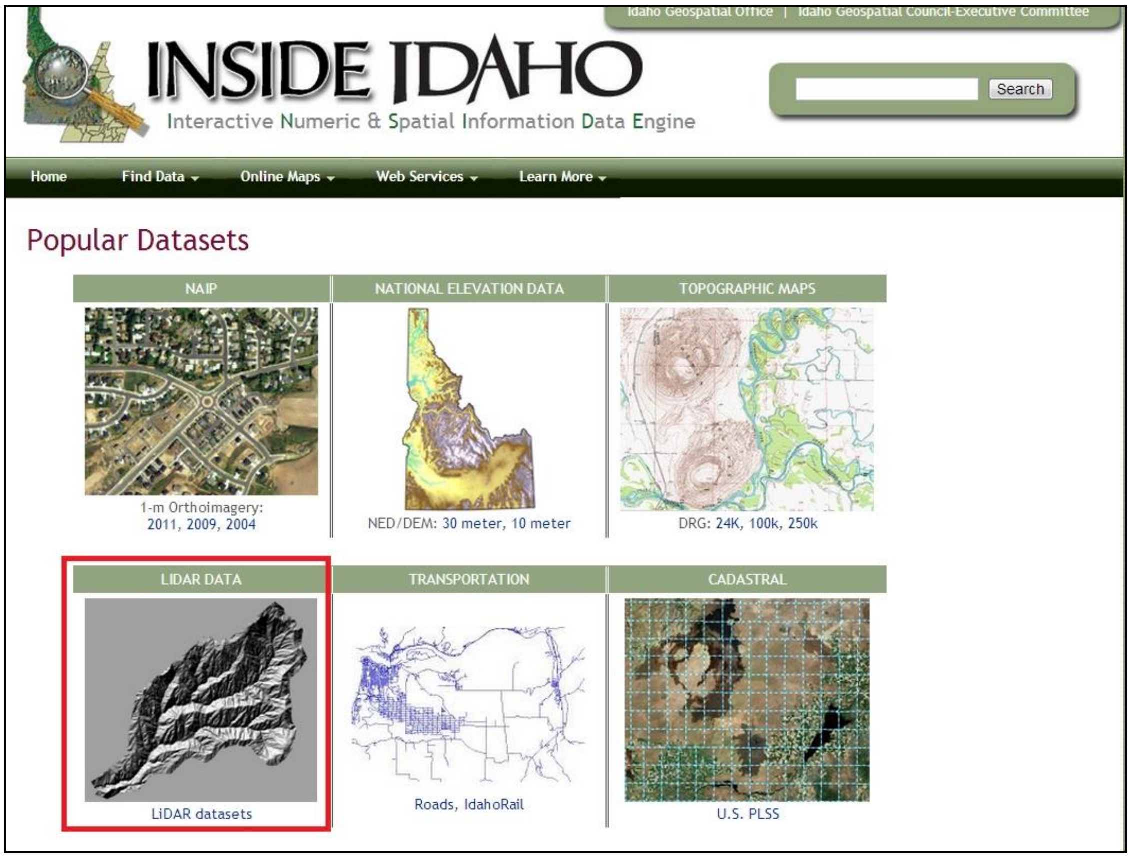
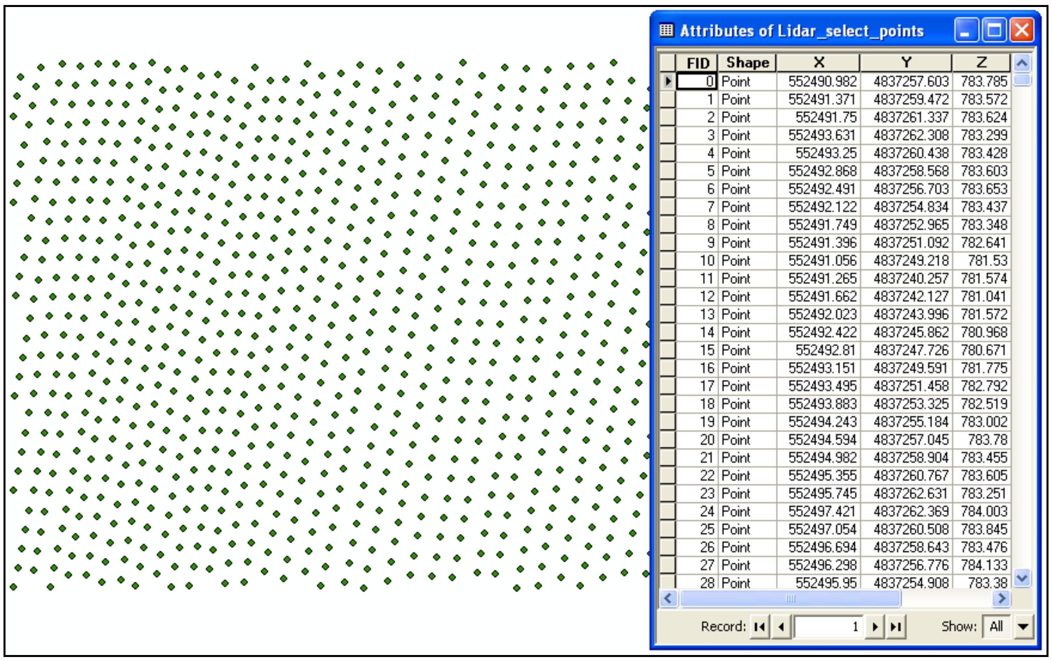


Figure 4- 21 Source of the selected LiDAR data.

LiDAR data are cheaper and thus provide a more efficient way for creating digital elevation data, especially when automated processing methods are used to generate elevation data. An example of raw LiDAR data are illustrated in Figure 4-22 and Figure 4-23.



FID	Shape	X	Y	Z
0	Point	552490.982	4837257.603	783.785
1	Point	552491.371	4837259.472	783.572
2	Point	552491.75	4837261.337	783.624
3	Point	552493.631	4837262.308	783.299
4	Point	552493.25	4837260.438	783.428
5	Point	552492.868	4837258.568	783.603
6	Point	552492.491	4837256.703	783.653
7	Point	552492.122	4837254.834	783.437
8	Point	552491.749	4837252.965	783.348
9	Point	552491.396	4837251.092	782.641
10	Point	552491.056	4837249.218	781.53
11	Point	552491.265	4837240.257	781.574
12	Point	552491.662	4837242.127	781.041
13	Point	552492.023	4837243.996	781.572
14	Point	552492.422	4837245.862	780.968
15	Point	552492.81	4837247.726	780.671
16	Point	552493.151	4837249.591	781.775
17	Point	552493.495	4837251.458	782.792
18	Point	552493.883	4837253.325	782.519
19	Point	552494.243	4837255.184	783.002
20	Point	552494.594	4837257.045	783.78
21	Point	552494.982	4837258.904	783.455
22	Point	552495.355	4837260.767	783.605
23	Point	552495.745	4837262.631	783.251
24	Point	552497.421	4837262.369	784.003
25	Point	552497.054	4837260.508	783.845
26	Point	552496.694	4837258.643	783.476
27	Point	552496.298	4837256.776	784.133
28	Point	552495.95	4837254.908	783.38

Figure 4- 22 Visualisation of LiDAR sample points and their attributed values (X, Y, and Z) in 2D.

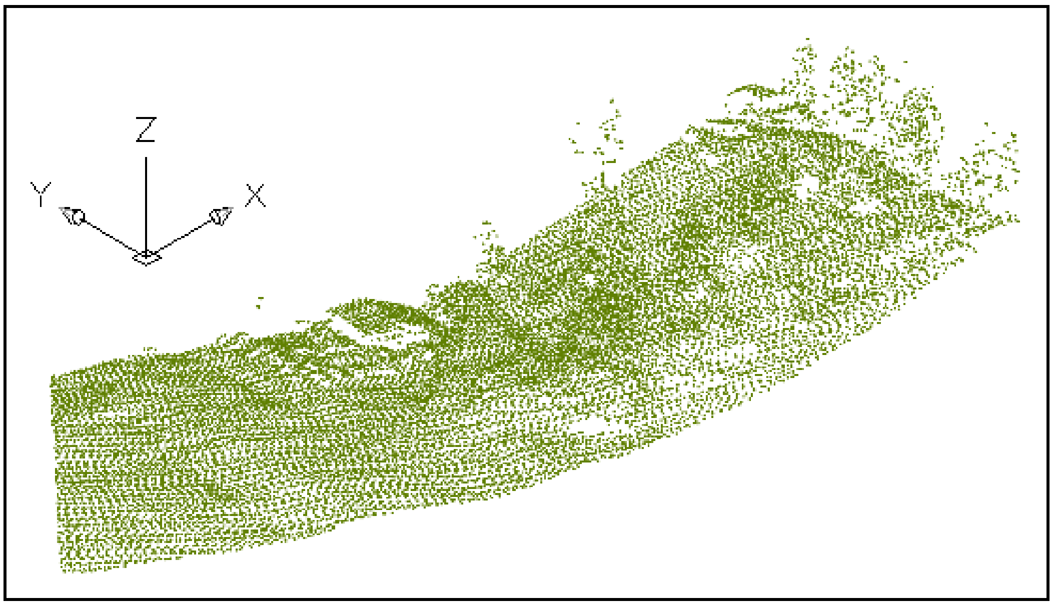


Figure 4- 23 Visualisation of LiDAR sample points in 3D.

In this research, LiDAR data are used for three purposes: first, as the input for the interpolation functions that generate the DEM surface that can be used to represent a continuous surface; second, to produce additional data, such as deriving the slope value from the DEM; and finally, LiDAR data are used for their integration with other map layers for spatial analysis purposes, e.g. combining a DEM with land use for the location analysis model used in the third case study.

It should be noted that the amount of selected LiDAR points and the size of the study area is increased gradually across the case studies in order to validate the accuracy, capability, and efficiency, i.e. computation time, of the CG approach and the newly developed CG functions. Figure 4-24 shows the specific details of the selected LiDAR points and the size of the study area. This figure also highlights that case study 1 used a minimum set of LiDAR points and had the smallest study area, then these increased steadily in the following case studies, until finally in case study 3 one million LiDAR points (1000 times larger than the case study 1's) are utilised and the study area is around 50,000 square metres, 12.5 times larger than in case study 1.

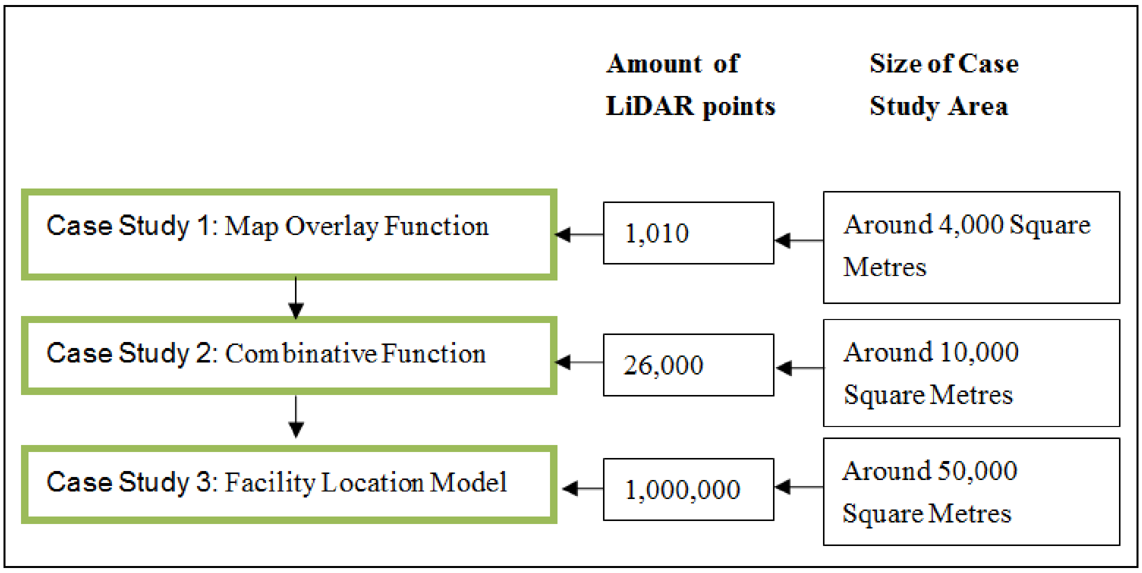

Amount of LiDAR points
Size of Case Study Area
Case Study 1: Map Overlay Function
1,010
Around 4,000 Square Metres
Case Study 2: Combinative Function
26,000
Around 10,000 Square Metres
Case Study 3: Facility Location Model
1,000,000
Around 50,000 Square Metres

Figure 4- 24 Number of selected LiDAR points and size of the study area in the three case studies.

4.6 Chapter Summary

The three case studies were introduced that are used in this research to implement the CG approach by applying simple and then progressing to more complex functions and models. These case studies allow the practical implementation of the CG approach and also enable the evaluation of the conceptual CG model that was introduced in Chapter 3. The case studies involve the implementation of the Map Overlay function (case study 1), a CG function (case study 2) and a complex geo-processing model for Facility Location (case study 3).

This chapter has also described a set of methods that have been used to implement the CG computations. A High-Order Function provides a basic way to implement the CG functions, while Recursive Algorithms were also discussed as they further enable the implementation of Higher-Order Functions. Lazy Evaluation provides a method to control the computation sequence and avoid duplicate computations.

This chapter has introduced functional and imperative programming languages and it was explained why a functional programming language is the most suitable for the implementation of the CG approach. Scheme, a functional programming language was reviewed, as it is the basic programming language used in this research thesis for the development of the function-based layers and CG functions. Finally, the computational environment and selected data were also described.

The three case studies are discussed separately in the following chapters, starting with the first case study which is discussed in Chapter 5.

5 Comparing a Raster Overlay Function between Map Algebra and Combinative Geo-processing

5.1 Introduction

The first case study concerned with the development and implementation of a GIS overlay function for the integration of two raster layers with different grid sizes, using the CG approach and the traditional geo-processing approach (i.e. Map Algebra). Section 5.2 starts with a discussion of the 'Raster Overlay with Raster' function and Section 5.3 explains how the 'Raster Overlay with Raster' function is implemented using Map Algebra, which is commonly used within the context of traditional geo-processing in order to overlay more than one raster data layers. This section also discusses the 'Raster Overlay with Raster' function within the context of the CG approach; its similarities and differences from traditional geo-processing.

Section 5.4 describes the datasets and in specific the reference and sample data that are used in this case study. These datasets are used to create the map layers, which are then integrated using the 'Raster Overlay with Raster' function. The implementation strategy of the 'Raster Overlay with Raster' function is described in Section 5.5 and Section 5.6 presents the results. Section 5.7 provides a more detailed comparison of the Map Algebra and the CG approach results and Section 5.8 discusses their differences. Finally, Section 5.9 provides a summary and concludes with the main issues that are discussed in this chapter.

5.2 Case Study 1: 'Raster Overlay Function Review'

The first case study provides an investigation of the CG approach development on the multi-layers operations, such as overlay different GIS layers together. Amongst the several available overlay functions provided by various GIS software packages, the 'Raster Overlay with Raster' function is of high significance. Raster data are widely used for capturing and representing real world phenomena, and thus 'Raster Overlay with Raster' function is one of the most popular spatial analysis methods that it is used for the integration of two or more raster layers in order to understand complex spatial problems.

Figure 5-1 illustrates an example of the 'Raster Overlay with Raster' function, using the addition operation, and which in this case is used within the context of site suitability analysis. As it can be seen from Figure 5-1 three raster layers (i.e. steep slopes, soils, and vegetation) are ranked for their suitability on a scale from one to seven. When the layers are added together each cell is ranked on a scale from three to 21 to produce the map shown at the bottom of Figure 5-1. The pixels with the largest values (i.e. closer to 21) represent the areas which are more suitable for the development of new facilities within the area of analysis.

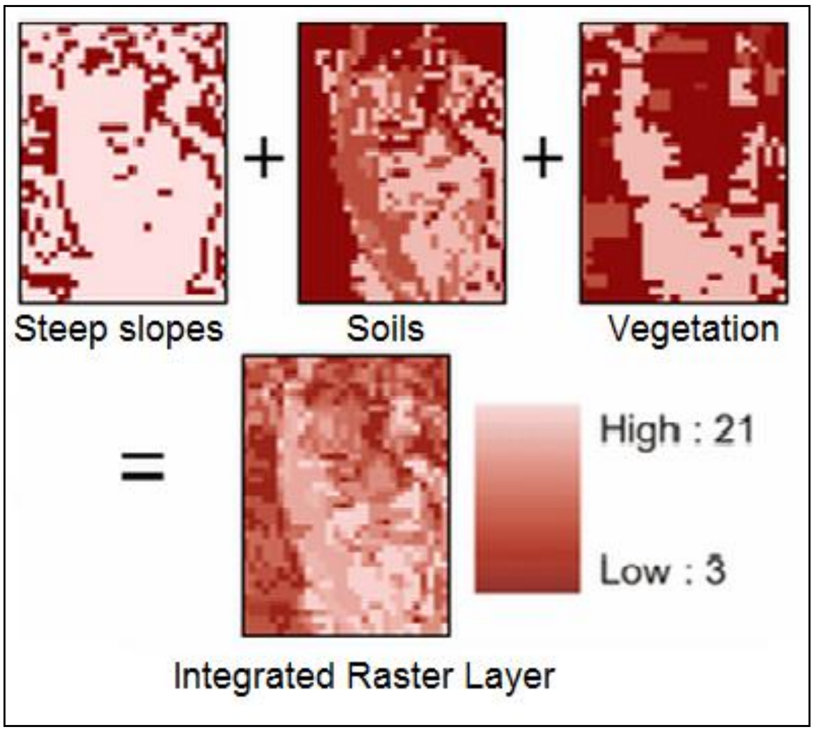


Figure 5-1 Example of 'Raster Overlay with Raster' function ('Overlay Analysis', ESRI ArcGIS Resource Centre Online, 2008).

Another example of the 'Raster Overlay with Raster' function is illustrated in Figure 5-2, which aims to understand the influences of topographical features (e.g. elevation and slope) on the locations of resident activities. This model is developed from the original example of Map Stack, which is used to explain how a group of raster data could be organised and combined through a raster layer overlay operation (Madden 2009). As it can be seen from Figure 5-2, the input datasets include a set of activity sampling points and raw LiDAR points. The activity sampling points represent the most popular locations of human activity in the study area, and the raw LiDAR points are a group of points which record the elevation values. In this model, the activity sampling points are processed by using IDW_1 function (using 1.5 metres resolution) to produce the activity map (Grid) showing the distribution of activity evens in the entire study area. The raw LiDAR points are calculated by using IDW_2, IDW_3 and Slope_1 functions (using one metre resolution) to create the elevation map1 (Grid) and slope map (Grid). The results of processing the raw LiDAR points are used in order to investigate the variation of topographical features in the study area. Finally, the three raster layers, which displayed as activity, elevation and slope in the Map Stack, are integrated together to produce the final output in order to answer the question related to human activity and the topographical features.

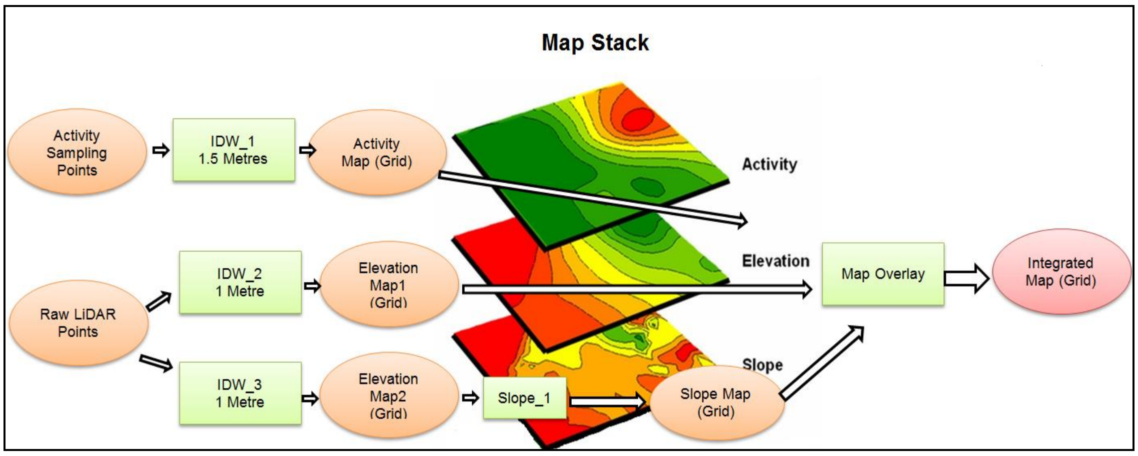


Figure 5-2 Another example of 'Raster Overlay with Raster' function (After Madden 2009).

To better understand how the 'Raster Overlay with Raster' function can be implemented within the CG approach, the next section describes the geo-processing model of Case Study 1 that utilises the function and which is similar to the geo-processing models that discussed in the examples.

5.2.1 Geo-processing Model (Case Study 1)

Figure 5-3 illustrates this case study's geo-processing model, which as it can be seen includes two IDW functions (i.e. 'IDW1' and 'IDW2') that are used to produce two raster layers (i.e. 'Raster Layer1' and 'Raster Layer2') with different grid sizes (i.e. one metre and 1.5 metres respectively). The two raster layers are combined to produce the final integrated map layer (i.e. 'Final Result'). Although the geo-processing model that it applied in this chapter is a simple model - as it only uses two layers and one 'plus' operation, while spatial problems may involve the integration of more than two layers, which may result in more complex geo-processing models - this case study still provides the foundations for improving our understanding with respect to the development, implementation and use of the 'Raster Overlay with Raster' function within the CG approach context.

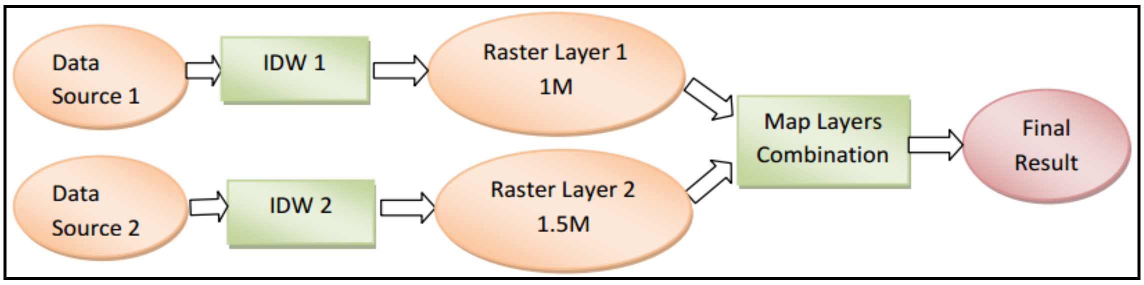


Figure 5-3 Case study 1: Geo-processing model ('Raster Overlay with Raster' Function).

The next section explains the implementation of the 'Raster Overlay with Raster' function using Map Algebra and the CG approach.

5.3 Methodology: 'Raster Overlay with Raster' Function Implementations

This section discusses separately the different 'Raster Overlay with Raster' function implementations in traditional geo-processing (Section 5.3.1) and in the CG approach (Section 5.3.2), which purpose is to compare and validate the accuracy of new raster overlay CG function between the CG approach and the traditional approach.

5.3.1 ' Raster Overlay with Raster' Function Implementation in The Traditional Geo-processing Approach: Map Algebra

Within the context of traditional geo-processing, Map Algebra is a popular computation method for the utilisation of the 'Raster Overlay with Raster' function to integrate raster data layers. It was originally introduced by Tomlin (1990) as the process of combining co-registered raster layers of identical size and resolution.

Map Algebra provides the vocabulary and conceptual framework for combining map data in order to produce new maps (Tomlin 1990). Map Algebra's common operations include arithmetical calculations, classification and statistical calculations (De Smith et al., 2007). Arithmetical calculations are based on algebraic operators such as plus, minus and multiply which are used to integrate layers of the same grid size. The classification method provides a tool that can be used to re-code, slice (classify) single input layers, and combine multiple layers using a range of local and focal operators. Finally, a number of statistical tools for grid processing can be used, including focal and zonal statistical calculations.

When Map Algebra is used to integrate various raster layers, all input grids must have identical extent and cell sizes. The selection of the most appropriate grid extent and cell size complicate the process of integrating these various layers as it is further demonstrated by Figure 5-4, which illustrates the workflow for implementing the Map Algebra geo-processing model that it is used in the first case study. As Figure 5-4 shows the input data, which consist of LiDAR points, are loaded into a single GIS function (e.g. IDW1 and IDW2) which is then used to produce two raster layers. These two raster layers can be combined using the Map Algebra function in order to produce the final result. If the raster layers have different resolution, then the 'Resampling' function should be firstly used in order to convert them into an identical grid size before they can be integrated using Map Algebra.

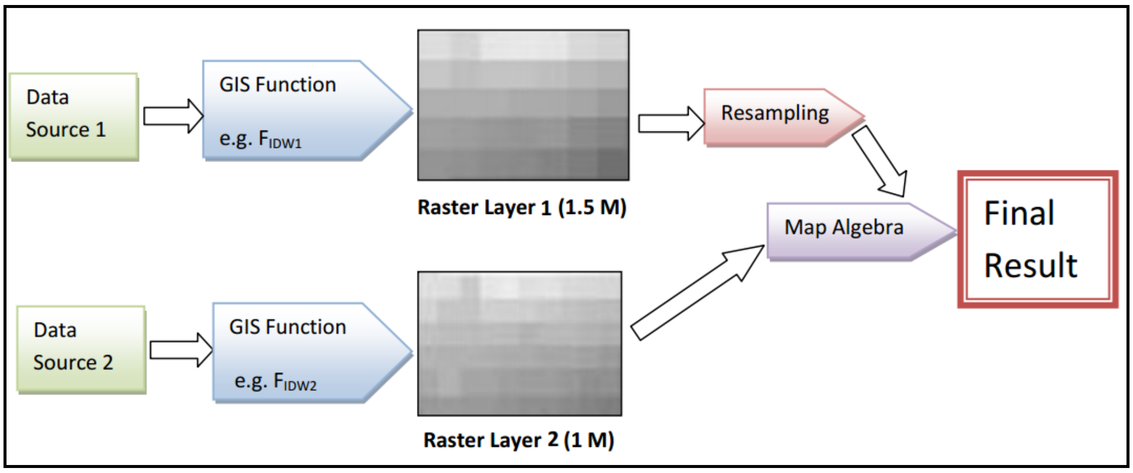


Figure 5-4 'Raster Overlay with Raster' function workflow in traditional geo-processing (Map Algebra).

The corresponding equations of Figure's 5-4 geo-processing model is provided below by Formula (5.1). The functions 'F_{IDW1}', 'F_{IDW2}', and '$F_{Map\ Algebra}$' represent the IDW and Map Algebra functions respectively. Functions 'F_{IDW1}' and 'F_{IDW2}' use different input datasets and resolution values to produce the new raster data layer. 'Single Map Layer1' and 'Single Map Layer2' are the outputs of 'F_{IDW1}' and 'F_{IDW2}' respectively and the input of the '$F_{Map\ Algebra}$' function. The 'Final Output' represents the final integrated layer, which is the outcome of the Map Algebra function.

$$F_{IDW1}\ (\text{Data Source 1}) = \text{Single Map Layer1}$$

$$F_{IDW2}\ (\text{Data Source 2}) = \text{Single Map Layer2}$$

$$F_{Map\ Algebra}\ (\text{Single Map Layer1, Single Map Layer2}) = \text{Final Output} \qquad \textbf{[5.1]}$$

The next section discusses how the same geo-processing model can be implemented using the CG approach.

5.3.2 ‘ Raster Overlay with Raster’ Function Implementation in The Combinative Geo-processing Approach

Figure 5-5 illustrates the ‘Raster Overlay with Raster’ function workflow in the CG approach. As it can be seen the final result is the direct output of the CG function, which in this case is composed of two function-based layers (‘GIS Function 1’ and ‘GIS Function 2’). In other words, the ‘Resampling’ function which is used in traditional geo-processing can be avoided here because during the processing there are no requests for intermediary data.

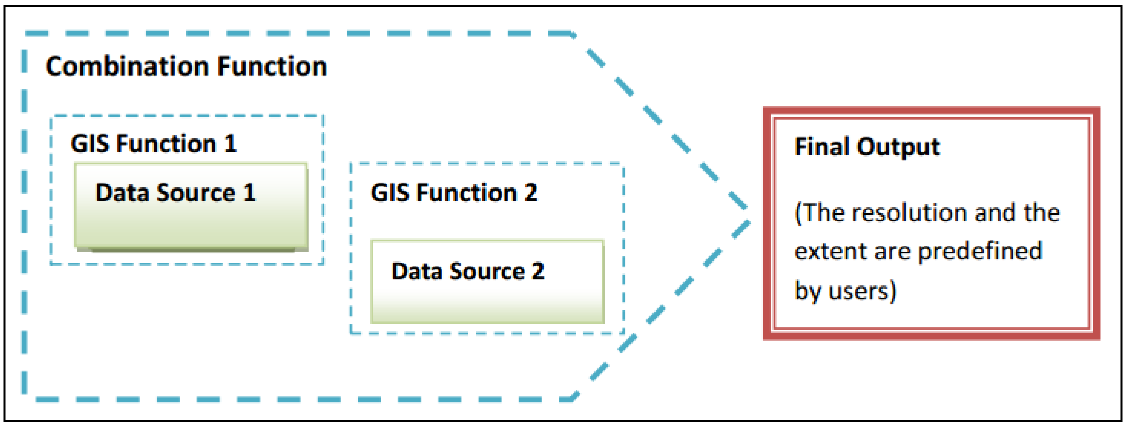


Figure 5-5 ‘Raster Overlay with Raster’ function workflow in the CG approach.

The corresponding mathematical model for the implementation of the ‘Raster Overlay with Raster’ function using the CG approach is provided by Formula (5.2) below. In Formula (5.2), ‘CG $F_{Overlay}$’, ‘CG F_{IDW1}’, and ‘CG F_{IDW2}’ represent the CG functions of ‘Raster Overlay with Raster’ and IDW respectively. ‘CG Dataset1’ and ‘CG Dataset2’ represent the input data. The final output is directly produced when running the ‘Raster Overlay with Raster’ function (i.e. ‘CG $F_{Overlay}$’) in the CG approach.

$$\{\text{CG } F_{Overlay} (\text{CG } F_{IDW1} (\text{CG Dataset1})) (\text{CG } F_{IDW2} (\text{CG Dataset2}))\} = \text{Final Result} \quad \textbf{[5.2]}$$

Sections 5.3.1 and 5.3.2 described two different approaches for the implementation of the map overlay geo-processing model. The key difference, as previously noted, is that while Map Algebra uses the ‘Resampling’ operation to manipulate raster layers with different resolutions, this step is completely avoided when using the CG approach. The next Section (5.4) discusses the datasets that are used in the first case study.

5.4 Case study 1: ‘Raster Overlay with Raster’ Function Implementation Datasets

The input dataset that is used in this case study to implement the ‘Raster Overlay with Raster’ function consists of LiDAR points. Raw LiDAR points are manipulated in two different datasets, to produce the reference and sample data, which are discussed separately in Sections 5.4.1 and 5.4.2.

5.4.1 Reference data

Figure 5-6 illustrates a total of 1010 LiDAR points were selected from a dataset of raw LiDAR points, as well as, the geographical location (i.e. around 4,000 square metres) and the topographical features within the study area (shown by the yellow rectangle in Bing Maps satellite image in Figure 5-6). The sample dataset includes 1010 points that were selected from the original raw LiDAR dataset (i.e. the first group of the LiDAR dataset[3]), and which are used as reference data in this case study to represent the actual observed values. Moreover, the purpose of the reference data is to produce the reference layers, which include the actual observed values and are later used to validate the CG approach and Map Algebra results.

[3] Technical information of the first group of raw LiDAR dataset is provided in the Appendix A (Table A.1).

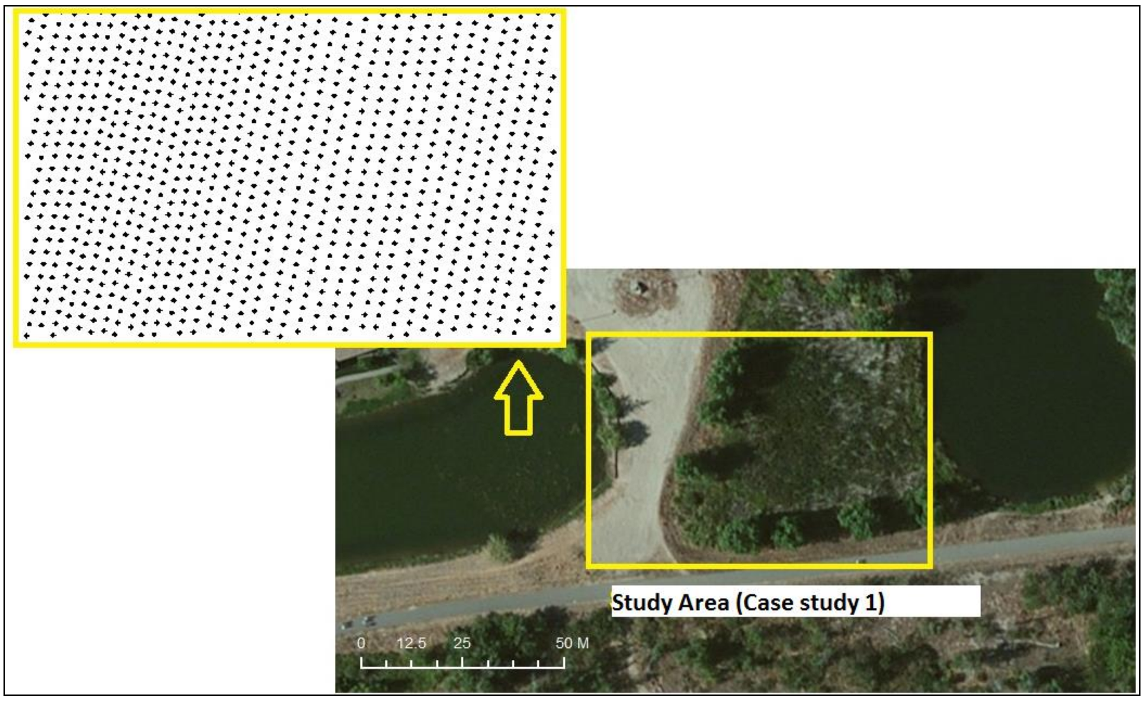


Figure 5-6 Reference data (Case study 1).

5.4.2 Sample Data

The sample data consist of two sample datasets that were randomly selected from the reference data and they are used in this case study to produce the sample layers, which will be later integrated using the 'Raster Overlay with Raster' function. Although the both of sample datasets are selected from the same data source (i.e. reference data of Case study 1), the different percentages of the amount of points are used in order to create two different sample layers. Specifically, the first sample dataset contains an 80% of randomly selected reference data points (i.e. 1010 * 0.8 ≈ 819 points)[4]. The first sample dataset contains a 70% of randomly selected reference data points (i.e. 1010 * 0.7 ≈ 742 points)[5].

The next section discusses in detail the implementation of the 'Raster Overlay with Raster' function in Case study 1.

[4] The first sample dataset is illustrated in the Appendix B (Figure B-1).

[5] The second sample dataset is illustrated in the Appendix B (Figure B-2).

5.5 ‘ Raster Overlay with Raster’ Function Implementation Strategy

In the first case study, five GIS implementation of IDW were tested (ArcGIS, MapInfo, Manifold GIS, R and CG appraoch). As a consequence of previous study, R and the CG approach provided the same and best results of IDW therefore R was used in here to produce the reference data. ArcGIS, MapInfo and CG approach were used for creating the test layers (i.e. sample layers).

Figure 5-7 illustrates the implementation procedure of the ‘Raster Overlay with Raster’ function in this case study. As can be seen from Figure 5-7 from the raw LiDAR points the reference and sample data were selected. Following this, single map layers were constructed using R for the reference layers and ArcGIS, MapInfo, and the CG approach was used for the construction of the sample layers. The ‘Raster Overlay with Raster’ function was implemented for the layers’ integration using both the CG approach and Map Algebra. The results of the various implementations are finally compared in order to explore data quality implications.

