Towards a Capacity-based optimal allocation of storm pipes' replacements: Considering the effects of Climate Change and Urbanization

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This is to certify that the thesis prepared

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ABSTRACT

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Reza Maghsoudi

Storm pipes are a major component of any municipal infrastructure system, however, poor attention is commonly paid to their management and replacement of pipes is typically guided by condition criteria. Pipes replacement also faces the issue that their capacity is not considered, and the proposed pipes replacements are of the same diameter as the previous ones. However, lagged replacements of storm pipes can compromise urban system ability to drain runoff-water from rainfall and this could lead into flooding. This research extents optimal condition-based allocation of pipes by considering demand-capacity ratios, in order to prevent flooding. The effects of urbanization and climate change are also incorporated. A general method for detecting the impacts of urbanization currently exist, however, a simplified approach due to the lack of data is suggested. A case study of the city of Kindersley in Saskatchewan is used to illustrate the application of the method. Hydrological models based on current and future land uses were used to estimate changes in demand-capacity ratios for each pipe in the system. Performance curves for capacity and condition were developed, and validated by change detection of observed historical land use cover for the past 25 years. An extra 18% rainfall intensity was used to model the impacts of climate change. It was found that CAN$40,000 were enough to sustain current levels of condition and capacity-demand ratios, however, condition was at unacceptable level. Budget was raised and weights were adjusted until a combination with 45% capacity and 55% condition with $100,000 was found to be the departure at which compliance begins to reach desirable point minimum levels

of demand-capacity ratios and condition, possibly higher values of budget would be necessary as the municipality adjust such minimum requirements to the desired ones.

DEDICATION

To

MUM AND DAD

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I would like to thank my lovely mother who taught me self-sacrificing, loyalty and honesty, my father who taught me generosity and warm heartedness. I would like to thank superstars of my life, my wonderful brothers and sister, who supported me throughout my whole life.

At the end, I would like to thank God for this beautiful life.

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LIST OF ABBREVIATIONS

AASHTO	American Association of State Highway and Transportation Officials
AM	Annual Maximum
ANN	Artificial Neural Network
CC	Climate Change
CD	Change Detection
CN	Curve Number
DOT	Department of Transportation
ENVI	Exelis Visual Information Solution
ETM	Enhanced Thematic Mapper
FHWA	Federal Highway Administration
GCM	General Circulation Model
GCP	Ground Control Point
GIS	Geographic Information System
IDF	Intensity Duration Frequency
LP	Linear Programming
LOS	Level of Service
LULC	Land Use Land Cover
ML	Maximum Likelihood
M&R	Maintenance and Rehabilitation
NARCCAP	North American Regional Climate Change Assessment Program
NDE	Nondestructive test Evaluation
NDVI	Normalized Difference Vegetation Index

NRCS	Natural Service Conservation Service
RCM	Regional Climate Model
RS	Remote Sensing
SCS	Soil Conservation Service
SHM	Structural Health Monitoring
SWMM	Storm Water Management Model
TAC	Transporation Association of Canada
TM	Thematic Mapper
USGS	U.S Geological Survey
UTM	Universal Transverse Mercator

Chapter 1 Introduction

1.1 Background

Infrastructure assets comprise buildings and facilities that provide services required for encouraging good quality of human living environments. They must be regularly maintained by continuing replacement and revamping of its components (NAMS 2006). Infrastructure assets include transport systems (roads, airport and rail facilities, pavements etc.), pipe networks (water distribution, storm water drainage and wastewater collection and treatment systems), and energy supply and telecommunication grids among others. All these assets should be properly preserved as they support the living environment and encourage economic development.

Pavement management was the first system to see the light back in the 1980's, more systems such as those for bridges and pipes joined later on (Haas and Hudson 1994). Infrastructure asset management became a process driven by a decision making framework responsible for assessing thousands of possible courses of action to maintenance, rehabilitation and upgrading of infrastructure assets (Tessier and Haas 1997). Such a process attempts to keep all the assets in the best possible level of service, which unfortunately, has been interpreted as condition in many cases. Since the late 20th century global attention has been paid to infrastructure management systems and their economic benefits (Vanier and Rahman 2004). Governments and federal agencies discovered how protecting different assets and maintaining sustainability during their life-cycle could help them save money (NAMS 2006).

Infrastructure management provides a lifecycle approach to strategic, tactical and operational planning to effectively safeguard their integrity and to provide satisfactory levels of service to the public while managing risk in a sustainable and environmentally responsible manner (Hudson et al. 1997, NCHRP 2002, and Krugler et al., 2006).

The importance of storm water systems is sometimes neglected, although they are a vital component of urban infrastructure (catch basins, manholes, ditches, storm pipes, culverts and other conduits, even sometimes pump stations). Many drainage systems at developed countries (like United States) date for over a century. Urban drainage systems are a critical part of Canada water infrastructures that removes only storm-water runoff from urban areas. They are managed by municipalities, utility companies and departments of transportation (DOTs) in order to collect rainfall, control storm peak flow, and reduce the risk of flooding during storm events. A properly designed and maintained system will reduce the vulnerability of any city, but a poorly maintained one could make them defenseless to rainfall extremes, specifically due to the lack of consideration to what occurs when the design criteria are exceeded.

Management of drainage systems is especially critical in an era of climate change and rapid urbanization, when more persistent and more intense (than normal) precipitations and floods are expected to occur. Increased urban population density causes a substantial increase in the amount of impervious surfaces from which rainfall runs off quickly into the pipe system. These surfaces include: building roofs, paved areas and roads, among others. In urbanized zones, new constructions increase the extensiveness of impervious areas and the additional runoff is expected to provoke pollution, and soil erosion after rainwater discharges in a river, decreasing onsite water infiltration and all this will possibly result in extreme floods (Mailhot and Duchesne 2010). According to Environment Canada, urbanization of natural drainage basins can increase water runoff to more than 400 per cent (Storm water Guideline EPB 322 2014). Furthermore, sea level rising and increase in the amount of precipitation and rainfall extremes are recognized as a vital impacts due to climate change (Larsen et al., 2008) . Trends from recent decades, show an increasing frequency of extreme precipitation events in many regions because of climate change (Madsen et al., 2009) . Indeed, based on reports for the late 20^{th} century there is strong evidence of global augmentation in the frequency of extreme rain storms as a result of global warming and this trend is very likely to continue into the 21 century (IPCC 2007).

A comprehensive knowledge of urban runoff phenomenon would simplify engineering solutions and helps to enhance planning and management (Bormil et al., 2003), (Andrieu and Chocat 2004), such a knowledge could be accomplished by urban hydrological modeling and developing extended databases of detailed spatiotemporal information (Parkinson and Mark 2005).

1.2 Problem Statement

Storm sewer drainage networks are considered one of the major infrastructure assets in any country, however, poor attention is given to them and priority is shifted to other types of infrastructure deem more critical. Few governments count with a storm pipe management systems, and most of them implement the wrong practice of considering condition as main indicator of performance, few –if none- have incorporated in their management systems the fact that storm pipe network adequacy should be based on provision of sufficient capacity to prevent flooding at urban areas. Storm water drainage is affected by urban development and climate change, in the last decades urban watersheds have faced land use changes due to population growth accompanied by change of pervious areas to impervious areas. Construction of houses, commercial buildings, parking lots, paved roads, and streets, all them increase the impervious cover at urban catchments and thus reduce infiltration, triggering erosion and the discharge volume of storm runoff. Another effect is the decreased time of concentration and corresponding increase watershed's response to precipitation (Draper 1981, USDA-NRCS 1986). These factors accelerate the volume and velocity of runoff and result in larger peak flood discharges from urbanized watersheds than those occurred in the pre-urbanized condition (Chow et al., 1988). In addition, storm water infrastructures are designed based on the assumption that the probability distribution of precipitation extreme events is statistically stationary. This assumption is called into question by climate change, causing uncertainty about the future performance of systems created under this paradigm (Rosenberg et al., 2010) . Climate change causes significant increases in precipitation and evaporation, leading to an intensification of the water cycle leading to an increase in the intensity and frequency of occurrence of extreme events. Consequently, many storm pipe networks could soon be working closely to their designed capacity. Demand-Capacity ratios of storm pipes should be at the core of any decision making systems for the allocation of pipe replacements.

1.3 Overall Goal

The overall goal of this research is to extend current decision making framework used to optimally allocate storm pipe replacements by considering expected changes in pipe's network demand-capacity ratios in addition to condition. Three specific tasks were identified to address the overarching scope of this research.

1.3.1 First specific task

The first task is to predict changes in the flow-demand patterns of individual pipes from the effects of urbanization. An approach based on remotely sensed data and GIS technologies is recommended to estimate changes across time of impervious areas, runoff and flow to the pipe system for an entire catchment. This approach is strongly suggested for practical applications and used for validation on this research. However, it was only partially implemented in this research given the absence of data. A simplified method is proposed and explained in task 2.

1.3.2 Second specific task

This task was concerned with the development demand-capacity curves. Current and future rainfall-runoff-flow to storm pipes are estimated from current and future land use, this is a simplified method in lieu of the impossibility to use the one described on task one. The estimation of future water flow to pipes come from the impact of climate change and was incorporated by presuming an 18% more severe rainfalls (this estimation provides a rich field for future research), the aim was to demonstrate the applicability of the proposed method. Estimated future demand and current demand are used to develop demand-capacity curves.

1.3.3 Third specific task

A dynamic linear programming formulation with two objectives was used to identify allocation of pipe replacements to achieve adequate network levels of service defined by pipe's capacity and condition.

1.4 Scope and Limitations

This research proposes the application of remote sensing and GIS technologies to detect historical changes in land cover to estimate flow-demand on storm pipes in order to extrapolate and develop demand capacity curves useful to schedule replacements in an optimized capacity /condition framework. The effects of climate change have been incorporated in the model, however, future research could develop better means to estimate them. Age/damage related condition is considered in this research, however, due to lack of information, other elements that leads to hydraulic failure such as the number of blockage occurrences are not considered.

Future research may want to look into creating a hydrological model to validate the proposed one. Future intensity of the rainfall should be implemented over the basis of climatic simulations considering general circulation models (GCMs) and regional climate models (RCMs) and as a result of them local impact studies using statistical downscaling should be used to obtain local-scale climate.

This research was limited by the availability of high resolution images such as Quick Bird (QB) earth observation, such satellite imageries are considerably expensive and they are recommended for practical applications of the method herein proposed. Medium resolution satellite images have been used instead for change detection purposes because, at first, high resolution images are not available before the year 2000, and secondly because of their cost. A simplified alternate method for forecasting demand –capacity was employed.

The case study for this research is taken from the Saskatchewan province, Canada, given available detailed spatial storm water network data. This research takes advantage of this case study to demonstrate the applicability of the method in practice. The data required was provided by the municipality of Kindersley and Environment Canada.

1.5 Organization of the Thesis

This thesis is presented in five chapters as follows. Chapter one contains a brief background, it describes the problem, objectives and structure of the thesis. Chapter two is divided into two major areas, one concentrated in the literature related to the modeling of pipes demand and the other in the allocation of pipes replacements, it covers subtopics related to urban sprawl, remote sensing and change detection, hydrological modeling, and a review of infrastructure management concentrated onto pipes networks. Chapter three, is divided into two sections. The first section presents an integration of remote sensing and Geographic Information system (GIS) for mapping urban land use and land cover (LULC) in order to show changes over time. The second section, presents a decision making approach for allocation of pipes replacements by employing condition and capacity- based performance models and optimization tools. In chapter four, the town of Kindersley in Canada was used to illustrate the methodology proposed. Finally, the last chapter presents extracted conclusions from this study and also outlines future works that could be done to improve this field of study.

Chapter 2 Literature Review

2.1 Introduction

The goal of this chapter is to justify the need for a better method for the management of storm drainage infrastructure. This chapter is divided into two major sections: the first one, provides a review of state of the practice in urban sprawl, change detection and remote sensing technology. Also an overview of urban hydrology and the impact of climate change and urbanisation on urban watershed management is presented. The second section, focuses on infrastructure asset management, reviewing background and current decision support models.

2.2 Modeling pipes demand capacity ratios

Changes in climate and urbanization affect the design and operation of storm drainage systems, as these two factors are directly considered for the design of storm pipe infrastructures. Urbanization, directly increases the amount of rainfall runoff and changes in the climate could cause more intense and frequent rainfalls. Change detection and remote sensing can be used to measure the impacts of urbanization and urban hydrology to estimate the amount of runoff water arriving at each pipe of the system. Once runoff has been estimated the determination of demand and capacity follows conventional hydrological methods.

2.2.1 Urban sprawl

Global population growth rate is currently declining but, demographic momentum indicates that population growth will continue until the year 2100 (O`Neil et al., 2001). According to the United Nations, most if not virtually all of this population growth is predicted to occur in urban areas. United Nations` estimates showed that more than 50% of the world total population were living in urban areas in 2006 and will approach 60% by the year 2020 (Schell and Ulijaszek 1999, Zanganeh Shahraki et al., 2011).Small and middle sized urban areas are experiencing the highest rates of urban growth, however, most of the studies on urban sprawl focus on large cities and metropolitan areas. For example, largest urban expansion in Zhujiang Delta in China occurred in Donggun, Baoan, Nanhui and Zhuhai which are relatively small cities (Weng 2001). Population growth of Ajmer city, a medium sized city in India was tripled and a substantial increase in urban land cover from 488 ha in 1977 to 1259 ha in the 2002 (Jat et al., 2008) was observed.

After World War II, urban sprawl has been observed in developed countries (Gill, 2008). Sprawl is a pattern of land use indicating low levels of eight well-known dimensions: concentration, continuity, density, nuclearity, clustering, mixed uses and proximity (Glaster et al., 2001), and causes an increase in land, water and energy consumption, as well as increases in pollutants and waste. Sprawl is commonly considered a threat for sustainable urban development. Causes of urban sprawl vary from consumer preferences to new policies of capital accumulation in cities through real estate expansion (Muniz et al., 2007). Extent of coverage of impervious surfaces are a direct consequence of urban sprawl. They come in the form of artificial structures with impenetrable materials that water cannot infiltrate and are built by human activities such as pavements (roads, sidewalks, driveways) and buildings (Slonecker et al., 2001) . In addition, impervious surfaces are considered an important parameter for urban sprawl evaluation (Torrent and Albert 2000, Barnes et al., 2001, Epstein et al., 2002).

2.2.2 Change detection and Remote Sensing

Change Detection (CD) is the process of determining the differences in an object by observing it at different times (Singh 1989). Land cover (LC) and land-use (LU) change information are key sources of information in different fields such as, transportation, hydrology, urban expansion, planning and land management, disaster monitoring, damage assessment, agriculture and forestry. In general, change detection attempts to recognize changes in the probability distribution of a stochastic process or time series. Remote sensing data are used to facilitate the analysis of land use transformation to understand the historical relationships between environment and human activities and forecast trends for landscape conversions. Remote sensing is a vital source for change detection studies because of some features such as high temporal frequency, brief view, digital format suitable for computation, and wider selection of spatial and spectral resolution (Lunetta et al., 2004, Coops et al., 2006, Chen et al., 2012). The objectives of change detection in remote sensing are to distinguish geographical locations, type of changes and to evaluate the changes and determine the accuracy of change detection results (Coppin et al., 2004, Im and Jenson 2005). There are various change detection methodologies including both pixel-based (Mas 1999) and object-based (Arya and Hergarten 2008). It is the purpose of the each study that defines the appropriate change detection technique. For example pixel-based CD methods, are not considered appropriate for very high resolution remote sensing data (VHR RS), in which object-based classification is preferable. The size of the study area and the spatial resolution can also significantly impact the selection of a change detection technique. Typically, low resolution images are used to monitor changes over larger areas. At the regional level, per-pixel based methods, using medium spatial resolution image such as Landsat Thematic Mapper (TM) and ETM+ are recommended. VHR RS data (e.g. Quick Bird, IKONOS, and Orb View) is advised for local scale studies as it provides greater spatial resolution.

Remote sensing is concerned with recording, determining and analysing the information related to objects or phenomenon by means of spatial devices. In other words, detecting information of objects without being in contact with them, commonly using aerial technologies to identify and classify objects on the earth's surface by means of propagated signals (Schowengerdt, 2007). There are two forms of remote sensing, namely passive and active remote sensing. In passive technique, sensors normally identify the reflected and emitted energy wavelength from the object. The common source for passive remote sensing is reflected sunlight. Infrared technology, and film photography are some common applications of this method (Blaschke 2010). On the contrary, energy or wave is released from active remote sensing technology in order to scan and analyse the proposed phenomenon; in this case the mirrored or backscatter radiation from the target should be detected by active sensors. RADAR and LiDAR are the main examples of active remote sensing. In most sensors, information of earth`s surface are recorded by determining transmission energy from different parts of the electromagnetic (EM) spectrum.

Some examples of remote sensing can be found in: environmental assessment and monitoring, global change detection and monitoring, agriculture land identification, spatial location of non-renewable resources, metrology and military applications. Many researchers have used remote sensing, for instance Wilson and Lindsey (2005) explored the changes in land use of central Indiana by classification and change detection analysis of Landsat satellite imageries. Remotely sensed data was used by Ryznar and Wagner (2001) to detect the changes in vegetation in Detroit's metropolitan area. In addition, Geographical Information Systems (GIS) and remote sensing techniques are popular in change detection studies at developed and developing countries in order to investigate the relationship among spatial and temporal patterns and environmental impacts. Satellite remote sensing technologies and multispectral aerial imagery are used as a common source for remote classification of vegetation purposes (Landgrebe, 1999). Yin et al. (2010) integrated an urbanization index with GIS methods to evaluate the scale, intensity, and spatial diversity of urban growth in Shanghai, China. Furthermore, Satellite remote sensing now has the potential to provide extensive coverage of key variables such as precipitation (Smith et al., 1996, Sturdevant-reesa et al., 2001); soil moisture (Sano et al., 1998) and flooding (Townsend and Foster 2002) as well as many of the parameters such as vegetation cover (Nemani et al., 1993) vegetation change (Nemani et al., 1996) and imperviousness (Slonecker et al., 2001) that are important inputs to modern hydrological models. However, it is worth to mention that remote sensing like any other technology has some limitations and drawbacks. One of the main problems of remote sensing satellite images is cost. In another words, high resolution data are usually expensive and low resolution data are not reliable. Another problem of remotely sensed data is the lack of fully automated actions and missing data standards, therefore during processing some modifications are necessary (Taubenbock et al., 2012).

2.2.2.1 Data Selection and Preprocessing

Raw data needs to be transformed into accurately calibrated measures of precisely located physical variables such as reflectance, emittance and temperature during the pre-processing. Sensor characteristics aid to determine the particular type of preprocessing required, since the aim of preprocessing is to remove unwanted image characteristics caused by the sensor.

Image preprocessing typically includes some stages in order to reduce or eliminate external factors. Natural factors such as climatic effects, atmospheric conditions and solar angle differences must be modified by applying suitable actions (Song and Woodchock 2003). Also, systematic errors such as sensor calibration, time recording inaccuracy, and geometric distortions must be rectified (Song et al., 2001, Jianyaa et al., 2008). Images are compared on the basis of pixel techniques, so accurate registrations between images are necessary in order to have appropriate borders for all preliminary data (Schowengerdt 2007).

Absolute and relative corrections, are two typical methods used for radiometric modifications in order to normalized remotely sensed image for time serious intercomparision (Cohen et al., 2003, Coppin et al., 2004). Extracting the absolute reflectance of scene targets at surface of the earth is the goal of absolute radiometric correction. This method needs the input of coincident atmospheric properties and sensor calibration, which are difficult to investigate in many cases, particularly in historic data (Chavez 1996). Eliminate or decreasing atmospheric and other unpredicted variation among multiple images by correcting the radiometric properties of target images to match a base image is the goal of relative radiometric correction (Hall et al., 1991).

Relative radiometric correction (RRC) is employed in order to adjust atmospheric and other variations of multiple images by correcting the radiometric properties of target images to match a base image (Yuan and Elvidge 1996, Jenzen et al., 2006). It can adjust noise from the atmosphere, sensor, and other sources in one process, and is broadly used. The RRC contains some methods such as dark object subtraction (Chavez, 1988), automatic scattergram controlled regression (ASCR) (Elvidge et al., 1995) , Ridge method (Song et al., 2001), Pseudo Invariant Features (PIF) (Chen et al., 2005) and second simulation of the satellite signal in the solar spectrum (6S) (Vermote et al., 1997) In Figure 2-1 DOS method used; the image on the right is the modified image by applying DOS technique, as indicated the haze from the left image will be decreased significantly and the image becomes more clear and visible.

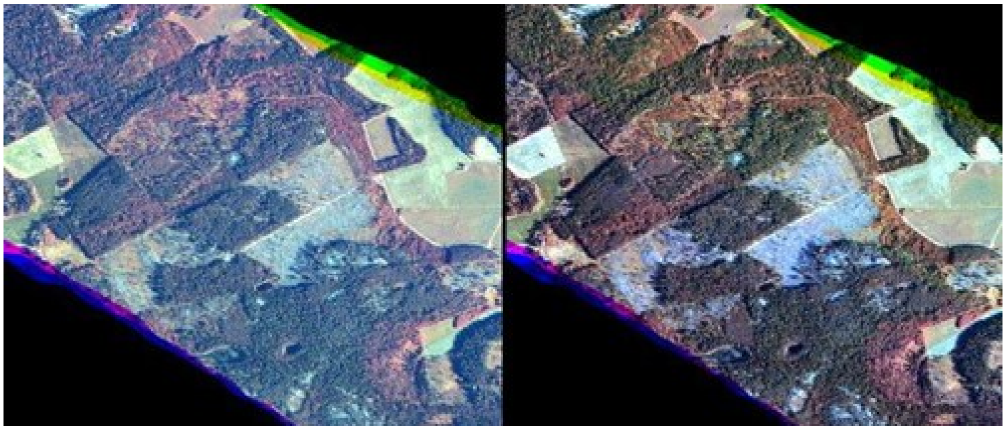


Figure 2-1: Dark Object Subtraction Concept (Kukko et al. 2005)

In addition, in remote sensing, precise geometrical representations are essential. Error sources which cause geometrical image misrepresentations related to the platform vector (attitude, altitude, speed), the sensor (distortions and oblique viewing), and to the earth (rotation, earth curvature, ellipsoid, relief) must be corrected. Figure 2-2 indicates a schematic depiction of geometric corrections.

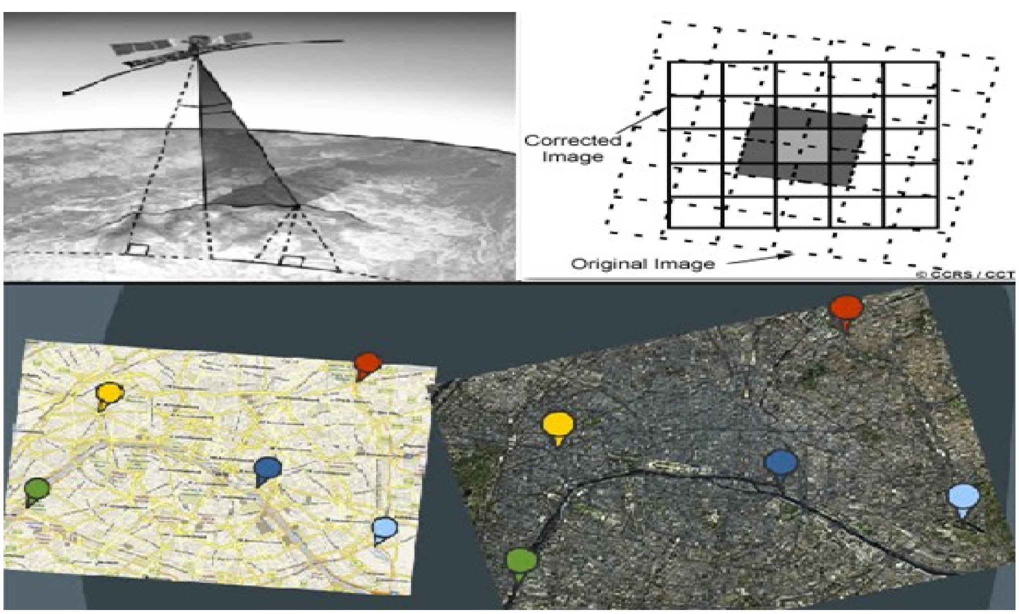


Figure 2-2: Geometric correction concept (Natural Resources Canada 2014), (Toutin 2004)

2.2.2.2 Data Processing and Image classification

The most adequate technique for change detection should be chosen depending on the purpose of each study. There are different algorithms for change detection and they can be classified as belonging to either of two main techniques: pixel or object-based (Lu et al., 2011). Pixel-based change detection algorithms are commonly applied to low and medium resolution imagery and not so often to very high resolution (VHR) imagery as their results would be limited (Im and Jensen. 2005, Lefebvre et al., 2008). Different functionalities, advantages and disadvantages of pixel-base methods can be found elsewhere (Coppin et al., 2004, Lu et al., 2004, Ilseverand and Unsalam, 2012). Variety of pre-classification change detection methods based on image algebra exist: image rationing, image differencing, vegetation index differencing, regression analysis, change vector analysis (CVA), principle component analysis (PCA), and tasselled cap transformation (KT). The level of change information derived from remote sensing images can be categorized into two groups; those identifying simple binary change (i.e. change vs. no change) such as image rationing, image differencing, regression analysis, CVA, PCA and KT and second, those that detailed "from-to" change (e.g. post classification comparison) (Im et al., 2007). A simple binary change vs. no change is usually enough for many studies (Im et al., 2008). More sophisticated, machine-learning techniques such as artificial neural networks, support vector machine, decision tree and also some GIS based methods have been employed for complex change studies.