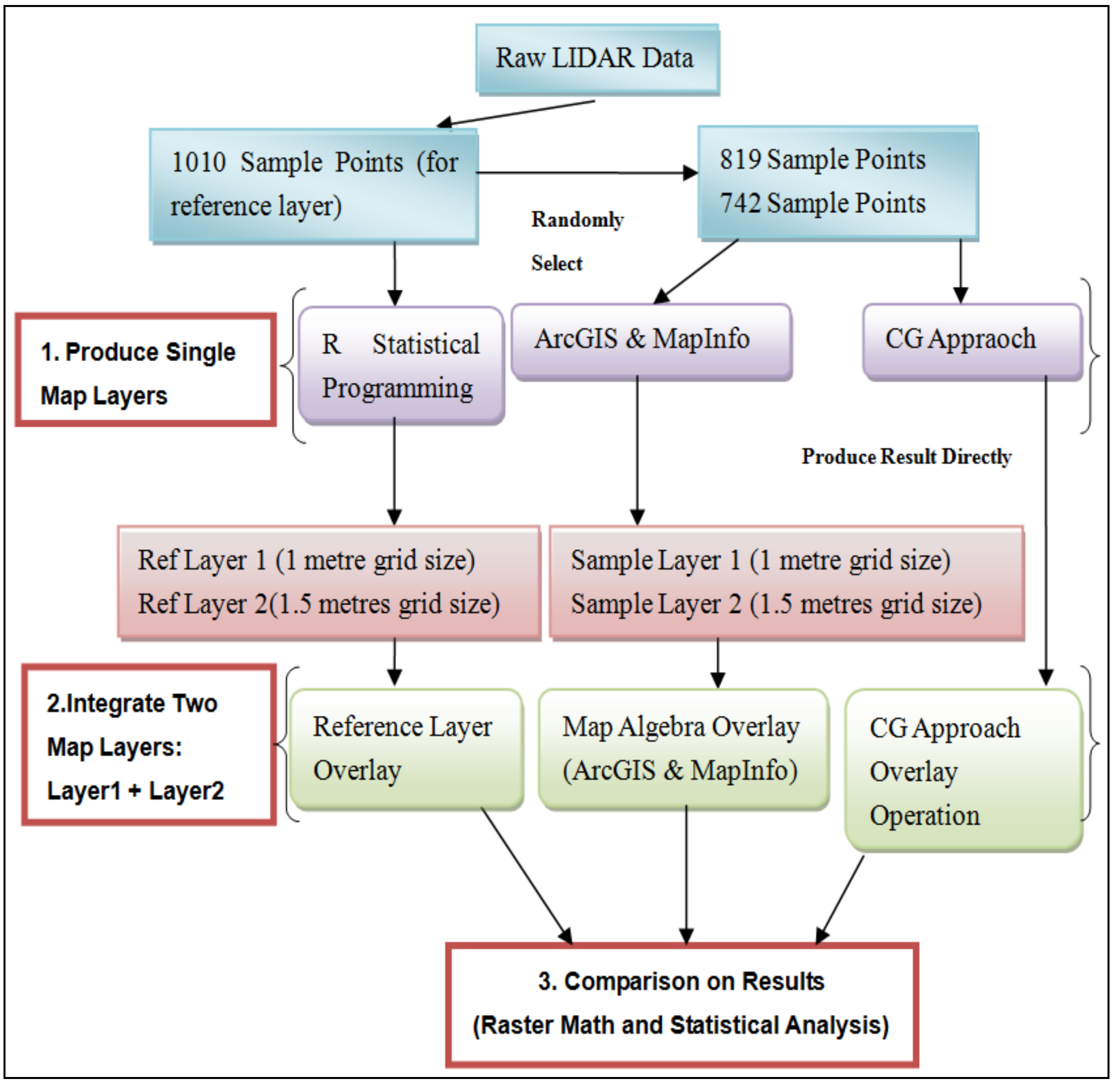

Raw LIDAR Data
1010 Sample Points (for reference layer)
819 Sample Points
742 Sample Points
Randomly Select
1. Produce Single Map Layers
R Statistical Programming
ArcGIS & MapInfo
CG Appraoch
Produce Result Directly
Ref Layer 1 (1 metre grid size)
Ref Layer 2(1.5 metres grid size)
Sample Layer 1 (1 metre grid size)
Sample Layer 2 (1.5 metres grid size)
2.Integrate Two Map Layers: Layer1 + Layer2
Reference Layer Overlay
Map Algebra Overlay (ArcGIS & MapInfo)
CG Approach Overlay Operation
3. Comparison on Results (Raster Math and Statistical Analysis)

Figure 5-7 'Raster Overlay with Raster' function implementation steps (Case study 1).

Moreover, it should be noted that for the IDW implementation the search radius was set to eight meters, and the grid size was set to 1 metre for 'Layer1' and 1.5 metres for 'Layer2'.

The next two sections (Section 5.5.1 and 5.5.2) review in more detail the creation of the single and integrated map layers.

5.5.1 Single Layers

This Section discusses separately the construction of the single reference layers and the single sample layers.

The single reference layers were used to construct the reference data in the later comparison step. As Figure 5-8 shows the IDW function in R was used to create the two different single reference layers (i.e. 'Reference Layer 1' and 'Reference Layer 2') in order to make a comparison with the two sample layers (i.e. 'Sample Layer 1' and 'Sample Layer 2'),

The key difference compared with the sample layers is that the 'Reference Layer 1' and 'Reference Layer 2' are produced using the full sample data (i.e. 1010 reference data points). Moreover, there is a grid size of one metre for 'Reference Layer 1' and a grid size of 1.5 metres of 'Reference Layer 2'.

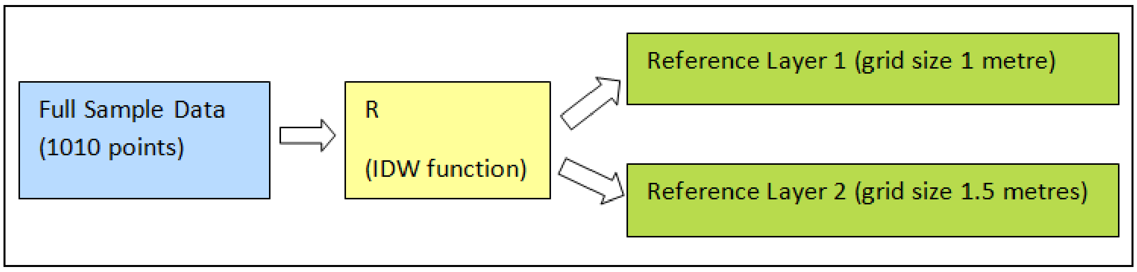

Full Sample Data
(1010 points)
R
(IDW function)
Reference Layer 1 (grid size 1 metre)
Reference Layer 2 (grid size 1.5 metres)

Figure 5-8 Case study 1: The process of generating the reference layers using R.

The single sample data were used to create the sample layers. As Figure 5-9 illustrates, two sample datasets (i.e. 'Sample Data 1' and 'Sample Data 2') were used to produce two different raster layers using the IDW function in ArcGIS and MapInfo (i.e. 'Sample Layer 1' and 'Sample Layer 2') with a grid size of one metre for 'Sample Layer 1' and 1.5 metres for 'Sample Layer 2'.

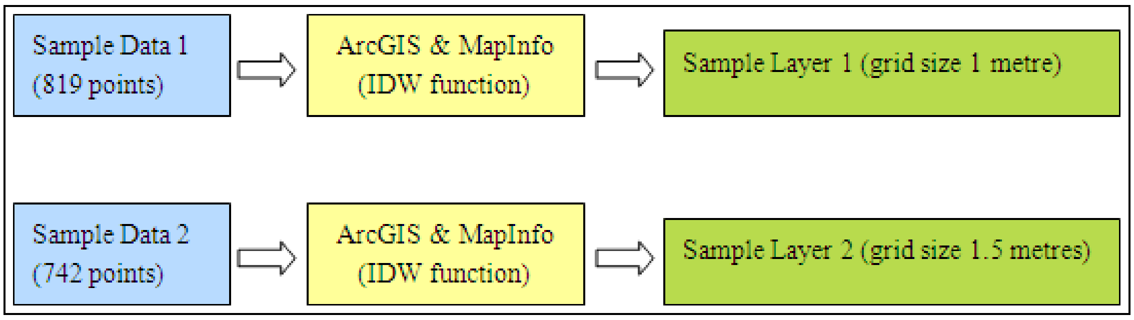


Figure 5-9 Case study 1: The process of generating the simple layers using ArcGIS and MapInfo.

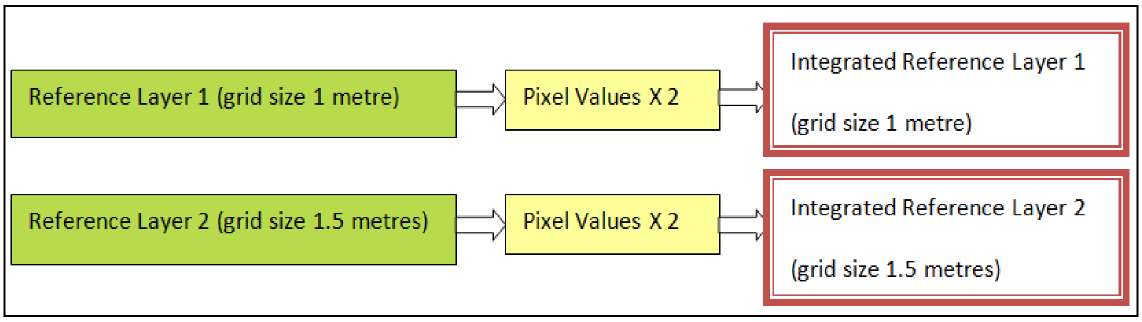
It should be noted that the CG approach does not require generating the sample layers separately, as the integrated layer is produced directly without any intermediary steps.

5.5.2 Integrated Layers

After the generation of the single reference and sample layers, the next step involved their integration using the 'Raster Overlay with Raster' function.

<u>1) Integrated Reference Layer (IRL)</u>

Based on the grid extents and the resolution of the sample layers, two different IRLs were produced in R (Figure 5-10). It should be noted that as R does not support Map Algebra's functionality for the integration of the two raster layers, each pixel cell was multiplied by two, which returned the same result with the addition operation in the 'Raster Overlay with Raster' function (addition operation).

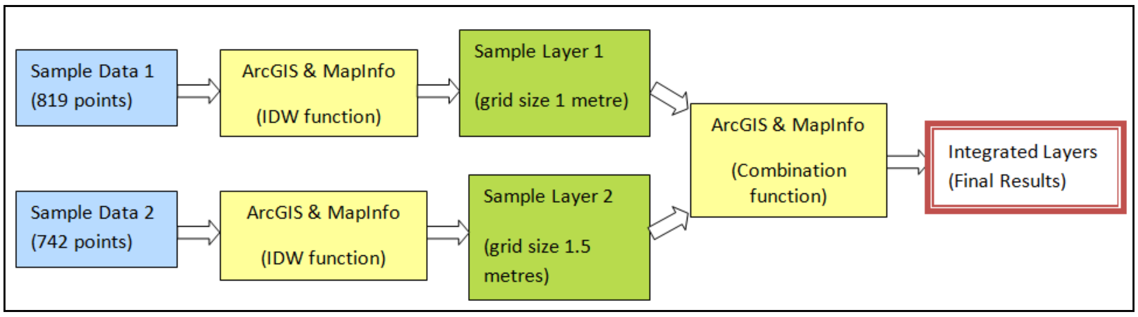


Reference Layer 1 (grid size 1 metre)
Pixel Values X 2
Integrated Reference Layer 1 (grid size 1 metre)
Reference Layer 2 (grid size 1.5 metres)
Pixel Values X 2
Integrated Reference Layer 2 (grid size 1.5 metres)

Figure 5-10 Case study 1: The process of generating the Integrated Reference Layer (IRL) using R.

2) Integrated Sample Layer (ISL)

As it was previously noted ArcGIS and MapInfo were also used for the integration of sample layers. Figure 5-11 illustrates the workflow for the implementation of the 'Raster Overlay with Raster' function in ArcGIS and MapInfo. The two single map layers that were produced using the IDW function (i.e. 'Sample Data 1' and 'Sample Data 2'), were loaded into the 'Raster Overlay with Raster' function in ArcGIS and MapInfo in order to create the ISLs separately.



Sample Data 1 (819 points)
ArcGIS & MapInfo (IDW function)
Sample Layer 1 (grid size 1 metre)
Sample Data 2 (742 points)
ArcGIS & MapInfo (IDW function)
Sample Layer 2 (grid size 1.5 metres)
ArcGIS & MapInfo (Combination function)
Integrated Layers (Final Results)

Figure 5-11 Case study 1: The process of generating the Integrated Sample Layer (ISL) using ArcGIS and MapInfo.

For the CG approach, as Figure 5-12 illustrates, the same single map layers were used (i.e. 'Sample Data 1' and 'Sample Data 2') but the 'Raster Overlay with Raster' function was used directly without any intermediary steps such as generating 'Sample Layer 1' and 'Sample Layer 2'. It was expected that avoiding this step could potentially reduce data uncertainty during processing.

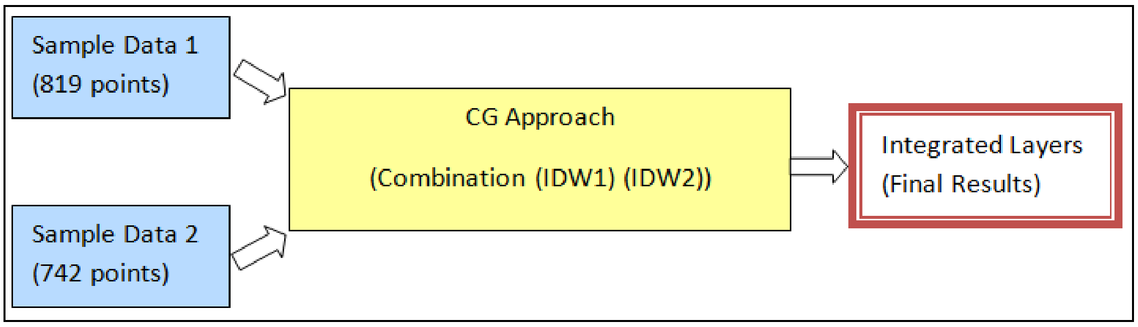


Figure 5-12 Case Study 1: The process of generating the Integrated Sample Layer (ISL) using the CG approach.

The GIS software packages that were used in this case study provide different algorithms for the implementation of the 'Raster Overlay with Raster' function. Thus, it was expected that the results and the quality of the generated integrated layers will not be the same. The next section critically assesses the quality of the various results.

5.6 'Raster Overlay with Raster' Function Results

Section 5.6.1 focuses on the single map layers results and Section 5.6.2 on the integrated map layers results.

5.6.1 Single Layers

Six single layers, including two single reference layers and four single sample layers, were created in total and they are discussed in this section. The single reference layer results that were created using R and the single sample layer results that were generated using ArcGIS and MapInfo.

Two single reference layers, with different grid sizes (i.e. one and 1.5 meters) were created using R and they are illustrated by Figures 5-13a and 5-13b. These two single reference layers were integrated to produce the final integrated reference layer in R.

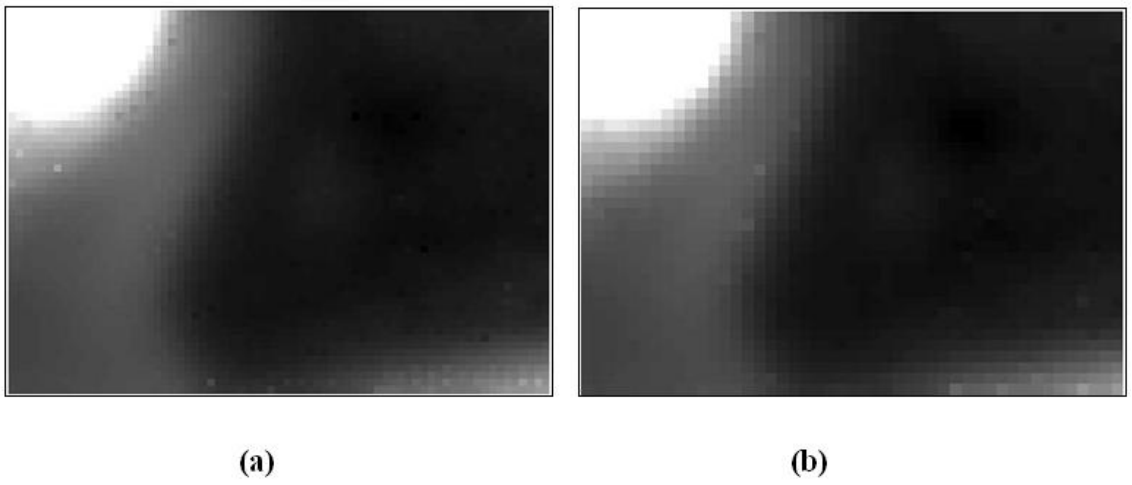


Figure 5-13 Single reference layer

(a) Single reference layer 1 (output of IDW, 1M grid size) generated using R.

(b) Single reference layer 2 (output of IDW, 1.5M grid size) generated using R.

Figures 5-14a to 5-14d present the single sample layers that were generated using the IDW function in ArcGIS and MapInfo. These four single reference layers were used to produce the integrated sample layers using Map Algebra in ArcGIS and MapInfo.

As it can be seen from Figures 5-14c and 5-14d MapInfo's results show a significant 'edge effect' compared to the results generated in ArcGIS (Figures 5-14a and 5-14b). As it is discussed in the next Section (5.7), the edge was cut off to enable the comparison of the IDW results within the same region.

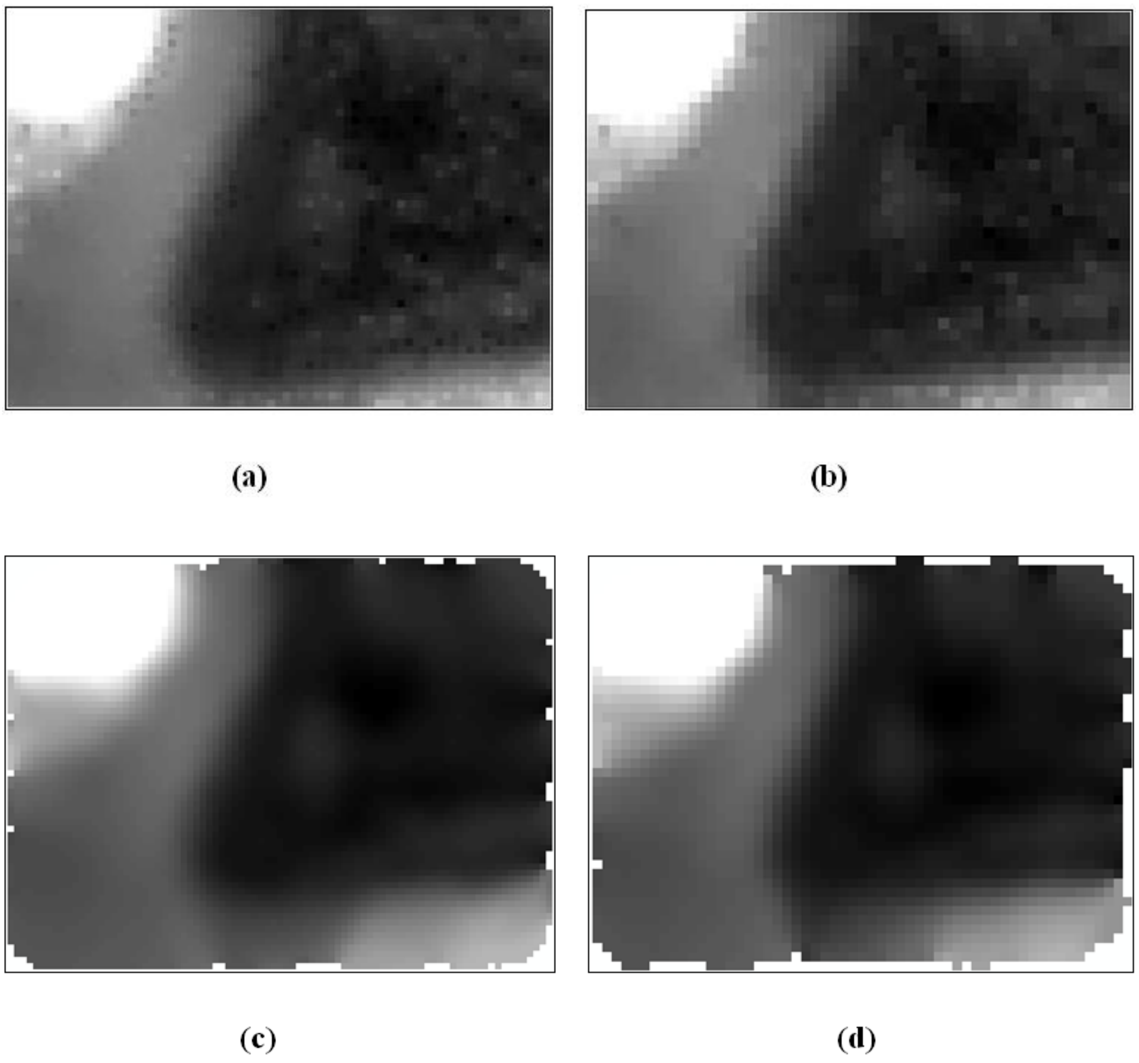


Figure 5-14 Single sample layer

(a) Single sample layer 1 (output of IDW, 1M grid size) generated using ArcGIS.

(b) Single sample layer 2 (output of IDW, 1.5M grid size) generated using ArcGIS.

(c) Single sample layer 1 (output of IDW, 1M grid size) generated using MapInfo.

(d) Single sample layer 2 (output of IDW, 1.5M grid size) generated using MapInfo.

5.6.2 Integrated Layers

This section presents the results of the 'Raster Overlay with Raster' function, which including two IRLs using R and four ISLs using ArcGIS, MapInfo, and the CG approach.

The IRLs produced in R are illustrated in Figures 5-15 and 5-16. These two layers are used to validate the 'Raster Overlay with Raster' function results that were produced in ArcGIS, MapInfo, and the CG approach.

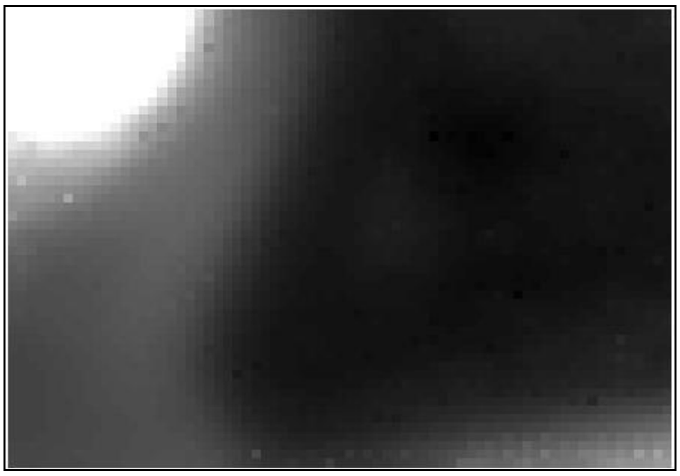


Figure 5-15 Integrated Reference Layer (1M) generated using R.

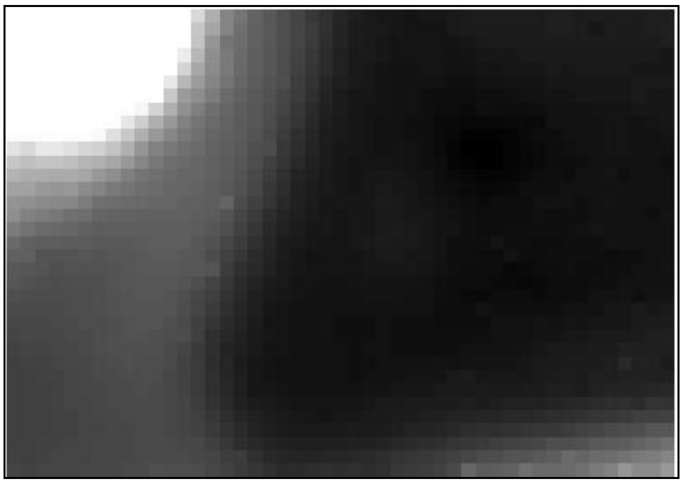


Figure 5-16 Integrated Reference Layer (1.5M) generated using R.

The ISLs that were produced using ArcGIS is shown in Figure 5-17, using MapInfo is shown in Figure 5-18, and using the CG approach are shown in Figures 5-19 and 5-20. It should be noted that there is a critical difference between the ArcGIS and MapInfo results. While the grid size of the resulting integrated layer in ArcGIS is 1.5 metres, in MapInfo is one metre by software's default. This difference is probably due to the fact that the algorithm in ArcGIS uses the raster layer with the largest grid size (1.5 metres) to specify the resolution of the resulting integrated layer, while the MapInfo algorithm operates in the opposite manner (i.e. uses the raster with the smallest grid size to define the resolution of the resulting integrated layer).

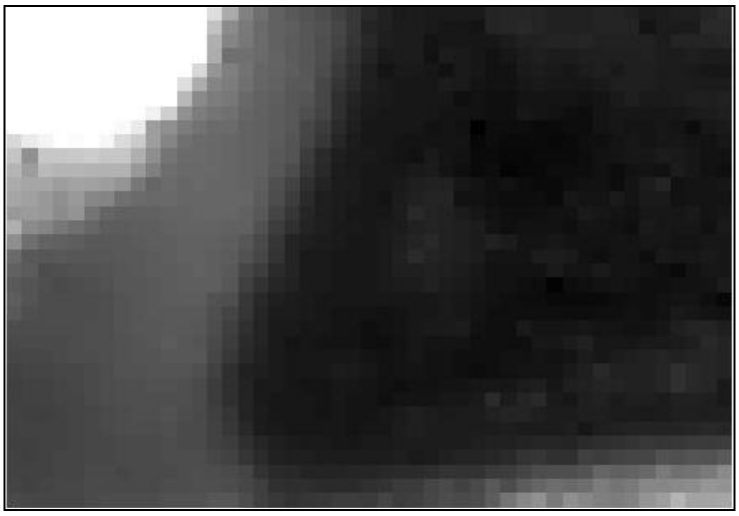


Figure 5-17 Integrated Sample Layer (1.5M) generated using ArcGIS.

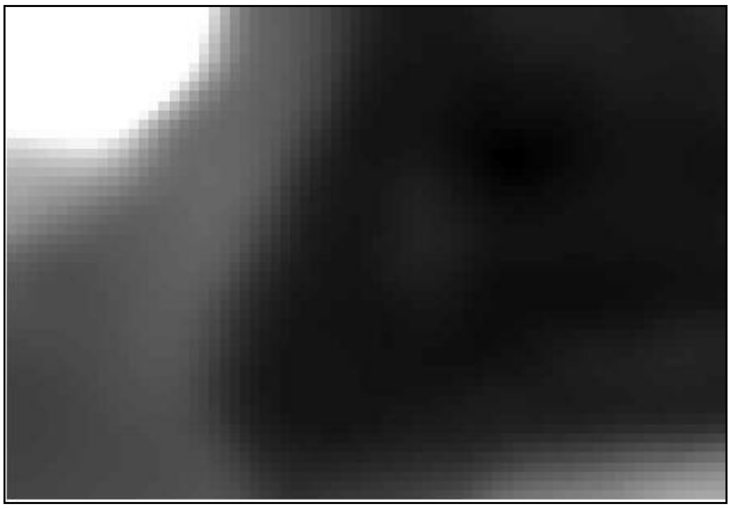


Figure 5-18 Integrated Sample Layer (1M) generated using MapInfo.

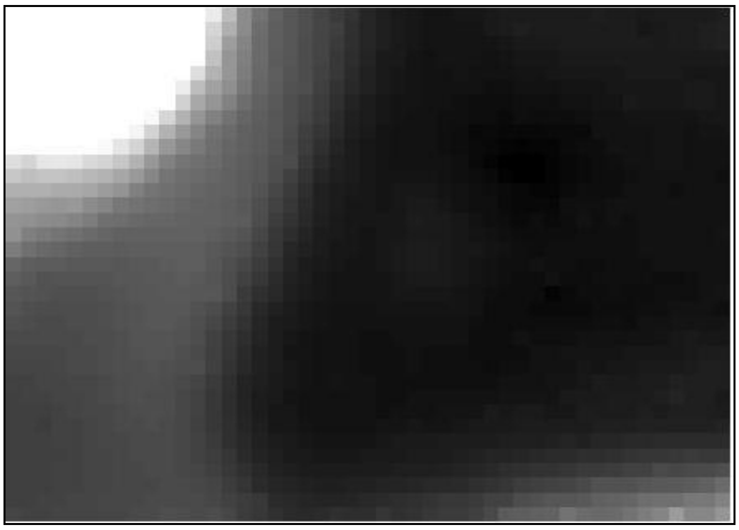


Figure 5-19 Integrated Sample Layer (1.5M) generated using the CG approach.

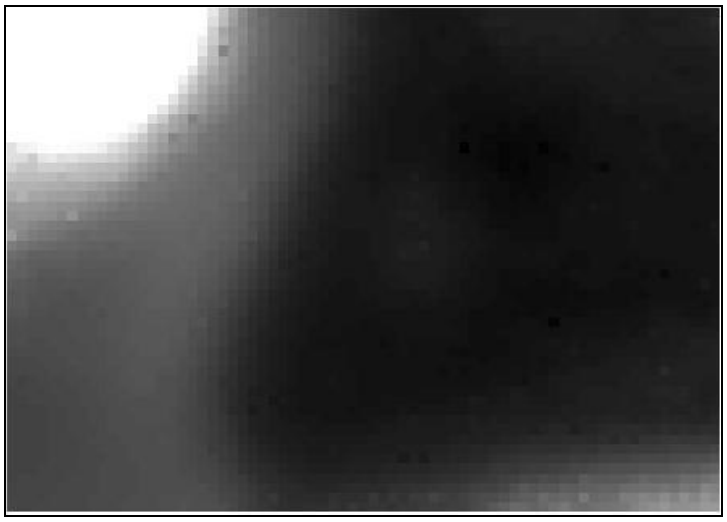


Figure 5-20 Integrated Sample Layer(1M) generated using the CG approach.

The next section discusses the differences of the various ‘Raster Overlay with Raster’ function outputs.

5.7 Case Study Results Comparison

Raster Algebra (Section 5.7.1) and Statistical Analysis (Section 5.7.2) are used to explore and validate the quality of the various results of the traditional geo-processing and the CG approaches.

5.7.1 Raster Algebra

As it was explained in the previous Chapter (Section 5.7.1), Raster Algebra’s minus function subtracts the value of the second input raster from the value of the first input raster on a cell-by-cell basis and supports investigating the difference of grid cells between the actual, observed values that are stored in the Integrated Reference Layers (IRLs) and the derived values that are stored in Integrated Sample Layers (ISLs).

Figure 5-21 illustrates the Raster Algebra results. As it can be seen the top images of Figure 5-21 illustrate the results for the 1.5 meter grid size raster layer that were produced using ArcGIS and the CG approach. The bottom images illustrate the results for the one meter grid size raster layer that were produced using MapInfo and the CG approach. Moreover, it should be noted that in Figure 5-21, the grid values represent the difference between the (new derived) values of the various ISLs, and the (observed) values of the IRLs. These grid values are classified using the ‘Natural Break’ option. For example, the black grid cells with grid values ‘Smaller than (<) -0.1’ and ‘larger than (>) 0.1’, are defined by the gaps of the classified data and represent the groups with bigger differences. It is clear from Figure 5-21 that in the ArcGIS and MapInfo results (top and bottom left hand side images) the black grid cells occupy the majority of the study area. This means that the results produced using Map Algebra in ArcGIS and MapInfo have more differences between the derived values and the actual, observed values (i.e. the reference data) than the CG approach derived values which are much closer to the observed values, as the black grid cells occupy a much smaller part of the study area (top and bottom right hand side images).

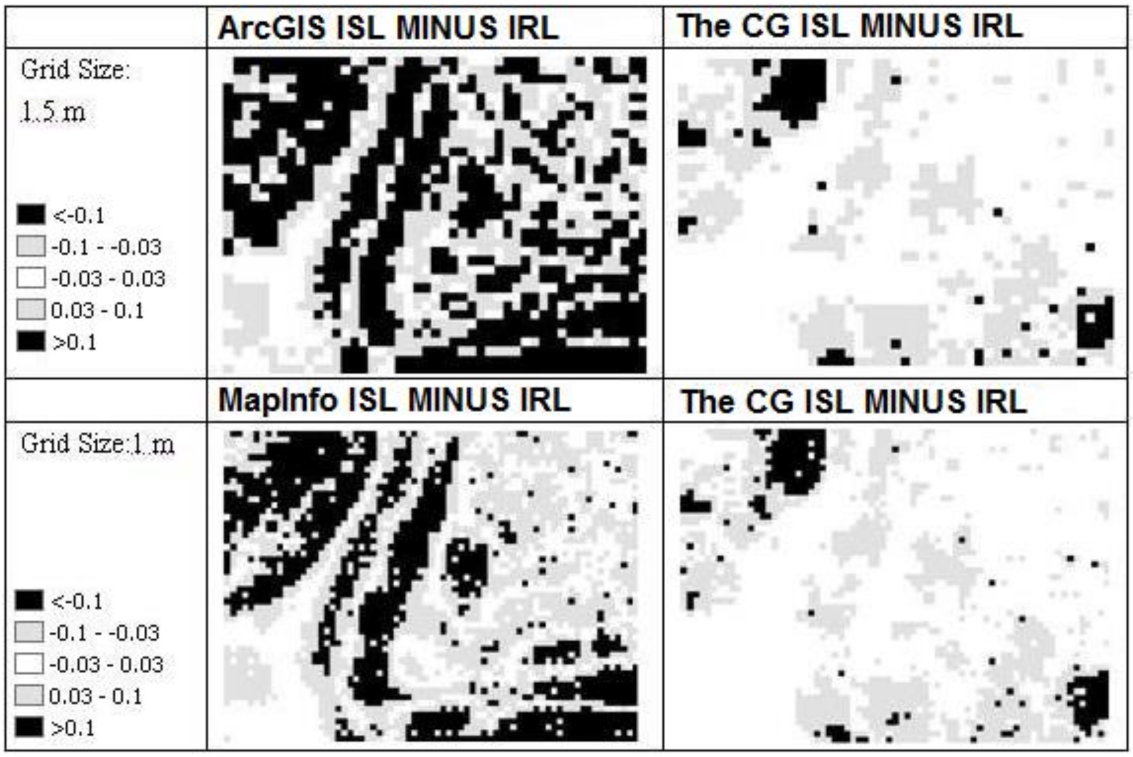


Figure 5-21 Raster Algebra: Comparison of the 'Raster Overlay with Raster' function outcomes.

5.7.2 Statistical Analysis

Descriptive statistical analysis was also undertaken in order to compare the Raster Algebra (Minus) results in more detail. For the purposes of this comparison, the Maximum (Max), Minimum (Min), and the Standard Deviation values are used.

The results are summarised in Table 5-1. In this table, the highest Standard Deviation value (StDev=0.209) is observed when we compare the ArcGIS integrated sample layer with the integrated layer (i.e. ArcGIS ISL MINUS IRL). The lowest Standard Deviation value (StDev=0.055) is observed when we compare the CG approach integrated sample layer with the integrated reference layer (i.e. CG ISL MINUS IRL). Moreover, the highest Maximum and Minimum values (Max=1.14, Min=-1.284) are observed when ArcGIS integrated sample layer is compared with the integrated reference layer (i.e. ArcGIS ISL MINUS IRL). The lowest Maximum and Minimum values (Max=0.401, Min=-0.3) are observed in the CG approach amongst the integrated sample layer and the integrated reference layer (i.e. CG ISL MINUS IRL). These results confirm the Raster Algebra findings and they further show that the results of the CG approach are much closer to the actual, observed values of the reference data layer. Thus, it can be concluded that the CG approach provides higher precision results.

Table 5-1 Statistical analysis results.

	ArcGIS ISL MINUS IRL (grid size 1.5 m)	**CG** ISL MINUS IRL (grid size 1.5 m)	**MapInfo** ISL MINUS IRL (grid size 1 m)	**CG** ISL MINUS IRL (grid size 1 m)
Standard Deviation	0.209	0.055	0.165	0.073
Maximum	1.14	0.401	0.659	0.442
Minimum	-1.284	-0.3	-0.773	-0.433

The next section provides a discussion of the various 'Raster Overlay with Raster' function findings.

5.8 Discussion

Currently, raster-based data and its related algorithms are widely used in spatial analysis for describing real world phenomena. As demonstrated in this case study, while ArcGIS and MapInfo have different Map Algebra algorithms, their common aspect is that they both need to transform multiple two-dimensional raster datasets into a unique resolution, (e.g. ArcGIS selects 1.5 metres resolution for the both of IDW1 and IDW2 outputs), for entry into conventional Map Algebra functions. When a GIS tool selects automatically the largest of the raster layers to define the resolution of the resulting layer, then the accuracy and precision of the final result are influenced. For example, it was demonstrated that ArcGIS selects the largest grid size and as a result the derived values in ArcGIS have more differences with the reference data.