On the other hand, object-based classification methods are implemented as a new and innovative technique, particularly for applications conducting human-made features. According to Blaschke (2010) and Chen et al. (2012), object-based analysis methods are considered more appropriate for VHR images. Moreover, when change detection for a specific location is required, object-oriented techniques are more commonly applied (Lu et al., 2011).

The main objective of remotely sensed data in LCLU studies is to create a classification map of the recognizable and meaningful features or classes of land cover types in a scene (Jasinski 1996). In addition, because most of the environmental and socioeconomic applications depend on the classification results, the interest of remote sensing community have attracted to the researches on image classification based remote sensing (Lu and Weng 2007). It can be considered as a combination of both image processing and classification methods. In the field of remote sensing, image classification is the allocation of pixels to classes. By comparing pixels to one another and to those of known characteristics in order to match the observed information to categories. Choosing a suitable classification technique can have a substantial consequence on the results. Useful results can be extracted from advanced classification technologies and large quantities of remotely sensed imagery (Richard 1999). The two main types of pixel-based image classification are Supervised and unsupervised algorithms. Selection of the number of clusters or groups is one main concern about unsupervised classification techniques, such as clustering. Selecting a few or too many clusters affect the outcome and produce different results (Richard and Jia 2006). According to Lu et al. (2004) unsupervised classifications encounter difficulty in detecting and labeling change directions.

For supervised classifications, the sequence of operations is as followed; 1. Defining the training sites, 2. Extraction of signature, 3. Classification of the image. However, picking precise training sample sets for image classification is usually difficult and time consuming (especially for historical image data classification) but, quality, accuracy and completeness of training data are very important to generating more precise classification and hence better CD (Erbek et al., 2004, Nackaserts et al., 2005). Training sites are completed with digitized features. Generally, two or three training sites are selected. Better results can be achieved by training more sites and the quality of a supervised classification depends on the quality of the training data. Such procedure warrants both the accuracy of classification and correct interpretation of outcomes. After digitizing training site area, statistical characterizations of information (signatures) can be produced and finally classification methods applied. Five popular available supervised algorithms using multispectral data are Parallelepiped classifier, minimum distance technique, maximum likelihood, artificial neural network (ANN) classifier and mahalanobis distance. Some of these classifications such as minimum distance and parallelepiped are statistically deterministic, while others like popular maximum likelihood (ML) are based on stochastic mechanisms. In image classification, more recent developments, such as use of image segmentation and object oriented analysis methods are also suitable for high resolution spectral data.

Maximum likelihood classification utilizes training data by means of estimating means and variance of the classes, which used to evaluate probabilities and also consider variability of brightness values in each class. This classifier is based on Bayesian probability theory and is one of the most widely used algorithm and the most powerful classification technique when precise training data is provided (Permal and Bhaskaran, 2010). Figure 2-3 shows the concept of maximum likelihood classification.

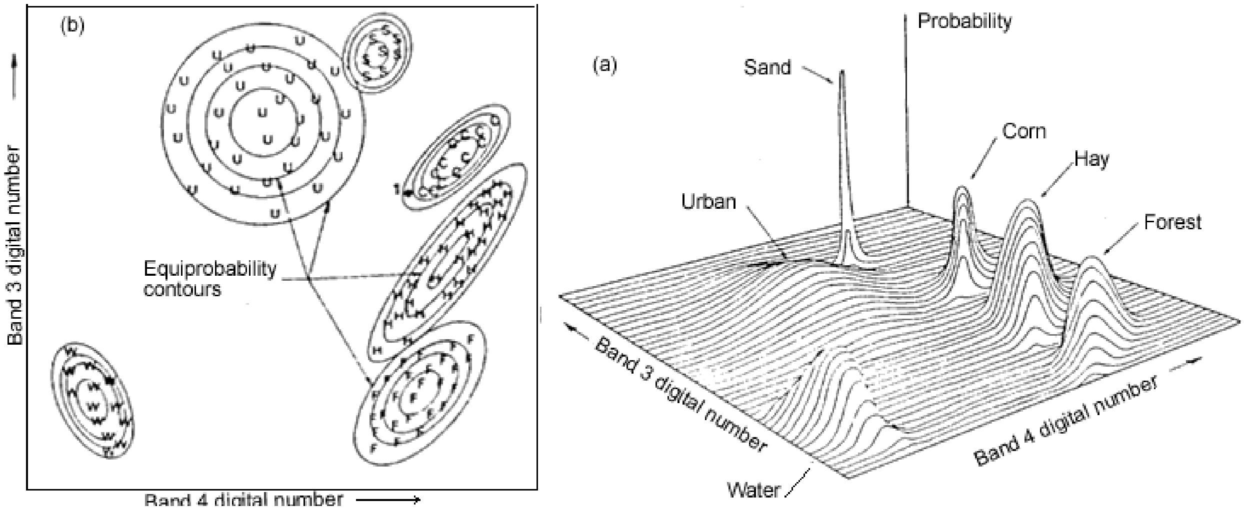


Figure 2-3 :probability density function derived from multispectral training data in maximum likelihood classification (Gopinath 1998).

The probability that a pixel with signal (s) belongs to a class (i) with mean (M_i) and standard deviation (σ_i) is formulated as following equation (Gopinath 1998).

$$P_i = \frac{1}{\sqrt{2\pi}\ \sigma_i}\ e^{\frac{-(s-Mi)^2}{2\sigma_i^2}} \tag{2-1}$$

2.2.2.3 Normalized Difference Vegetation Index (NDVI)

Normalized difference vegetation index (NDVI) is one of the most popular indexes. It is a combination of red and near infrared reflectance measurements (Ramsey et al., 2004) and has been widely used as an indicator of the state of vegetation over many spatial and temporal resolutions, (Leprieure et al., 2000, Zhao 2003). NDVI index is calculated based on the concept of vegetation absorption, most of the red light is absorbed and a large portion of the near-infrared spectrum of incident electromagnetic radiation is reflected by energetically growing healthy vegetation cover

(Tucker and Seller 1986). Moreover, the wave properties and wavelength information do not change over time and accordingly, researchers can take advantage of NDVI in order to monitor vegetative coverage in the same location in a given time period (Breuste et al., 1998).

Over the past years NDVI has proven to be particularly useful in land cover/land use distribution studies. Based on available literature, NDVI has been extensively used in most city development prediction and sustainable urban development studies. For example, Yang and Artigas (2008) compared the vegetation fraction from Spectral Mixture Analysis (SMA) and NDVI to evaluate impervious surfaces area for an urban watershed in New Jersey, United States.

NDVI index has a high capability in order to detect green spaces as well as its compatibility with TM and ETM+ data make it a powerful tool to analyze and assess the green space reduction of municipal zones over a period of times (Shahabi et al., 2012). NDVI for TM and ETM+ images can be calculated using the following formula:

$$\mathbf{NDVI} = \frac{\boldsymbol{\rho}\mathbf{NIR} - \boldsymbol{\rho}\mathbf{R}}{\boldsymbol{\rho}\mathbf{NIR} + \boldsymbol{\rho}\mathbf{R}} \qquad (2\text{-}2)$$

Where:

NDVI: Normalized Difference Vegetation Index

ρNIR: Available pixels in the fourth band of image (Representing near Infrared spectral bands)

ρR: Available pixels in the third band of image (Representing Red spectral bands)

NDVI values range from -1 to +1 and there is a lack of agreement among authors for the correspondence between NDVI sub-intervals and land classification. According to experimental measurements with various soil backgrounds (Huete and Jackson 1985), maximum values of NDVI at fractional vegetation, range from 0.8 to 0.9. In remote sensing studies, Glenn et al. (2008)

reported a bare soil value scaled at 0, and 100% vegetation scaled to +1. Normally, water zones in the image are represented by negative values. Values around zero with a 0.1 variance ranging in the -0.1 to +0.1 signify unproductive areas of rock, sand, clay or snow. Some impervious surfaces such as asphalt, concrete, buildings etc. and bare lands (e.g., bare soil, rock, dirt, etc.) have NDVI values near zero because they have similar reflectance in the red and the near infrared (Thanapura et al., 2006). Based on a comprehensive literature review, values between 0.1 and 0.2 indicate locations with low vegetation density, values between 0.2 and 0.3 represent a medium vegetation density, values between 0.3 and 0.4 correspond to high vegetation density cover and finally values beyond 0.4 indicate areas with very high vegetation coverage (Shahabi et al., 2012) . Commercial software such as ArcGIS can easily calculate NDVI.

2.2.6 Urban hydrology

Urban hydrology has been the focus of increasing attention (Jens and Mcpherson 1964). Climate change will likely lead us to warmer temperatures which will probably strengthen the hydrological cycle, resulting in an increase in precipitation's intensity and the number of storm events (Houghton et al., 1996). In addition, the rise of urban population density has been accompanied by an increase in impermeable surfaces coverage and urban runoff volumes, as well as in the frequency of flooding events.

A better understanding of the urban runoff phenomenon would facilitate engineering solutions and improve management and planning (Andrieu and Chocat 2004), (Pakinson and Mark 2005). Modeling of the impact of urban runoff flow drainage on storm pipes using GIS techniques could help to better understand the magnitude of the problem (Zheng and Baetz 1999) and support the development of comprehensive databases of detailed spatiotemporal information.

2.2.6.1 Flow estimation models

There are different available methods for modeling rainfall runoff. One of the most common methods of predicting runoff is the curve number developed by the USDA (United States Department of Agriculture) Natural Resources Conservation Service (NRCS) formerly the Soil Conservation Service (SCS). The amount of impervious area, soil group, land cover type, hydrological condition, and antecedent runoff are included in the prediction of runoff in this methodology (USDA- NRCS 1986). Examples of hydrological models using this method include TR-55, Hydro CAD, SWAT and SWMM. The other major model for rainfall runoff modeling is the rational method which utilizes the relationship between discharge, rainfall intensity and catchment area (Beven 2001).

2.2.6.2 The SCS Curve Number method

The SCS curve number method is a simple technique used on large scale for determining the approximate runoff value corresponding to a certain rainfall event in a specific area. Although the method is designed for a single storm, it can be scaled up to calculate the annual values for runoff in a given area. The origin of the method was probably based on the proposal of Sherman (1949) for plotting direct runoff versus storm rainfall. The runoff curve number (also called a curve number or simply CN) is an empirical parameter corresponding to different soil-vegetation-land use combinations that relies implicitly on the assumptions of extreme runoff events and represents an appropriate representation of the potential maximum soil retention, S (Ponc and Hawkins 1996). The Curve Number is used in the determination of S. Values for the CN for different land use, soil types and soil moisture conditions can be found in table 2-1.

Table 2-1 Runoff curve number for urban areas (USDA 1986)

Cover description: Cover type and hydrologic condition	Average percent impervious area	Hydrologic soil group: A	B	C	D
Fully developed urban areas (vegetation established)					
Open space (lawns, parks, golf courses, cemeteries, etc.)					
Poor condition (grass cover < 50%)		68	79	86	89
Fair condition (grass cover 50% to 75%)		49	69	79	84
Good condition (grass cover > 75%)		9	61	74	80
Impervious areas:					
Paved parking lots, roofs, driveways, etc. (Excluding right-of-way)		98	98	98	98
Streets and roads:					
Paved; curbs and storm sewers (excluding Right-of-way)		98	98	98	98
Paved; open ditches (including right-of-way)		83	89	92	93
Gravel (including right-of-way)		76	85	89	91
Dirt (including right-of-way)		72	82	87	89
Western desert urban areas:					
Natural desert landscaping (pervious areas only) 4/		63	77	85	88
Artificial desert landscaping (impervious weed barrier, Desert shrub with 1- to 2-inch sand or gravel mulch and basin borders)		96	96	96	96
Urban districts:					
Commercial and business	85	89	92	94	95
Industrial	72	81	88	91	93
Residential districts by average lot size:					
1/8 acre or less (town houses)	65	77	85	90	92
1/4 acre	38	61	75	83	87
1/3 acre	30	57	72	81	86
1/2 acre	25	54	70	80	85
1 acre	20	51	68	79	84
2 acres	12	46	65	77	82
Developing urban areas					
Newly graded areas (Pervious areas only, no vegetation)		77	86	91	94

It is difficult to trace back the origin of the CN array tables. The only known papers indicating what watersheds the original data may have come from Rallison (1980) and Fennessey (2001). However, there also seems to be a misconception as to the scale of the data that were essentially used to develop the CN array table, or the CN's accuracy for making peak runoff rate estimates (Matei 2012). The lack of information on the backgrounds of this technique and the lack of scientific testing of the results increases some doubts about its precision, but the method is used everywhere in the world when a simple way to estimate some discharge values is needed.

The point of the departure of the CN method is the equation:

$$\frac{\mathbf{p-I-Q}}{\mathbf{S}} = \frac{\mathbf{Q}}{\mathbf{P-I}} \tag{2-3}$$

Where

P= cumulative storm rainfall (in)

S= a factor related to watershed storage (in)

I= initial abstraction (in)

Q= runoff volume (in)

After transformation, Equation 2-3 takes the form given in Equation 2-4 which is readily suitable for obtaining maximum flow (Q), using just few variables

$$\mathbf{Q}= \frac{(\boldsymbol{P}-\boldsymbol{I})\text{^}\mathbf{2}}{(\boldsymbol{P}-\boldsymbol{I})+\boldsymbol{S}} \tag{2-4}$$

To make the estimation procedure more convenient, SCS introduced some further simplifications. First, I = 0.2s has been recommended from experience gained in the United States, Q takes the form given by equation 2-5

$$\mathbf{Q}=\frac{(\boldsymbol{P}-\mathbf{0.2}\boldsymbol{S})\text{^}\mathbf{2}}{\boldsymbol{P}+\mathbf{0.8}\boldsymbol{S}} \tag{2-5}$$

$$\mathbf{P} \geq \mathbf{0.2}\boldsymbol{S}$$

The curve number is given in Equation 2-6

$$\mathbf{CN}=\frac{\mathbf{1}}{\mathbf{10}+\boldsymbol{S}} \tag{2-6}$$

Proper selection of CN's also involves using tables containing specifications on soil groups, patterns of land use and cover, types of fanning treatment, and hydrologic conditions (Bosznay 1989).

2.2.6.3 The rational method

The rational method is extensively used for design of hydraulic structures, such as storm sewers and culverts. This method has endured over 150 years since its original description by Irish engineer Thomas Mulvany in 1851 (Dooge 1957). The rational method indicates the way in which maximum discharge is supposed to increase with the catchment area and rainfall intensity. In addition, the rational method is a popular and easy to use technique for approximating peak flow in any small drainage basin having mixed land use. It generally should not be used in basins larger than 1 square mile.

For estimating maximum design discharges on small streams, rational method is considered a simple and convenient approach. Since its introduction to the United States in 1889 (Kuichling 1889), the rational method has been used to design billions of U.S. dollars' worth of drainage infrastructure. However, such a method is usually restricted to small and unregulated drainage areas but still remains a popular hydrologic analysis and design tool for engineers. Moreover, for larger unregulated drainage areas, engineers typically use regional flood-frequency relations; computer modeling is employed if flow in the watershed is significantly regulated. Even when these more sophisticated techniques are used in design, a quick check or validation will be done with the rational method.

The Rational formula is commonly written as:

$$\boldsymbol{Q = K\ C\ i\ A} \tag{2-7}$$

Where:

Q = design discharge (m3/ second) for the recurrence interval

K = unit conversion factor

C = rational runoff coefficient; the coefficient is the proportion of rainfall that contributes to runoff.

i = rainfall intensity (mm/h)

A = watershed area (km2), upstream of the point of interest.

Rainfall intensity i is selected from intensity duration-frequency (IDF) curves for the return period of interest using a duration that is equal to a characteristic time (or averaging period) for the watershed. The watershed time of concentration t_c is frequently used to define the rainfall duration.

The runoff coefficient *C*, is employed to show that not all the rain falling to the ground contributes to discharge. The ratio between storm runoff volume and storm rainfall volume is represented by the storm runoff coefficient (Pandit and Gopalakrishnam 1996). Typically, there are tables with values of this coefficient related to various land uses that can be employed for estimation of the maximum flow. Concrete and asphalt have the highest *C* values (above 0.9) (Richman et al., 1999).

Predicting variation of urban runoff is rather a difficult task because of high variability of the urban catchment characteristics such as topography, basin drainage area and especially impermeable cover area. Pauleit et al. (2005) reported an increase in runoff coefficient for an urban zone in the United Kingdom from 0.49 in 1975 to 0.75 in 2000; Supangat and Murtoni (2002) reported a range of variations in runoff coefficient, from 0.1 to 0.4 (with one sub-watershed having an average runoff coefficient of 0.65) observed between 1991 and 2000. There are a variety of other factors influencing runoff coefficient potential, such as catchment topography, soil cover, surface micro-topography (Bormil et al., 2003) , and variations in rainfall intensity. During storm events, the urban street network acts as a collector and conveyor of concentrated storm water runoff, draining from impervious surfaces. Urban catchments, exhibit significant non homogeneity of land use, in this case, an average coefficient is recommended and can be can easily be determined by multiplying the percentage of each land use in the catchment by its fitting coefficient.

2.2.7 Climate change and Land use impacts on urban watersheds

We live in a world of changing climate with growing urban populations, with increased human influence on the global environment and its impacts on hydrology of the impact of hydrology (Praskievicz and Chang 2009). Climate and land use changes, possibly affect both water quantity and quality, at global, continental, regional, and basin scales in different geographic areas around the world (Chang and Franczyk 2008). Separate and combined influences of the impacts of climate change and urbanization on water resources, must be studied for sustainable water resource management (Praskivicz and Chang 2009).

There are some integrated watershed modeling studies that have looked into the relation between land use changes, climate and water resources. (See, Chen et al. 2005, Ducharne et al, 2007, Choi 2008, Franczyk and Chang 2009).

Urban land use is well-known to have a huge control on hydrologic dynamics. Studies of the impact of urbanization on the hydrology of an area can be found (Jacobson 2011).

Since the 1960s, (at the beginning of the expansion of urban areas in US and European cities), According to Leopold (1968) changes in total runoff, changes in water quality, flow characteristics and hydrology are four interrelated but separable effects on the hydrlogic regime of an urban area associated with urbanization. Urban watersheds, have considerably different hydrologic characteristics from natural land covers (Arnold and Gibbon 1996). The expansion of an urban area inevitably leads to an increase in impermeable surface cover. Indeed, different factors influence the amount of runoff but an indicative finding from Rose and Peter (2001) is that peak flows are from 30% to more than 100% greater in urbanized catchments compared to the less urbanized and non-urbanized catchments. The hydrological impacts of urbanization originates from the reduction of perviousness of an urban area compared to rural and other bare. In other words, total impervious area (TIA) is the main key in urban catchments and has been used widely sudied as a metric to evaluate the impact of urban land use on hydrologic responses (Snyder et al., 2005). It could potentially decrease infiltration rate and runoff response time, resulting in an extremely variable stream flow and an increased flood frequency and magnitude (Ramier et al., 2004, Konard and Booth. 2005, Mentens et al., 2005). By converting permeable agriculture and forest lands to highly impermeable urban land cover, less water penetrate to the soil to recharge aquifers. In addition, the velocity of the flow which is given by Manning's equation is indirectly related to the roughness of the land surface (Leopold et al., 1995) , storm water flows more rapidly across smooth urban surfaces than across rough surfaces.

Although the hydrological and geomorphic processes associated with urbanization are not completely understood, current knowledge can be applied to simulate future changes in urbanized catchments. Runoff models can be used as tools to estimate how changes in urban catchments will impact urban stream flows, and also to measure how probable impacts of climate change and changing rainfall patterns are on urban runoff. For example, Carlson (2004) used estimates of urban surfaces derived from remotely sensed imagery as input to the urban growth model called SLEUTH to predict land use changes up until the year 2025 and then these data were combined with other methods (e.g. the SCS method) to predict future runoff and impacts of land use change. An urban growth model and a semi distributed hydrology model are coupled to predict stream flow in response to future urban growth by Choi and Deal (2008).

Furthermore, urban land surfaces may also have an indirect effect on the hydrological regime. For example, Gero et al. (2006) used the RAMS (Regional Atmospheric Modelling System) climate model over Sydney, Australia to evaluate the impact of land cover change on storms and found that dense urban surfaces appeared to cause intense storms. Similarly, Lei et al. (2008) also predicted little change in total runoff as a result of land use change, confirming the claim that high flows tend to increase with urbanization (Gou 2006).

In addition, climate change is the other factor that has a substantial impact on hydrological regimes. Recently, the scientific community and the public at large have extended concerns over the possibility of the climatic changes due to increase in radioactively active gases at the atmosphere are increasing, a phenomenon commonly referred to as “climate change”. In the past century, human activities such as rapid urbanization and industrialization have added significant quantities of heat retaining gases to the atmosphere (Prodanovic and Simonovic 2007). The Intergovernmental Panel on Climate Change (IPCC) estimates that by 2100, an increase in temperature of between 1˚C and 3.5˚C could will be observed due to increases in greenhouse gases (Houghton 1996) and also an increase in sea level of between 13 and 94 cm (Warrick et al., 1996). Furthermore IPCC claims that there is a 90% chance of increased frequency of heavy rainfall events in the 21st century and a probable increase in higher-latitude storm water runoff by as much as 40% (IPCC 2007). According to IPCC reports, warmer temperatures also will most probably strengthen the hydrological cycle, resulting an increase in precipitations intensity and number of storm events (Houghton et al., 1996) .

Design of drainage infrastructures is based on the capacity to handle a given discharge, with a given period of return such as a 1-in-100 year flood, or the possible maximum flood in which the consequence of failure is extreme.

Due to an increase in precipitation and more notably an increase in the intensity of precipitation because of climate change in urban watersheds, magnitude of the design discharge has increased.

Design and assessment of the future performance of water-related infrastructures have become a challenge as they may be subject to significantly different discharges and flow volumes than those known today. Hydraulic infrastructure design is usually based on a given design storm event, either historical or synthetic. The first design step generally involves a return period, with a corresponding magnitude that generally reflects an acceptable tradeoff between construction costs and damage costs caused by flooding, maintenance, and inconvenience (Wenzel, 1982). Storm water management facilities, erosion and sediment control structures, flood protection structures, and many other civil engineering structures involving hydrologic flows are designed based on historic rainfall event statistics (intensity(i), return period and duration(t) (Singh and Zhang 2007). Rainfall intensity—duration—frequency (IDF) curves are a probabilistic tool which deliver a simple means of communicating information about extreme precipitation characteristics for the purpose of designing hydraulic structures and assessing flooding risk (Guo 2006, Wolcott et al., 2009).

In Canada, IDF curves are usually developed based on a single-site frequency analysis of the annual maximum rainfall series for durations varying from five minutes to 24 hours (Hogg and Carr, 1985). Predicting the potential impact of climate change (as manifested by IDF curves) on the infrastructures and adapting to them is one way to reduce vulnerability to adverse impacts (Prodanovic and Simonovic 2007). Based on simulations in Canada, almost all regions will experience an increase in Annual Maximum (AM) precipitation and median values of the distribution of relative projected changes will possibly range from 12 to 18 % increase in precipitation. An overview of Canada regional estimates is illustrated in figure 2-9, revealing a number of interesting features. It indicates, variations in intense precipitation (Y-axis) as a function of the return period (X-axis in years) over different Canadian regions due to climate change. According to figure 2-4, a large increase of annual maximum rainfall depths for all periods of return and durations is observed. GLSO region is the most affected region with an approximate increase of 25% for 20 year return period (Mailhot et al., 2012).