In contrast to the traditional geo-processing approach, the CG approach applies function-based layers to store and process spatial data. For the 'Raster Overlay with Raster' implementation, the CG approach does not need to produce any intermediate results during computations. This enables reducing potential data uncertainty issues (e.g.

spatial data resolution and raster data conversion) in the CG approach. The findings of this case study show that the ‘Raster Overlay with Raster’ function in the CG approach resulted in values that are much closer to the actual values of the reference data layer. For example, the Raster Algebra results (Figure 5-21) reveal that the difference between traditional geo-processing’s derived values and actual values of the reference data layer cover almost 50% of the study area, while this difference in the CG approach covers only about 10% the study area. Also, the statistical analysis results demonstrate again that the calculated Standard Deviations of the traditional geo-processing values (i.e. ArcGIS and MapInfo’s) are much larger than the Standard Deviation of the CG values, which means the results of traditional geo-processing values have more data uncertainties.

5.9 Summary

This case study focused on the implementation of the ‘Raster Overlay with Raster’ function in the CG and traditional geo-processing (Map Algebra) contexts. The basic idea of ‘Raster Overlay With Raster’ function was reviewed in the first part of this case study. Then, this chapter discussed how the ‘Raster Overlay With Raster’ function can be implemented in the CG approach and the traditional approach. In specific, in the traditional geo-processing the single raster layers were firstly produced and then the derived data (i.e. ISL) were produced from the single raster layers’ (i.e. Raster layer1 and Raster layer2) integration. However using the CG approach the final result (i.e. ISL) were produced directly from the original input datasets (i.e. Sample Data1 and Sample Data2). Moreover, this chapter reviewed the implementation datasets (i.e. reference data and sample datasets) and further illustrated the ‘Raster Overlay with Raster’ implementation strategy.

The first case study described various ‘Raster Overlay with Raster’ implementations using the CG approach, ArcGIS, MapInfo, and R. The various results were compared and it was found that the CG approach resulted in values that are much closer to the observed values (i.e. reference data). In addition, this case study also demonstrated that the new approach improves flexibility as the ‘Raster Overlay with Raster’ function can be implemented using different grid sizes. As a result, it can be concluded that the CG approach offers many advantages over traditional geo-processing for the integration of two or multiple raster map layers within a geo-processing model.

However, it should be acknowledged that there are additional concerns that influence the development of the CG approach. For example, one of the key characteristics of the CG approach is the use of a combinative CG function in order to process an entire geo-processing model, which may include various computation tasks. Thus, how various computation tasks can be linked together within a combinative CG function is a major concern, which will be investigated in the next case study, which is discussed in Chapter 6.

6 Implementing a Simple Chain Processing Using the Combinative Geo-Processing Function

6.1 Introduction

The case study that was described in Chapters 5 was used to respectively demonstrate the implementation of the 'Raster Overlay with Raster' functions using the CG approach. The results of this case study demonstrate that the CG approach has the potential to improve the data quality of GIS function implementation. This Chapter is concerned with the implementation of a simple chain processing model, which is not only a fundamental geo-processing operation, but it may provide the basis to develop more complex GIS models, which are also essential in spatial analysis.

Section 6.2 discusses the characteristics of a generic simple chain processing model and describes the geo-processing model that it is used in this case study. Section 6.3 describes the two different approaches that may be used for the implementation of any simple chain processing model; the traditional geo-processing approach using the ModelBuilder tool in ArcGIS and the CG approach. Section 6.4 presents the datasets that are used in Case study 2. Section 6.5 discusses in detail the exact implementation and strategy for executing the simple chain processing model in this case study using both the traditional geo-processing and the CG approaches. Section 6.6 presents the results of this case study. In Section 6.7 Monte Carlo simulation is used to compare the influences of data uncertainties in both simple chain processing implementations and presents the Monte Carlo simulation results. Section 6.8 discusses the differences amongst the various Monte Carlo simulation outcomes and Section 6.9 provides a summary of the main issues that are discussed in this Chapter.

6.2 Case study 2: Simple Chain Processing Model Review

Simple chain processing models are very popular in GIS analysis and they are fundamental operations in traditional geo-processing. Figure 6-1 illustrates the workflow of a generic simple chain processing model, with 'Function1' and 'Function2' representing two different computation tasks. In specific, 'Function1' uses the 'Input Value' to produce 'Output1', which is then used as an input for 'Function2' to return the final 'Result'. A simple chain processing model may form the basis for building more complex chain processing models, such as the one that it is presented and discussed in the next Chapter (Chapter 7).

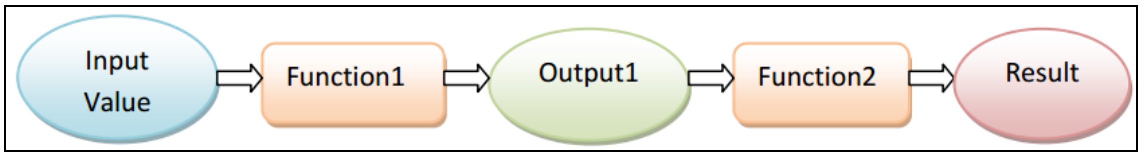


Figure 6-1 The workflow of a generic simple chain processing model.

Figure 6-2 illustrates the geo-processing model that it is used in this case study, which has two basic computation tasks; these are the IDW and Slope functions, which are commonly used in geo-processing, as the model aims to produce slope values from a set of LiDAR points. The IDW function was extensively reviewed in Chapter 5 and thus the next section only introduces in detail the Slope function.

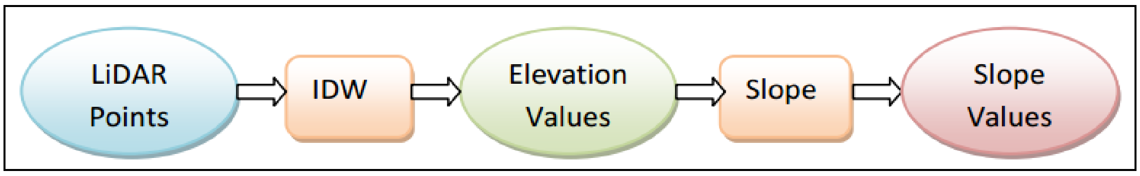


Figure 6-2 Case study 2: Geo-processing model (Simple chain processing model).

6.2.1 Slope Function

'Slope' is a commonly used spatial analysis processing model with many applications especially in the environmental context (e.g. in hydrological modelling) (Hunter and Goodchild 1997). The original Slope algorithm is a raster-based method in spatial computations. Burrough and McDonnell (1998) explain that the hypsometric curve is computed locally from each cell in the elevation matrix from data within a 3 X 3 grid 'window', as demonstrated by Figure 6-3.

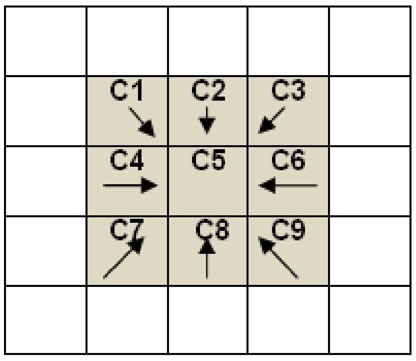


Figure 6-3 Example of elevation matrix used for Slope computation.

The geo-processing model of this case study uses the same Slope algorithm that it is also used in ArcGIS. The same geo-processing model is used in order to later compare the ArcGIS and the CG results and explore any data quality issues. The ArcGIS Slope algorithm is a third-order finite difference estimate of the gradient in east-west and south-north directions (Horn 1981). The computational equation is given by Formula 6.1.

$$\textbf{\textit{Gradient (x)}} = [(C3 + 2C6 + C9) - (C1 + 2C4 + C7)] / (8 * бx)$$

$$\textbf{\textit{Gradient (y)}} = [(C3 + 2C6 + C9) - (C1 + 2C4 + C7)] / (8 * бx) \qquad [6.1]$$

Slope is commonly measured in degrees based on the algorithm given by Formula 6.2 below.

$$\textit{Slope Degrees} = ATAN(\sqrt{}\,([Gradient (x)]^\wedge 2 + [Gradient (y)]^\wedge 2)) * 57.29578 \qquad [6.2]$$

The next section demonstrates the methodological approach for the implementation of the simple chain processing model in both traditional geo-processing and the CG approaches.

6.3 Methodology: The Simple Chain Processing Model Implementations

This section discusses the simple chain processing model implementation using the traditional geo-processing approach (Section 6.3.1) and the CG approach (Section 6.3.2) separately.

6.3.1 Simple Chain Processing Model Implementation in Traditional Geo-processing: Sequential Computation

It was already explained in Section 3.2 that sequential computation is one of the most commonly used computational approaches for the execution of a set of functions and geo-processing models in commercial GIS software. Figure 6-4 illustrates a simple chain processing model in ArcGIS ModelBuilder, which combines an IDW and a Slope function. This model involves two main computation steps: first, the raw LiDAR points are loaded into the IDW function, using one-metre grid size; second, the IDW output is loaded into the Slope function to finally produce the Slope result, as a raster representation.

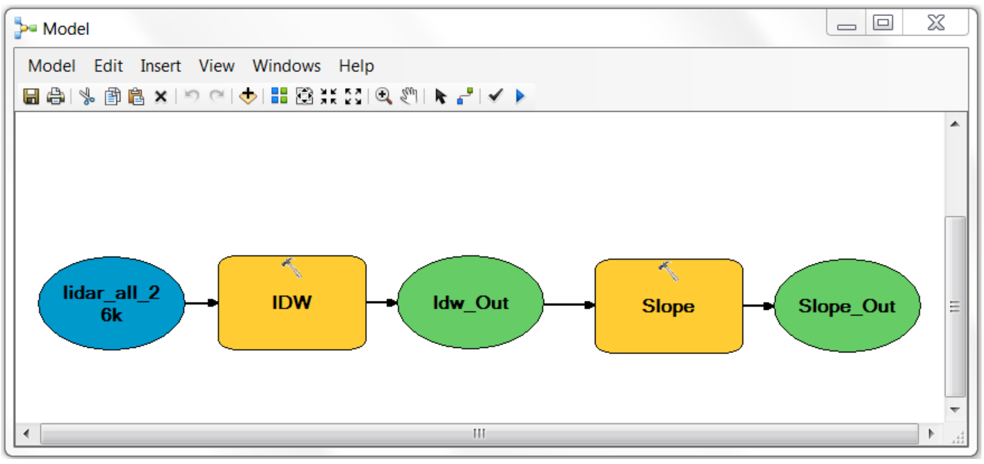


Figure 6-4 Case study 2: Simple chain processing model in ArcGIS ModelBuilder.

The corresponding mathematical model for the geo-processing model illustrated by Figure 6-4, is given by Formula 6.3; where 'F_{SLOPE}' and 'F_{IDW}' represent the Slope and IDW functions. '$Output_{IDW}$' is the output of the IDW function and '$Output_{SLOPE}$' is the final output of the Slope function.

$$F_{IDW}\ (LiDAR\ points) = Output_{IDW}$$

$$F_{SLOPE}\ (Output_{IDW}) = Output_{SLOPE} \qquad [6.3]$$

The next section introduces how the simple chain processing model is implemented using the CG approach.

6.3.2 Simple Chain Processing Model Implementation in Combinative Geo-processing

The major steps for the implementation of a simple chain processing model using the CG approach are illustrated in Figure 6-5. These include loading the raw LiDAR points into the combinative function {(IDW) (Slope)}, which will generate the final Slope value only upon user request (i.e. the system can directly generate the slope values on a set of randomly selected locations, which are defined by a group of coordinate values).

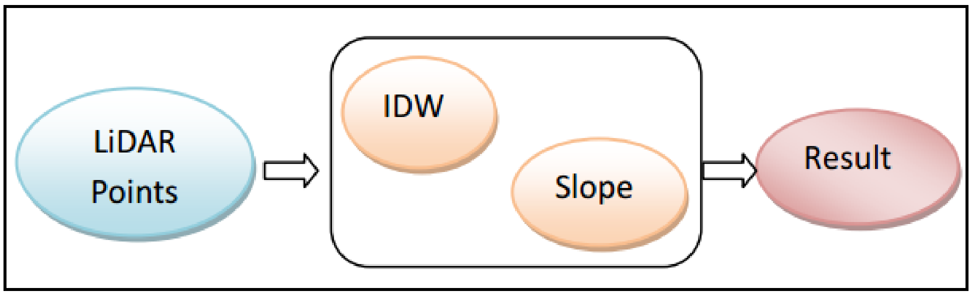


Figure 6-5 Case study 2: Simple chain processing model in the CG approach.

Formula 6.4 provides the mathematical model for the implementation of the simple chain processing model which was illustrated by Figure 6-5. This mathematical model was built using the concept of function-based layers in order to directly generate the final result (i.e. slope values) and minimise the influence of data uncertainties. In more detail, the 'CG Function' is a combinative CG function, which was constructed using two function-based layers: the CG Slope function (i.e.'CG F_{SLOPE}') and the CG IDW function (i.e. 'CG F_{IDW}'). In this geo-processing model 'CG dataset', the input data of the 'CG Function', includes a set of coordinate values. 'CG dataset' aims to define the location of the study area and extract the final slope values. Finally, the 'LiDAR Points' represent the input of the CG IDW function.

CG Function (CG dataset) =

{CG F_{SLOPE} (CG F_{IDW} (LiDAR Points)) (CG dataset)} [6.4]

Sections 6.3.1 and 6.3.2 discussed two different approaches that can be used for the implementation and execution of a simple chain processing model. The fundamental difference, is that in traditional geo-processing (i.e. ModelBuilder in ArcGIS) a sequential computation approach is used to process the model and its tasks, while in the CG approach a combinative function is used to directly execute it.

6.4 Case study 2: The Simple Chain Processing Model Dataset

Figure 6-6 shows the sample of raw LiDAR point data used in this case study, as well as, the geographical location (around 10,000 square metres) and the topographical features within the study area (shown by the yellow rectangle in Bing Maps satellite image in Figure 6-6). The sample dataset includes 26,499 points that were selected from the original LiDAR dataset (i.e. the second group of the LiDAR dataset[6]). It should be noted that in contrast to the first case study where 1,000 points were selected from the original LiDAR dataset, this case study uses a significantly higher number of points in order to further test the time performance of the CG approach in terms of processing large spatial datasets.

[6] Technical information of the second group of raw LiDAR dataset is provided in the Appendix A (Table A.2).

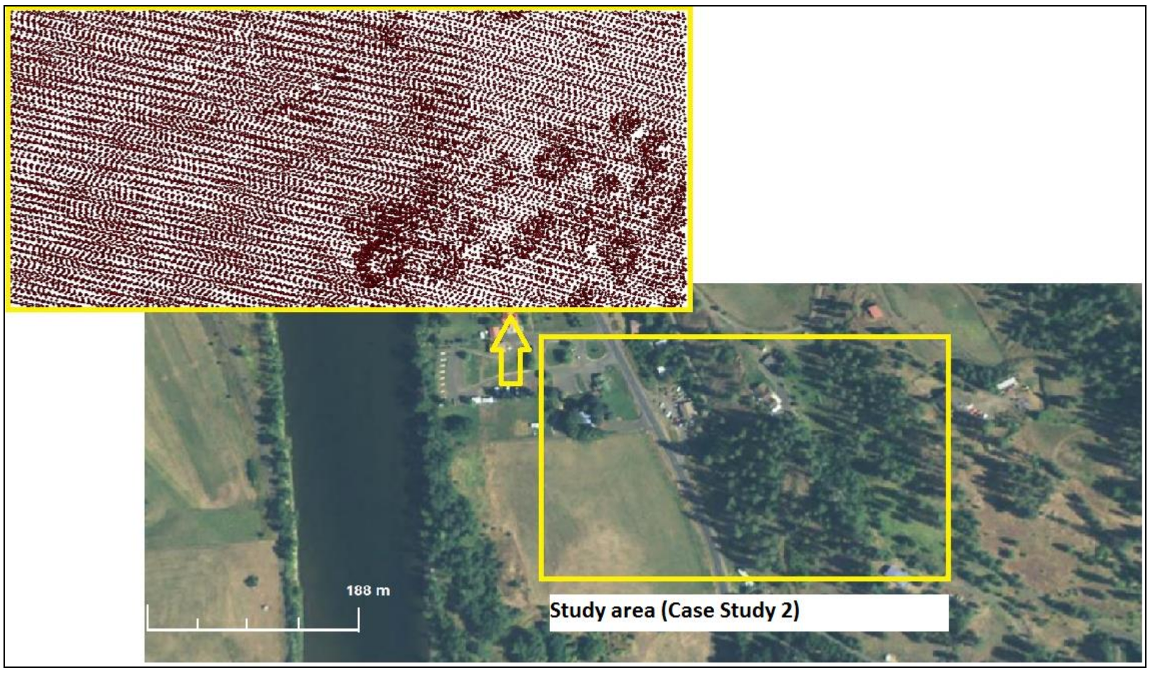


Figure 6-6 Case study 2: Raw LiDAR point data and case study area (yellow rectangle in Bing Maps satellite image).

The next section describes the implementation strategy for the execution of the geo-processing model in this Case Study.

6.5 The Simple Chain Processing Model Implementation Strategy in Case study 2

The framework of the simple chain processing model implementation and validation process, within the context of both traditional geo-processing and the CG approaches, is illustrated in Figure 6-7. It involves calculating the slope values using the two different geo-processing approaches and validating their results using Monte Carlo simulation and includes four major steps. The first step involves loading the raw LiDAR points separately in the two different geo-processing tools (i.e. Modelbuilder in ArcGIS and the CG approach); the second step involves the data processing and the execution of the IDW and Slope functions; the third step focuses on data query and provides a set of results which are used for data validation purposes and; finally the fourth step, involves using the geostatistical method of Monte Carlo simulation to compare the results (i.e. slope values) that were produced using the two different approaches.

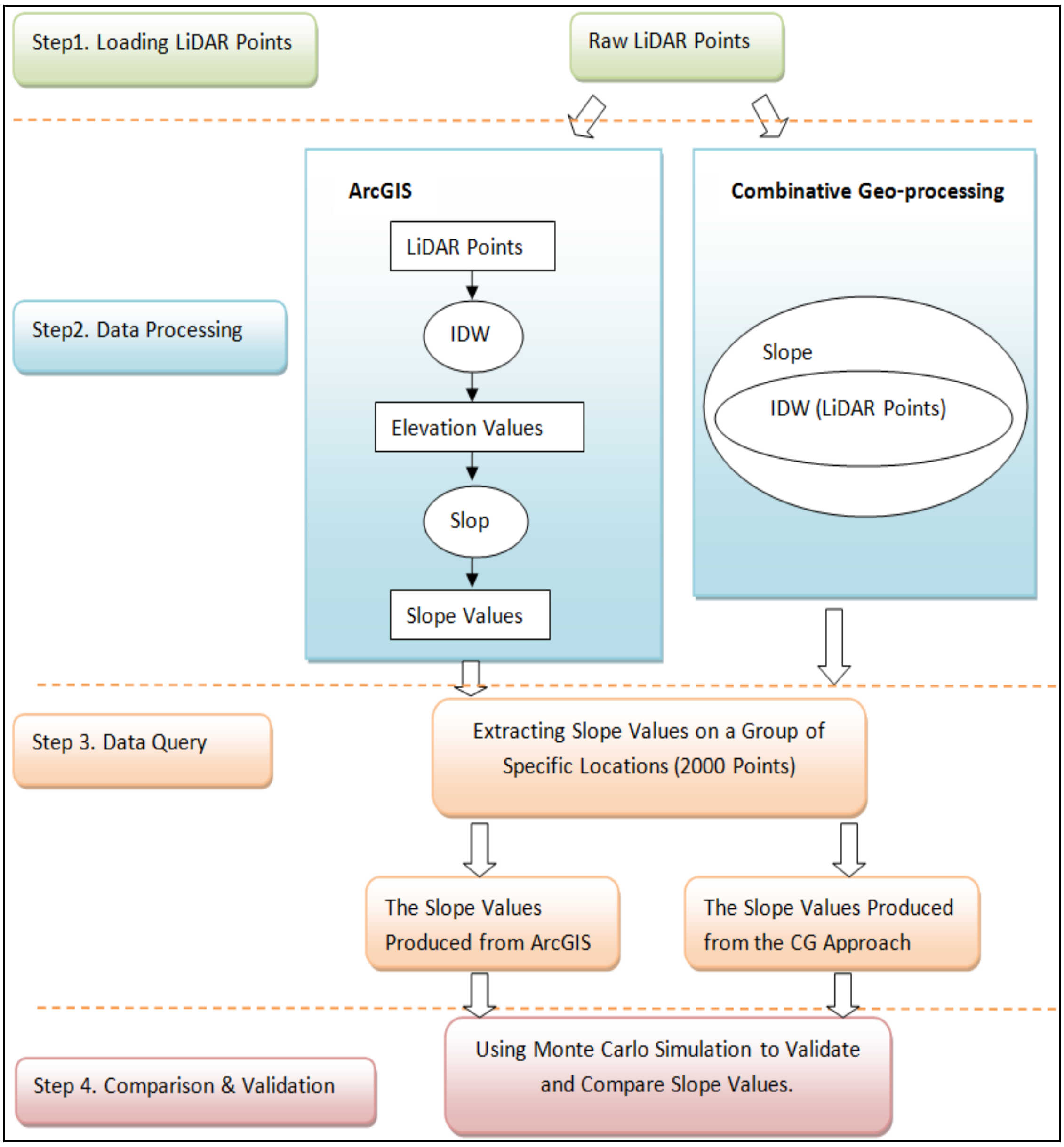

Step1. Loading LiDAR Points
Raw LiDAR Points
Step2. Data Processing
ArcGIS
LiDAR Points
IDW
Elevation Values
Slop
Slope Values
Combinative Geo-processing
Slope
IDW (LiDAR Points)
Step 3. Data Query
Extracting Slope Values on a Group of Specific Locations (2000 Points)
The Slope Values Produced from ArcGIS
The Slope Values Produced from the CG Approach
Step 4. Comparison & Validation
Using Monte Carlo Simulation to Validate and Compare Slope Values.

Figure 6-7 Case study 2: Implementation strategy of simple chain processing model.

As it is illustrated by Figure 6-7, Step 2 (i.e. Data processing) involves the implementation of the simple chain processing model using ArcGIS and the CG approach which is followed by Step 3 (i.e. Data Query), which focuses on extracting the slope values from the sampling locations. In the traditional geo-processing approach, slope values are usually stored and calculated in a raster data model to represent a surface object, but its quality is influenced by the grid size and the storage capacity of computer memory (Burrough and McDonnell 1998). Therefore, in this case study slope values were extracted from real geographical locations in order to reduce the influence of grid size and further providing the accurate values for the comparison of the results.

Figure 6-8 shows that 2,000 sampling locations, which are randomly selected from the case study area, as well as, the geographical location and the topographical features in the study area (shown by the yellow rectangle in Bing Maps satellite image in Figure 6-8). In this case study, these 2,000 sampling locations are used in Step 3 (i.e. Data Query) to extract the slope values.

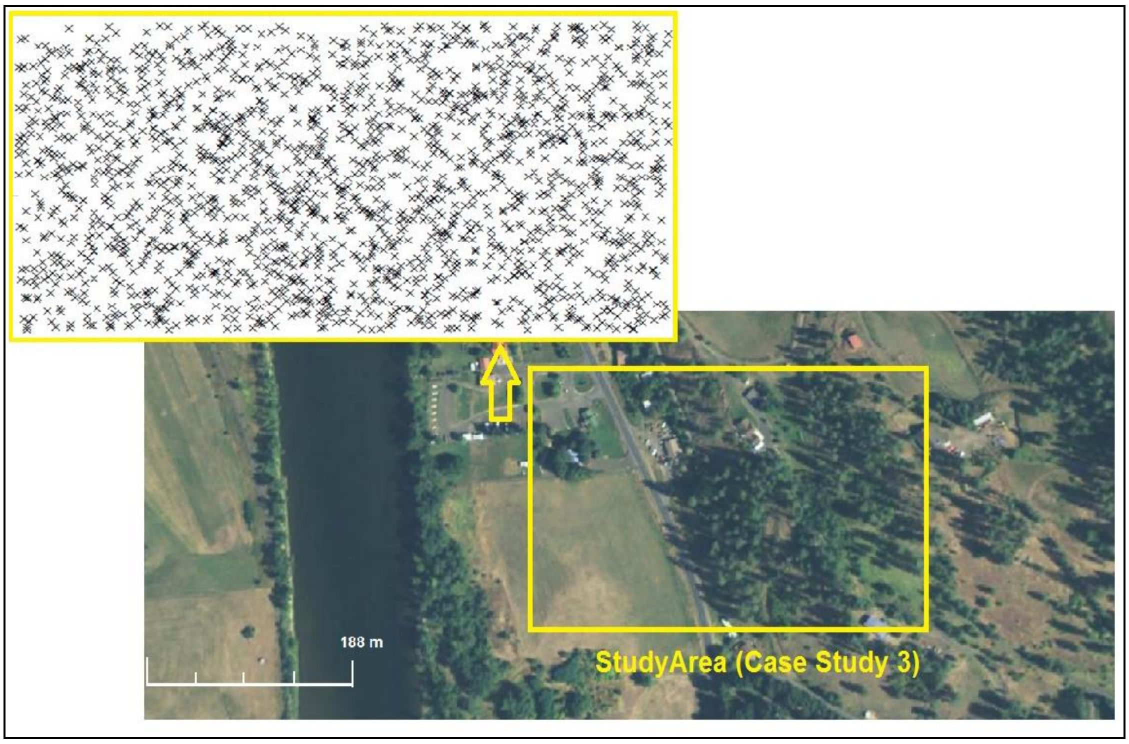


Figure 6-8 Case study 2: The 2,000 sampling locations and the case study area (shown by the yellow rectangle in Bing Maps satellite image).

Two additional functions are used in ArcGIS, as it is illustrated by Figure 6-9, in order to further query the slope values from the sampling locations. The first is the ‘Raster to Polygon’ function, which converts raster data into a vector format, as a set of polygons. The resulting map layer is then digitised on a single pixel boundary and has an individual slope value. The second function is the ‘Spatial Join’ which merges the polygons and the sampling locations in order to subsequently query the slope values of the requested locations.

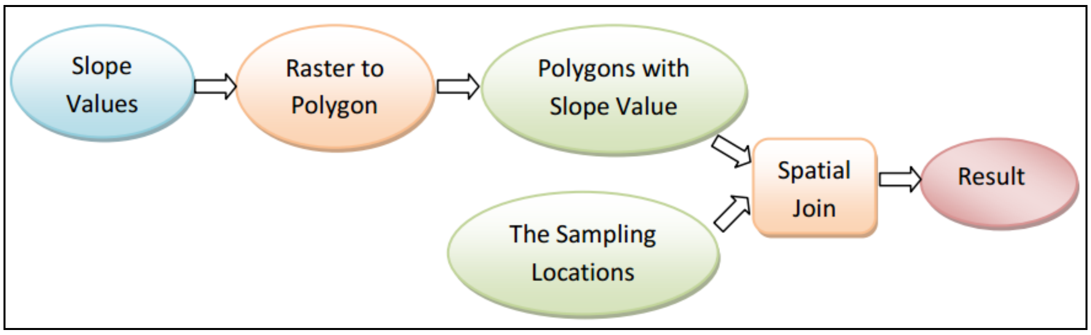


Figure 6-9 Case study 2: ArcGIS model for querying slope values from the sampling locations.

In the CG approach the same process requires only specifying the coordinate values (i.e. the X, Y coordinate of the sampling points within the CG function), before it will directly produce the slope values. This computation step is summarised by Formula 6.5 below.

$$\boldsymbol{CG\ Function\ (X, Y) = \{CG\ F_{SLOPE}\ (CG\ F_{IDW}\ (LiDAR\ Points))\ (X, Y)\}} \qquad [6.5]$$

Two different GIS tools (i.e. ModelBuilder in ArcGIS and the CG approach) were used in this case study for the implementation of the simple chain processing model. It is expected, as it was found in previous case studies, that the results will again vary. The next section discusses the results of the two simple chain processing model implementations.

6.6 The Simple Chain Processing Model Results

Figure 6-10a and Figure 6-10b illustrate the slope results of the randomly selected sampling locations, that were generated using respectively the CG approach and ArcGIS ModelBuilder. The slope values, as it can be seen in both figures, are classified in five groups using the ‘Natural Break’ option, which means that the classification is based on the natural distribution of the slope values and the gaps amongst them. As the legend illustrates, the bottom group with slope values from 60.1 to 85 degrees includes locations which have the highest slope values, while the top group with slope values from 0 to 10 degrees, represents the sample locations which have lowest slope values. The other groups include slope values, which range from ‘10.1 to 25 degrees’, ‘25.1 to 40 degrees’, and ‘40.1 to 60 degrees’.

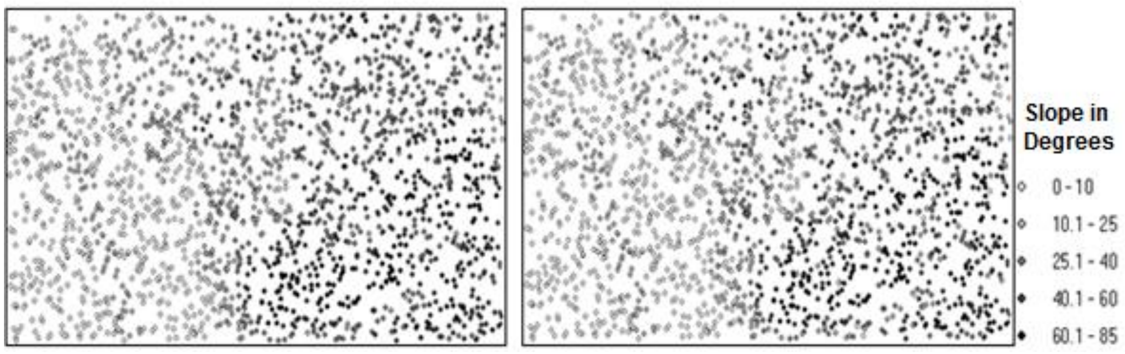


Figure 6-10 (a) Slope values of sample points (CG approach). (b) Slope values of sample points (ArcGIS).

Figure 6-11 illustrates the results of the MINUS function that was used in order to investigate the difference in the results produced using the CG approach and ArcGIS Model Builder. In other words, the points in Figure 6-11 represent the slope values differences in degrees and which are classified in seven groups using again the 'Natural Break' option. It is clear from Figure 6-11 that there is a difference in the slope values produced using the CG approach and ArcGIS; for example, the highest difference is 61 degrees (i.e. the highest value in the legend) and around 30% of slope values in the corresponding sampling locations (i.e. more than 600 sample location points) differ in more than 10 degrees. It should be noted that these differences are observed in the south-eastern part of the case study area, where the slope is steeper, due to the existence of hills.

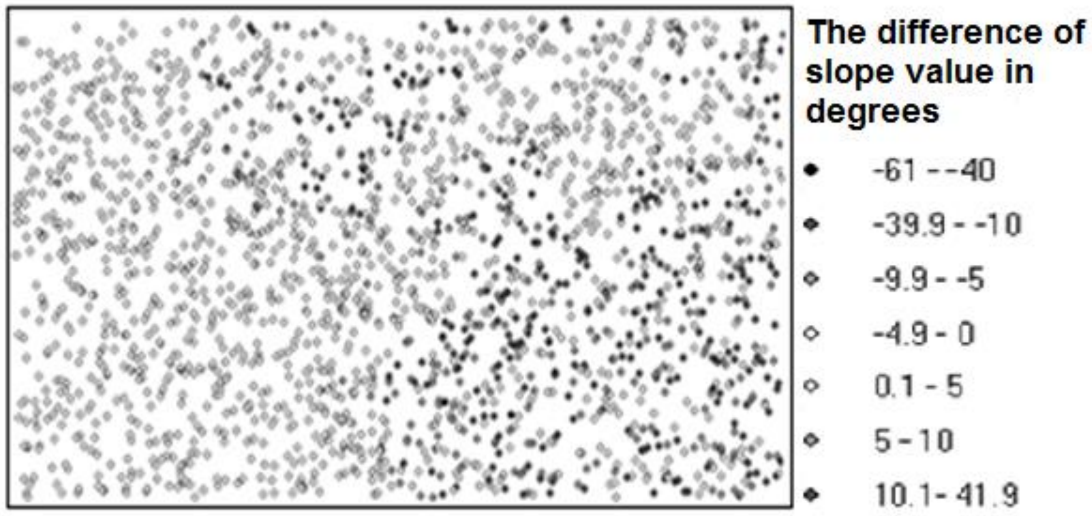


Figure 6-11 Difference in sample slope value results that were produced using the CG approach and ArcGIS ModelBuilder.

The next section provides a further discussion and comparison of the results that were produced using the CG approach and traditional geo-processing.

6.7 Case study 2: Comparison and Validation of results

This section provides a further investigation of the two different chain processing model implementations using Monte Carlo Simulation in order to trace the influences of data uncertainties in both geo-processing approaches.

6.7.1 Monte Carlo Simulation Model

In this case study, Monte Carlo simulation is used to calculate the results' mean and variance in order to investigate the influence of data uncertainties in both simple chain processing model implementations.

Monte Carlo Simulation is used to compute the result of the slope algorithm repeatedly using randomly selected, from the case study area, input values. In specific, this process includes the following three steps:

(1) Repeat the following computation steps 50 times:

(a) Randomly select 60% of raw LiDAR points, which were previously illustrated by Figure 6-6.

(b) Generate the slope values of the selected LiDAR points using both ArcGIS and the CG approach.

(2) Store the results of Monte Carlo Simulation (i.e. the generated slope values for all 50 iterations).

(3) Based on the Monte Carlo simulation results compute the mean, maximum and minimum values, as well as, the sample variance and standard deviation. A brief description of mean, maximum and minimum values and the standard deviation was provided in Section 2.3.6.2. This case study further requires calculating the sample variance, which is a measure of how far a set of samples is spread out, in order to understand the influence of data uncertainties.

Heuvelink (2006) describes extensively the computation method of Monte Carlo Simulation and explains that one of its limitations is its numerical load, which is caused by the number of required iterations,as the simulation must be executed 'N' times in order to provide a sufficient estimation of the mean, variance and standard deviation values. In GIS research, most studies run the Monte Carlo Simulation with only 20 or even ten iterations (Fisher, 1999; Goodchild et al., 1992), but Goodchild et al (1992) claim that ten iterations are not sufficient to obtain an accurate estimation of the results.

Heuvelink (2006) suggests that in most cases Monte Carlo Simulation should take at least 50 computational iterations and thus 50 iterations are also used in this case study.

6.7.2 Monte Carlo Simulation Results

The results of Monte Carlo Simulation are illustrated in Figure 6-12 for the CG approach and Figure 6-13 for ArcGIS. The results are based on the 50 computational iterations of Monte Carlo Simulation, and include the distribution of sample Mean, Maximum and Minimum values. These values are sorted by the mean slope values from lowest to highest degree (e.g. shown by the blue dots in both Figure 6-12 and Figure 6-13). In specific, the X-axis of both Figures 6-12 and 6-13, represents the index of sampling locations (i.e. 1 - 2,000) and the Y-axis represents the slope values in degrees. It is clear that the ArcGIS results illustrated by Figure 6-13 spread wider, which indicates that the slope results in ArcGIS have more noise and a larger variance than the CG approach results.

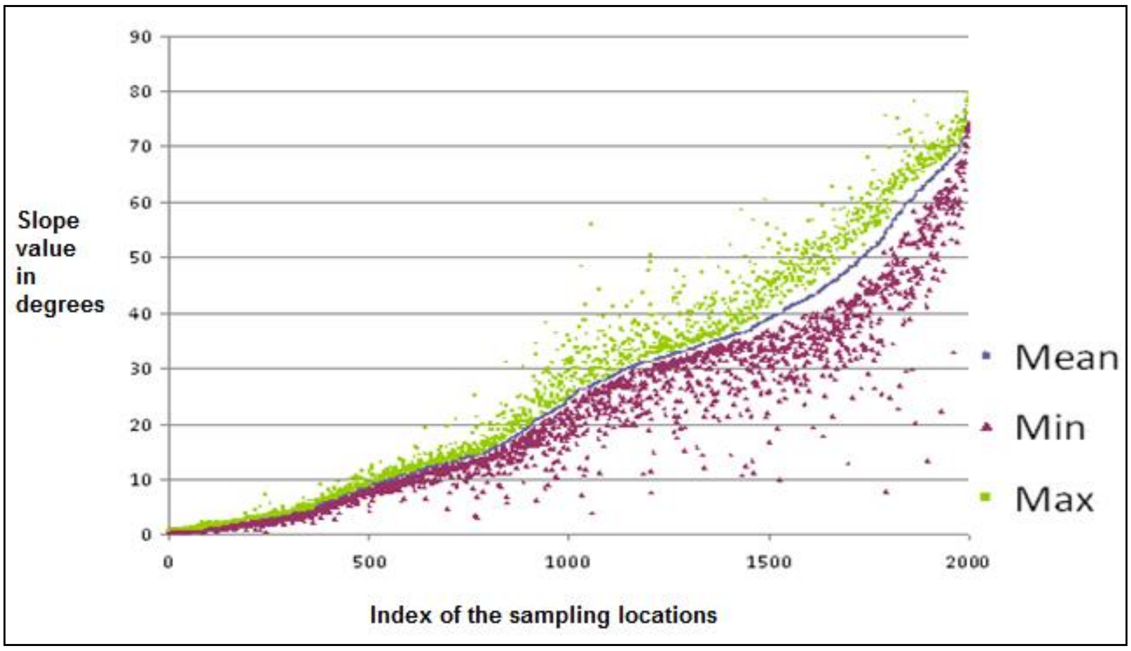


Figure 6-12 Case study 2: Monte Carlo Simulation (CG approach results).