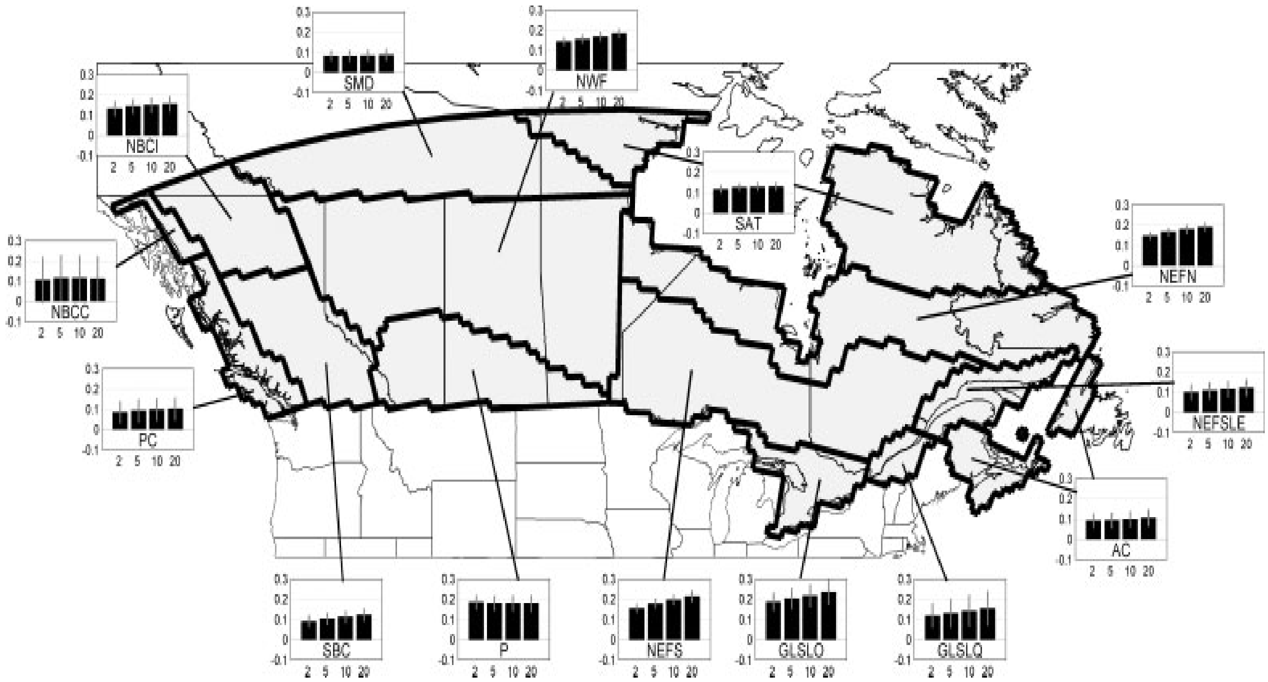


Figure 2-4: Regional relative changes in AM precipitation for 12h Histogram (Mailhot et al., 2012)

A few number of studies have been reported on the impact of climate change on urban storm water discharges compared to the analysis of the changes in precipitation related to climate change. For example, Niemczynowicz (1989) studied the impact of climate change on the sewerage system of the city of Lund in Sweden. In this research, the intensitiy of rainfall (IDF) curves was increased arbitrarily by 10, 20 and 30 percent then SWMM (Huber and Dickinson 1988) was employed in order to simulate rainfall-runoff. Flooding and increased pollution were cited as destructive consequences of the increased runoff volumes, and construction of new conduits and detention facilities was proposed as a possible adaptive measure.

2.3 Allocation of pipes replacements

Once determination of pipes demanded capacity for a long period of time has been done, then the only thing that remains is the optimal timing for replacements in such a way that overall network capacity remains constant or increases in response to the effects of urbanization and climate change. Another common objective is that of pipes condition as conditioned by available annual budget.

2.3.1 Civil Infrastructure management

The term "asset management" has been traditionally associated with maximizing profits of investors in the financial sector by handling a financial portfolio of securities, shares and bonds. Infrastructure asset management was inspired by the same goal of optimizing assets returns but the focus is on sustaining public infrastructure by making appropriate decisions about facilities' lifecycle investments. Infrastructure management uses engineering fundamentals coped with Business and management principles, all integrated into powerful tools that facilitate an organized and reasonable decision making process.

The origins of civil infrastructure management can be traced back to pavement management systems which date back to 1960`s (Haas and Hudson 1978). Pavement management systems are widely employed in developed countries (Haas et al., 1994, NAMS. 2006). Modern asset management is an important method that could take advantage of economic assessment of trade-offs between available alternatives (USDOT 1999), and cost effective decision could be supported based on that information (Ouertany et al., 2008).

Several agencies including the Transportation association of Canada (TAC); (Federal Highway Administration1999, AASHTO 2010) have suggested the use of infrastructure management to encourage a suitable framework for conducting short and long-range planning.

From their perspective, asset management is an organised combination and calibration of human, information and technology to most effectively funds among alternative (TAC 1999).

Improving the efficiency of the decision making by using the best rehabilitation strategies for a specific project was the first scope of pavement management systems in 1960 (Haas and Hudson 1978) but researchers progressively distinguished that system could be applied at a network level as well (Haas et al.,1994). At the network level the management seeks to find an optimal combination of interventions and alternatives for the entire network during their life-cycle, while at the project level the aim is to find optimum treatments (M&R) during the lifespan of the infrastructure (Huang and Mahboub 2004).

Infrastructure management can be disaggregated into network inventory, condition evaluation, performance prediction models and planning methods as seen on Figure 2-5. All infrastructure management systems require of: (1) an asset inventory, (2) the assessment of condition, and (3) reliable information regarding the future expected system performance. Once this information is available the system will consider the whole life-cycle cost of an asset in order to explore an efficient and cost effective economic.

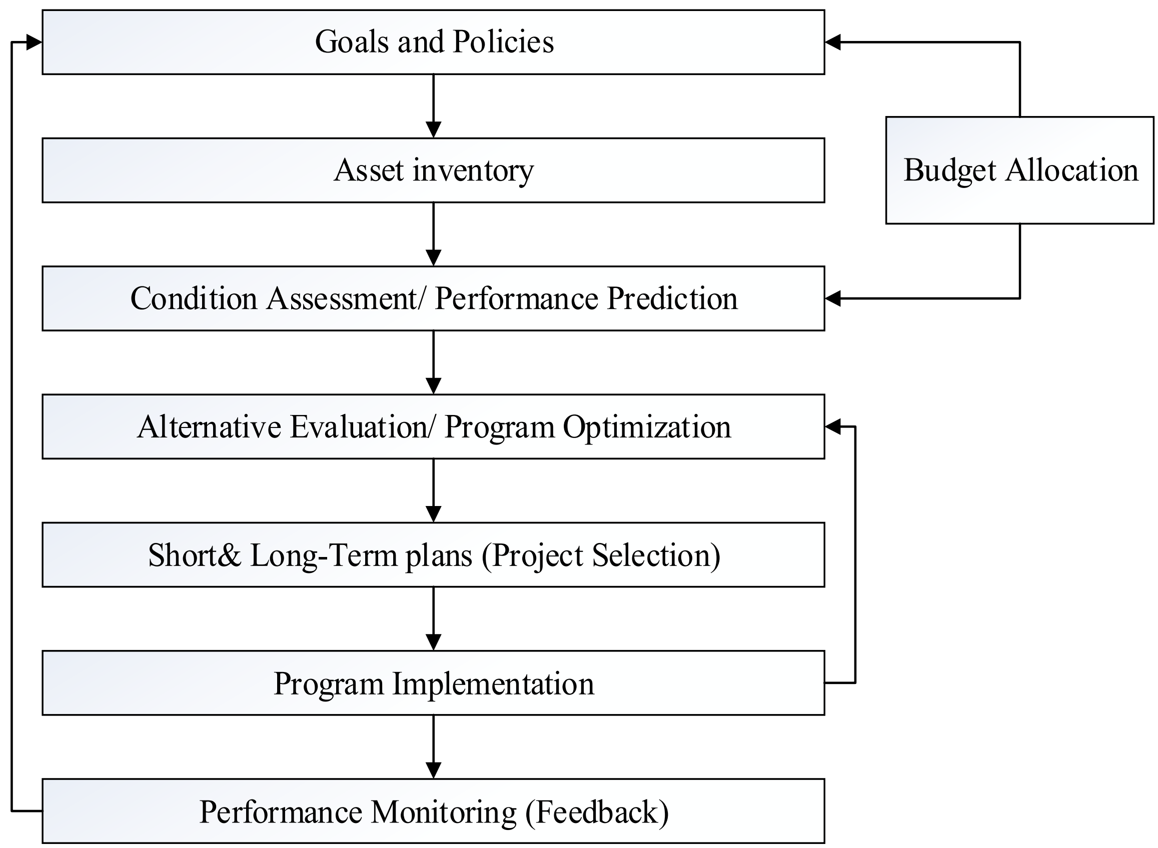


Figure 2-5: Generic Infrastructure asset management framework (After FHWA, 1999)

The process starts from a top down approach in which the agency establishes goals, targets and policies, formulates plans and conducts evaluation of the impact of different decisions and funding scenarios on the system performance and their compliance with current and future user expectations (Gerardo et al., 2004). All this information is employed by decision makers in order to prepare short, medium and long-term plans (FHWA 1999).

One of the main components of asset management is that of asset performance prediction. This is typically done over time and at the Network-level in order to detect suitable maintenance, replacement, rehabilitation or expansion investment strategies for each type of infrastructure (Gerardo et al., 2004). The following sections provide a detailed description of each components from the perspective of a Storm Drainage System due to the scope of this research.

2.3.2 Databases and Condition Assessment

Efficient asset inventories are at the heart of infrastructure management systems and play a crucial role in the overall framework. Any infrastructure management system relies on having reliable data of the network with adequate estimation of operational and functional characteristics. For a network of storm drainage pipes this means the need to characterize the structural integrity and functional properties (i.e. length, diameter, material, geometric characteristics and so on) and according to these properties define performance indicators (i.e. capacity index, erosion indicators, deteriorating index and so forth).

Condition evaluation is used to identify deficiencies of the various elements of the pipe network for maintenance and rehabilitation actions. According to the type of infrastructure and to the required actions, different types of evaluations are used. For storm pipes, the misconception is that performance is related to condition and many efforts have been deployed to evaluate pipe's integrity (i.e., cracking). However, a single evaluation is not suitable and performance should be based on characteristics that could lead into service disruptions or negative impacts to the public at large. A suitable indicator of pipes performance could be that of demand over capacity ratios (Xu and Goulter 1998).Once an indicator is identified, the system proceeds to the development of prediction models that will forecast future states of the pipe infrastructure.

2.3.3 Performance Prediction

Prediction should be based on adequate indicators of performance and the identification of expected lifespan. Life expectancy for pipes depend on their main purpose. Pressurized pipes (i.e. water mains) last for 80 to 100 years (lack of consensus is common for PVC pipes). Those working by gravity exhibit lives that vary from 40 to 70 years (sanitary and storm sewerage). The practice is to use 70 to 100 years for linear depreciation of storm water pipes (Micevski et al., 2002).

Pipes and their components should be categorized into groups with similar characteristics such as material, capacity, function, diameter, etc. These groups are commonly called homogeneous groups and the main idea is that the performance of their members exhibit similar variations across time. Performance models will predict the future, allowing the analyst to estimate the expected consequences down the road of his/her actions. Only in this way can the modeler proceed in a systematic way for the maintenance of storm pipe infrastructures. Models employed to anticipate the expectations of future performance of infrastructures could be deterministic or probabilistic (George et al., 1989, Prozzi and Madanat 2003).

Deterministic models consider a perfect world in which we can tell with full certainty future states of nature, that is, we are capable of having a fixed relationship between the model inputs and its results, which graphically can be seen as a curve that relates the performance indicator to some time-related variable (accumulation of loads, repetition of cycles, or simply time). On the other hand, stochastic models allow for uncertainty through fluctuations from the deterministic trend. They generate results with given associated probabilities of occurrence.

Models for urban drainage and storm water are predominantly deterministic models. Applications of models for urban drainage and storm water systems are as followed, 1: Urban drainage and storm water models are generally set up and applied to perform specific tasks including design of new pipe systems, 2: Analyses of the existing systems and identification of flooding risk and other urban drainage problems and 3: Analyses of upgrading measures (replacement) for the purpose of improving existing systems. This may include rehabilitation of the drainage system, or improved control strategies for pumps, weirs and gates. In addition, each model can be subdivided into two sections: a deterioration model and a decision making model.

Deterioration models are used for the prediction of ageing corresponding to loss of condition or loss of serviceability, and they will be used in decision models to determine the optimal times for maintenance and evaluation. In most of the cases a cost-optimal maintenance policy is determined with respect to the performance constraints (Frangopol et al., 2004).

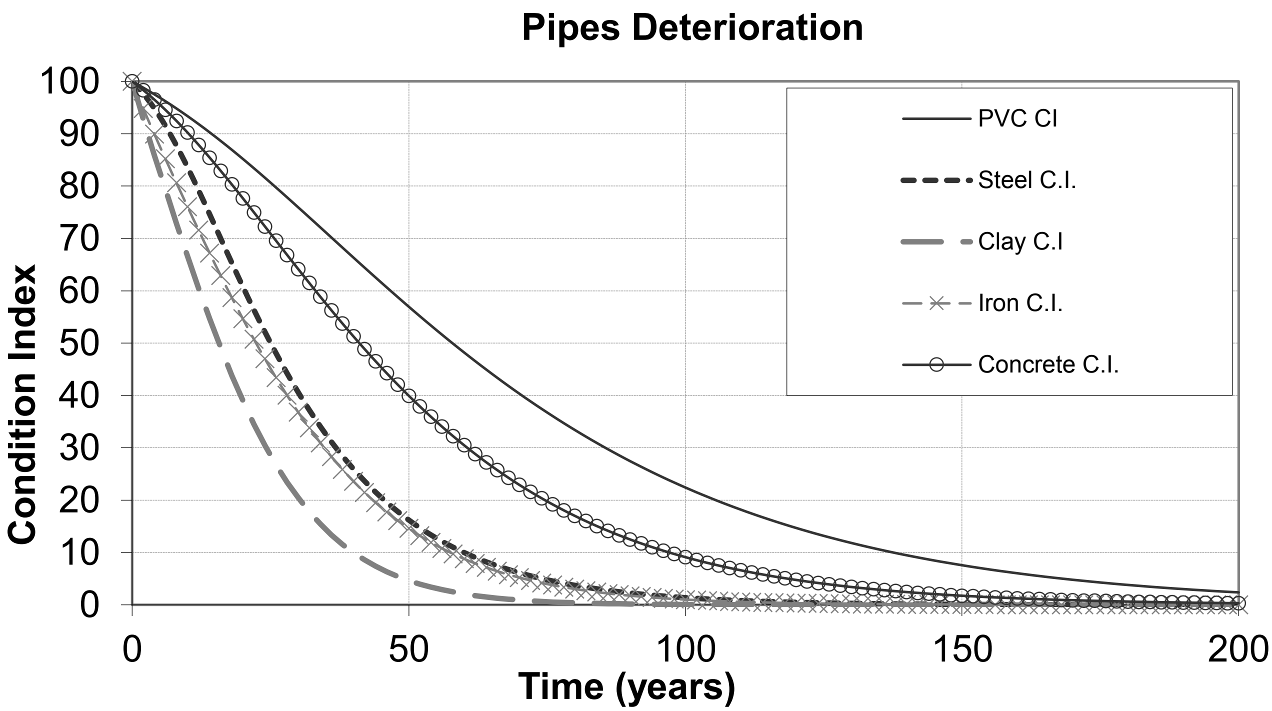


Figure 2-6: Pipe Deterioration (Amador and Magnuson, 2011)

2.3.4 Decision making for Storm Water Pipe Network Management

Reasonable maintenance and rehabilitation is required to preserve the overall performance of the network at acceptable levels. In pipe management, resource allocation plays an important role to sustain capacity above demand and prevent flooding. However, because of financial restrictions, most utilities and municipalities schedule replacements on a lagged fashion and commonly lack consideration of demand capacity ratios as oppose to conducting preventive flushing and sustaining capacity at adequate levels.

As a result of financial limitations different methods have been developed to find the best way to allocate resources. Optimization techniques and decision making approaches such as linear programming and heuristic methods are currently used by public agencies and governments responsible to manage public infrastructure assets.

During the past decades, researchers have worked on scheduling maintenance and rehabilitation (M&R) and on the development of analytical tools in order to investigate the best optimum solution for allocating funds across different interventions, however for pipes there are only two possible actions, to keep the system clean of obstructions and to replace pipes when they are close to break or their capacity is obsolete or has become hazard to human health (for instance asbestos cement pipes)

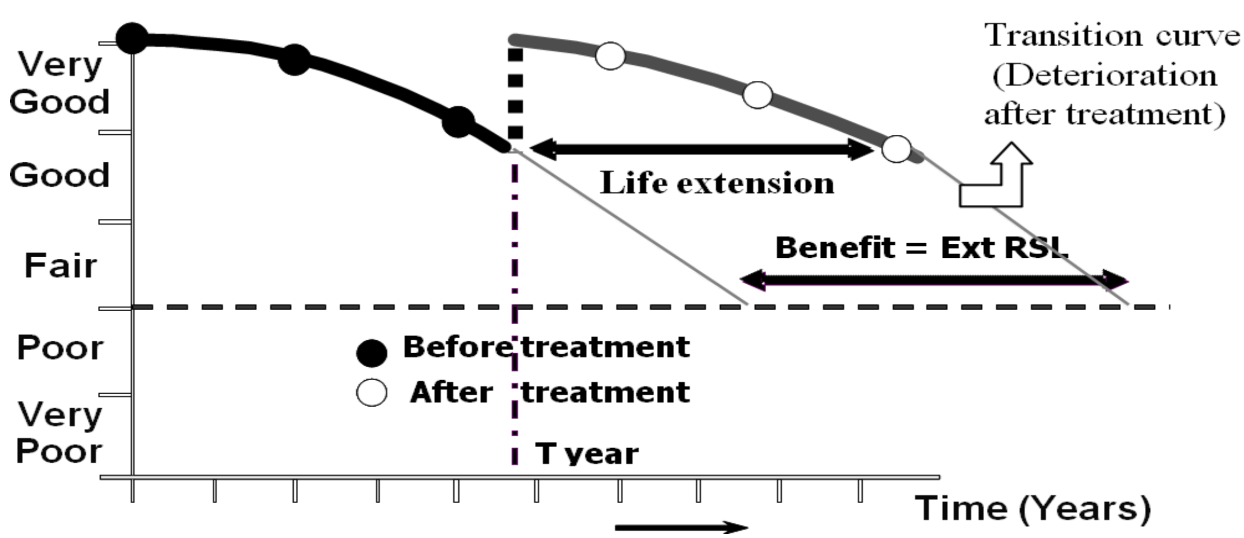


Figure 2-7: Performance modeling and treatment effectiveness for pavements (Amador and Mrawira, 2009)

Linear programming could be employed to find the optimal path of the assets, treatments type and time to achieve the best outcome of objectives by maximizing the benefits (or minimizing costs). Among others: maximize condition of the infrastructure asset, minimizing disruptions, minimizing environmental impacts over the entire network of assets in the long run (Faghih-Imani and Amador 2013).

Effective management of storm water pipe networks requires an accurate assessment of the condition of the pipes. The aging of storm water pipes adversely affects their performance. Figure 2-7 shows condition index versus pipe deterioration for pipes with different materials.

In other words, two different types of performance models can be defined for storm pipe networks, first deterioration of pipes in terms of condition which divided to structural and loss of serviceability (blockage or intrusion of the pipe) and second, drop in pipe`s remaining capacity (remaining level of service for rainfall run-off flow). Almost all of the performance models to date are based on the first approach, however, because of recently considerable urban developments and climate change, this kind of models need to be revised.

There exist commercial software to conduct the prioritization of optimal pipe replacement. This research uses Woodstock Remsoft (Feunekes et al., 2011), which is a powerful commercial software recently applied in the field of asset management, however, such program needs to be adapted as its origins come from forestry(spatial planning and harvest scheduling). Other similar programs are VEMAX (Vemax. com) and Deighton (www. Deighton.com). Long-term planning optimization problems are formulated based on linear binary dynamic-programming including goal and objective programming models. LP solver (e.g., MOSEK, LPABO) is commonly used in order to solve the problem which exhibit time dependencies among decision variables. The New

Brunswick department of transportation (NBDoT) took advantage of this software for its asset management program in 2006 (http://pubsonline.informs.org/doi/abs/10.1287/inte.1100.0520).

2.3.5 Mathematical Algorithms

As above mentioned optimization models are based on mathematical formulations. In these formulations linear objective functions such as maximizing the level of service (Q) and minimizing costs (C) subject to linear equality and inequality constraints are defined for the purpose of optimizing a network of infrastructure assets in which each links size (L) is considered and in many cases non-declining conditions established (Vitale et al., 1996, Li et al., 1998, Revelle et al., 2003).

Objectives and constraints can be replaced by each other: objectives can be expressed in terms of total costs of the interventions, while constraints can be expressed in terms of levels of service (LOS) indicators. Obviously, the effort is to minimize or fix total costs of actions meaning that LOS indicators for current years should consistently increase across time. The mathematical formulation identify values for the decision variable (X) to optimize total network levels of service (LQ) given total annual cost (CXL) and presented in following equations.

$$MINIMIZE\ Z = \sum_{t=1}^{T} \sum_{i=1}^{b} \sum_{j=1}^{J} C_{t,j}\, x_{t,i,j}\ L_i \tag{2-8}$$

Subject to:

$$\sum_{t=1}^{T} \sum_{i=1}^{a} Q_{t,i}\, L_i \le \sum_{t=1}^{T} \sum_{i=1}^{a} Q_{t-1,i} L_i \tag{2-9}$$

$$\sum_{j \in J_{t,i}} X_{t,i,j} \le 1 \qquad \text{\{For all times T and for each asset i…\}} \tag{2-10}$$

Where $X_{t,i,j}$= {0,1}; "1" if treatment j is applied on asset i on year t, "0" if no action is applied

$\mathbf{Q_{i,t}}$ = Level of service of asset i on time t,

$\mathbf{C_{t,j}}$ = Monetary cost ($) of treatment j on year t

Li = length of pipe segment *i* (m)

B_t= planning budget on time t

Indeed, the other way is to maximize LOS and pipe capacity, while not going beyond a certain annual budget that is imposed to the system. Equations 2-11 and 2-12 present such mathematical formulation:

$$MAXIMIZ\ Z = \sum_{t=1}^{T} \sum_{i=1}^{b} \mathbf{Q_{i,t}\ L_i} \tag{2-11}$$

Subject to:

$$\sum_{t=1}^{T} \sum_{i=1}^{b} \sum_{j=1}^{J} \mathbf{C_{t,j} X_{i,t,j}\ L_i \leq B_t} \tag{2-12}$$

With the same definition of variables

The mathematical formulation is supported by a total enumeration process by (Watanatada et al., 1987). Which can be reduced into a transfer function or law of motion across condition states (Figure 2.8). Expected impact of applying an available treatment at a pipe at a given time is mapped through time (Figure 2.8). Various chains of alternatives are generated; one of these chains is the optimal set of actions with respect to the defined objectives and certain constraints.

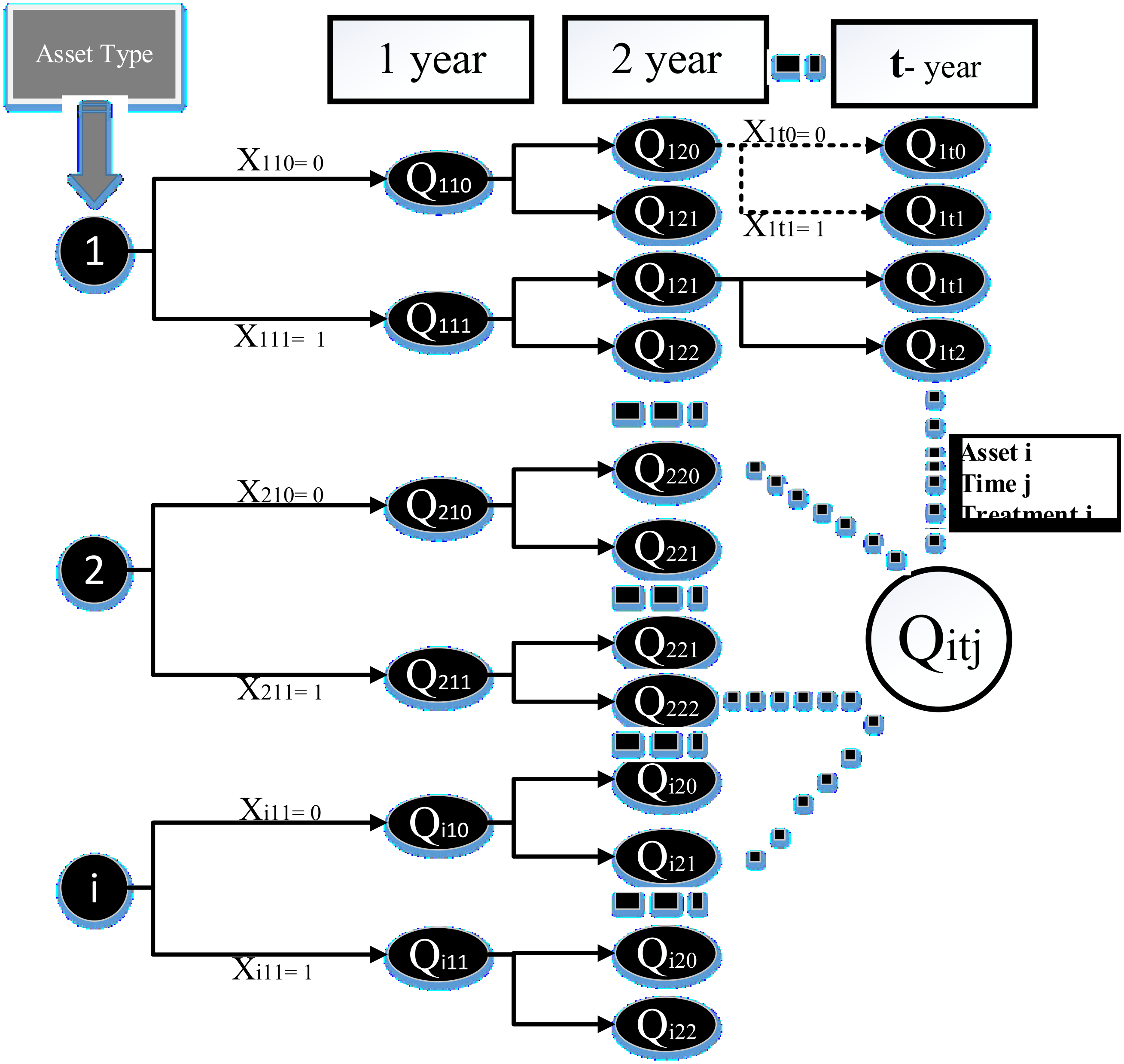


Figure 2-8: Total enumeration process

Chapter 3 Methodology

3.1 Introduction

Storm water pipe networks in Canada, play an important role in the nation`s infrastructure, particularly for urban areas. Engineering decisions on the basis of annual planning are taken in order to keep their level of service in good standing. Their primary task is to transport storm water at urban areas as quickly as possible in order to diminish the chance of flooding and to avoid runoff water becoming stagnant. One of the key task when managing a storm water network is to consistently upkeep available capacity. However, this indicator has been neglected and many management systems are developed over condition/deterioration indicators for the pipes. Furthermore, important issues such as climate change, and urban changes should be considered. Storm drainage networks are more critical in Canada because, over the period 1948 to 2010, the average annual temperature in Canada has increased by 1.6 °C, a higher rate of warming than in most other regions of the world possibly resulting in more intense and unregularly rainfalls as compare to other parts of the world (Environment Canada 2014).