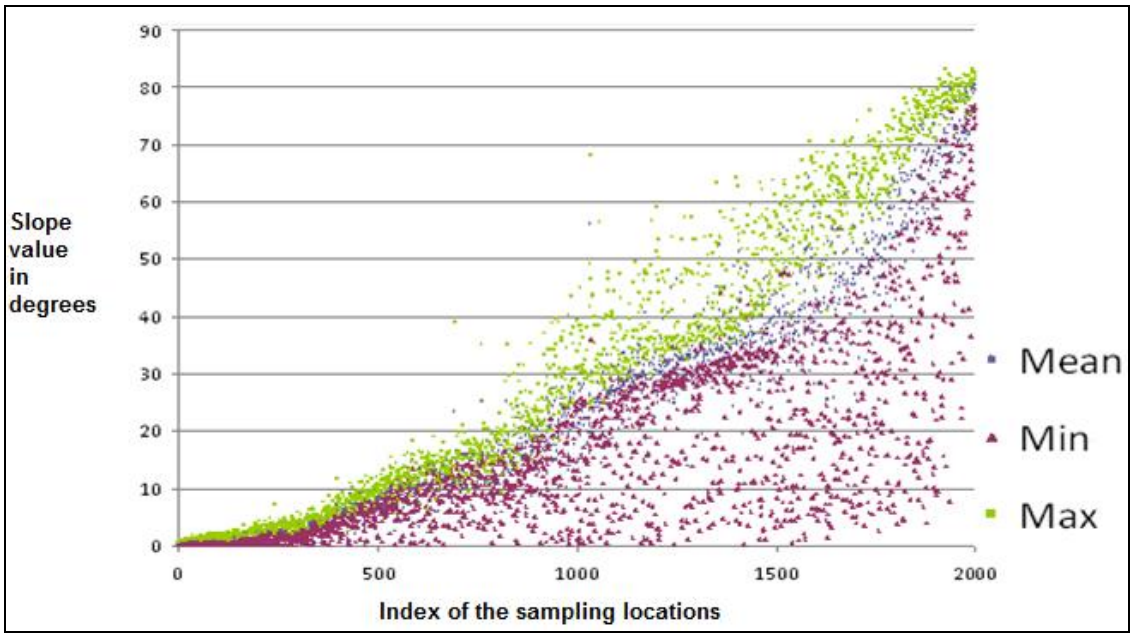


Figure 6-13 Case study 2: Monte Carlo Simulation (ArcGIS results).

The standard deviation results of Monte Carlo simulation for the sampling locations are illustrated in Figure 6.14 for the CG approach and Figure 6.15 for ArcGIS. In Figures 6.14 and 6.15 the standard deviations are classified in five groups using the ‘Natural Break’ classification option. As the legend illustrates, the dark black points represent the sampling locations with the highest standard deviation of slope values, which ranges from 10.1 to 20 degrees. The white points show the sampling locations with the lowest (i.e. from 0.01 to 2 degrees) standard deviation of slope values. In addition, there are three other groups , where the standard deviation of the slope values ranges from ‘2.1 to 5 degress’, ‘5.1 to 8 degress’, and ‘8.1 to 10 degrees’.

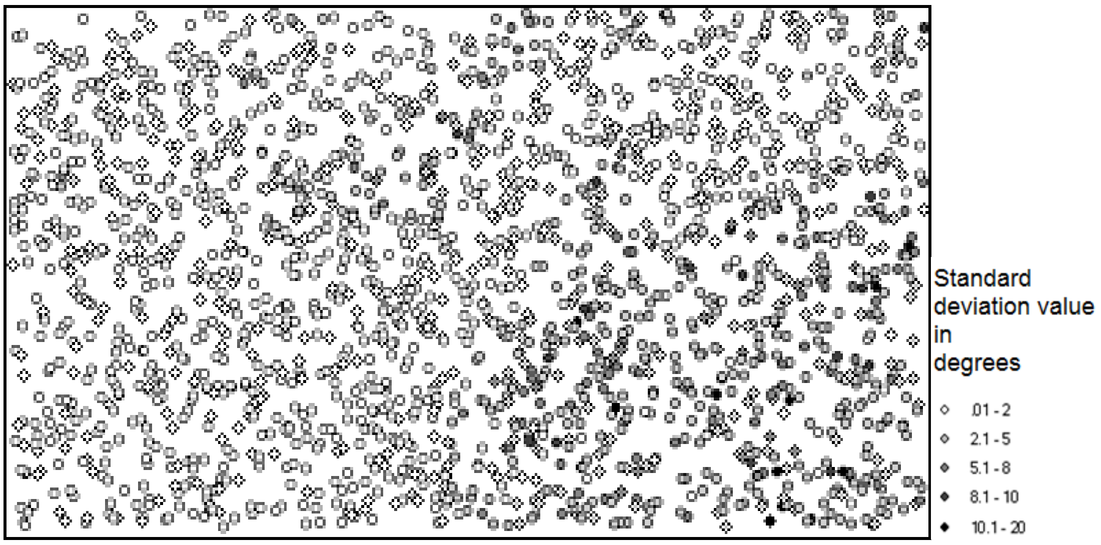


Figure 6-14 Case study 2: Standard deviation on sample locations (CG approach results).

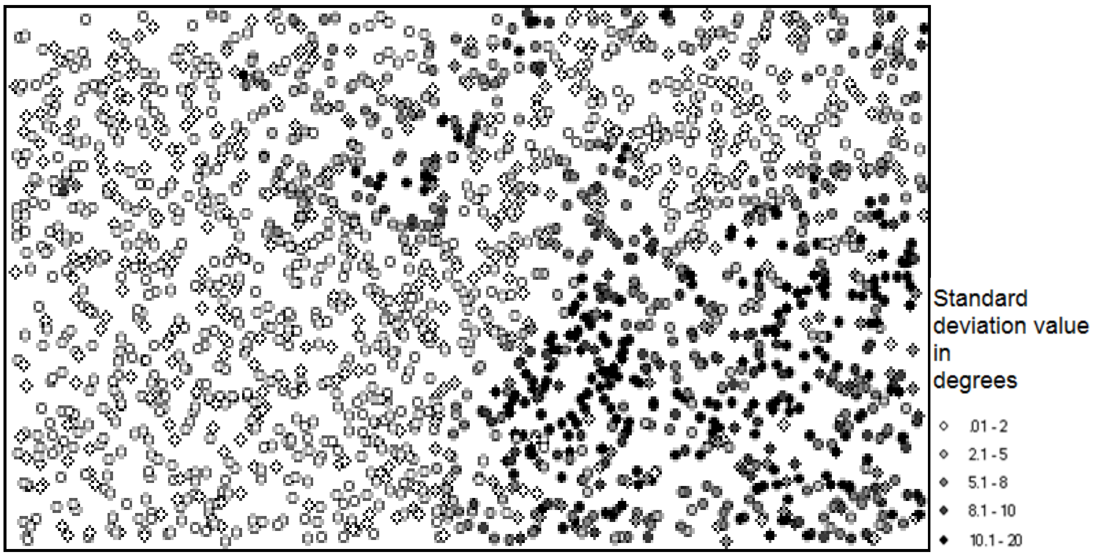


Figure 6-15 Case study 2: Standard deviation on sample locations (ArcGIS results).

The ArcGIS results which are illustrated in Figure 6.15 include a higher number of dark black points, which means that the slope standard deviation is much higher than the slope standard deviation of the CG approach results. This indicates that the traditional geo-processing approach (i.e. ModelBuilder in ArcGIS) results spread over a large range of values and thus may include data uncertainties.

Table 6.1 shows the average value of the sample variance and the standard deviation based on the slope values of the 2,000 sampling locations. The average variance (i.e. confidence interval) in ArcGIS is 31.818 degrees-squared, and it is nearly four times larger than CG approach's average variance, which is 7.304 degrees-squared. Also the average standard deviation in ArcGIS, which is equal to 3.844 degrees, is nearly two times larger than CG approach's standard deviation, which is equal to 1.811 degrees. Table 6-1 further indicates that the ArcGIS results have a larger distribution than the CG approach results, which means that they include data uncertainties.

Table 6-1 Case study 2: A comparison of variance and standard deviation.

	ArcGIS Results (Average value)	CG Results
Average of Variance	31.818 degrees-squared	7.304 degrees-squared
Average of Standard Deviation	3.844 degrees	1.811 degrees

6.8 Discussion

Monte Carlo simulation analysis revealed many differences between the CG and traditional geo-processing results. These may occur due to mainly two reasons, which are discussed in the following paragraphs.

First, the two approaches differ in terms of storing numerical numbers. In traditional geo-processing, numerical computation is a common method to store the results. However, one problem with numerical computation is round-off values, which may result in round-off errors (Goldberg 1994). Table 6-2 provides some examples of round-off errors that may occur in numerical computation. For example, if '$\log_{10} 2$' is rounded to three decimal places (i.e. 0.301), the total round-off error is '0.000 029 995 663 981 195 21'. It should be noted that increasing the number of decimal digits may reduce the magnitude of round-off error, but limited computer storage memory may still cause round-off errors in various real numbers. On the other hand, the CG approach uses symbolic computation, which improves the precision of various calculations. Moreover, in the CG approach round-off errors do not exist because symbols and algebraic relationships are manipulated without storing numerical values (Recktenwald 2006).

Table 6-2 Example of round-off errors in numerical computation.

Real Number	**Representation Value**	**Approximation Value**	**Round-off Error**
1/7	0.142 857	0.142 857	0.000 000 142 857
ln 2	0.693 147 180 559 945 309 41...	0.693 147	0.000 000 180 559 945 309 41...
$\log_{10} 2$	0.301 029 995 663 981 195 21...	0.301	0.000 029 995 663 981 195 21...
$\sqrt[3]{2}$	1.259 921 049 894 873 164 76...	1.25992	0.000 001 049 894 873 164 76...
$\sqrt{2}$	1.414 213 562 373 095 048 80...	1.41421	0.000 003 562 373 095 048 80...

Second, spatial attributes, such as elevation and slope, are represented as raster layers in the traditional geo-processing approach, which have an arbitrary resolution and may cause data uncertainties (Haklay 2004). For instance, Figure 6-16 shows how slope can be represented in a raster-based layer, where each grid is assigned with a value that records the slope value from the centre of the grid (shown by the red cross in Figure 6-16). In the traditional geo-processing approach, all geographical points, that belong to the grid are assigned with the same slope value, which is assigned to the centre of the grid. As a result, the distance shift (shown by the black arrow in Figure 6-16) between the randomly selected locations and the centre of the grid may cause distortions in the slope values. These data uncertainties may be propagated when the slope values are used as an input into further computation tasks in a traditional geo-processing model.

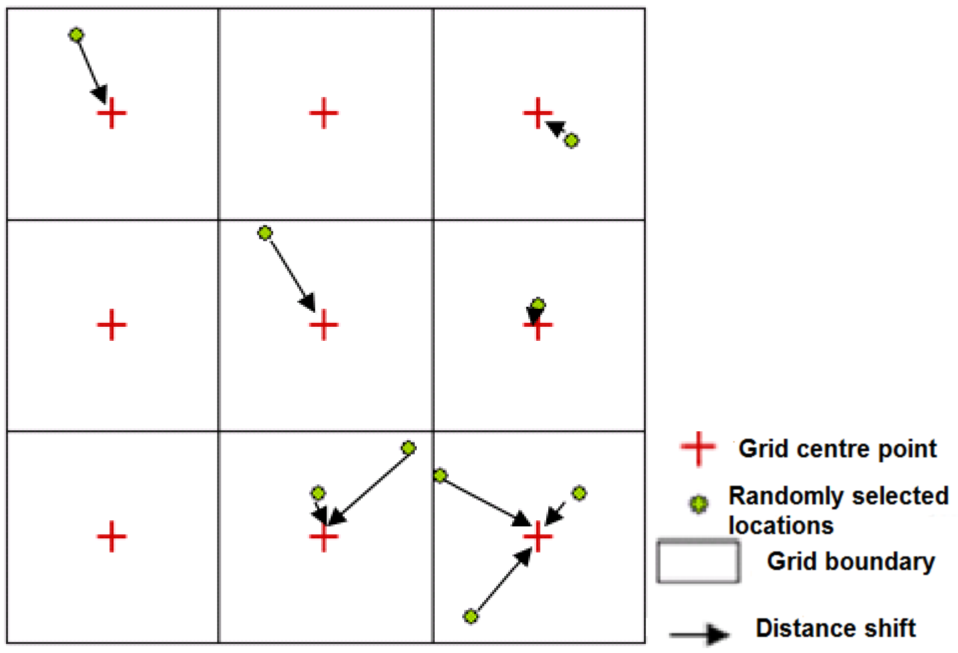


Figure 6-16 The slope representation (i.e. raster-based) and the distance shift (i.e. the cause of distortion) between randomly selected location and grid centre point.

In contrast to raster-based layers that are used in ArcGIS, the CG approach applies function-based layers to store and process spatial data. With the CG approach no intermediary results are produced during implementation of a geo-processing model. As a consequence, there is no need to produce any raster images in order to store elevation or slope values, while the slope values are calculated based on the specific locations that are defined by the users. For example, if users want to query the slope values from the randomly selected locations illustrated in Figure 6-16, the CG approach should calculate the slope values based on their specific geopraohical locations (i.e. does not assign the slope value to the centre of the grid). Therefore, any potential data uncertainties caused by raster data representation can be minimised within the context of the CG approach.

6.9 Summary

This Chapter described the implementation of a simple chain processing model using the CG and traditional geo-processing approaches. First, a generic simple chain processing model, as well as, the model used in Case study 2 were reviewed. It was also discussed how the simple chain processing model can be implemented using the CG and traditional geo-processing approaches. In specific, it was explained that in traditional geo-processing the computation tasks (i.e. IDW and Slope) are executed one by one, and the intermediate result (i.e. the output of IDW) is used as the input of Slope function in order to generate the final result. However, using the CG approach the final result (i.e. slope values) is produced directly from the input dataset (i.e. the LiDAR point) and the CG function (i.e. a combinative CG function of IDW and Slope).

The results of Case study 2 were compared using Monte Carlo simulation. It was found that the CG approach provides improved Monte Carlo simulation results. For example, the CG approach's average variance (i.e. 7.304 degrees-squared) was nearly four times lower than the ArcGIS's average variance (i.e. 31.818 degrees-squared), also the average standard deviation in the CG approach (i.e. 1.811 degrees) was nearly two times lower than ArcGIS's standard deviation (i.e. 3.844 degrees). The results of Monte Carlo simulation indicated that the CG approach results include less data uncertainties when compared with traditional geo-processing; this is because the CG approach uses symbolic computation and function-based layers for the execution of the various computation tasks. In addition, this case study was also found that round-off errors in numerical computation and the data uncertainties caused by raster data representations in traditional geo-processing may further influence the results' accuracy.

A potential limitation of the CG approach is that it can be time consuming when large datasets and complex models are involved. Thus, improving computational efficiency (i.e. time cost) is a critical concern, which is discussed in the next Chapter (Chapter 7).

7 Implementing a Complex Chain Processing Model Using Combinative Geo-processing Function

7.1 Introduction

The previous Chapter (Chapter 7) demonstrated how a simple chain processing model is implemented in the CG approach. The Monte Carlo simulation results of Case Study 2 show that the CG approach helps to overcome and improve data uncertainty problems which exist in the traditional geo-processing. Nevertheless, it is should be noted that the simple chain processing model implementation using the CG approach increases the required computation time, possibly due to the inefficient computation strategy used in the execution and manipulation of geographical data and GIS functions. To further investigate and resolve this implication this case study focuses on the efficiency (i.e. computation time) of the computation strategy of the CG approach.

Section 7.2 discusses the implications of inefficient computation strategy in geo-processing and introduces the concepts of computation flexibility and computation sequence. Section 7.3 proposes the concept of CG computation priority, which aims to reduce the overall computation time of geo-processing through the use of an improved computation strategy. Section 7.4 reviews the complex chain processing model that it is applied in this case study and Section 7.5 discusses how the model is implemented in traditional geo-processing and the CG approach using computation priority. Section 7.6 presents the datasets that are used in Case study 3. Section 7.7 discusses in detail the exact implementation and strategy for executing the complex chain processing model in this case study using the two different geo-processing approaches. Section 7.8 presents the results of the complex chain processing model implementations. Section 7.9 compares the implementation results of the overall computation time and Section 7.10 discusses the significant differences of the results. Finally, Section 7.11 provides a summary of the main issues that are discussed in this Chapter.

7.2 The Implications of Computation Strategy in Geo-processing

The first two case studies described in Chapters 5 and 6, mainly focused on the improvement of data uncertainty using the CG approach. Nevertheless, it became evident that a problem of the previous CG implementations was concerned with the required computation time. Specifically, intensive computation time is usually required to implement the various CG functions and the computations based on Higher-Order Functions in order to reduce the influence of data uncertainties in the geo-processing. In some case studies, especially those which involve large spatial datasets (e.g. in Case Study 3), the computation time of processing the LiDAR point dataset (around 26,000 points) and the CG functions (‘IDW’ and ‘Slope’) required several hours in the current CG approach (i.e. without an efficient computationa strategy). To further investigate and address this problem, Case study 3 focuses on computational efficiency and it involves the implementation of a complex geo-processing model with larger spatial datasets.

This section discusses the implications of computation strategy as it is a fundamental element for improving computational efficiency (Loogen et al., 1993; Fijany et al., 1995). Computation strategy represents a plan, which is used to solve one or more goals by applying an optimum method in order to efficiently control the computations (Martin and Virseda 2005). For example, Loogen et al., (1993) discuss a computation strategy for lazy conditional narrowing, which is based on the idea of transforming patterns into decision trees to manage the computation; Manoranjan et al., (2004) also describe new efficient similarity metric and generic computation strategy for pattern-based very low bit-rate video coding. These examples show that an optimum computation strategy may potentially improve computational efficiency.

In this thesis, the computation strategy of the traditional geo-processing approach has been discussed in Case Studies 1 and 2, which showed that the computation tasks (i.e. GIS functions) of a geo-processing model are executed sequentially in the traditional geo-processing approach. Moreover, it was also found from these case studies that there are two factors which frequently influence the existing computation strategy and which may extend the overall computation time, and these refer to computation flexibility and computation sequence. Computation flexibility refers to the procedures that can manage the allocations of costly resources, such as time, memory, or information (Martin and Virseda 2005). Computation sequence represents the execution order of computation tasks in a geo-processing model.

Computation flexibility may influence the efficiency of a computation strategy implementation because an optimum computation strategy needs a capability to control the computations and manage the costs, such as amount of computation resources and calculations (Martin and Virseda 2005). The earlier case studies showed that the current geo-processing approach executes computation tasks or GIS functions straightforward, and does not provide a capability to manage the cost, such as the amount of computations to solve a spatial problem.

Figure 7-1 demonstrates an example of a complex chain processing model in order to illustrate the problem related to computation flexibility in the traditional geo-processing approach. This model is trying to solve the spatial analysis problem of finding a suitable location for a dairy farm (Sujoni and Hardjomidjojo, 2010). As it can be seen from Figure 7-1 the input datasets include a DEM and a land use map. The DEM data provide the elevation, which could be further used to investigate the temperature and humidity in the case study area. The land use map provides the soil types, which could be used to understand the food supplements for animals, such as pasture supply. Then, these input data are processed using five computation tasks, (i.e. 'Feature to Raster', 'Reclassify', 'Slope', 'Reclassify2', and 'Weighted Overlay'), to produce the final result. It should be noted that all the outputs of each computation task have to be processed on the entire region of the study area because it is the default option in the traditional geo-processing tools, such as Modelbuilder, ArcGIS. This problem may lead to redundant computations in the geo-processing model and potentially increase the required computation time.

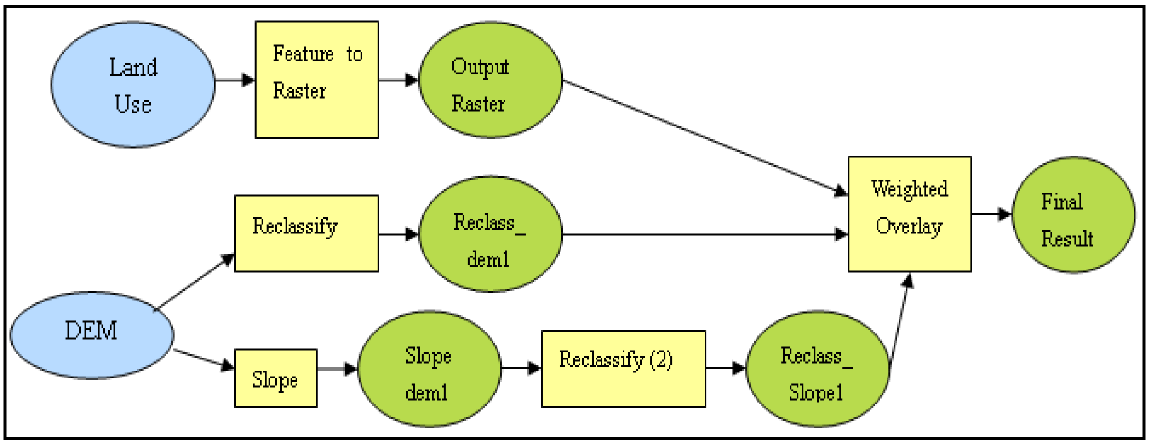


Figure 7-1 The geo-processing model for identifying a suitable location for a dairy farm site (After Sujoni and Hardjomidjojo, 2010).

The redundant computations could be avoided by improving computation flexibility, such as managing and reducing the amount of computations based on specific criteria. In geo-processing models, different types of criteria are frequently used to identify GIS user's interested areas, such as five metres buffer to a road network or the area has elevation values lower than 100 metres. These selected areas could be defined as ROI in a geo-processing model. In principle, a ROI represents a selected subset of samples within a dataset identified for a particular purpose, and possibly covers only a part of the entire study area.

For instance, in the geo-processing model displayed in Figure 7-1, one of the site selection criteria is that the proposed for the dairy farm site should be located within a pasture area. This means that any data located outside the pasture area will not be considered in the GIS analysis, so no further processing of these data is required. As Figure 7-2 shows the ROI of this geo-processing model, which includes the pasture area, takes approximately 20% of the entire region, which means that the outside of the ROI area data, (almost the 80% of the entire region), will not require any further processing. Therefore if further processing of data outside of the ROI area can be avoided, it could significantly improve computational efficiency.

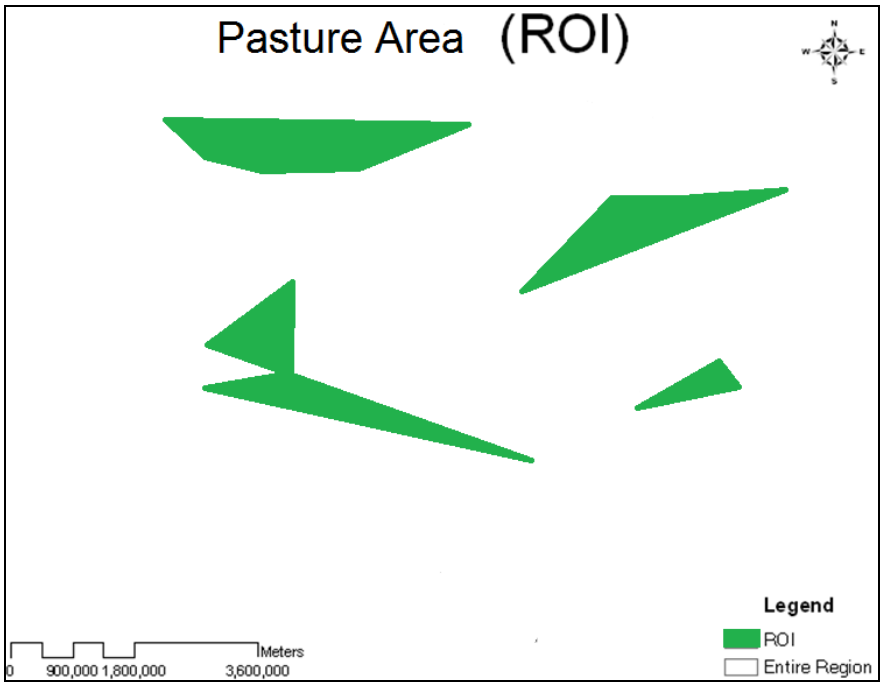


Figure 7-2 Region Of Interest (ROI), which shows the pasture area of the dairy farm model.

Moreover, computation sequence, which provides an order to execute various computation tasks in a geo-processing model, may also influence the efficiency of the computation strategy. As was discussed in Chapter 3 that current geo-processing tools use a sequential computation sequence to execute the computation tasks that are included in a geo-processing model. This is mainly because popular geo-processing tools (e.g. ArcGIS and MapInfo) are developed using programming languages such as JAVA and C, where the so-called 'Call-by-Value' computation strategy is used to store and calculate a value. The major characteristic of the 'Call-by-Value' computation strategy is that the argument of a function (e.g. x is a single argument in the function:

$f(x) = x^2 + 2$) is calculated before the argument is used and the resulting values are bound to the corresponding variables in the function (Lengrand 2003).

For instance, the implementation of a single GIS function in ArcGIS, which is developed in C programming language, includes: (a) the ‘input’, which is an argument; (b) when the ‘input’ loads into a GIS function, the resulting value is executed and bounded to the corresponding variable (i.e. output). This computation strategy is repeatedly applied in a chain sequence in order to implement all computation tasks of a geo-processing model. Nevertheless, this chain computation sequence may not be efficient when large geo-processing models are involved; it may include computations that are not necessary to be executed at run time (Muchnick 1997, p.117).

Due to the previously noted computation strategy implications, the next section introduces the concept of CG computation priority, which aims at improving the overall computation time of a geo-processing model.

7.3 Implementations Combinative Geo-processing Computation Priority

CG computation priority is an important computation rule in this research. It is used in the CG approach and enables the execution of computation tasks or functions that are included in a geo-processing model using a different computation strategy. Specifically, the computation tasks are assigned initially with different priority values, and then they are implemented according to this priority value, from highest to lowest.

7.3.1 Improving GIS Computational efficiency

Nowadays, GIS have been widely used in various fields, such as transportation, environmental modelling, asset management, and citizen science. Nevertheless, computational efficiency is a major concern of GIS development as the size of spatial datasets and the complexity of spatial problems are dramatically increasing (Brown and Coenen 2000).

There are many methods that can be used to improve computational efficiency and performance of existing GIS technologies, such as spatial data structure and data access methods which provide a way to access and query larger spatial databases more efficiently. For example, Guttman (1984) states a spatial data access method, the so-called R tree, to store, search, and query spatial information. R-tree provides an efficient way to query a spatial database as computer memory and temporary database usage are reduced in this method. R-tree has been widely used in different applications of spatial data management. For example, R-trees are commonly used to store spatial data such road networks and city locations, and then for querying the data quickly and efficiently such as ‘Find a shortest distance from city A to city B’ or ‘Find a nearest motorway access point around city C’. Moreover, Kriegel et al., (1993) discuss a method which combines spatial access and computational geometry concepts in order to improve the performance of GIS operations. The method could be applied in different applications or algorithms, such as map overlay and map merge. However, the current method relies on certain criteria (e.g. the robust spatial access method) and the further investigation is needed to design efficient algorithms based on spatial access methods and computational geometry for all retrieval operations.

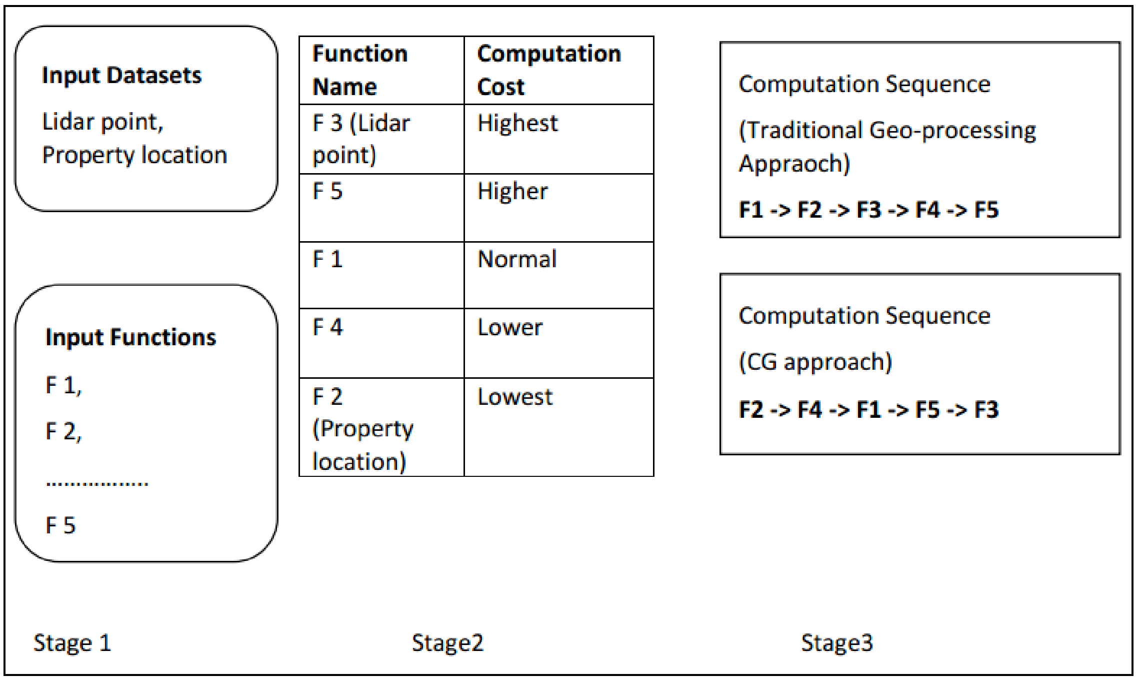
The previously noted methodologies contribute to the GIS computations, especially with respect to accessing and querying large spatial datasets. Nevertheless, these methods do not improve the efficiency of executing a large group of computation tasks in a geo-processing model.

7.3.2 Computation Combinative Geo-processing (CG) Computation Priority

Computation priority, or scheduling, is a common method used to effectively use computation resources and improve computation performance (Jones et al., 1997). In computer science, the priority (or scheduling) is used for implementing multiple computation tasks. For example, the scheduling could be used to suspend a computation task which has a low priority, or a computation task which is allocating a large amount of memory in order to free up main memory for other computation tasks, implementing the computation task later when more computer memory is available (Stallings 2004). Moreover, the priority (or scheduling) has also been widely applied in GIS, mainly for the purposes of determining least cost paths across a continuous surface (De Smith et al., 2007).

Similarly to the priority rule that it is used in computer science or in spatial problems of path selection, the CG computation priority is trying to provide a new computation strategy in geo-processing to implement various computation tasks more efficiently, or in other words, using the minimum computation time and computer resources. Specifically, the basic principle of CG computation priority is that the CG approach starts with an analysis of the computation tasks or GIS functions included in the geo-processing model and then the system assigns priority values to each computation task or function. Finally the computation tasks or functions are executed according to the priority values assigned to them starting from the highest to the lowest.

An example of a simple workflow in geo-processing with CG computation priority is given in Figure 7-3 in order to demonstrate the characteristics of the new computation strategy. Specifically a set of GIS functions (F_1, F_2, F_3,…, F_5) and input datasets (LiDAR Point, …) are first provided. The system defines the computation cost of each function. It should be noted that the term computation cost in this thesis is a generic idea, which refers to some composite factors that vary during a geo-processing model implementation (e.g. time complexity of an algorithm, processing area, and spatial data volume), and which needs to be taken into account when computation tasks or GIS functions are executed. It should be also noted that the lowest computation cost will be given the highest computation priority. The CG computations are executed according to the priority assigned to them, from highest to lowest. As a result, an original computation sequence in traditional geo-processing approach (e.g. 'F1 ->F2 ->F3 ->F4 ->F5') will be re-organised in a new computation sequence in the CG approach (e.g. 'F2 ->F4 ->F1 ->F5 ->F3').



Function Name	**Computation Cost**
F 3 (Lidar point)	Highest
F 5	Higher
F 1	Normal
F 4	Lower
F 2 (Property location)	Lowest

Figure 7-3 An example of applying the CG computation priority in a simple geo-processing model.

The example of the CG computation priority displayed in Figure 7-3 indicates that the new proposed computation strategy has the potential to provide more flexibility and a new computation sequence for calculating a geo-processing model. Specifically, the system executes first the highest priority functions because they cost the least computation time and resources. Then the lower priority functions are further executed, as they usually allocate more computation resources and extend the overall computation time.

We can now turn to the geo-processing model that it is used in this case study. Specifically, Case study 3 utilises the CG functions developed from the earlier three case studies, (e.g. 'IDW', 'Slope', and 'Raster Layer Overlay' functions), in order to understand how the CG computation priority can be implemented using the CG approach and the new computation strategy.

7.4 Case study 3: The Complex Chain Processing Model Review

This section describes the implementation of CG computation priority in a complex chain processing model, which involves a site selection for new property development problem. Compared to the geo-processing model implemented in Case Study 3, a higher number of computation tasks and a larger dataset are involved in this case study in order to evaluate the overall computation time of the CG approach using the CG computation priority rule. The specific details of the complex chain processing model are explained in the following paragraphs.

Figure 7-4 illustrates this case study's geo-processing model, which involves three main steps. The first step refers to data input and involves input of the original spatial data, which includes LiDAR Points, property locations, and road network data (shown by the blue circles in Figure 7-4). LiDAR points are used to produce elevation and slope values. Property locations and road network are applied to understand additional problems such as examining the local noise levels. The second step refers to data processing and there are five main types of computation tasks which are applied in this geo-processing model, which are shown by the orange circles in Figure 7-4. These are:

1. ***IDW***: Create grid digital elevation surface (grid size: five metres).
2. ***Slope***: Produce slope value from digital elevation surface.
3. ***Selection 1 to Selection 4***: According to a group of criteria, the model will select the potential area for new property development. The specific criteria include: Selection 1 is to choose elevation values that are less than 100 metres; Selection 2 is to identify the slope values that are less than 30 degrees; Selection 3 is to find the locations with a distance to the existing property locations which is

more than 30 meters; Selection 4 is to find the locations with more than 50 meters distance to the road network which.

4. ***Distance 1 and 2***: Calculate the distance to existing property locations and road network.
5. ***Map Layers Overlay***: Produce the final output from an integration of all GIS layers.

The green circles in Figure 7-4 represent the output of each computation task. Finally, the objective of this model is to produce the Final Output, which is illustrated by the red circle in Figure 7-4 and which shows the potential locations for constructing new residential properties.

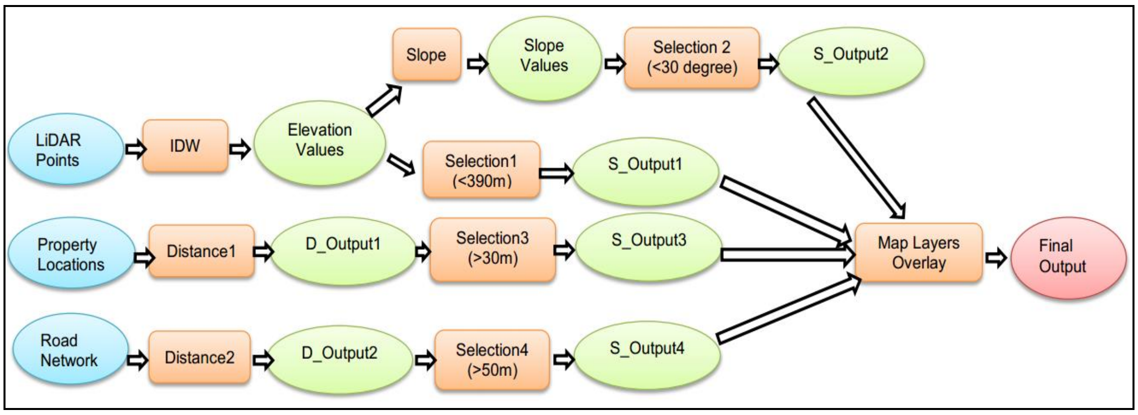


Figure 7-4 The complex chain processing model used in Case study 3.

The next section provides more details about the exact methodological approach that it is used to implement the complex chain processing model.

7.5 Methodology: The Complex Chain Processing Model Implementations

7.5.1 The Complex Chain Processing Model Implementation: ModelBuilder, ArcGIS

Figure 7-5 illustrates the implementation steps of the complex chain processing model in traditional geo-processing using ArcGIS ModelBuilder tool. Specifically, the blue circles represent the input datasets, the yellow circles represent the computation tasks (i.e. GIS functions), and the green elliptical circles represent the output of each computation task. Furthermore, the lowercase letters (i.e. a, b, c,…, I) indicate the computation sequence of the complex chain processing implementation. It should be noted that the computation sequence is based on the workflow of the complex chain processing model (i.e. from first computation task to the next one).

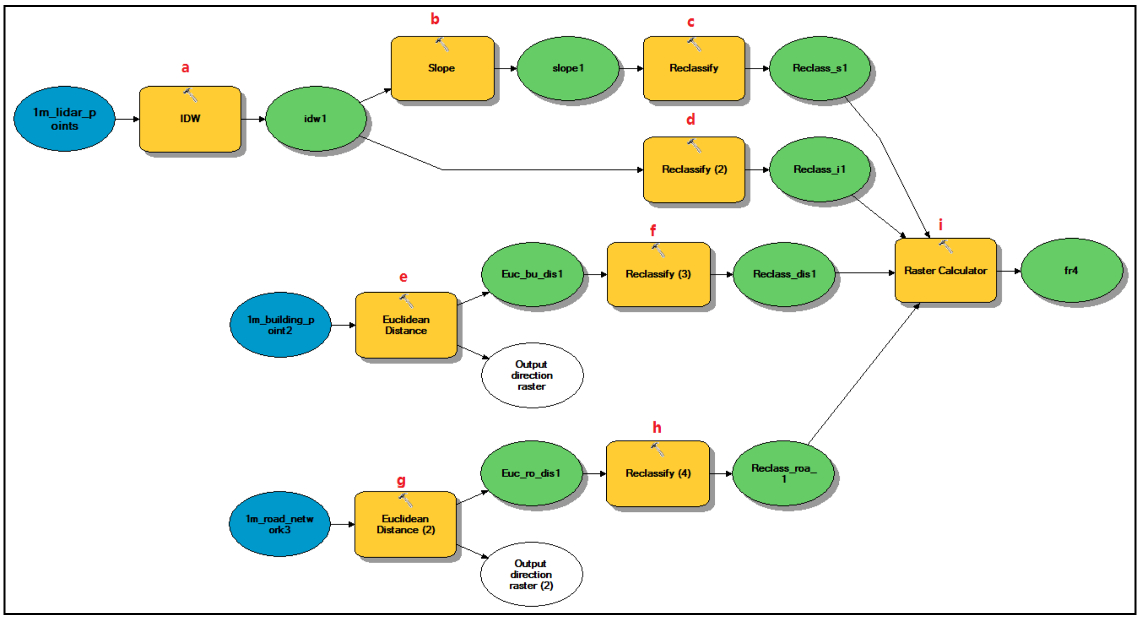


Figure 7-5 Case study 3: Example of complex chain processing model in ModelBuilder (ArcGIS).

The corresponding mathematical model for the geo-processing model illustrated by Figure 7-5, is given by Formula 7.1; where the entire geo-processing model is implemented using nine GIS functions (i.e. 'F_{IDW}', 'F_{SLOPE}', '$F_{\text{RECLASSIFY}}$', '$F_{\text{RECLASSIFY (2)}}$', '$F_{\text{EUCLIDEAN DISTANCE}}$', '$F_{\text{RECLASSIFY (3)}}$', '$F_{\text{EUCLIDEAN DISTANCE (2)}}$', '$F_{\text{RECLASSIFY (4)}}$', '$F_{\text{RASTER CALCULATOR}}$') and which are listed based on their sequential computation sequence (i.e. from a to i). The nine GIS functions and their computation tasks are further summarised in Table 7-1 to provide further information about the complex chain model and how it is built using ModelBuilder ArcGIS.

a. F_{IDW} (LiDAR points) = $Output_{IDW}$

b. F_{SLOPE} ($Output_{IDW}$) = $Output_{SLOPE}$

c. $F_{RECLASSIFY}$($Output_{SLOPE}$) = $Output_{RECLASSIFY}$

d. $F_{RECLASSIFY(2)}$($Output_{IDW}$) = $Output_{RECLASSIFY(2)}$

e. $F_{EUCLIDEAN\ DISTANCE}$ (Property Locations) = $Output_{EUCLIDEAN\ DISTANCE}$

f. $F_{RECLASSIFY(3)}$($Output_{EUCLIDEAN\ DISTANCE}$) = $Output_{RECLASSIFY(3)}$

g. $F_{EUCLIDEAN\ DISTANCE(2)}$ (Road Network) = $Output_{EUCLIDEAN\ DISTANCE(2)}$

h. $F_{RECLASSIFY(4)}$($Output_{EUCLIDEAN\ DISTANCE(2)}$) = $Output_{RECLASSIFY(4)}$

i. $F_{RASTER\ CALCULATOR}$($Output_{RECLASSIFY}$ + $Output_{RECLASSIFY(2)}$ + $Output_{RECLASSIFY(3)}$ + $Output_{RECLASSIFY(4)}$) = Final Result

[7.1]

Table 7-1 A summary of GIS functions in the complex chain processing model.

	Function Name	Computation Task	Input	Output
a	F_{IDW}	Create five metres grid digital elevation surface	LiDAR points	$Output_{IDW}$
b	F_{SLOPE}	Produce slope value from the digital elevation surface	$Output_{IDW}$	$Output_{SLOPE}$
c	$F_{RECLASSIFY}$	To identify the slope values that less than 30 degrees	$Output_{SLOPE}$	$Output_{RECLASSIFY}$
d	$F_{RECLASSIFY(2)}$	To choose elevation values that less than 100 metres	$Output_{IDW}$	$Output_{RECLASSIFY(2)}$
e	$F_{EUCLIDEAN\ DISTANCE}$	Calculate the distance to existing property locations	Property Locations	$Output_{EUCLIDEAN\ DISTANCE}$
f	$F_{RECLASSIFY(3)}$	To find the locations which have distance to the existing property locations more than 30 meters	$Output_{EUCLIDEAN\ DISTANCE}$	$Output_{RECLASSIFY(3)}$
g	$F_{EUCLIDEAN\ DISTANCE(2)}$	Calculate the distance to the existing road network	Road Network	$Output_{EUCLIDEAN\ DISTANCE(2)}$
h	$F_{RECLASSIFY(4)}$	To find the locations which have distance to the road network more than 50 meters	$Output_{EUCLIDEAN\ DISTANCE(2)}$	$Output_{RECLASSIFY(4)}$
i	$F_{RASTER\ CALCULATOR}$	Produce the final output from an integration of the GIS layers	$Output_{RECLASSIFY;}$ $Output_{RECLASSIFY(2);}$ $Output_{RECLASSIFY(3);}$ $Output_{RECLASSIFY(4)}$	Final Result

The next section introduces how the complex chain processing model is implemented using the CG approach with computation priority.

7.5.2 The Complex Chain Processing Model Implementation: Combinative Geo-processing (CG) Approach

The implementation of the complex chain processing model using the CG approach is illustrated in Figure 7-6. Specifically the implementation includes first loading the input datasets (i.e. LiDAR Points, property locations, and road network) into the combinative CG function, which includes nine CG functions and generates the final result only upon user request and it only involves processing the computations within the ROI areas. The mathematical model and structure of the combinative CG function are further discussed in the following paragraphs in order to explain how the CG computation priority is implemented in this case study.

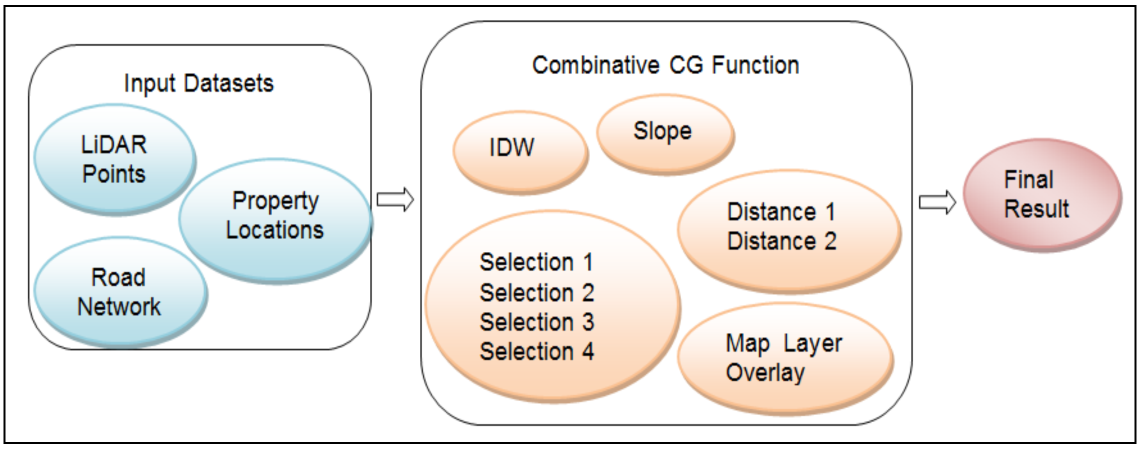


Figure 7-6 Case study 3: Complex chain processing model in the CG approach.

Formula 7.2 provides the mathematical model for the implementation of the complex chain processing model which is illustrated by Figure 7-6. This mathematical model was built using the same method that it was used in Case Study 3 for the simple chain processing model. Specifically, the 'CG Function' was constructed using the following nine functions: 'CG_{IDW}', 'CG_{Slope}', '$CG_{Selection1}$', '$CG_{Selection2}$', '$CG_{Selection3}$', '$CG_{Selection4}$', '$CG_{Distance1}$', ' $CG_{Distance2}$', '$CG_{Map\ Layers\ Overlay}$'. These functions involve the same computation tasks with those involved in ModelBuilder and which were presented in section 7.5.1. The main difference is that in CG the computation tasks are assigned with different computation priority values in order to improve computational efficiency.

$$\textbf{\textit{CG Function (CG dataset)}} = \{ \text{CG}_{\textit{Map Layers Overlay}}$$
$$\{CG_{Selection1}\ (CG_{IDW}\ (LiDAR\ Points))\}$$
$$\{CG_{Selection2}\ (CG_{Slope}\ (CG_{IDW}\ (LiDAR\ Points)))\}$$
$$\{CG_{Selection3}\ (CG_{Distance1}\ (Property\ Locations))\}$$
$$\{CG_{Selection4}\ (CG_{Distance2}\ (Road\ Network))\}$$
$$(CG\ dataset)\} \qquad \textbf{[7.2]}$$

The structure of the mathematical model is displayed in Figure 7-7 using different size of blue dashed outline boxes which are used to illustrate how the CG functions are organised. For example, the largest blue dashed outline box represents the ‘Map Layers Overlay’ function, which aims to integrate the results from the four sub-functions, a, b, c, d, which have different functionalities in the complex geo-processing model as it is explained below:

a. ***$\{CG_{Selection1}\ (CG_{IDW}\ (LiDAR\ Points))\}$*** // The main functionality is to select the suitable area by the elevation value criterion.

b. ***$\{CG_{Selection2}\ (CG_{Slope}\ (CG_{IDW}\ (LiDAR\ Points)))\}$*** // The main functionality is to select the suitable area by the slope value criterion.

c. ***$\{CG_{Selection3}\ (CG_{Distance1}\ (Property\ Locations))\}$*** // The main functionality is to select the suitable area by the distance to existing property locations.

d. ***$\{CG_{Selection4}\ (CG_{Distance2}\ (Road\ Network))\}$*** // The main functionality is to select the suitable area by the distance to the road network.

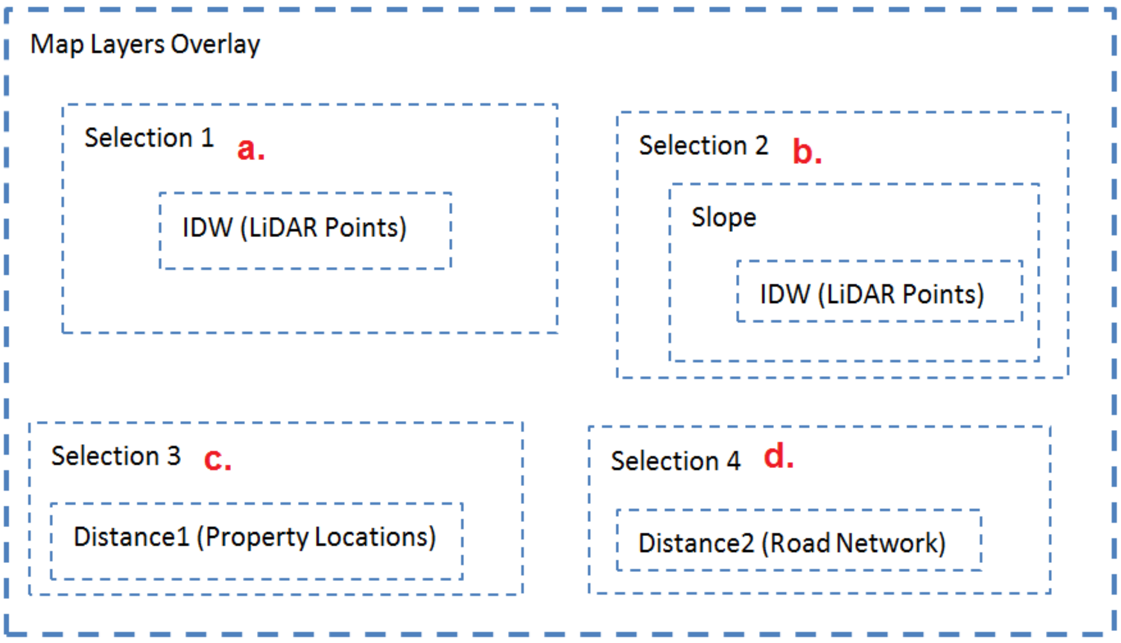


Figure 7-7 Case study 3: The structure of the CG function in the complex chain processing model.

As noted, the main characteristic of the CG computation priority is to assign the different priority values to each function and then implement them starting with the highest priority to finish with the execution of the function which was given the lowest priority. Therefore, in the next paragraphs the a, b, c, d sub-functions are used as an example to illustrate how the different priority values could be assigned to these functions in this complex chain processing model.

In this case study, the CG computation priority is defined considering the computation cost of each function. As was explained in Section 7.2.3, the term computation cost refers to a group of composite factors, including computation complexity, processing area, and spatial data volume. The corresponding generic mathematical model for computation cost assessment is described in formula (7.3). In this formula, $\mathrm{VALUE}_{\mathrm{Computation\ Cost}}$ is the computation cost value of a CG function or a computation task, $\mathrm{Factor}_{\mathrm{complexity}}$, $\mathrm{Factor}_{\mathrm{processing\ area,}}$ and $\mathrm{Factor}_{\mathrm{data\ volume}}$ are the different composite factors which influence on the computation cost assessment. Finally, $\mathrm{W}_{\mathrm{complexity}}$, $\mathrm{W}_{\mathrm{processing\ area}}$, and $\mathrm{W}_{\mathrm{data\ volume}}$ are the weight value of each factor. It should be noted that, the further details of $\mathrm{Factor}_{\mathrm{complexity}}$, $\mathrm{Factor}_{\mathrm{processing\ area,}}$ and $\mathrm{Factor}_{\mathrm{data\ volume}}$ are illustrated in Table 7-2, while the $\mathrm{W}_{\mathrm{complexity}}$, $\mathrm{W}_{\mathrm{processing\ area}}$, and $\mathrm{W}_{\mathrm{data\ volume}}$ are simplified as the same weight value (i.e. value 1) in Case study 3.

$$\mathbf{VALUE}_{\textbf{Computation Cost}} = (\mathbf{Factor}_{\textbf{complexity}} \times W_{\text{complexity}} + \mathbf{Factor}_{\textbf{processing area}} \times W_{\text{processing area}} + \mathbf{Factor}_{\textbf{data volume}} \times W_{\text{data volume}}) \qquad \textbf{[7.3]}$$

Specifically, Sipser (2006) discusses that time complexity represents the number of instructions which a program executes during its running time and time complexity is usually used to quantify the amount of time taken by an algorithm. The computation complexity could be expressed by using the Big O Notation, which is a mathematical model and applied to classify algorithms according to how they respond (e.g., in their processing time or computing memory requirements) to changes in input dataset size (Cormen et al., 2001). For example, if an algorithm on input datasets of size N is $10N^2 + 5N$, it's time complexity is $O(N^2)$, where O represents an O - notation. The result of the example (i.e. $O(N^2)$) is produced according to two simplification rules in Big O Notation (Cormen et al., 2001):

a) If the function or algorithm f(x) is a sum of several terms, the one with the largest growth rate is kept, and all others omitted.

b) If the function or algorithm f(x) is a product of several factors, any constants (terms in the product that do not depend on x) are omitted.

Moreover, the example of the time complexity shows that the size of the input dataset N, which could be measured by using the data processing area and the volume of data, is a fundamental element to calculate the computation time of a function or an algorithm. Therefore, the processing area and spatial data volume are also applied in the CG computation priority to assess the priority values.

Figure 7-8 shows the customised CG computation priority for the sub-functions a, b, c, d. In this example, the priority values are defined by the composite factors of time complexity using the Big O Notation, the processing of the area involved, and the input data volume, which are described in Table 7-2.

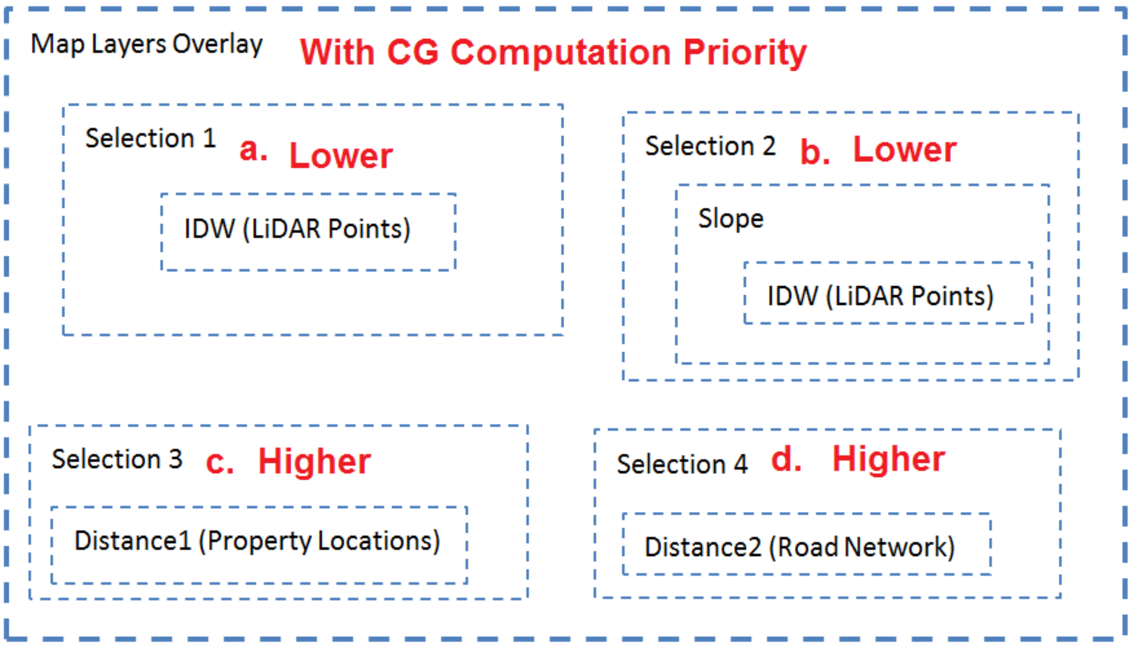


Figure 7-8 Case study 3: The structure of the CG functions in the complex chain processing model (assigned to CG computation priority values).

Table 7-2 further explains how the priority values are assessed in the specific functions. As shown in this table, the four sub-functions a, b, c, d have the same time complexity, but the values of the data processing area and the input data volume vary. Specifically, the time complexity of sub-functions a, b, c, d is produced by using the two simplification rules in Big O Notation and the algorithms of the sub-functions a, b, c, d. The data processing areas of the sub-functions a and b are derived from the entire size of the case study area as the LiDAR points are randomly distributed to the whole case study area. The data processing areas of the sub-functions c and d are calculated from their selection criteria, which refer to identifying areas that are 30 metres away from existing property locations and 50 metres away from the road network. The input data volumes refer to the amount of points which are processed in the sub-functions a, b, c, d.

Table 7-2 Case study 3: Input data volume of the functions.

Function Name	Time Complexity (Big O)	Data Processing Area	Input Data Volume
a	$O(n^2)$	400,000 M^2	One million points (LiDAR points)
b	$O(n^2)$	400,000 M^2	One million points (LiDAR points)
c	$O(n^2)$	138,469 M^2	250 points (Existing Property Locations)
d	$O(n^2)$	312,000 M^2	510 points (Vertex of Road Network)

As it can be seen from Figure 7-8, Function a: ***{CG$_{Selection1}$ (CG$_{IDW}$ (LiDAR Points))}*** and Function b: ***{CG$_{Selection2}$ (CG$_{Slope}$ (CG$_{IDW}$ (LiDAR Points)))}*** are given lower priority b as they deal with the larger LiDAR dataset which contains one million LiDAR points (i.e. nearly 2000 times larger than the input dataset volumes of Function c and d) and the larger data processing areas, while Function c: ***{CG$_{Selection3}$ (CG$_{Distance1}$ (Property Locations))}*** and Function d: ***{CG$_{Selection4}$ (CG$_{Distance2}$ (Road Network))}*** are given higher priority as they deal with a smaller dataset size and data processing area.

There are four computation steps in the CG approach implementation using the CG priority computation rule, which include:

1. The system firstly executes Function c: ***{CG$_{Selection3}$ (CG$_{Distance1}$ (Property Locations))}*** and Function d: ***{CG$_{Selection4}$ (CG$_{Distance2}$ (Road Network))}*** as they given higher priority. The outputs of this step record two criteria (i.e. the ROI areas of Case study 3), which are produced from the distance to property locations and road network and which could be used to investigate the necessary computations in order to avoid potential redundant computations in the next step. It should be noted that the outputs are stored in the RAM temporarily.

2. Before calculating the lower priority computation tasks, the system processes and analyses the necessary computations. For example, the temporary results (i.e. the boundary of ROIs) from the previous step will be used to select the essential LiDAR points which satisfy the criteria, or else, the LiDAR points which are located within the ROIs. So the raw point dataset ***(LiDAR Points)*** is transferred to the necessary point dataset ***(Necessary LiDAR Points)*** according to the ROIs criterion.

3. The next step is to execute Function a: ***{CG$_{Selection1}$ (CG$_{IDW}$ (Necessary LiDAR Points))}*** and Function b: ***{CG$_{Selection2}$ (CG$_{Slope}$ (CG$_{IDW}$ (Necessary LiDAR Points)))}.***

4. The last step is to run the 'Map Layers Overlay' function in the CG approach.

Sections 7.5.1 and 7.5.2 explained the two different approaches that can be used for the implementation and execution of the complex chain processing model. The fundamental difference is that in traditional geo-processing (i.e. ModelBuilder in ArcGIS) a sequential computation method is used to process the model and its computation tasks, while in the CG approach the CG functions are implemented based on their priority values.

The following section discusses the input datasets that are used in Case study 3.

7.6 Case study 3: The Complex Chain Processing Model Dataset

As it was already explained in Figure 7-4, the input datasets of Case study 3 include LiDAR Points, property locations, and road network. They are separately described in this section.

1) LiDAR Points (Case study 3)

The LiDAR Points are randomly selected from the original raw LiDAR dataset that also used in the previous case study. It should be noted that there is a significant increase in the number of LiDAR points used; from 26,666 points (i.e. the amount of LiDAR points selected in Case Study 3) to 1,000,000 points. The purpose of using a large LiDAR point dataset is to test and compare the overall computation time between the traditional geo-processing approach and the CG approach, where CG computation priority is further used. Figure 7-9 shows the sample of raw LiDAR point data used in this case study, as well as, the geographical location and the topographical features of the study area (shown by the yellow rectangle on top of the Bing Maps satellite image).

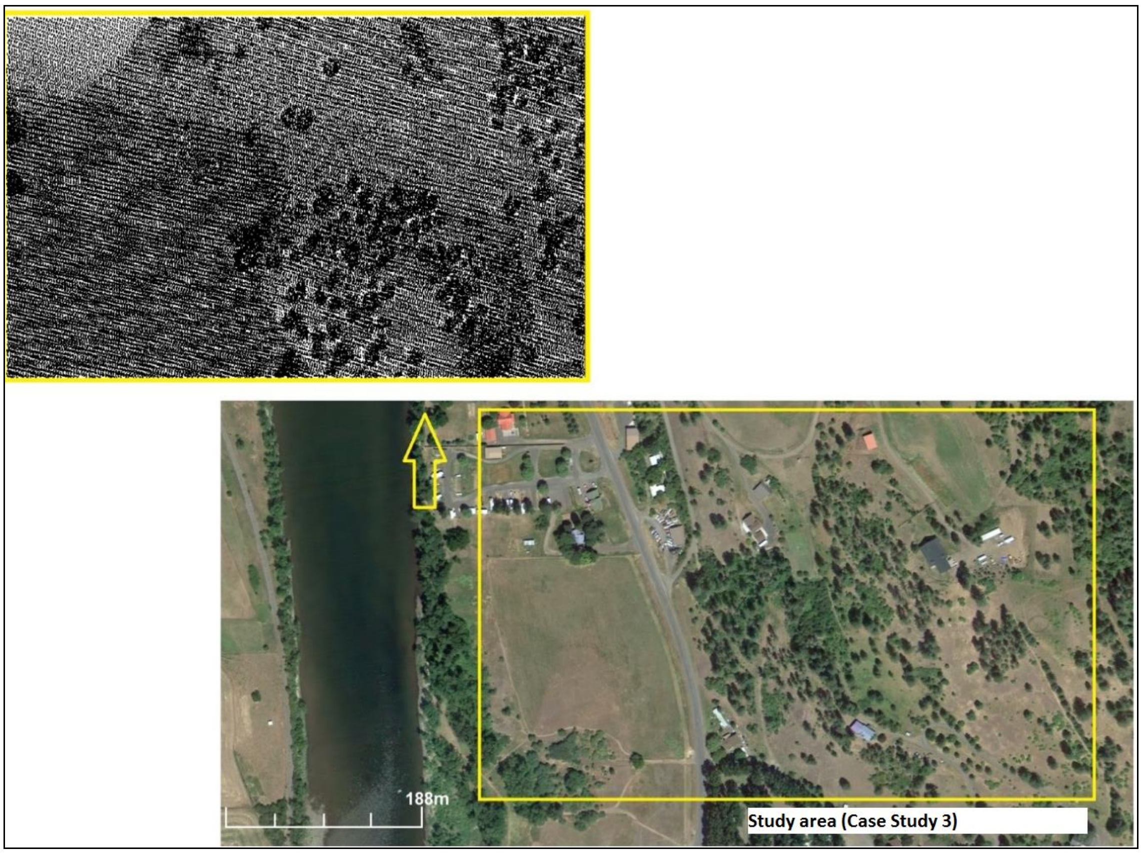


Figure 7-9 Case study 3: Raw LiDAR point data (one million points) and case study area (yellow rectangle on Bing Maps satellite image).

In this case study, the raw LiDAR points dataset is stored using Qtree, which is a common spatial data structure and which is widely applied in many GIS software packages to store spatial database (Rigaux et al., 2001), such as ArcGIS and MapInfo.

2) Property Locations

One of the site selection criteria in this case study involves is that the new building locations should be 30 metres away from the existing property locations. Figure 7-10 shows the existing property locations in the case study area, which were digitised from the Bing Maps satellite image.

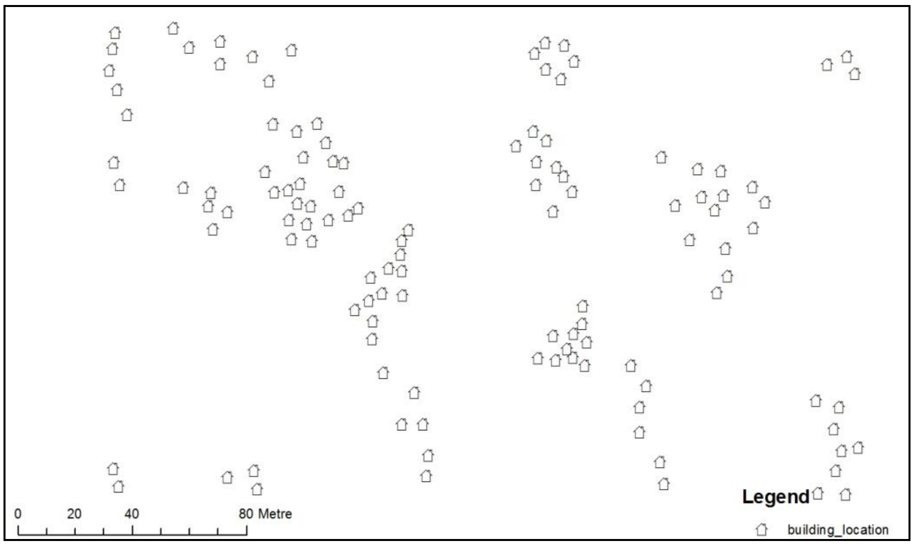


Figure 7-10 Case study 3: Existing property locations.

3) Road Network

Another site selection criterion is that the new building locations should 50 metres away from the existing road network to avoid any noise pollution problems due to local traffic. Figure 7-11 shows the existing road network data in the case study area. In order to simplify the data processing, this study uses vertices (i.e. point) with a ten metres interval for representing the road network (i.e. polyline). Road network data were also digitised from the Bing Maps satellite image.

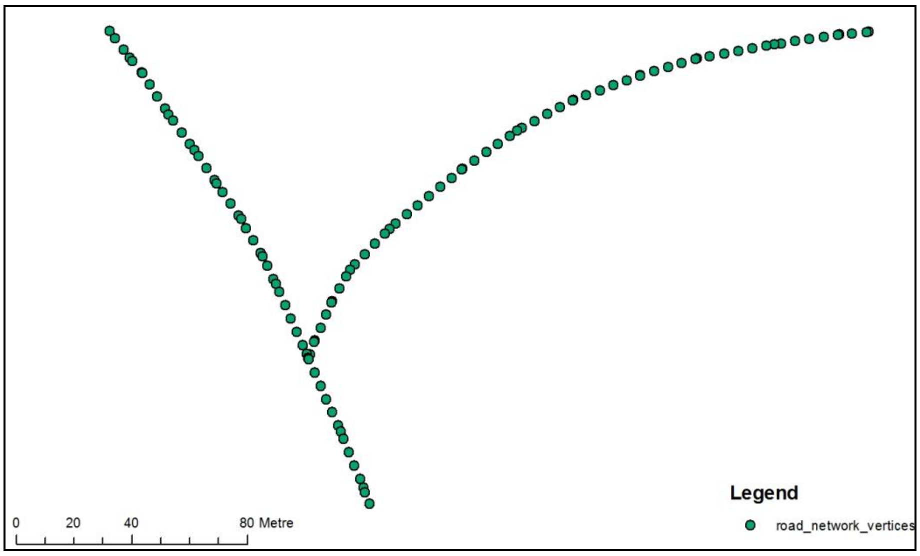


Figure 7-11 Case study 3: Road network represented by vertices.

The next section describes the complex geo-processing model implementation using the two different geo-processing approaches.

7.7 The Complex Chain Processing Model Implementation Strategy in Case study 3

The framework of the complex chain processing model implementation and validation process, within the context of both traditional geo-processing and the CG approaches, is illustrated in Figure 7-12. It involves analysing the potential residential property locations using the two different geo-processing approaches and comparing their overall computation time using Monte Carlo simulation and includes three major steps.

The first step involves loading the LiDAR points, property locations, and road network in the two different geo-processing tools (i.e. Modelbuilder in ArcGIS and the CG approach using computation priority). The second step involves the data processing and the execution of the complex chain processing model. The third step focuses on the comparison of the results, using the geostatistical method of Monte Carlo simulation to compare the overall computation time of the two different approaches.

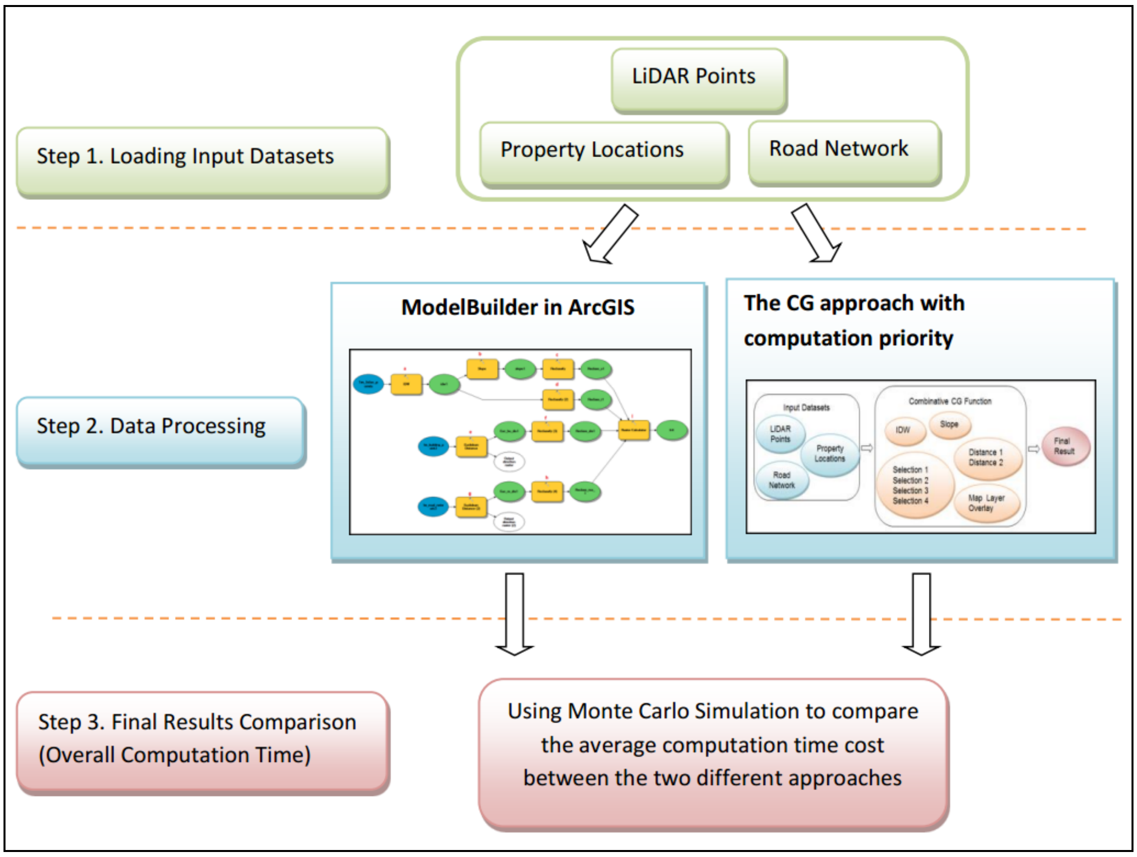

LiDAR Points
Step 1. Loading Input Datasets
Property Locations
Road Network
ModelBuilder in ArcGIS
The CG approach with computation priority
Step 2. Data Processing
Input Datasets
LiDAR Points
Property Locations
Road Network
Combinative CG Function
IDW
Slope
Distance 1 Distance 2
Selection 1 Selection 2 Selection 3 Selection 4
Map Layer Overlay
Final Result
Step 3. Final Results Comparison (Overall Computation Time)
Using Monte Carlo Simulation to compare the average computation time cost between the two different approaches

Figure 7-12 Case study 3: Implementation strategy of complex chain processing model.

It is expected, as it was also the case with the previous case studies that the results of the two approaches would again vary, especially with respect to the overall computation time.

7.8 The Complex Chain Processing Model Results

7.8.1 The Complex Chain Processing Model Results: ModelBuilder ArcGIS

The outputs of the complex chain model, which is implemented by using ArcGIS ModelBuilder, are illustrated according to the sequential computation sequence in the traditional geo-processing approach (i.e. as displayed in Figure 7-5, it ranges from computation task ***a*** to ***i***):

a. Load the LiDAR points in the *'IDW'* function, in order to produce the elevation values. The result (illustrated by Figure 7-13) shows a range of elevation values from 359.89 metres to 517.91 metres.