In order to address the issues of storm management system, this chapter integrates existing methods to create a new approach to manage storm pipes. It is divided into two sections; the first section explains a method to estimate dynamic changes on flow-demand to pipes using the integration of remote sensing and geographic information systems (GIS) for mapping urban land cover changes from urban development. A simplified alternative approach is used to create current and future hydrological models to estimate maximum flow for each sub catchment area.

The second section presents the extension of an optimization approach to make sustainable decisions in storm water drainage management. A multi objective optimization based on a dynamic model, is proposed to achieve and sustain good level of service for capacity and condition of the pipe segments during the analysis period.

3.2 Change detection method

This section presents the general approach suggested to estimate how urbanization impacts the imperviousness of an urban area and in turn the amount of rainfall runoff water draining into each pipe. A simplified method is proposed in the following section.

An integration of remote sensing and geographic information systems (GIS) can be used for mapping urban land cover in order to detect changes from urbanization and evaluate the imperviousness and green space changes over an area of interest at a given time frame. The methodology used to proceed in such a way should considers satellite image preprocessing/processing and image classification. Images were taken from the U.S Geological Survey (USGS) which provided impartial information about the earth surface. TM and ETM+ satellite images were selected to be analyzed in order to detect changes. Data employed for remote sensing elapsed at 5-year intervals in order to record major land cover changes, summer images (June - August) were used to maximize spectral variability between different land cover classes and seek images that maximize the coverage of the watershed while minimizing clouds coverage.

In the preprocessing step, external impacts on the proposed data should be diminished by suitable tools and techniques. When image data is recorded by satellite or aircraft sensors, there are errors in geometry and in the measured brightness values of the pixels. These errors should be corrected before processing. In addition, often images are not registered, meaning that their location is not well establish, therefore their coordinates should be well known before detecting changes. Many landmarks and discernible points are considered in order to achieve this goal.

Modified images from the preprocessing were used at the processing step. The processing was conducted using the NDVI differencing method. NDVI values were employed for classifying the data into the different tangible classes, such as, impervious areas (roads, buildings), green space, bare soil and so on. Finally, the proportion of each land use within the study area was obtained from the pixels (Figure 3-1).

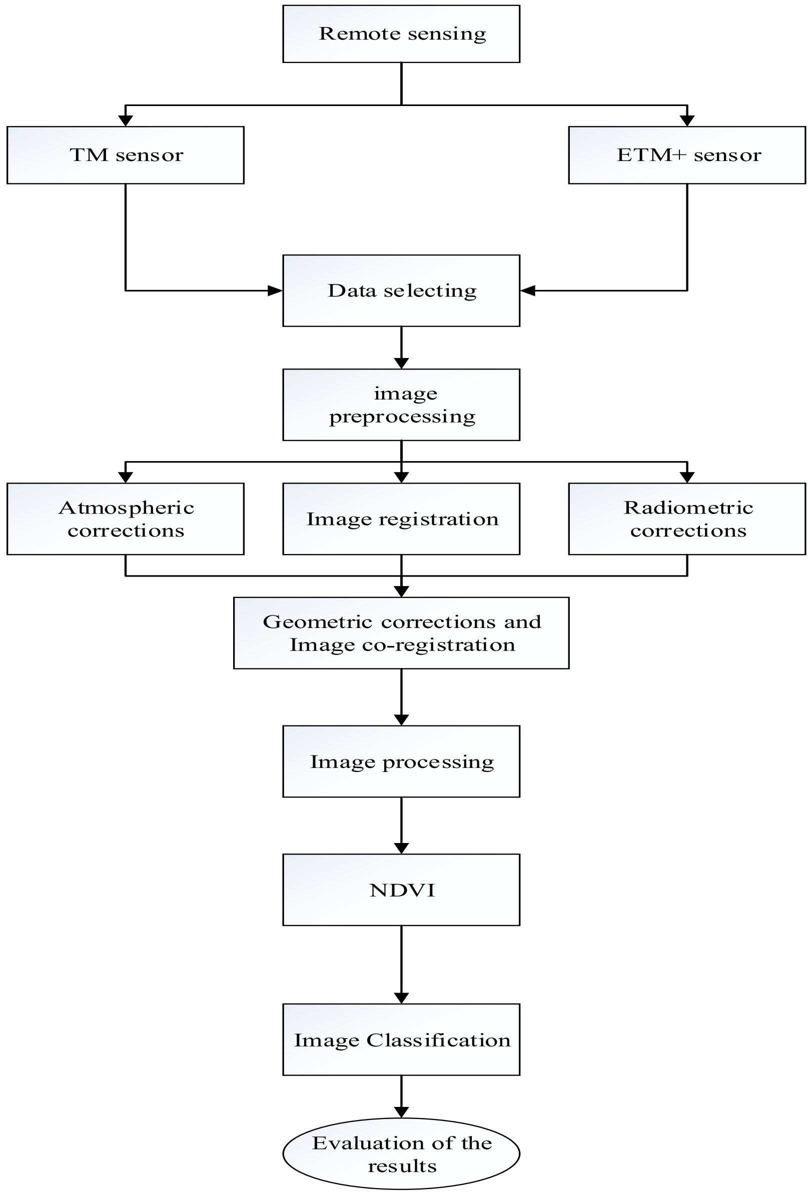


Figure 3-1: Conceptual framework of change detection (Adapted from Shahabi et al., 2012)

3.2.1 Image Preprocessing

Preprocessing of satellite images prior to image classification and change detection is crucial and usually includes a series of consecutive operations, including atmospheric correction or normalization, image registration, geometric correction, and masking. (e.g. for clouds, water, irrelevant features) . Since the purpose of preprocessing is to remove unwanted image characteristics caused by the sensor, its characteristics define a particular type of preprocessing. Reflectance must be comparable (radiometric transformations) and images must be superimposed (geometric corrections).

Primarily, natural factors such as climatic effects, atmospheric conditions and solar angle differences must be adjusted by applying suitable actions. The effects of sun angle, seasons and phonological difference have been removed by using the data from the same sensor and near anniversary acquisition dates. In this research, Dark Object Subtraction (DOS) technique for radiometric corrections was used to correct relative atmospheric distortions. This approach assumes the existence of dark objects (zero or small surface reflectance) throughout the sensor scene and a horizontally homogeneous atmosphere. The minimum digital number (DN) value in the histogram from the entire scene is thus accredited to the effect of the atmosphere and is subtracted from all the pixels.

In addition, geometric distortion in an image means that the image features positions do not correctly relate to scene on map or on ground positions. Earth rotation during imaging acquisition, earth curvature and satellite altitude, attribute, and velocity variations are the major source of geometric distortions. There are two types of geometric distortions; systematic and random distortions. The former can be modified by applying formulas derived by modeling the source of the distortion mathematically and using these models to create correction formulas while the latter are corrected by establishing mathematical relations between the coordinates of pixels in an image and the corresponding coordinates of those points on the ground. The second approach is used in this research. It includes finding raw images coordinates (i.e. row, column) of several clearly noticeable points, called ground control points (GCPs), in the distorted image, and map them either to georeferenced image (corrected before), coordinates of corresponding points (image to image registration), or to their true positions in ground coordinates (e.g. latitude, longitude) measured from a map (image to map registration), through to mathematical transformation, that will convert the raw image coordinates into the preferred coordinates. After that, resampling process must be done in order to reanalyze the gray level values for pixels in the transformed output image based on pixel values in uncorrected image.

3.2.2 Processing and image classification:

After conducting the preprocessing step on the suitable dataset which are selected for change detection, the processing step must be applied on the modified images. In this case the processing will be conducted by utilizing the NDVI differencing method. In this study, NDVI values are used in order to classify the data into different tangible classes, such as impervious areas (roads, buildings), green space, bare soil and so on. This analysis has been conducted by using ArcGIS software which is a powerful tool in order to evaluate and analyze GIS data. This software can support a variety of task of such as spatial analysis, data management, mapping and visualization, advanced editing, geocoding, and advanced imagery, map projections and data sharing. By using the appropriate raster calculator equations, NDVI values for the proposed image can be estimated with Arc GIS software.

NDVI index can be determined as the ratio of the measured intensities in the red (R) and near infrared (NIR) spectral bands.

$$\boldsymbol{NDVI} = \frac{\boldsymbol{B_4 - B_3}}{\boldsymbol{B_4 + B_3}} \tag{3-1}$$

Where:

NDVI: Normalized Difference Vegetation Index

B_3: Available pixels in the third band of image (Representing Red spectral bands)

B_4: Available pixels in the fourth band of image (Representing near Infrared spectral bands)

The calculated the NDVI values falls between -1 and +1 and were used further to assign pixels to classes. Typically, groups of similar pixels found in remotely sensed data into classes are collected, by comparing pixels to one another and to those of known characteristics in order to match the information categories of user interest.

A Supervised classification method (Maximum Likelihood) has been employed for image classification. Maximum likelihood classification utilized training data by means of estimating means and variance of the classes, and was used to evaluate the probabilities and the variability of brightness values in each class. Generally, two or three training sites are selected. In this research over 10 training sites were selected. Better results can be achieved by more training sites and the quality of a supervised classification depends on the quality of the training data. After digitizing training site area, statistical characterizations of information (signatures) are produced and finally, after classifying the images into the variety groups based on the NDVI output images, the changes in different times for the same locations were analyzed in order to evaluate the urban development and green space changes during the given period of time.Furthermore, this classifier is based on Bayesian probability theory and is one of the most widely used algorithm and the most powerful classification technique when precise training data is provided.

The land cover and land use changes of each sub catchment in urban areas are investigated with the procedure mentioned before. In addition, these steps are implemented in order to create an integrated spatial information such as amount of imperviousness and green area, slope and type of soil, and from them the composite runoff coefficient index geographic model in order to calculate the amount of maximum flow to each pipe within the sub catchment. This allows to create an equation that best fits the data to forecast future demand assuming that historical observed trend can be extrapolated. Equation below, shows the composite runoff index geographic model applied in this methodology.

$$\mathbf{RI_S} = \sum[\mathbf{f}_{(\frac{\mathbf{k}}{\mathbf{A}})} \times \mathbf{RI_{(K)}}\ ] \tag{3-2}$$

Where:

RI_S = Runoff Index $_{sub\ catchment}$, is the sum of the component runoff indexes within the sub catchment with a specified area (A)

F = fraction of area covered $(\frac{k}{A})$ is the component (k) of area (A) divided by the total area (A)

$RI_{(K)}$ = runoff index of component (k) of the area (A) determined by the characteristics of the surface

Many researchers have demonstrated the implementation of this approach for urban change detection, for instance (Xian et al., 2006, Peijun et al., 2010), and also the estimation of runoff coefficient (See Thanapura et al., 2007, Savary et al., 2009, Gupta et al., 2012).

3.3 A simplified method to estimate expected demand on a storm pipe network

A simplified method could be used initially in the absence of sufficient good spatial resolution historical images. The method proposed in the previous section could be implemented once this requirement is satisfied. Spatial resolution of a satellite image refers to the coarseness of a raster grid. In order to effectively map impervious areas and open spaces, high spatial resolution images are required (such as Quick bird satellite images), in which grid cells correspond to ground areas of one square meter or less.

Remotely sensed data whose grid cells range from 15 to 80 meters, such as TM and Landsat ETM+ are considered medium resolution, such data are somehow coarse for accurate GIS spatial modeling to determine the rational coefficient and the amount of maximum flow. In this cases a simplified method based current and future land use maps (from community plans and expert opinion estimations) could be used to estimate changes in pipe's network demand across time, assuming perfect foresight of planned land used (i.e., realization of planned or estimated). Of course this method is only advisable as a first approach as many deviations from the future could occur. This research illustrates the use of this method through a case study presented on chapter four.