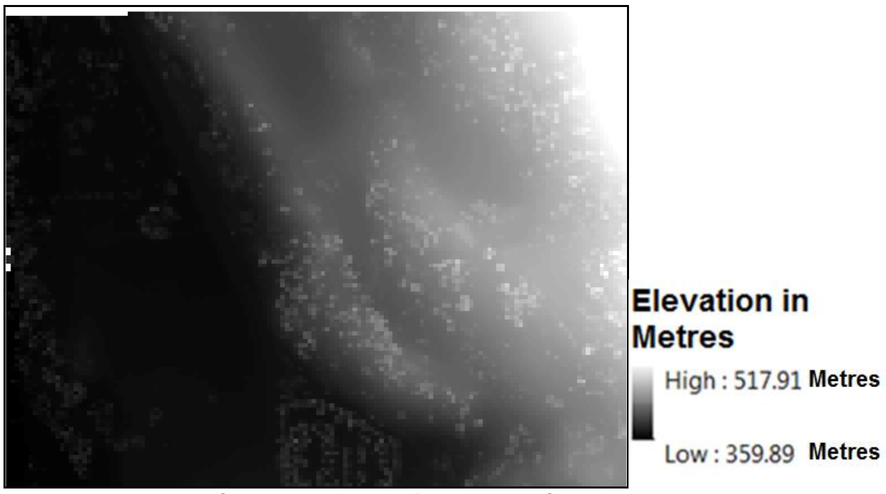


Figure 7-13 Outcome of computation task *a* (*'IDW'* function).

b. Load IDW's result in the *'Slope'* function, in order to produce the slope values. The result (illustrated by Figure 7-14) shows a range of slope value from 0.02 degrees to 69.28 degrees.

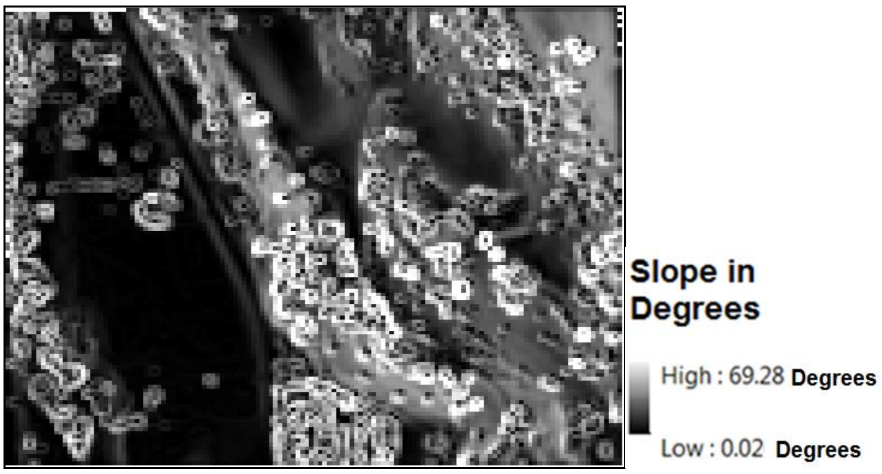


Figure 7-14 Outcome of computation task *b* (*'Slope'* function).

c. Load Slope's result in the *'Reclassify'* function, in order to calculate the potential suitability for the new development area, which should have a slope value less than 30 degrees. It is shown from the result (illustrated by Figure 7-15) that Class 0

(False) represents the not accepted area and Class 1 (True) represents the accepted area.

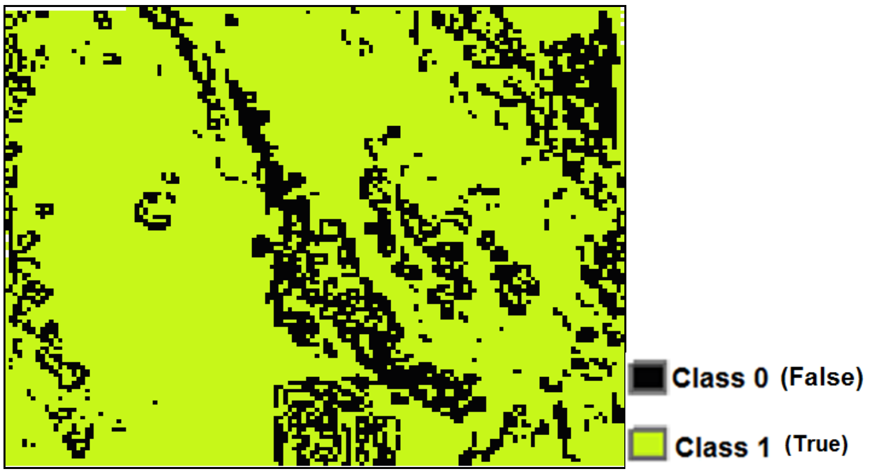


Figure 7-15 Outcome of computation task *c* **('*Reclassify*' function).**

d. Load IDW's result in the *'Reclassify (2)'* function, which will calculate the potentially suitable area, which needs to have an elevation value less than 390 metres. It is shown from the result (illustrated by Figure 7-16) that Class 0 (False) represents the not accepted area and Class 1 (True) represents the accepted area.

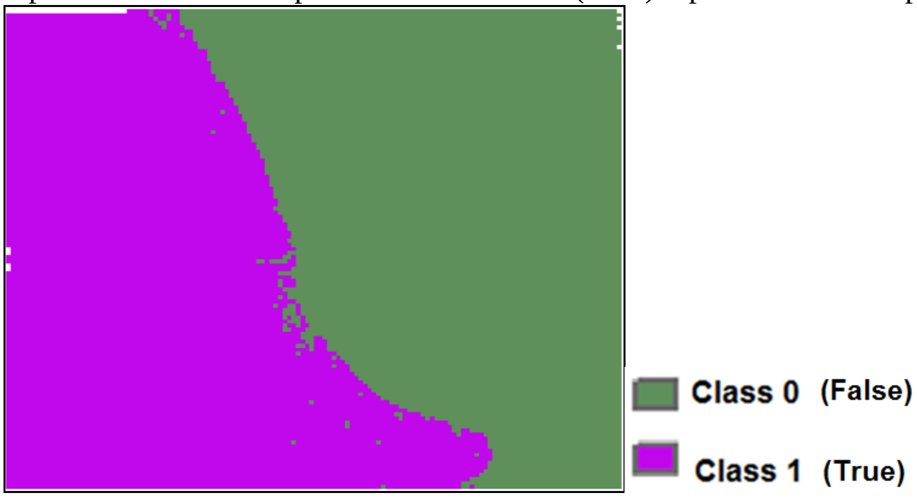


Figure 7-16 Outcome of computation task *d* **('*Reclassify (2)*' function).**

e. Load 'Property Location' in the *'Euclidean Distance'* function, to calculate the shortest distance to existing property locations. The result (illustrated by Figure 7-17) shows a range of distance values from 0 metres to 250.79 metres. The result will be further used in the '*Reclassify (3)*' function to select the locations, which have a minimum distance of 30 metres to the existing properties.

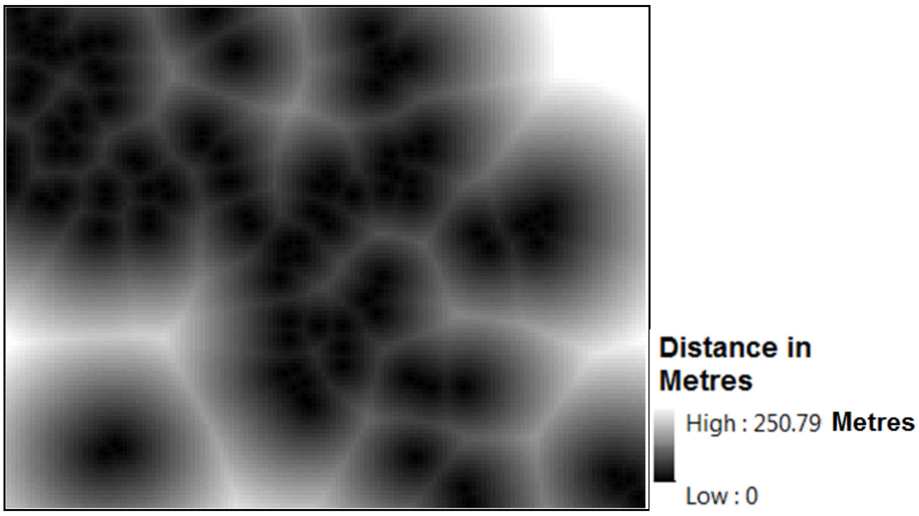


Figure 7-17 Outcome of computation task *e* **(‘*Euclidean Distance’* function).**

f. Load Euclidean Distance’s result in the *‘Reclassify (3)’* function, in order to calculate the potentially suitable areas, which should have a minimum 30 meters distance from existing property locations. It is shown from the result (illustrated by Figure 7-18) that Class 0 (False) represents the not accepted area and Class 1 (True) represents the accepted area.

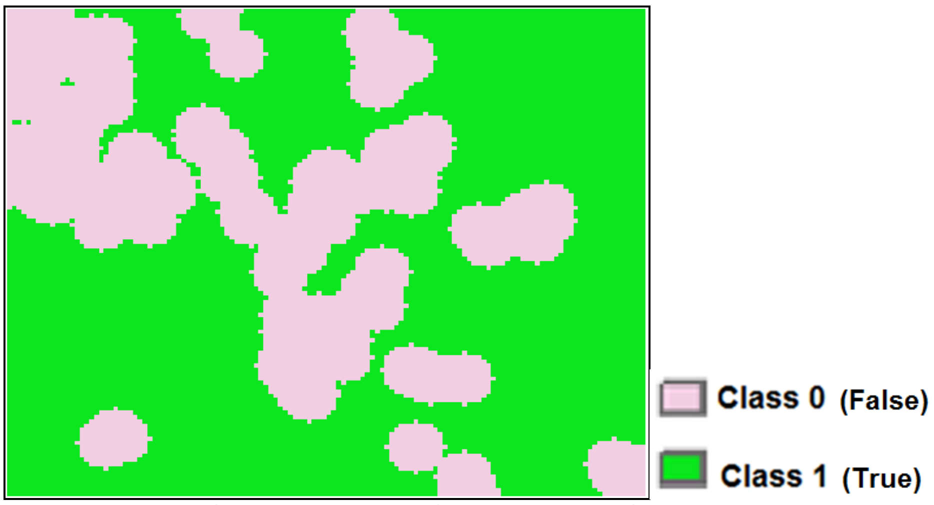


Figure 7-18 Outcome of computation task *f* **(‘*Reclassify (3)’* function).**

g. Load ‘Road Network’ in *‘Euclidean Distance2’* function, in order to calculate the shortest distances to the road network (vertices). The result (illustrated by Figure 7-19) shows a range of distance values from 0 metres to 264.76 metres. The result will be further used in the ‘*Reclassify (4)’* function to select the locations, which have a minimum distance of 50 meters to the road network.

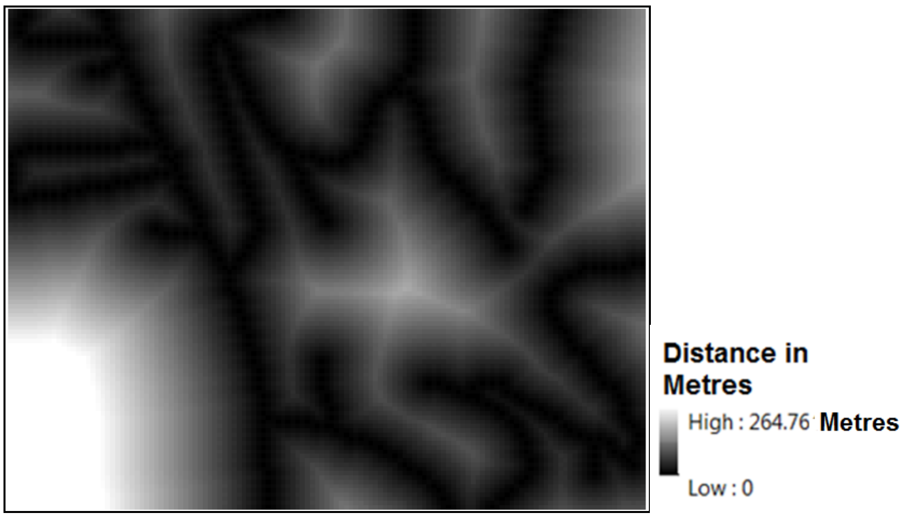


Figure 7-19 Outcome of computation task *e* (*'Euclidean Distance2'* function).

h. Load Euclidean Distance2's result in the *'Reclassify (4)'* function, in order to calculate the potentially suitable areas, which should have a minimum of 50 meters distance from the road network. It is shown from the result (illustrated by Figure 7-20) that Class 0 (False) represents the not accepted area and Class 1 (True) represents the accepted area.

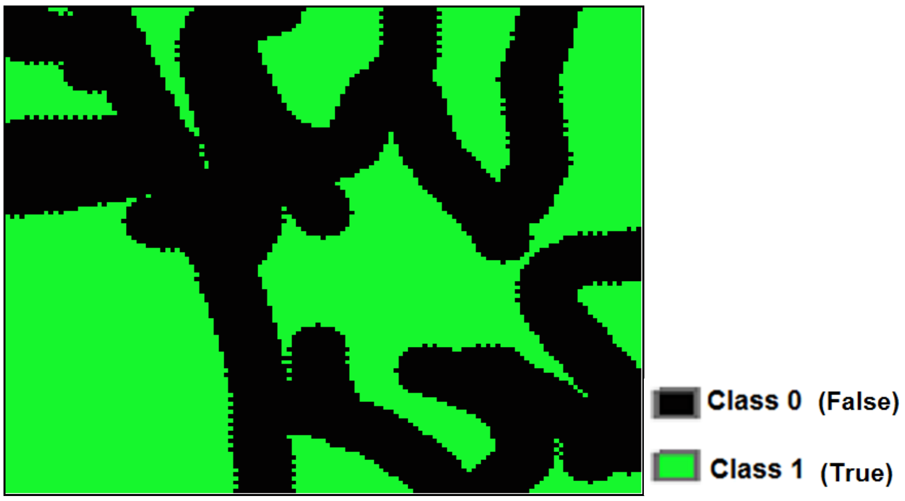


Figure 7-20 Outcome of computation task *f* (*'Reclassify (4)'* function).

i. Finally, load the results of *'Reclassify'*, *'Reclassify (2)'*, *'Reclassify (3)'*, *'Reclassify (4)'* in the function *'Raster Calculator'*, in order to integrate the intermediate outcomes and produce the final result of the site selection analysis. It is shown from the result illustrated by Figure 7-21 that the case study area is represented using five classes. Specifically, the area with blue colour (*'Class 4'*) represents the accepted locations for the new property development as it satisfies all the criteria, while *'Class 0'* to *'Class 3'* represents the not accepted locations as they have at least one criterion which is not satisfied.

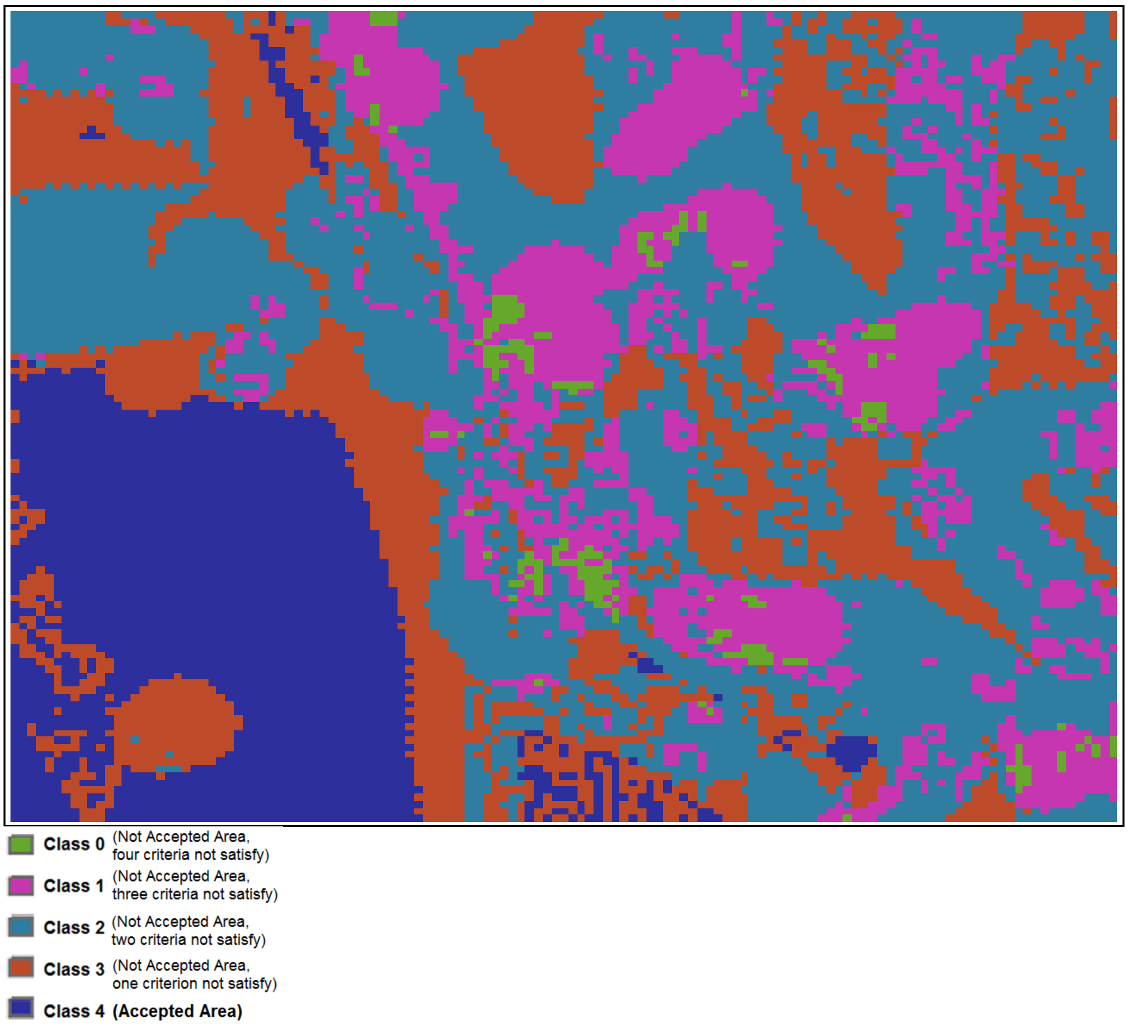

🟩 Class 0 (Not Accepted Area, four criteria not satisfy)
🟪 Class 1 (Not Accepted Area, three criteria not satisfy)
🟦 Class 2 (Not Accepted Area, two criteria not satisfy)
🟧 Class 3 (Not Accepted Area, one criterion not satisfy)
🟦 Class 4 (Accepted Area)

Figure 7-21 Case study 3: The final result of the site selection analysis (produced using ModelBuilder, ArcGIS).

7.8.2 The Complex Chain Processing Model Results: The CG Approach using Computation Priority

Figure 7-22 illustrates the final result from the CG approach using CG computation priority, where the potentially suitable areas for the new property development are illustrated by the blue region (i.e. ‘Class 2’). ‘Class 1’ represents the not accepted areas that satisfy only one criterion, such as elevation smaller than 390 meters or slope value less than 30 degrees. ‘Class 0’ represents the not accepted areas that do not meet any of the suitability criteria.

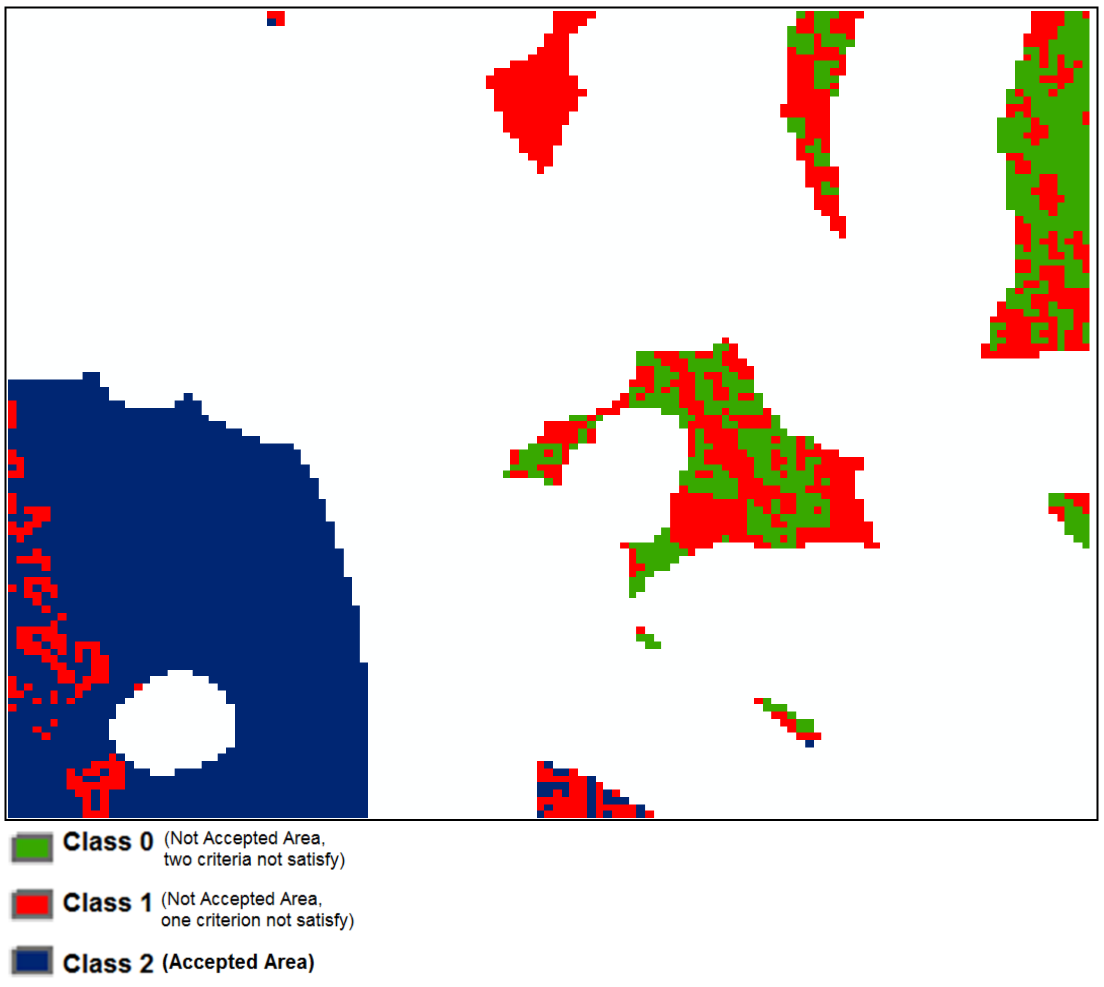

Class 0 (Not Accepted Area, two criteria not satisfy)
Class 1 (Not Accepted Area, one criterion not satisfy)
Class 2 (Accepted Area)

Figure 7-22 Case study 3: The final result of the site selection analysis (produced using the CG approach using CG computation priority).

Figure 7-22 shows that the entire case study area is divided by only three classes, as opposed to the previous Figure 7-21 which illustrated the ArcGIS results and where there were five classes. This is due to the new computation strategy (e.g. ROI), which is applied in the CG approach. Specifically, as was explained in Section 7.2, ROI is used to avoid the potential redundant computations in order to reduce the amount of computation time. In this case study, when the site selection model is processed using the CG approach with CG computation priority, the outcomes of the CG functions ***{CG$_{Selection3}$ (CG$_{Distance1}$ (Property Locations))}*** and ***{CG$_{Selection4}$ (CG$_{Distance2}$ (Road Network))}*** are applied to identify the boundary of ROIs, such as the regions which have 30 meters distance from existing property locations and also have 50 metres distance from the road network. As a result, the computations are only implemented inside these ROIs, and thus there are only three classes which are applied in the final result to further investigate the other two criteria. They refer to the elevation values which should be smaller than 390 meters and the slope value which should be less than 30 degrees.

Moreover, the white colour area displayed in the final result (Figure 7-22) represents the locations, which did not involve any further processing as they are located outside the ROIs.

This section presented the results of the complex chain processing model. The main difference between the two approaches is that in the CG approach the final result is directly produced, while the geographical data which is within the ROI are processed. In contrast, the traditional geo-processing approach requires the sequential execution of all the functions involved, which processes the data within the entire case study area.

7.9 Case study 3: Comparison of Results

We can now investigate the two different implementations of the complex chain processing model with respect to their overall computation time. Monte Carlo simulation is continuously applied in this case study to trace the average computation time (i.e. mean value) of both geo-processing approaches.

7.9.1 Monte Carlo Simulation Model (Case study 3)

The Monte Carlo simulation model of this case study is given in Figure 7-23, which involves three main steps:

1) The first step is to randomly select 90% of the LiDAR points as one of the input datasets, which also include the property locations and the road network.
2) In the second step, the input datasets are loaded into the two different approaches for data processing.
3) Finally, the average computation time of each approach is calculated and compared.

It should be noted that the number of iterations used in the Monte Carlo simulation model was increased to 100 iterations compared to the 50 iterations that were used in the previous case study. The larger iteration number applied in this case study is due to two reasons: (a) the amount of LiDAR data are gradually increased to one million points from 26,499 points, which is the amount of LiDAR data used in the third case study; (b) the geo-processing model applied in this case study is more complex than the one used in Case Study 3 (i.e. the combinative function of ‘IDW’ and ‘Slope’). As a result, this case study uses 100 iterations in the Monte Carlo simulation model. Moreover, Heuvelink (2006) claims that 100 iterations are sufficient to obtain a reasonable estimate of the mean value (e.g. the average value of computation time) in a Monte Carlo simulation.

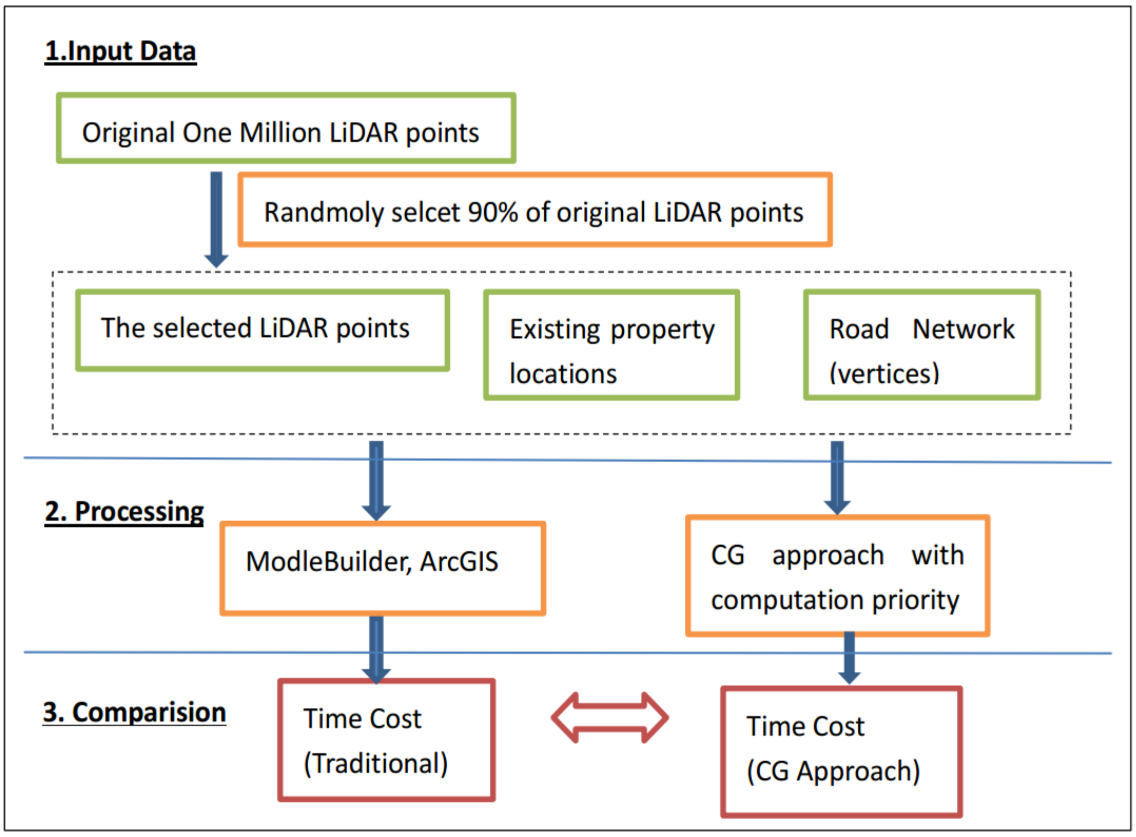

1.Input Data
Original One Million LiDAR points
Randmoly selcet 90% of original LiDAR points
The selected LiDAR points
Existing property locations
Road Network (vertices)
2. Processing
ModleBuilder, ArcGIS
CG approach with computation priority
3. Comparision
Time Cost (Traditional)
Time Cost (CG Approach)

Figure 7-23 Case study 3: the validation process (Computation time).

7.9.2 The Result of Monte Carlo Simulation Model (Case study 3)

The Monte Carlo simulation results are displayed in Figure 7-24 and Table 7-3. Figure 7-24 shows the results of the overall computation time in ArcGIS and the CG approach. In this figure, the X axis represents the index of the 100 iterations running test, while the Y axis shows the computation time of each single test. It is clear that there is a significant difference in the computation time between the two geo-processing approaches. Specifically, the computation time in ArcGIS ranges from 57 seconds to 75 seconds, while the computation time in the CG approach ranges from 43 seconds to 50 seconds. Thus, the results indicate that the CG approach has a lower overall computation time than the traditional geo-processing approach (i.e. ArcGIS).

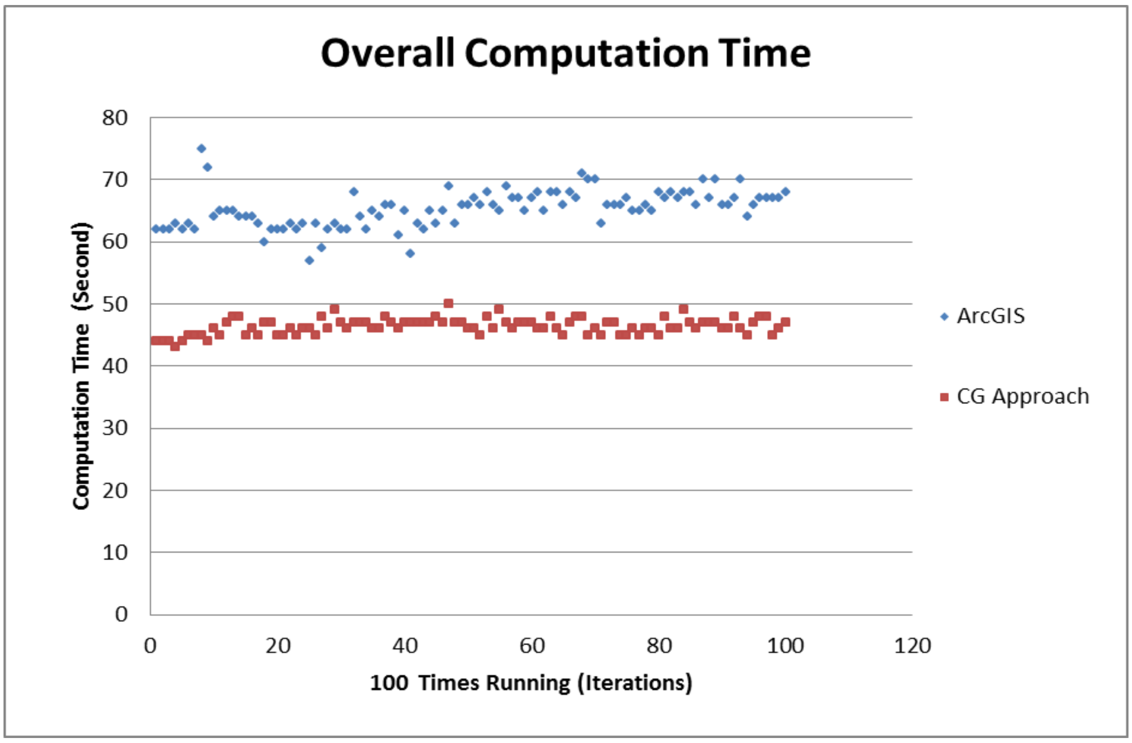


Figure 7-24 Case study 3: Overall computation time in traditional geo-processing and the CG approach.

In addition to Figure 7-24, Table 7-3 summarises the statistical result of the Monte Carlo simulation's 100 iterations. It can be observed that the mean value (i.e. the average of 100 iterations' computation time) of the CG approach is 46.35 seconds, which is 29.2% lower than the ArcGIS's mean value (i.e. 65.31 seconds). The maximum computation time occurs in ArcGIS (i.e. 75 seconds), but the minimum computation time is observed in the CG approach (i.e. 43 seconds). The standard deviation value also indicates that the CG approach's results are very close to the mean value, while the ArcGIS's results are spread out over a larger range of values which may lead to a higher computation time.

Table 7-3 The statistical results of overall computation time between the ArcGIS and CG approach using CG computation priority (Unit: Second).

	Mean	Max	Min	Standard Deviation
ArcGIS	65.31	75	57	2.94
CG Approach	46.35	50	43	1.26

7.10 Discussion

It was demonstrated by Figure 7-24 and Table 7-3 that the Monte Carlo simulation analysis revealed that there are differences in the CG and traditional geo-processing approaches with respect to their computation time. The average computation time of the CG approach (i.e. 46.35 seconds) is nearly 20 seconds less than the traditional approach's computation time (i.e. 65.31 seconds). This difference in the computation time occurs due to mainly two reasons, the new computation sequence and computation flexibility that are applied in the CG approach with computation priority.

First, in the CG approach the implementation sequence of the computation tasks is re-organised according to their computation cost in order to use more efficiently the computer's memory and resources. For instance, the functions with the lowest computation cost were the first that were executed. Second, computation flexibility is used in the CG with computation priority, which also helps to avoid execution of redundant computations. For example, the specific criteria were used to define ROIs in this case study and the data only within these ROIs were processed. This means that only a portion of the data of the whole case study area was used in processing and this helped to reduce the required computation time.

Furthermore, it should be noted that total computation time that it is required to process 100 iterations of the geo-processing model of Case study 3 in Monte Carlo simulation, which using the CG approach with computation priority is 4,635 seconds. In other words the CG approach with computation priority in this case saves about 1,896 seconds, as the computation time of ArcGIS to process 100 iterations of the geo-processing model of Case study 3, in Monte Carlo simulation is 6,531 seconds. Thus, the amount of total computation time may be significantly reduced if the CG computation approach with computation priority is repeatedly used in geo-processing models to implement their computations.

Although site selection geo-processing models are popular, it might be argued that these models are not used by a significant amount of people so that also significant savings of computation time occur due to the repetitive application of the proposed improved approach in its existing form. However, it should be noted that the CG approach with computation priority in its current form (i.e. without further research and subsequent improvements) can be used in applications such as web mapping or online mapping, which is used by thousands of people on a daily basis and which could significantly improve computation time, as it is explained in the next paragraphs.

Web mapping provides a new way to design, implement, generate, and deliver geographical information on the World Wide Web (Fu and Sun 2010). As web mapping has many advantages, such as it could easily deliver information through internet network, it can combine different data sources which are published online, and it could work cross browsers and various operating systems to provide mapping services, while there is a larger amount of users that are using web mapping services every day (Haklay et at., 2008). In the early 2000s, the major characteristic of the web mapping is that geo-processing functions can be executed on the powerful server's side in order to process geographical data and reduce in that way the computations that would be required to execute on the client side (i.e. the user computer) (Peng and Tsou 2003). Then Google Map applications which appeared in 2005, and the number of users is dramatically increasing as Google Map applications provide a lot of convenient online map services. For example, Google Maps API, which is a server side web mapping service, provides a function to overlay user's own data on a customized 2D Google Map, and Google Earth, which is a client side web mapping service, offers a function to overlay user's own data on a customized 3D Google Map. Nowadays, Google Map applications are widely used in various fields to implement different tasks, such as data visualisation, geo-processing and spatial data integration.

If geo-processing functions are provided on web mapping services using the CG approach with computation priority, significant computation time can be saved to the service provider. For example, if the site selection geo-processing model implemented using the CG approach in the Case study 3 is published on the server side for analysing and sharing the information of potential property locations. The time saved could be represented by 'Number of Users' times by 'X seconds', where 'Number of Users' describes how many people use this web mapping service and 'X seconds' means the time saved of a single implementation. It might not be important for one user to save 20 seconds, which is based on the average computation time between the CG approach and ArcGIS as demonstrated by Table 7.3, but for the provider it means that his the services can save ‘Amount of Users’ x 20 seconds.

Therefore, based on the results of this case study and the earlier case studies (i.e. Case Study 1 to 3), it can be concluded that the CG approach using computation priority offers many advantages (i.e. improved data quality and better computation time) over the traditional geo-processing approach for the implementation of a geo-processing model.

7.11 Summary

This Chapter introduced the concept of CG computation priority, which was used in order to improve the computational efficiency (i.e. the overall computation time) of geo-processing. In the beginning, this Chapter reviewed the current problems related to computational efficiency and introduced the concept of the CG computation priority. Compared to the traditional geo-processing approach, the CG computation priority provides an alternative computation strategy. Specifically, with the CG computation priority the computation tasks or GIS functions of a geo-processing model are implemented in a way that takes into account their computation cost, which is defined by the size of the data involved and the computation complexity. In other words, the function which involves a smaller data size and less complexity will be executed first.

The third case study focused on the implementation of a complex chain processing model using the two different geo-processing approaches in order to demonstrate the main characteristics of CG computation priority. The implementation results were compared and it was found that the CG approach can produce the final result directly and process the geographical data included in ROIs, while the implementation of traditional geo-processing approach was executed sequentially and included processing of the data within the entire case study area. The outcome of Monte Carlo simulation, which was used to compare the computation time between two different geo-processing approaches, confirms that the average of overall computation time in the CG approach is 29.2% lower than the traditional geo-processing approach’s result. The results of Monte Carlo simulation indicated that the CG approach using CG computation priority, compared to the traditional geo-processing’s computation strategy, provides an improved computation strategy for dealing with the complex geo-processing model and the larger GIS datasets.

Although the CG approach with computation priority improved the computation time, it may be argued that it only resulted in a very small fraction of computation time reduction (around 20 seconds). Thus, it should be acknowledged that there are additional concerns with respect to the implementation of CG computation priority.

It was explained in Section 7.3.2, the current method produces computation priority values according to the composite factors, such as time complexity, processing area, and input data volume. It should be noted that this current assessment progress may extend the overall computation time as the composite factors are observed and evaluated one by one until to produce a final priority value. Therefore, improving the speed of priority value assessment is an important research question that should be addressed in the further research, which does beyond the scope of this thesis, to further reduce the overall computation time of geo-processing. For example, the computation priority could be assessed by using an optimum computation algorithm, where the different computation cost factors could be automatically and efficiently calculated.

The site selection geo-processing model was applied this this case study to demonstrate how the CG approach with computation priority could be implemented. Moreover, the site selection geo-processing model was used in the Monte Carlo simulation to validate the computation time between the CG and traditional geo-processing approaches. However, only a single geo-processing model implementation may not enough to support the final conclusion of the new geo-processing approach if inappropriate inputs were entered into the model, such as grid size and data volume. Therefore, various implementation models are needed in the further CG approach development, although these are beyond the scope of this thesis, to validate the performance of the CG approach with computation priority.

8 Conclusion

8.1 Introduction

This thesis has described the development of a new geo-processing approach, the CG approach, which was aimed at improving data processing issues related to data quality and computational efficiency. Within this context, this thesis has described how the data quality and computation time cost of geo-processing models can be optimised using the CG approach. The research findings have been implemented and evaluated through three test case studies, which focused on using the CG approach to optimise a set of primitive geo-processing model implementations.

This chapter summarises the major findings of this research and discusses its contributions, limitations and future research directions. Section 8.2 commences with a brief overview of the research undertaken, whilst Section 8.3 discusses the research questions of this thesis, and Section 8.4 discusses the contributions of this thesis. Finally, the chapter concludes with a critical discussion of the limitations of the current development of the CG approach (Section 8.5) and provides suggestions for future research (Section 8.6).

8.2 Overview of the Research

This thesis has focused on the improvement of data quality and computational efficiency in geo-processing. Although current geo-processing tools are used to model and solve spatial decision-making problems, there are many significant concerns with respect to the quality of their geo-processing results and the computational cost of a geo-processing model. These were extensively described in Sections 2.3 and 2.4, where the problems that are caused due to a sample's resolution, the propagation of errors in spatial information, and the extensive time cost were discussed. As the aim of this thesis was to identify a solution in order to overcome these problems, a new geo-processing approach was proposed which investigated how data quality problems can be minimised and how computational efficiency, i.e. the overall computation time, of geo-processing can be improved.

Chapter 2 reviewed geo-processing and the related issues, such as data quality and computational efficiency. The data quality of a geo-processing model is extremely important as it influences the final output of geo-processing models. Chapter 2 firstly reviewed data quality issues in traditional geo-processing and then explained that the current approach is influenced by different data quality problems, namely due to the limitations of raster and vector spatial data models, and numerical computation and error propagation. In order to minimise the spatial data representation problems and to reduce data error and uncertainty, this research proposed the use of a point-based spatial data model, i.e. spatial data representation, symbolic computation, and function-based layers in the CG approach, i.e. data error and uncertainty. Chapter 2 also reviewed the computational efficiency in geo-processing, as this can potentially influence computational performance. The computation strategy, based on sequential computation that it is used in traditional geo-processing, costs extra computation time and computer memory. In order to address this problem, a priority-based computation strategy is proposed in the CG approach, which is used to reduce computation time by re-ordering the computational sequence in which the computation tasks in geo-processing are implemented through the use of priority values from highest to lowest.

Chapter 3 introduced the conceptual model that links the main components of the CG approach and it was explained that this conceptual model involves three parts: the first focuses on the input level of the CG approach, such as the basic data model, functions, and computation framework; the second part involves the processing and computation rules that are used within the context of the CG approach; and the final part focuses on the output level of the CG approach, such as the result of a geo-processing model. This conceptual model of the CG approach provides the fundamental framework and the basis for the development of the CG approach. Chapter 3 also discussed the two main functionalities of the CG approach for executing spatial data and functions: (a) a CG function, which can be constructed from sub-functions, is used to implement an entire geo-processing model to reduce the impact of data errors and uncertainties; and (b) the priority-based computation sequence, which is used to execute the CG functions efficiently.

Chapter 4 discussed the case study design and the implementation of the methods. The three case studies were introduced, which were implemented in order to demonstrate how the CG function and the priority-based computation sequence could be practically implemented using the CG approach, and further supported the investigation of whether the CG approach improves data quality and computational efficiency. As the CG function and priority-based computation sequence requires a set of implementation methods, a ‘Higher-Order Function’, ‘Recursive Algorithm’ and ‘Lazy Evaluation’ were applied as the primary execution methods in the CG approach. The ‘Higher-Order Function’ and ‘Recursive Algorithm’ can be used to build up and execute CG functions, while ‘Lazy Evaluation’ can be applied to define the computational sequence. Furthermore, the computational environment was also discussed in this chapter to illustrate the software packages and computer tools which were used to implement the three case studies.

The first case study was described in Chapter 5, and drew attention to the overlaying raster layers in GIS. Due to the fact that this function is widely used by several geo-processing models, e.g. for integrating different map layers in a complex geo-processing model, this case study investigated and compared the computation strategy of the raster layer overlay function. The second case study described in Chapter 6, showed how a simple chain processing model can be implemented using the CG approach. This simple chain processing model is a fundamental operation in traditional geo-processing, as it forms the basis for building more complex geo-processing models. The last case study, discussed in Chapter 7, demonstrated the implementation of a complex chain processing model using the CG approach with computation priority, and also provided the basis to further investigate the issue of computational efficiency in order to investigate how the overall computation time cost in geo-processing can be reduced. Thus, in the third case study, this thesis also introduced the concept of CG computation priority in processing GIS data and functions. These three case studies are particularly important in the development of the CG approach, especially for data quality and computational efficiency improvement. The research findings from these three case studies are discussed in the next section.

8.3 Overview of Research Objectives and Findings

This section discusses the major finding of the development of the CG approach, specifically in relation to data quality improvement (Section 8.3.1) and computation time optimisation (Section 8.3.2) which was one of the thesis aims.

8.3.1 Improving Data Quality via the Combinative Geo-Processing Approach

The research findings from case studies 1 and 2 illustrated that some fundamental methods applied in the traditional geo-processing approach, such as spatial data representation and the basic computation method, may influence data quality, due to: (a) data conversion and re-sampling operations amongst raster and vector data models; and (b) approximated values and error propagation during numerical and sequential computation. It was concluded in Chapter 2 that the current spatial data representation and the basic computation methods applied in the traditional geo-processing approach can influence the data quality of the final results of a geo-processing model, and that there is a need to improve the existing approach to provide a better result.

Addressing data quality problems was one of the main concerns in this research and was an aspect of the CG approach at the conceptual and implementation levels. It was discussed in Section 2.3 that there are two issues in the traditional geo-processing approach, including the current method for spatial data representation and the basic computation method, as these issues can cause different data quality problems. Two case studies were undertaken in order to test the CG approach and to address these problems. The findings of these case studies are discussed in the following paragraphs.

The first case study focused on the multiple raster map layers integration, which is a common function commonly used in many geo-processing models and frequently influences and causes data quality problems. A comparison between the CG approach and the traditional geo-processing approach was demonstrated in the first case study through implementing an overlay function of two different raster layers, with different grid sizes. In particular, this case study involved the implementation of the raster layers overlay function using the CG approach, ArcGIS, and MapInfo. The various results of the raster layers overlay function were compared and it was found that the CG approach resulted in values that were much closer to the observed values, i.e. the reference data. As a result, it can be concluded that the CG approach offers an advantage over traditional geo-processing for the integration of two or multiple raster map layers within a geo-processing model.

The second case study also focused on data quality and was concerned with the implementation of a simple chain processing model. A simple chain processing model is central within geo-processing as it is used to build more complex and advanced models. The second case study involved the implementation of a model using the CG approach and the ModelBuilder tool provided by the ArcGIS software package. The implementation results were compared using the Monte Carlo simulation method. Monte Carlo simulations were used in this research to estimate standard deviation and variance values of the samples, thereby enabling the tracking of the propagation of uncertainties and errors of GIS computations. It was found that the CG approach provided improved results, for example in the CG approach the average variance (7.304 degrees-squared) was nearly four times lower than the average variance in ArcGIS (31.818 degrees-squared), in addition, the average standard deviation in the CG approach (1.811 degrees) was nearly two times lower than the ArcGIS standard deviation (3.844 degrees). The results of the Monte Carlo simulation indicated that the CG approach results included less data uncertainty when compared to traditional geo-processing, which is because the CG approach uses symbolic computation and function-based layers for the execution of the various computational tasks.

To conclude, this research illustrates how the data quality of the traditional geo-processing approach can be improved using the point-based spatial data representation, symbolic computation and functional programming in the CG approach. In specific, the point-based spatial data representation method improves the implementation of geo-processing models as it reduces the complexity of spatial data models, while any problems caused due to rasterisation and vectorisation of data processing functions can be completely avoided. Furthermore, a combination of symbolic computation and functional programming provides a novel approach in geo-processing for processing spatial data and functions more accurately. There are many advantages to applying symbolic computation and functional programming in the CG approach: first, both numerical and symbolic computations are supported in the CG approach to reduce the influence of an approximated value; second, computations can be suspended or reordered in order to implement them more efficiently; and third, results can be produced directly from a combination of functions thereby reducing data uncertainty. Furthermore, the point-based spatial data representation, symbolic computation and functional programming in the CG approach can contribute to many further contexts within GIS, such as point cloud geo-data and geocomputation and these contributions are discussed further in Section 8.4.

Apart from the data quality investigation, this thesis has also explored how computational efficiency, i.e. overall computation time, can be improved when the CG approach is applied in geo-processing. The findings of this investigation are separately summarised in the next section.

8.3.2 Improving Computational Efficiency through the Combinative Geo-Processing Approach

The sequential computation strategy applied in the traditional geo-processing approach is another issue, as it could result in problems related to computational efficiency. A common problem is that all functions need to wait for input data from the previous functions, and also unnecessary computations may occur in a complex geo-processing model. Together, these two problems can potentially increase the computational cost of geo-processing models. Thus, it may be concluded that the sequential computation sequence can influence the computational efficiency of a geo-processing model, and that there is a need to improve the existing approach in order to reduce the computation cost.

The computational efficiency problems in the traditional geo-processing approach have influenced the development of the CG approach. In order to reduce the total computation time, the design of the CG approach has focused on improving the sequential computation in the traditional geo-processing approach by using a priority-based computation strategy. The priority-based computation strategy attempts to overcome the problem of overall computation timeof geo-processing, especially when large spatial datasets and complex geo-processing models are involved. The priority-based computation strategy enables an alternative computation sequence to execute GIS functions in a geo-processing model, which is achieved by initially assigning computation tasks with different priority values, and then implementing them according to this priority value, from highest to lowest.

The third case study showed how the CG approach with the priority-based computation strategy can be implemented in a complex chain processing model. The model was implemented using the traditional approach (ModelBuilder in ArcGIS) and the CG approach with computation priority in order to compare the computation time costs of the two approaches. The implementation results revealed that the CG approach can produce the final result directly, i.e. without any interim outputs, and process geographical data included in ROIs, while the implementation of the traditional geo-processing approach was executed sequentially and included processing of the data within the entire case study area. Furthermore, a Monte Carlo simulation was used in this case study to compare the average of the overall computation time (based on 100 iterations) between the two different geo-processing approaches. The outcome of the simulation confirmed that the average overall computation time in the CG approach is 29.2% lower than in the traditional geo-processing approach. The results indicated that the CG approach using computation priority, compared to the traditional geo-processing computation strategy, provides an improved computation strategy for dealing with complex geo-processing models and larger GIS datasets.

To summarise, this research has illustrated how the computational efficiency of the traditional geo-processing approach can be improved using the priority-based computation strategy employed in the CG approach. Moreover, the priority-based computation strategy could create more contributions to high-performance geocomputations and daily geo-processing tasks, as it enables an efficient way to process GIS data and functions. The further contributions of the priority-based computation strategy are discussed in Section 8.4.

8.4 Contribution of Thesis

This thesis contributes to the area of geo-processing, which is a popular approach in GIS and has been widely used in various spatial analysis tasks. Specifically, it introduces novel thinking and an approach to the field of geo-processing computations, such as using function-based layers and a priority-based computation strategy to process GIS data and functions. Based on the previous discussion of the research findings, the primary contribution of the research undertaken can be concluded as: (a) the development of a new approach for processing GIS data and functions; (b) a demonstration of how the influence of data errors and uncertainties in geo-processing can be minimised using a point-based spatial model and a combination of symbolic computation and function-based layers; and (c) a demonstration of how the overall computation time of geo-processing can be improved using the priority-based computation strategy. The contributions of this thesis to different GIS research areas are discussed in the following paragraphs.

The point-based spatial data model provides a simplified way to represent spatial features. In other words, the CG approach uses point data to represent spatial features that include both discrete objects and continuous field features. It should be noted that a point-based spatial data model is not a new concept in GIS, as it is usually used to represent individual point objects in a geo-processing model, such as address points. However, this is the first time a point-based spatial data model has been used to represent both discrete and continuous data in a geo-processing model in order to reduce the influence of data quality issues, such as rasterisation and vectorisation.

Furthermore, the contribution of the point-based spatial data model has an important implication for the analysis of large point cloud geo-data. Point cloud geo-data are defined as X, Y, and Z coordinates within a geographical coordinate system, and aim to represent spatial objects, such as three-dimensional buildings (Höfle et al., 2009). Point cloud geo-data have been applied in different applications in order to represent spatial objects, for example, Oude and Vosselman (2009) stated that three dimensional modelling of complex highway interchanges could be represented using point cloud geo-data. In addition, Hentschel and Wagner (2010) discussed that Points Of Interests (POI), such as traffic signs, gas stations and restaurants, could be represented using point cloud geo-data.

Although point cloud geo-data are increasing in popularity, there are some existing data quality issues which may cause problems. In particular, Pauly et al. (2004) illustrated the data uncertainty and variability issues which exist in point cloud geo-data due to incomplete information captured by 3D acquisition devices. Joerg et al. (2012) discussed point cloud geo-data collected from different airborne sensors which are often integrated together to build a complete database, where massive point cloud data captured from different platforms and sensors create potential data quality problems for data integration and manipulation. If the point-based spatial data model in the CG approach could be applied to point cloud geo-data, then it will reduce the influence of data uncertainty and error propagation in point cloud geo-data processing and improve GIS representations.

The CG approach introduces a completely different way to process GIS data and functions using function-based layers. The basic idea of function-based layers was discussed in Section 3.3 and based on the first and second case studies, it was found that function-based layers provided a way to improve the data quality of geo-processing. For example, the influence of data uncertainties, e.g. error propagation and spatial data conversion, could be minimised by using symbolic computation and function-based layers in the CG approach, and increased flexibility was also provided in the CG approach as the resolution and extent of the output could be defined by the users according to a request.

The contribution of function-based layers has an important implication for improving the data quality of geocomputation. Geocomputation is an approach that it is used for interpreting spatial characteristics, explaining geographical phenomena, and solving spatial problems (Couclelis, 1998; Cheng et al., 2012). Nowadays, geocomputation is widely applied in various fields to understand complex geographical phenomena, such as health data analysis (Câmara and Monteiro, 2001) and geodemographics (Ashby and Longley, 2005). It should be noted that spatial data quality improvement is an ongoing topic in geocomputation due to many existing issues which were discussed in Section 2.3.3, such as data transformation and error propagation. If the function-based layers in the CG approach could be applied to geocomputation, then this will enable a different way to manipulate GIS data and functions and reduce the influence of data uncertainties and errors in geocomputation.

Aside from data quality, this thesis has also paid attention to the overall computation time through the concept of CG computation priority. It is particularly important to note that this is probably the first time priority values have been applied to GIS functions in order to improve computational efficiency. In contrast to the computation strategy of the traditional geo-processing approach, a more sophisticated variant of the CG computation priority is that each GIS function has a priority value derived from the particular computation cost, which is used to execute the available functions from highest to lowest priority. As a result, the overall computation time of geo-processing can be reduced, as the new approach enables a way to use computer resources efficiently and avoid redundant computations.

The novel CG computation priority has an important implication for improving the performance of geo-processing. Nowadays, many geo-processing research studies relate to high performance computation, such as parallel computation. For example, Dowers et al. (2000) suggested a framework and a series of software libraries, which allow the integration of parallel computation technology into the GIS software to improve computational efficiency. Parallel computation has two benefits for implementing multi-computational tasks in a geo-processing model; first, it supports an efficient platform to encompass a wider range of complex processes in a geo-processing model, which can be divided and achieved by multi-streaming sequential geo-processing tasks across different cores (Qin et al., 2014); and second, it enables a new platform to store the ocean of GIS data which are collected from spatial and temporal dimensions (Zhong et al., 2012). However, it should be noted that parallel computation focuses on how heavy computational tasks can be efficiently divided into smaller computational tasks via the use of a multi-core processor. This characteristic indicates that: (a) parallel computation doesn't change the sequential computation strategy in the traditional geo-processing approach; and (b) the problems related to sequential computation strategy still exist in parallel computation. These issues raise several questions for future research, such as can parallel computation be applied in the CG approach and can the priority-based computation strategy be integrated into the parallel computation? Although the integration between the two methods may further reduce the overall computation time of a geo-processing model, this integration also has some potential challenges in future development. For example, how could a combinative function divided into sub-computation tasks and how are sub-computation tasks prioritised in parallel computation?

The contribution of the CG approach could be further extended to several research contexts, e.g. environmental modelling, web mapping services, urban planning, risk assessment, or asset management, as it fundamentally improves geo-processing. People currently work in many different fields and use geo-processing models to solve many spatial problems. For example, scientists use geo-processing models to monitor and analyse daily atmospheric changes, such as temperature and air pollution, biologists use geo-processing models to track animal migration patterns, city planners and engineers use geo-processing models to help plan their response in the case of a natural disaster, such as an earthquake or hurricane and engineers and specialists use geo-processing models to plan local resources needed for energy services, like gas and electricity. Therefore, there are many potential opportunities for the CG approach to be applied to different fields in order to improve data quality and computational efficiency.

Last but not least, if the CG approach could be frequently and repeatedly used in Web GIS and online geo-processing, further computation time and computer resources could be saved. It should be noted that the current geo-processing tool, not only could be used in different GIS desktop software packages (e.g. ERDAS and ArcGIS) for spatial analysis and decision-making, but also has been widely and repeatedly applied in Web GIS and online geo-processing to support spatial data processing and map publishing services. Niu et al. (2013) discussed how geo-processing services could be provided using Web GIS and concluded that online geo-processing provides a convenient way to reduce the differences between platforms and programming languages, but that computational efficiency is a potential problem for online geo-processing and requires further investigation. Another example is Google Map applications which appeared in 2005, where the number of users dramatically increased as Google Map applications provide convenient online mapping services. If the popular online data processing functions that are repeatedly applied in GIS users' daily jobs could be implemented using the CG approach, then there are significant computation times that could be saved for web service providers and potential contributions that could be made for different web mapping service users. For example, the overlay of map layers and potential site selection, which were discussed in Chapters 5 and 7, are two popular functions and have been widely applied in online geo-processing. If these functions could be implemented using the CG approach, then this would improve data quality and the computational efficiency of online geo-processing.

The next section discusses the limitations of the CG approach.

8.5 Research Limitations

In this thesis different methods were used to develop the CG approach. For example, a conceptual model was discussed at the beginning of the thesis to build the framework for the development of the CG approach, then there are the three case studies that were applied to the CG approach implementation, and finally a geostatistical method (i.e. a Monte Carlo simulation) was used to trace the uncertainties, e.g. data quality and computation time cost, and evaluate the results of the case studies. These different methods, which each have their own limitations, were applied to answer the research question of this thesis and therefore they are critically discussed in this section.

8.5.1 Conceptual Model of the Combinative Geo-Processing Approach

The conceptual model of the CG approach was discussed in Chapter 3 in order to explain the major characteristics of the new approach, and this model plays an important role in the three case studies that were used for the development of the CG approach. However, it should be noted that there are some limitations with respect to the implementation of the conceptual model in the current CG approach, which mainly refer to the CG function library and the CG function output visualisation.

First, there is a barrier for many GIS users in comprehending the performance gains delivered by the CG approach because of the limited amount of CG functions and geo-processing models that were implemented in the development of the CG approach. As was discussed in Section 3.3, the CG function library is a core element in the input level of the CG conceptual model for storing and managing different CG functions effectively. CG functions can be developed and stored in the CG function library, and subsequently these functions were used in the case studies for the implementation of the CG approach. However, due to time restrictions, only a basic set of CG functions was created in the library for test purposes. Therefore, further research is required to expand the diversity of the functions that are included in the CG function library so that the approach will be eventually used to implement various CG functions and geo-processing models in different fields.

Second, although the CG approach provides flexibility regarding the data formats of the output level, it should be noted that there is a potential limitation with respect to data visualisation. Specifically, the results of the current CG approach need a further step to enable data visualisation. For example, if users want to display the CG approach result in raster format, then a point list data need to be converted using the 'ASCII to raster' function. Therefore, the CG approach would ideally require the development of a graphical user interface (GUI) to solve this limitation of data visualisation. This potential GUI of the CG approach would provide greater flexibility for data visualisation, as it could display the same list point data in various data formats (e.g. raster, vector, 3D). Moreover, as the CG approach can produce a function or functions for the results, then the GUI of the CG approach also needs to provide the ability to display these functions. For instance, instead of displaying raster or vector data, the GUI of the CG approach could visualise the function-based layers and their manipulation progress.

8.5.2 Design of Case Studies

Three different case studies were applied in this thesis for the development of the CG approach. These case studies have different limitations and implications, which are critically discussed in this section.

Although the results of case study 1 showed that the CG approach improved the results, especially when compared with the traditional raster layer overlay method in map algebra, it may still receive some criticism as the geo-processing model implementation involves a simple model which requires the integration of only two raster layers. Thus, a chain processing model, including two different GIS functions (IDW and Slope) was introduced in case study 2 in order to increase the complexity of the implementation model. In addition, the case study area and the sample data volume were gradually increased in case study 2 to validate the result of the CG approach.

Case study 2 showed how a combinative function (IDW and Slope) can be implemented using the CG approach. This case study can also be criticised with respect to the large amount of computation time that was required by both geo-processing approaches. Although this was mainly due to the large amount of sample data that were applied in case study 2, it is still evident that the existing geo-processing approaches, i.e. the CG approach without computation priority and the traditional geo-processing approach, do not encapsulate an efficient computation strategy that can be used to deal with large spatial data and complex computations. In order to overcome this limitation CG computation priority was introduced in the next case study to improve the overall computation time.

The objective of case study 3 was to develop the computational priority rule of the CG approach in order to improve the overall computation time. Although the final results showed that the average overall computation time in the CG approach with computation priority is 29.2% (around 20 seconds) lower than for the traditional geo-processing approach, this case study may subject to several criticisms. Case study 3 only resulted in a very small reduction in computation time (around 20 seconds) and it may not convince GIS users to use the CG approach with computation priority to execute their geo-processing tasks. Yet it is essential to highlight that if the CG approach with computation priority is used in geo-processing tasks which are frequently applied in daily jobs, such as web mapping services, then significant computation time can be saved for web mapping service providers, such as Google Maps and Bing Maps.

The speed of computation priority assessment in the current CG computation priority rule is not efficient, as the composite factors of computation priority are observed and evaluated one by one until a final priority value is produced. Improving the speed of the priority value assessment is an important research question that requires further investigation in order to reduce the overall computation time of geo-processing.

Finally, there is only one geo-processing model, i.e. the site selection model, that was applied in case study 3, and thus various additional implementation models are required to further validate the performance of the CG approach with computation priority.

8.5.3 Data Validation Method (Monte Carlo Simulation)

A Monte Carlo simulation was used in this research to evaluate the uncertainties of the final results. A Monte Carlo simulation was applied in case study 2 to calculate the mean and variance of the results in order to investigate the influence of data uncertainties in the simple chain processing model implementation. Furthermore, a Monte Carlo simulation was applied in case study 3 to trace the average computation time, i.e. mean value, of both geo-processing approaches. Although a Monte Carlo simulation provides a useful method to trace the uncertainties and compare the results of the CG and the traditional geo-processing approaches, it should be noted that a Monte Carlo simulation has two limitations with respect to the iteration times and input data, and these problems are discussed in more detail in the remainder of this section.

The first limitation in a Monte Carlo simulation is the numerical load or computation iterations, as the operation must be executed 'N' times. Heuvelink (2006) argued that the iteration time N is a limitation of a Monte Carlo simulation mainly due to two reasons: a) if a small number of iterations is applied in a Monte Carlo simulation, then the simulation can lead to misleading results as there are not enough computations; and b) if a larger number of iterations is applied then this may lead to heavy computations. These limitations therefore draw attention to the question of how many iterations should be used in the case studies presented in this thesis. This problem was discussed for both case studies 2 and 3 in order to identify a suitable number of computation iterations.

Most GIS studies run a Monte Carlo simulation with only 20 or even ten iterations (Fisher, 1999; Goodchild et al., 1992), although Goodchild et al. (1992) claimed that ten or twenty iterations are not sufficient to obtain an accurate estimation of the results. Furthermore, Heuvelink (2006) suggested that in most cases a Monte Carlo simulation should include at least 50 computation iterations. Therefore, case study 2 used 50 iterations in order to provide an accurate estimation of the influence of data uncertainties. In contrast, case study 3 used 100 iterations, for two main reasons: a) the amount of LiDAR data were gradually increased to one million points from 26,499 points, which is the amount of LiDAR data used in the third case study; and (b) the geo-processing model applied in this case study is more complex than the one used in case study 2, i.e. the combinative function of 'IDW' and 'Slope'. Moreover, Heuvelink (2006) claimed that 100 iterations are sufficient to obtain a reasonable estimate of the mean value (e.g. the average value of computation time) in a Monte Carlo simulation.

The second limitation of a Monte Carlo simulation is the input datasets, as simulations can lead to misleading results if inappropriate inputs are entered into the model (Ibbotson Associates, 2005). For instance, a small sized input dataset in a Monte Carlo simulation is not enough to support the outcomes based on statistical analysis (e.g. mean and standard deviation values) because the outputs may be totally changed based on different small sized datasets. This problem was investigated in Section 4.4, and the size of the sample dataset was gradually increased in the three case studies. For example, case study 2 used 26,000 points from the original LiDAR dataset, whereas in case study 1 1,000 points were selected from the original LiDAR dataset and in case study 3 one million LiDAR points were used to validate the overall computation time between the two different geo-processing approaches.

The next section discusses the future research directions for the CG approach.

8.6 Directions For Future Research

The CG approach was developed based on a limited number of sample data and case studies due to the complexities of model development and the limitations regarding time and knowledge. Therefore, a future research is requested to extend the functionalities and contributions of the CG approach. This section summarises some interesting directions for the future research.

a. Advancing the Combinative Geo-Processing Function Library

An ideal geo-processing approach needs to be supported by sufficient GIS functions, (i.e. different types of function libraries, such as the ModelBuilder in the ArcGIS software package which offers thousands of functions in its Toolbox in order to provide a powerful means of GIS modelling. However, only a basic set of common GIS functions was developed in the current CG function library due to time restrictions. Future research should also extend the development of more CG functions as part of the CG function library, in order to enhance the functionality and capability of the CG approach for a wider spectrum of GIS applications, e.g. 3D land surface models, weather temperature prediction models, hydrological models, and environmental risk assessment models.

b. Combinative Geo-processing Computation Priority

This thesis introduced the concept of CG computation priority as a solution for reducing the overall computation time of geo-processing. However, the current method for assessing computation priority is very slow and could extend the overall computation time. Therefore, improving the speed of the priority value assessment is an important research area that should be addressed in the future to further reduce the overall computation time of geo-processing. Future research should focus on identifying an efficient method that can assess the computation priority value through the design of an optimum computational algorithm to address this problem and its implementation. Furthermore, as was discussed in Section 8.4, in future research CG computation priority may be applied to parallel computation in order to further improve computational efficiency.

c. Developing New Combinative Geo-Processing Computation Rules

To date three computation rules have been introduced into the CG approach to improve data quality and computation time, and these include ‘suspending’, ‘computation priority’, and ‘symbolic computation’ (see Section 3.3.2). New computation rules could be developed in future research to further enhance the performance of the CG approach. For instance, the CG approach is in need of a reduction rule to simplify complex geo-processing models which are constructed of various function-based layers or CG functions. Therefore further investigation is needed to create a reduction rule in the CG approach to improve computational efficiency. A reduction rule based on the function-based layers should also be created to understand how data quality can be maintained during the reduction operations.

In conclusion, this thesis has used the CG approach to implement different types of geo-processing models, e.g. a single GIS function, a simple chain processing model, and a complex chain processing model. The results of the case studies show that the CG approach provides an improved methodology for geo-processing. Future investigations should focus on the improvement of CG computation rules, e.g. the reduction rule and the computation priority rule, and the enhancement of the CG function library, as these will further improve the performance of the CG approach and increase the potential number of users of the CG approach in wider GIS applications. It is hoped that this approach will continue to be developed in order to provide more accurate and efficient results for various geo-processing models in different GIS fields.

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Appendix A Chapter 4 LiDAR Data

As described in the Section 4.4.2, this research applied LiDAR points in the three case studies and these points were downloaded from the INSIDE IDAHO (Interactive Numeric and Spatial Information Data Engine) (http://inside.uidaho.edu/popular_data.html).

In specific, there are two groups of the raw LiDAR points that were downloaded from two different data capture projects undertaken in the INSIDE IDAHO (Interactive Numeric and Spatial Information Data Engine). The technical information about the two groups of the raw LiDAR points is given in the Table A.1 and Table A.2 separately.

Table A. 1 Technical information of the first group raw LiDAR dataset.

Project Name	**Boise River**
Download Web Link	http://www.idaholidar.org/data/45
Technical Description **(source from the Download Web Link)**	The United States Geological Survey (USGS) Center for Coastal and Watershed Studies, the National Aeronautics and Space Administration (NASA), United States Bureau of Reclamation (Reclamation), Idaho Department of Water Resources (IDWR) and a consortium of local city, county agencies and private entities (see supplemental information) are using airborne LiDAR to measure the submerged topography of the Boise River. The study area encompasses the 500 year floodplain from Lucky Peak Reservoir to the confluence of the Boise River and the Snake River. Elevation measurements were collected in March of 2006 using the NASA Experimental Advanced Airborne Research LiDAR (EAARL). Initially developed by NASA and Wallops Flight Facility (WFF) in Virginia and now administered by the USGS Coastal and Marine Geology Program, EAARL measures ground elevation with a vertical accuracy of roughly 15 centimeters. The data were processed by IDWR using the Airborne LiDAR Processing System (ALPS), a multi-tiered processing system developed by a USGS/NASA collaborative project for the use of subaerial and submarine LiDAR. The output from this processing is 2 meter resolution raster data that can be easily ingested into a Geographic Information System (GIS). The data were organized as 2 km by 2 km data tiles in ERDAS imagine format. Point data information is also available for first return, bare earth, submerged topography and a submerged topography/bare earth combination. These tiles are created for visual interpretation and regional quantitative analysis. The data are in UTM Zone 11 meters, NAD83, NAVD88 (Geoid 03 model). At the same time that the Boise River LiDAR data were collected, USGS collected cross sectional data using survey grade GPS at three separate sections along the river - upper, middle and lower. These ground observations were then used to quality check the LiDAR data and to provide a vertical accuracy assessment. The results of the quality assessment will be available by the end of December, 2009.

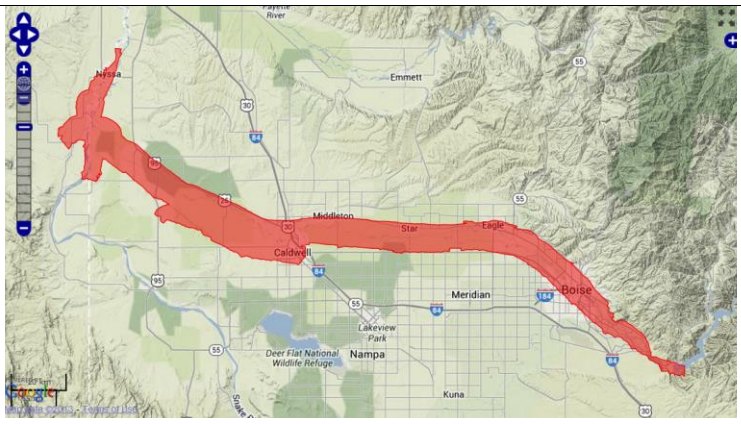
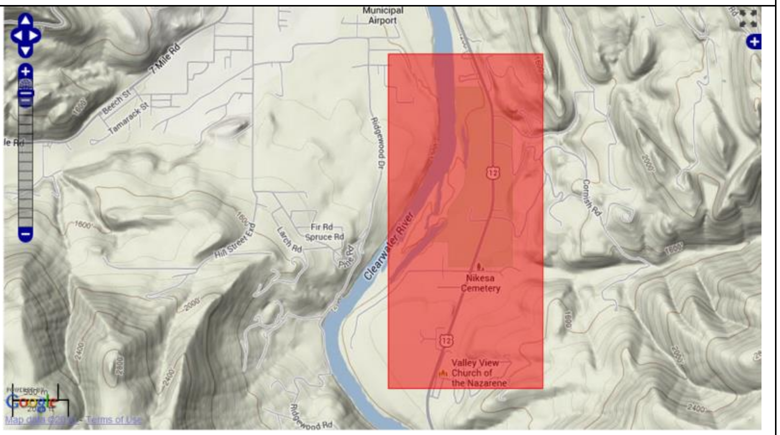
Project Location Map (The red polygon represents the captured LiDAR data area)	 Nyssa Emmett Middleton Star Eagle Caldwell Meridian Boise Lakeview Park Deer Flat National Wildlife Refuge Nampa Kuna Google
Acquisition Date	01/03/2007
Sensor	NASA EAARL

Table A. 2 Technical information of the second group of raw LiDAR dataset.

Project Name	**National Park Service Northern Idaho**
Download Web Link	http://www.idaholidar.org/data/41
Technical Description **(source from the Download Wed Link)**	The LiDAR data was collected by Terrapoint USA Inc. between November 16th and December 4th, 2008. This LiDAR project's purpose was to provide high accuracy, classified multiple return LiDAR, for approximately 89 square miles, in North Idaho. Part of the collection was over the Coeur d'Alene Reservation, the remainder of the collection was done for the National Park Service for their areas of interest. The LiDAR data was acquired and processed by Terrapoint USA to support engineering planning purposes. The product is a high density mass point dataset with an average point spacing of 0.7m. The original data was provided to the Coeur d'Alene Tribe in LAS 1.0 format. The area consists of (1) Asotin Creek (7.8 km2), (2) Captain John Creek (4.7 km2), (3) Deary Area (6.8 km2), (4) Jim Ford Creek (6.3 km2), (5) Nikesa Creek (3.1 km2), (6) South Fork Clearwater River (10.0 sq km2), and (7) White Bird Creek (19 km2).
Project Location Map (The red polygon represents the captured LiDAR data area)	 Municipal Airport 7 Mile Rd Beech St Tamarack St Ridgewood Dr Fir Rd Spruce Rd Larch Rd Hill Street Ext Clearwater River Nikesa Cemetery Valley View Church of the Nazarene Cornish Rd Google
Acquisition Date	16/11/2008 – 04/12/2008
Sensor	Optech ALTM 3100EA

Appendix B Chapter 5 Additional Data

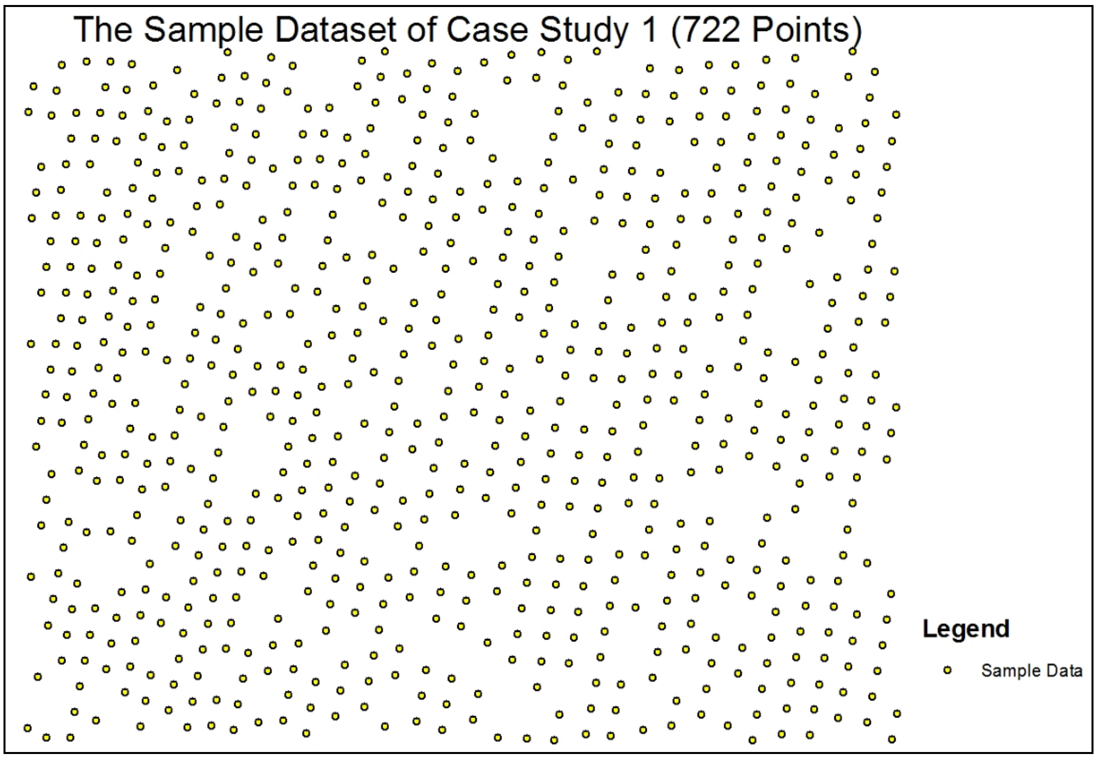


Figure B- 1 Sample dataset of Case Study 1.

Appendix C Chapter 6 Additional Data

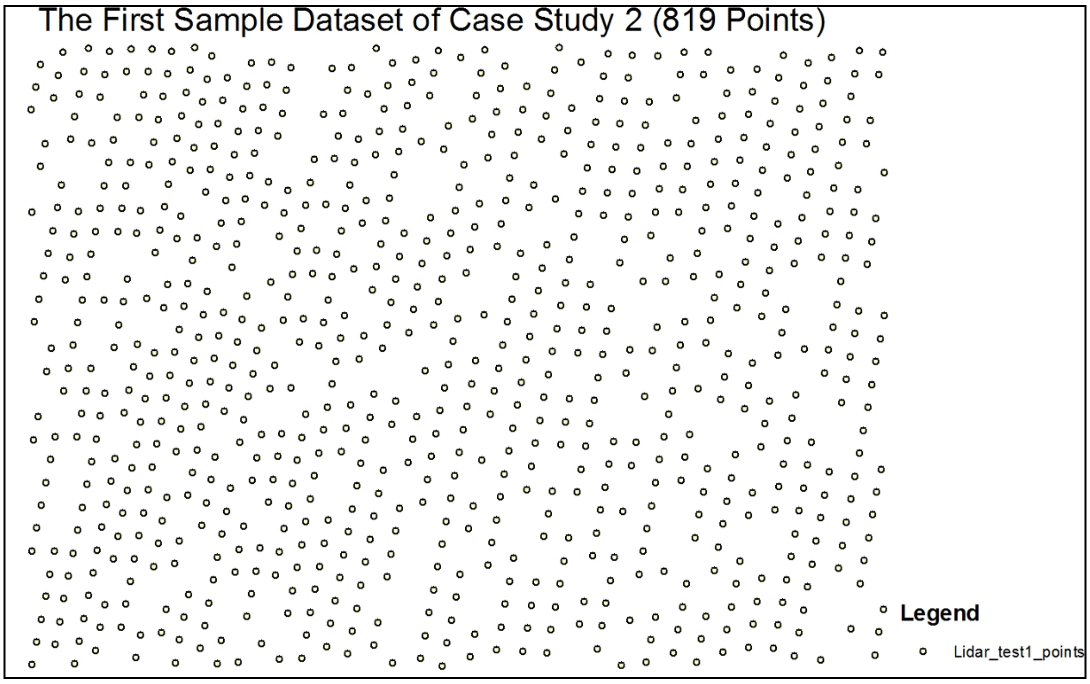


Figure C- 1 First sample dataset of Case Study 2.

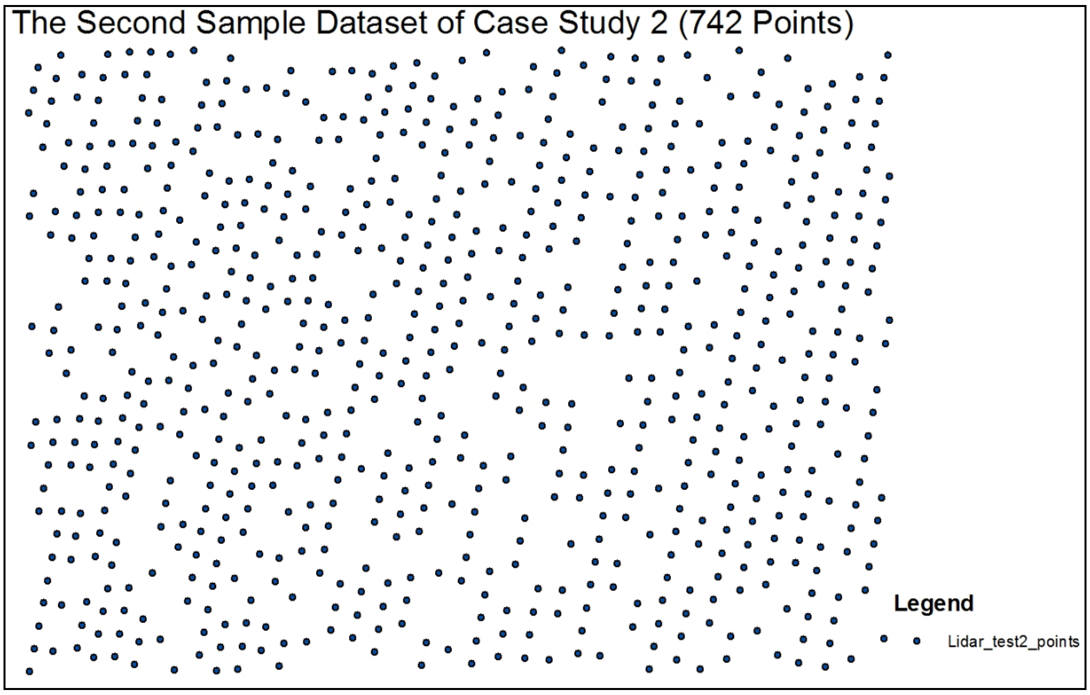


Figure C- 2 Second sample dataset of Case Study 2.

Appendix D IDW Algrithem

The basic principle of IDW is that it assigns weights to neighboring observed values based on distance and estimated grid values by averaging the values of sample data points in the neighborhood of each processing grid (O'Sullivan and Unwin, 2003).

The standard IDW algorithm can be summarised as:

First the interpolated value, Z_j, of a given point is estimated by:

$$\boxed{Z_j = \sum_{i=1}^{m} W_{ij} Z_i \qquad \textbf{(Equation 2.3)}}$$

In Equation 2.3, W_{ij} is a weight between 0 and 1 which is based on the distance from selected sample points to the estimated point, and Z_i is the elevation of the sample points. If distance is represented by D_{ij}, the value of each weight value is calculated by:

$$\boxed{Wij = \frac{(1/\,D_{ij})}{\sum_{i=1}^{m} 1/D_{ij}} \qquad \textbf{(Equation 2.4)}}$$

Where $(\sum_{i=1}^{m} 1/D_{ij})$ is the sum of all inverse distance weighted values and this rule gives the proportional weight of each selected sample point. We can determine that a large value of D_{ij} will give a small weight value, however, a close distance between a sample point and the estimated point will lead to a higher weight.

$$\boxed{\frac{1}{D_{ij}{}^{k}} \qquad \textbf{(Equation 2.5)}}$$

The weights of neighbouring observed values are calculated based on the geographical distance between the selected sample point and the target point. We can define the weight of distance by using an exponent k. Defining a higher value of k (greater than 1), will decrease the relative effect of distant points and create a peakier map; defining lower values of k (less than 1), will increase the relative effect of distant points and smooth the resulting surface (O'Sullivan and Unwin, 2003).

Normally, not all observation points are considered when estimating a new value; this means that each sample point within the pre-defined radius is weighted between 0 and 1 and all others outside it are not considered. To understand how this works, an example is provided below. Figure D-1 shows how a generic IDW algorithm works. The elevation value is calculated at the point shown as a hollow circle. There are four neighbourhood sample points (solid circles) that are selected, with z values equal to 75, 68, 99, 110 and 88. Table D-1 shows the required parameters and calculations in the IDW process. In this case, a pre-defined maximum search radius of three metres is used, therefore, the sample point (110) is not considered in this calculation. Finally, the estimated Z_j value is 81.679 in this example.

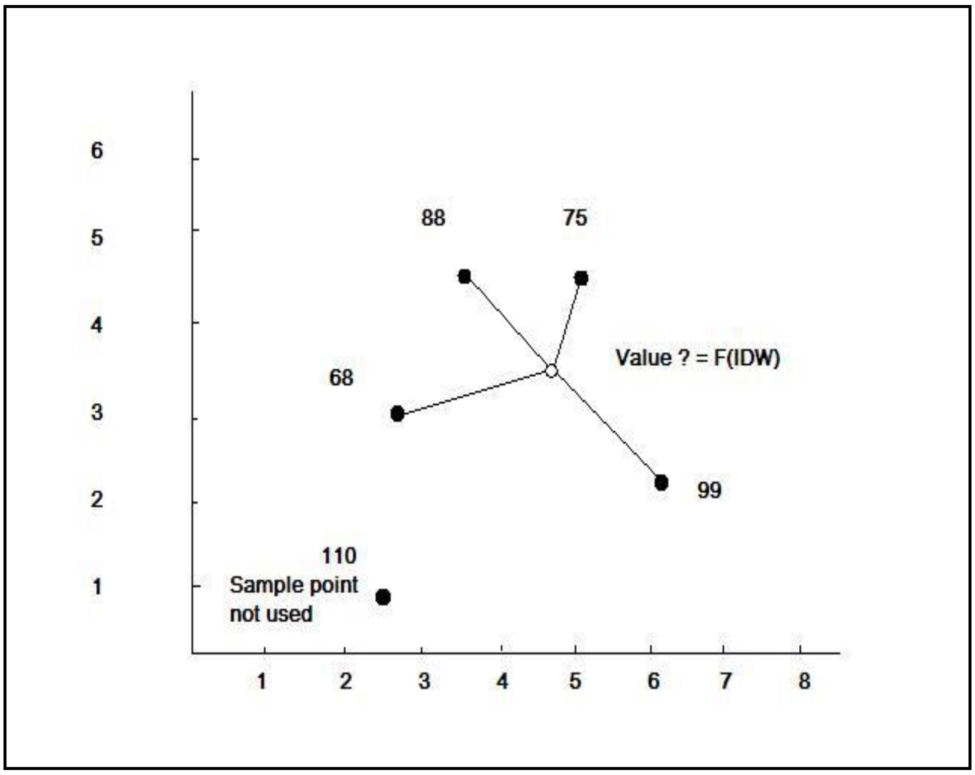


Figure D- 1 An example of IDW interpolation.

Table D-1 Results from the IDW example.

Sample point	**Elevation (Z) value**	**Distance (d)**	**Inverse distance (i=1/d)**	**Weight (w=i/[sum of i])**	**Weighted value (w*z)**
1	75	1.2	0.833	0.322	24.15
2	68	1.9	0.526	0.203	13.804
3	99	2.2	0.454	0.175	17.325
4	88	1.3	0.769	0.3	26.4
Sum			2.582	1	81.679

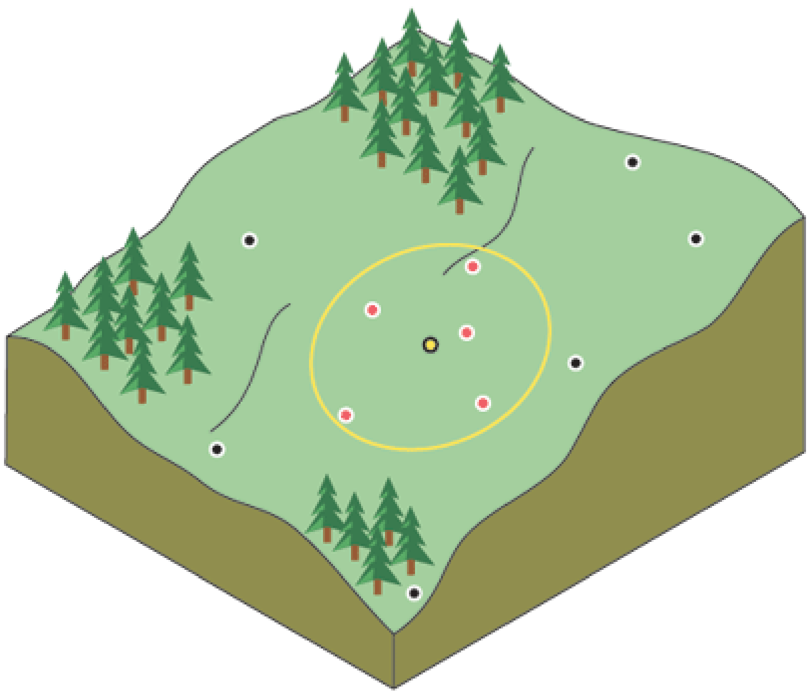
Appendix E Online Document For the GIS Fuctions

E.1 Implementing Inverse Distance Weighted (IDW) (ArcGIS Online Document)

Resource:

http://webhelp.esri.com/arcgisdesktop/9.2/index.cfm?TopicName=Implementing%20Inverse%20Distance%20Weighted%20(IDW)

Inverse Distance Weighted (IDW) is a method of interpolation that estimates cell values by averaging the values of sample data points in the neighborhood of each processing cell. The closer a point is to the center of the cell being estimated, the more influence, or weight, it has in the averaging process.



This method assumes that the variable being mapped decreases in influence with distance from its sampled location. For example, when interpolating a surface of consumer purchasing power for a retail site analysis, the purchasing power of a more distant location will have less influence because people are more likely to shop closer to home.

Power

With IDW you can control the significance of known points on the interpolated values based on their distance from the output point. By defining a higher power, more emphasis is placed on the nearest points, and the resulting surface will have more detail (be less smooth). Specifying a lower power will give more influence to the points that are farther away, resulting in a smoother surface. A power of two is most commonly used with IDW and is the default.

Search radius

The characteristics of the interpolated surface can be controlled by applying a fixed or variable search radius, which limits the number of input points that can be used for calculating each interpolated cell. You limit the number of points for each cell's calculation to improve processing speeds. You may also limit the number of points because points far from the cell location where the prediction is being made may have no spatial correlation.

Fixed search radius

A fixed search radius requires a neighborhood distance and a minimum number of points. The distance dictates the radius of the circle of the neighborhood (in map units). The distance of the radius is constant, so for each interpolated cell, the radius of the circle used to find input points is the same. The minimum number of points indicates the minimum number of measured points to use within the neighborhood. All the measured points that fall within the radius will be used in the calculation of each interpolated cell. When there are fewer measured points in the neighborhood than the specified minimum, the search radius will increase until it can encompass the minimum number of points. The specified fixed search radius will be used for each interpolated cell (cell center) in the study area; thus, if your measured points are not spread out equally (which they rarely are), there are likely to be a different number of measured points used in the different neighborhoods for the various predictions.

Variable search radius

With a variable search radius, the number of points used in calculating the value of the interpolated cell is specified, which makes the radius distance vary for each interpolated cell, depending on how far it has to search around each interpolated cell to reach the specified number of input points. Thus, some neighborhoods will be small and others will be large, depending on the density of the measured points near the interpolated cell. You can also specify a maximum distance (in map units) that the search radius cannot exceed. If the radius for a particular neighborhood reaches the maximum distance before obtaining the specified number of points, the prediction for that location will be performed on the number of measured points within the maximum distance. Generally, you will use smaller neighborhoods or a minimum number of points when the phenomenon has a great amount of variation.

Barrier

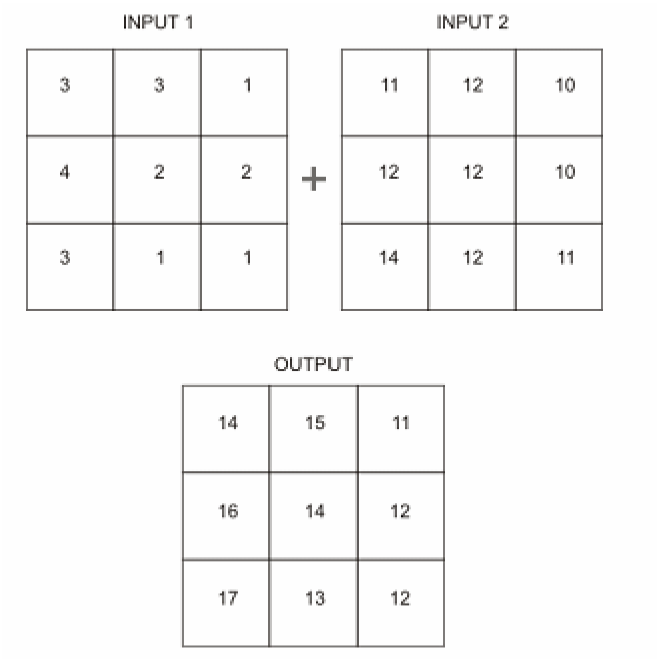
A barrier is a polyline dataset used as a breakline that limits the search for input sample points. A polyline can represent a cliff, ridge, or some other interruption in a landscape. Only those input sample points on the same side of the barrier as the current processing cell will be considered.

E.2 Raster overlay (ArcGIS Online Document)

Resource:
http://webhelp.esri.com/arcgisdesktop/9.2/index.cfm?TopicName=Overlay_analysis

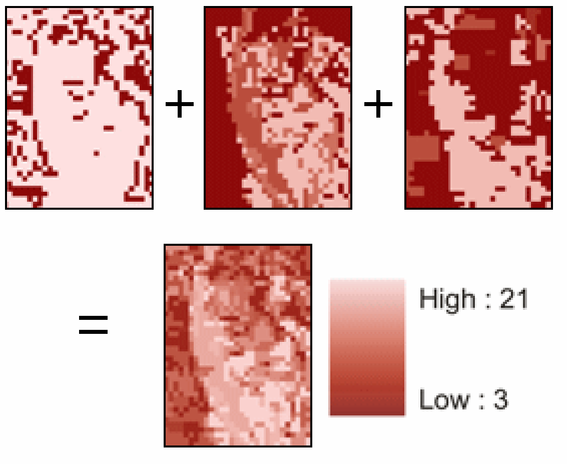
In raster overlay, each cell of each layer references the same geographic location. That makes it well suited to combining characteristics for numerous layers into a single layer. Usually, numeric values are assigned to each characteristic, allowing you to mathematically combine the layers and assign a new value to each cell in the output layer.

Below is an example of raster overlay by addition. Two input rasters added together to create an output raster with the values for each cell summed.



This approach is often used to rank attribute values by suitability or risk and then add them, to produce an overall rank for each cell. The various layers can also be assigned a relative importance to create a weighted ranking (the ranks in each layer are multiplied by that layer's weight value before being summed with the other layers).

Below is an example of raster overlay by addition for suitability modeling. Three raster layers (steep slopes, soils, and vegetation) are ranked for development suitability on a scale of 1 to 7. When the layers are added (bottom) each cell is ranked on a scale of 3 to 21.



Alternatively, you can assign a value to each cell in the output layer based on unique combinations of values from several input layers.

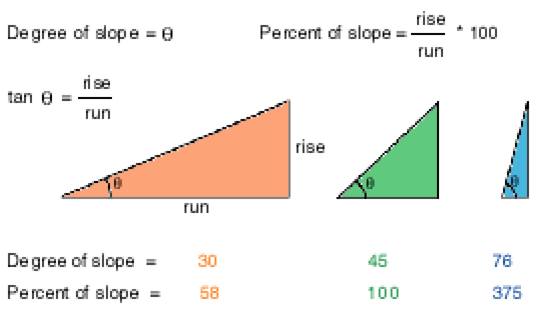
E.3 Calculating slope (ArcGIS Online Document)

Resource:

http://webhelp.esri.com/arcgisdesktop/9.2/index.cfm?TopicName=Calculating_slope

The Slope tool calculates the maximum rate of change between each cell and its neighbors, for example, the steepest downhill descent for the cell (the maximum change in elevation over the distance between the cell and its eight neighbors). Every cell in the output raster has a slope value. The lower the slope value, the flatter the terrain; the higher the slope value, the steeper the terrain. The output slope raster can be calculated as percent of slope or degree of slope.

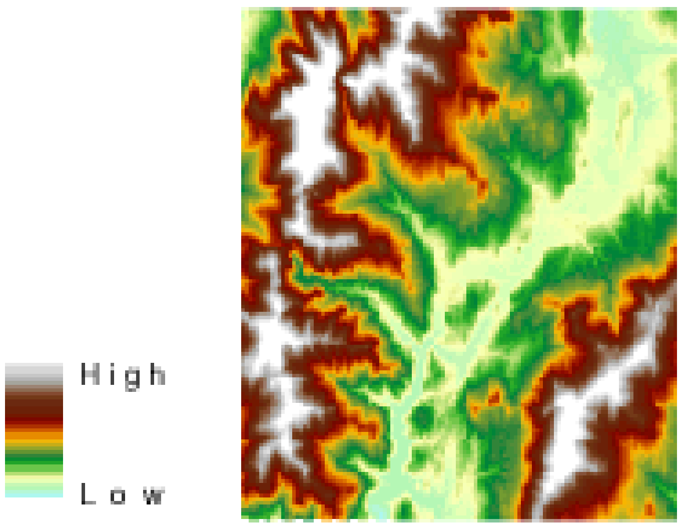
When the slope angle equals 45 degrees, the rise is equal to the run. Expressed as a percentage, the slope of this angle is 100 percent. As the slope approaches vertical (90 degrees), the percentage slope approaches infinity.



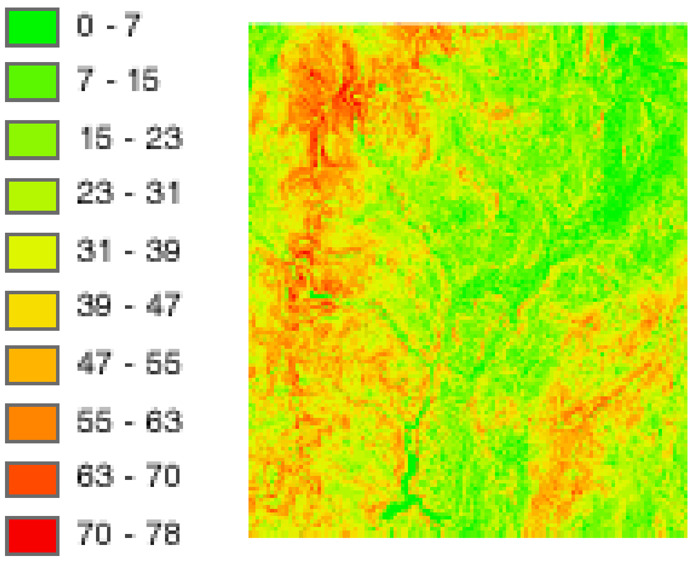
Degree of slope = θ
Percent of slope = rise/run * 100
tan θ = rise/run
rise
run
θ
Degree of slope = 30 45 76
Percent of slope = 58 100 375

The Slope tool is most frequently run on an elevation dataset, as the following diagrams show. Steeper slopes are shaded red on the output slope raster. However, the function can also be used with other types of continuous data, such as population, to identify sharp changes in value.

Elevation dataset



Output slope dataset (in degrees)



E.4 Selection (Understanding reclassification) (ArcGIS Online Document)

Resource:

http://webhelp.esri.com/arcgisdesktop/9.2/index.cfm?TopicName=Understanding_reclassification

The reclassification functions reclassify or change cell values to alternative values using a variety of methods. You can reclass one value at a time or groups of values at once using alternative fields; based on a criteria, such as specified intervals (for example, group the values into 10 intervals); or by area (for example, group the values into 10 groups containing the same number of cells). The functions are designed to allow you to easily change many values on an input raster to desired, specified, or alternative values.

All reclassification methods are applied to each cell within a zone. That is, when applying an alternative value to an existing value, all the reclassification methods apply the alternative value to each cell of the original zone. No reclassification method applies alternative values to only a portion of an input zone.

Some of the many reasons to reclassify are detailed below.

Replacing values based on new information

Reclassification is useful when you want to replace the values in the input raster with new values. This could be due to finding out that the value of a cell should actually be a different value, for example, the land use in an area changed over time.

Grouping values together

You may want to simplify the information in a raster. For instance, you may want to group together various types of forest into one forest class.

Reclassifying values of a set of rasters to a common scale

Another reason to reclassify is to assign values of preference sensitivity, priority, or some similar criteria to a raster. This may be done on a single raster (a raster of soil type may be assigned values of 1 to 10 to represent erosion potential) or with several rasters to create a common scale of values.

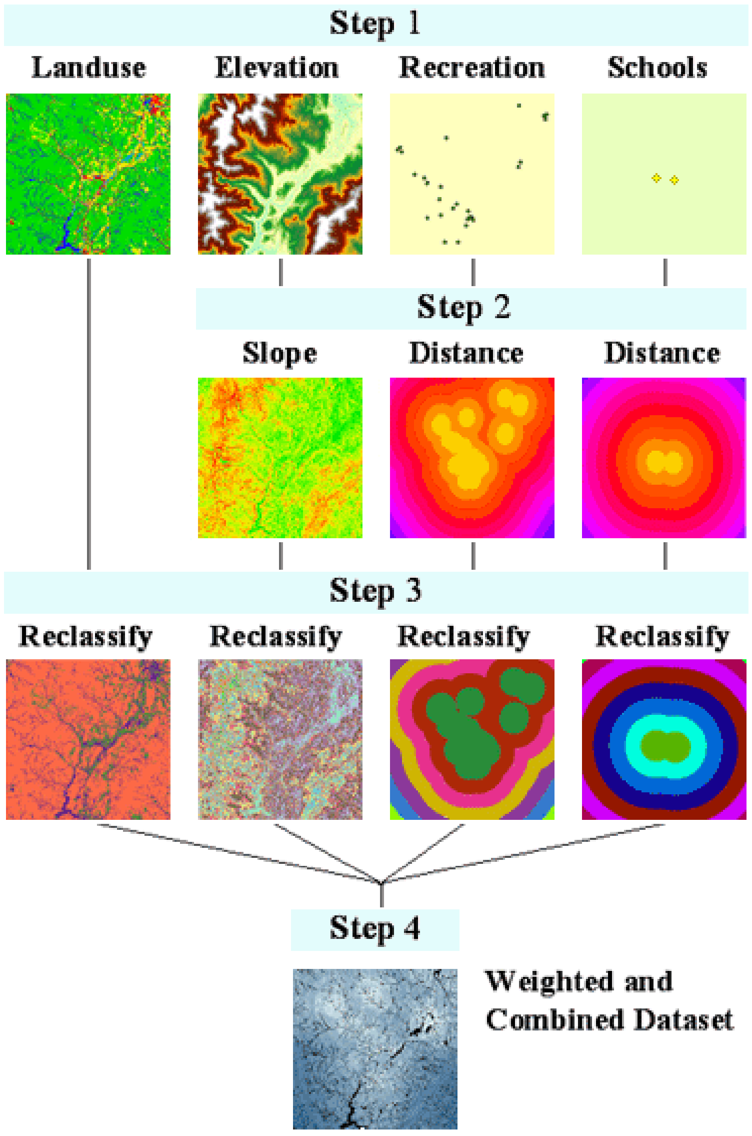
For example, a soil type may be good to build on when soils are being viewed as an input to a building suitability model. But for erosion, animal habitat, siting a pond, or identifying farm land, that same soil type will have a different suitability weighting based on the problem at hand. To represent a raster relative to these many different suitability weightings, the values on the raster must be changed from nominal values—values that represent a class—to interval or ratio values so that the values can be used in relation to one another. It does not make sense to add soil type and land use to obtain a building suitability raster. But if soil type and land use were in a measurement system that represented a relative weighting to building suitability, analysis could be completed freely between the rasters.

When identifying slopes most at risk of avalanche activity, input rasters might be slope, soil type, and vegetation. Each of these rasters might be reclassified on a scale of 1 to 10 depending on the susceptibility of each attribute in each raster to avalanche activity—that is, steep slopes in the slope raster might be given a value of 10 because they are most susceptible to avalanche activity.

Each of the above examples is considered a suitability model. There are usually four steps in producing a suitability map:

1. Input datasets. Decide which datasets you need as inputs.
2. Derive datasets. When applicable, create the datasets that you can derive from your base input datasets— for example, slope and aspect can be derived from the elevation raster. Create data from existing data to gain new information.
3. ssify datasets. Reclassify each dataset to a common scale (for example, 1 to 10), giving higher values to more suitable attributes.
4. Weight and combine datasets. Weight datasets that should have more influence in the suitability model if necessary, then combine them to find the suitable locations.

Below is a flow diagram of a sample for finding the best locations for a school. The input base layers are landuse, elevation, recreation sites, and existing schools. The derived datasets are slope, distance to recreation sites, and distance to existing schools. Each raster is then reclassified on a scale of 1 to 10. The reclassified rasters are added together with distance from recreation sites and other schools having a higher weight.



Setting specific values to NoData or setting NoData cells to a value

Sometimes you want to remove specific values from your analysis. This might be, for example, because a certain land use type has restrictions, such as wetland restrictions, which means you cannot build there. In such cases, you might want to change these values to NoData to remove them from further analysis.

In other cases, you may want to change a value of NoData to a value, such as when new information means a value of NoData has become a known value.

E.5 Distance (Understanding Euclidean distance analysis) (ArcGIS Online Document)

Resource:
http://webhelp.esri.com/arcgisdesktop/9.2/index.cfm?TopicName=Understanding_Euclidean_distance_analysis

The Euclidean distance functions describe each cell's relationship to a source or a set of sources.

There are three Euclidean functions:

1. Euclidean Distance gives the distance from each cell in the raster to the closest source. Example of usage: What is the distance to the closest town?
2. Euclidean Allocation identifies the cells that are to be allocated to a source based on closest proximity. Example of usage: What is the closest town?
3. Euclidean Direction gives the direction from each cell to the closest source. Example of usage: What is the direction to the closest town?

The input raster used in each of the Euclidean functions and a discussion about the output from the functions is described below.

The source

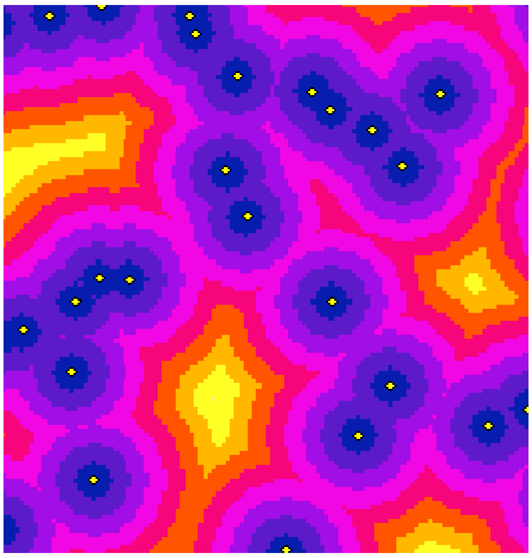
The source identifies the location of the objects of interest, such as wells, shopping malls, roads, and forest stands. If the source is a raster, it must contain only the values of the source cells while other cells must be NoData. If the source is a feature, it will internally be transformed into a raster when you run the function.

The Euclidean distance output raster

The Euclidean distance output raster contains the measured distance from every cell to the nearest source. The distances are measured as the crow flies (Euclidean distance) in the projection units of the raster, such as feet or meters and are computed from cell center to cell center.

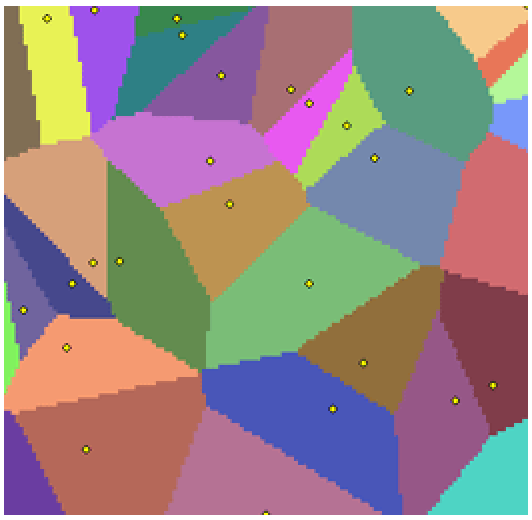
The Euclidean Distance function is used frequently as a standalone function for applications, such as finding the nearest hospital for an emergency helicopter flight. Alternatively, this function can be used when creating a suitability map, when data representing the distance from a certain object is needed.

In the example below, the distance to each town is identified. This type of information could be extremely useful for planning a hiking trip. You may want to stay within a certain distance of a town in case of emergency or know how much farther you have to travel to pick up supplies.



The Euclidean allocation output raster

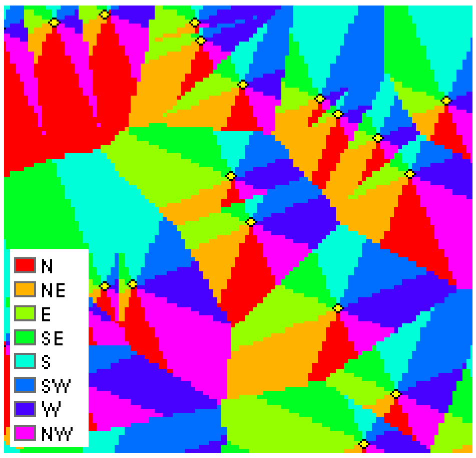
Every cell in the Euclidean allocation output raster is assigned the value of the source to which it is closest. The nearest source is determined by the Euclidean Distance function. Use this function to assign space to objects such as identifying the customers served by a group of stores. In the example below, the Euclidean Allocation function has identified the town that is closest to each cell. This could be valuable information if you needed to get to the nearest town from a remote location.



The Euclidean direction output raster

The Euclidean direction output raster contains the azimuth direction from each cell to the nearest source. The directions are measured in degrees, where north is 360 degrees.

In the example below, the direction to the nearest town is found from every location. This could provide useful information for an emergency helicopter when transporting an injured hiker to the nearest town for medical treatment.



The Euclidean Distance functions give you information according to Euclidean, or straight-line, distance. It may not be possible to travel in a straight line to a specific location; you may have to avoid obstacles such as a river or a steep slope. In such cases, you should consider using the Cost Distance function to achieve more realistic results.