3.4 Capacity and Condition-based optimization of pipe replacement

3.4.1 General Framework and Components

The proposed method for incorporation of storm water pipes capacity into the management system comprises three significant parts: (1) developing current and future hydrological models with respect to plausible changes, (2) creating demand-capacity- performance curves and finally an (3) optimization process to allocate replacement of pipes for a long term period of time. Most of the emphasis is given to the third component.

Two urban hydrological models based on the rational method for current and future rainfall runoff to the pipe storm system were created as recommended by the simplified method of section 3.3. As shown on Figure 3-2 runoff coefficient and intensity of the rainfall have a direct impact on the amount of flow, in the modeling, the objective is to estimate the storm water discharges to each sub catchment and to each pipe. The approach recommended by most storm-water drainage manuals is to compute the hydrologic response of each sub catchment to the design storms associated with different return periods. From a drainage perspective the most dominant characteristic of the urban landscape is the high degree of impervious ground cover. Population growth and changes in urban-land-use affect the extent of imperviousness of urban watersheds commonly leading to a rapid rate of increase on rainfall runoff. These factors result in more significant changes to the hydrologic regime in comparison with changes due to drainage works in rural and non-developed areas. Furthermore, the volume and rate of storm water runoff depends directly on the magnitude of precipitation. Statistical frequency analysis of Canadian global climate models series have shown that rainfall events will likely be more intense and frequent due to changes in the climate. Here, statistical downscaling models must be employed in order to downscale the GCMs based rainfall projections. After predicting future plausible changes due to climate change and urbanization, two models are built: one that represents each sub catchment in its current land use condition and current rainfall characterization and one that represents the catchment after development and future estimated rainfall intensity-duration based on projections from the climate change. The models estimated flow over capacity ratios of each of the storm pipes on the drainage network. Performance capacity curves were created from current and future estimations of pipe's demand. The concept of pipe's apparent age was used to model the time progression of demanded capacity and used for the performance-based optimization model. The final component takes care of optimal allocation of pipe's replacements, and will be further explained at sections 3.4.7 and 3.4.8.

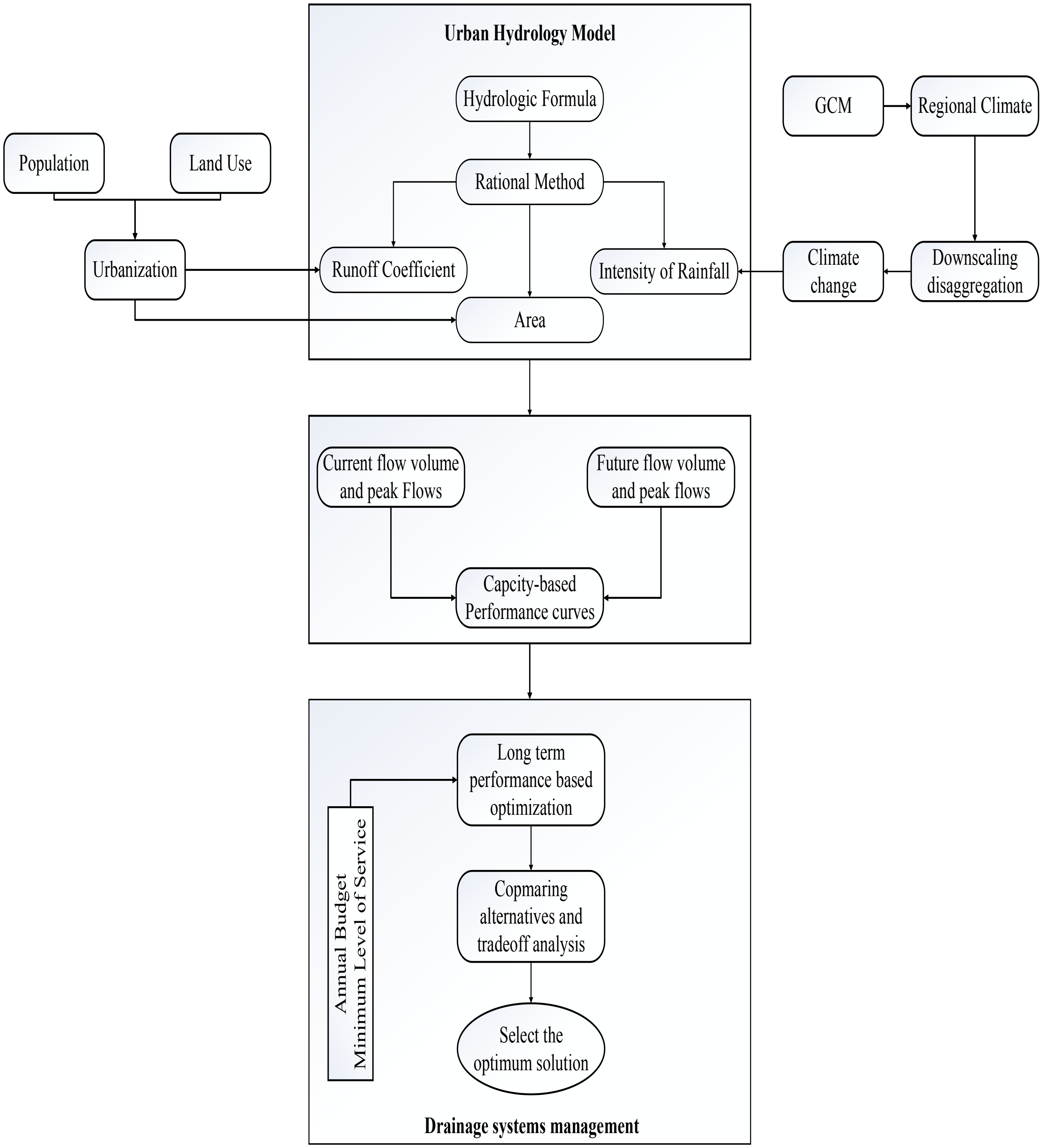


Figure 3-2: Incorporation of pipe capacity into storm water drainage system management, general framework

3.4.2 Database Construction

A proper runoff model has to answer some vital questions to be applicable for local authorities in constructing storm water drainage systems. The first and most crucial question in urban watersheds is: “where does the water flow? “ An elevation model of the area is needed to answer this question. The results are presented catchment area maps and flow directions. The next question which is more complex and needs essential operations, is “How much water flows?” Some data are required to apply the model in order to answer this question. Usually these data include rainfall intensity data, surface ground features, land use/cover, roads and areas for water accumulation. The amount of rainfall runoff in each catchment area is the result of this stage. The third question which is the most important part of a rainfall-runoff model is “how much is the discharge amount generated by the runoff in every point of interest on every sub-catchment area. Digital elevation models are very important in any spatially distributed hydrologic analysis. The terrain slope is important because, all the runoff processes depends on the movement of the water due to gravitation, therefore by knowing the topographic structure of the terrain, runoff movement can be modeled. A digital elevation model is typically used to determine the slope of the terrain and flow direction, which are used in turn for defining drainage sub-catchments for the analysis. The elevation data is typically organized in one of three data structures: GRID, TIN or isolines (contours). In this research, contour lines are used for determining the flow direction and slope of the terrain. A summary of the data used in this methodology is presented in table 3-1:

Table 3-1: Recommended data collection program

Data Group	Detailed	Collection Method
Catchment Surface Topographic Maps	Impervious area Land use classification	City's Engineering Department
Land use	Current Land use Future Land use	City's Engineering Department
Rainfall intensity data	Intensity Duration Frequency (IDF) curves (2013)	Environment Canada
Drainage System	Coordinates Catch basins location Manholes Location Pipe age Pipe diameter Pipe depth Pipe material Catch basins elevation	City's Engineering Department
Climate change data	Global rainfall projection	Outputs from GCM or RCM

3.4.3 Urban Drainage Model Development

This study used the rational method, a widely used technique to estimate the maximum rainfall runoff for the hydraulic structures.

The formula is frequently written as:

$$\mathbf{Q = K\,C\,i\,A} \tag{3-3}$$

The input variables are:

Where:

Q = Design discharge (m3/ second) for the recurrence interval

K = Unit conversion factor

C = Rational runoff coefficient; the coefficient is the proportion of rainfall that contributes to runoff.

i = Rainfall intensity (mm=h)

A = Watershed area (km2), upstream of the point of interest

Urban land cover runoff coefficient table of TR-55 is employed for assigning runoff coefficient for each types of land cover. As, there are different types of land cover within each sub catchment, a composite runoff index formula is created in order to investigate the value of runoff coefficient for the whole sub catchment. The formula is written as:

$$\mathbf{RI_c} = \sum[\boldsymbol{f_{j/A}} \times \boldsymbol{RI_j}] \tag{3-4}$$

Where RI_c or runoff index composite is the sum of the component runoff indexes within an area (A)

F: fraction of area covered (j/A) is the component (j) of the area (A) divided by the total area

IDF curves data from environmental Canada was used .This thesis used Bentley Storm CAD software, a program that provides comprehensive hydrological modeling for the design and analysis of the gravity of flow at pipe networks. Calculations for catchment runoff, inlets, junctions, gutters, pipe networks, and outfalls, were provided by this software. Storm CAD uses the rational method to calculate the peak flow of storm sewers. Models components for storm water runoff into urban catchments are specified in table 3-2. The modeling starts by defining the catchment area and breaking it down into sub-catchments. Land use categories and topography information was used to identify and determine the drainage area (acres) for each pervious land type and associated impervious area for each sub basin. Discharge water (runoff flow) is directed towards the related inlet through the sub catchment. For each sub catchment the rational runoff coefficient is assigned based on the composite runoff index formula. Next, time of concentration (Time needed for the storm water to flow from the most remote point in the sub catchment into the inlet) is defined for each of the sub catchments. Also, Intensity Duration Frequency data (Storm data) is defined into the model. In this research and for simplification purposes we have assumed one catch-basin / manhole component per sub-catchment as the main point to get discharge water into the pipes system. From each main inlet water goes to a pipe and an estimation of flow-demand can be analyzed.

Table 3-2: Components of the urban storm water network model

Model Components	Description
Urban Catchment	-The whole area of a city with specified boundaries managed by the local municipality or group of municipalities.
Sub-catchments	-A specified portion of a catchment area with similar surface characteristics. -Streets, commercial and industrial buildings, residential areas, parks, cemeteries, Households are modeled as parts of a sub-catchment urban area and runoff coefficient at individual levels can be changed by this manner -In the residential zones assumption of land use for modeling is 60/40, impervious/pervious, Roofs are considered as impervious while front and backyards are considered pervious area. -Streets and sidewalks are considered almost as 100 % impervious sub catchments -Storm water runoff of household and street surface is supposed to connect to the street junction.
Conduits	- Pipes are Circular and with PVC, Concrete, VCT types - Hydraulic deterioration is modeled through diameter change - Condition deterioration is modeled according to pipes age -Capacity-based performance curves are created according to current and future pipe`s demand-capacity
Inlets	-Inlets (such as catch basins) are used to collect storm water runoff from pavements and discharge it into an underground convenience system
Nodes	-Nodes are the storage elements -Connect links in the model -Include junctions, storage units, dividers and outfalls
Junctions	-Represent the confluence of manholes in a sewer system , pipe connection fitting or natural surface channels -Street junctions are considered connection points for sub-catchments and conduits
Outfall	-Storm water runoff conveyed through the links and nodes ultimately is discharged to the outfall. -Model must include at least one

3.4.4 Incorporating climate change and land use change effects in estimated demand

A very simple method to incorporate climate change and land use changes is proposed in this section, further research should further investigate better means to undertake this task. The main goal at this thesis was to outline a first cut model capable of leading the way: most of the effort was concentrated on getting a general procedure that will finally result into an optimal allocation of pipe replacements.

Climate change is expected to produce an increase in evaporation and precipitation, leading to an intensification of the water cycle at different temporal and spatial scales. There is strong evidence that this intensification will have consequences on the availability of water resources and also on the intensity and frequency of occurrence of extreme events in most regions of the world. On the other hand, urbanization is one of the main factors which has direct and indirect impacts on the urban hydrology and storm-water management. Higher levels of impervious surfaces result in a higher volume of runoff with higher peak discharge and shorter travel time. Hence, all of the future changes in climate change and development of urban areas must come into account in storm drainage planning, design and management.

The models used in this research apply the rational formula for simulating the peak discharges subjected to each pipe in the storm water network. In the future prediction urban hydrological model, runoff coefficient (amount of imperviousness), and rainfall intensity indicator are altered due to future trends in urbanization and climatic conditions respectively. For applying climate model precipitation scenarios for urban hydrological assessment, Climate change should be simulated by altering a high-resolution rainfall record according to the climate-change signal. In most climate change studies, General Circulation Models (GCMs) have been used to project future climatic variables. Furthermore, rainfall projections can be developed through dynamic downscaling (i.e. regional climate modeling) or statistical downscaling of GCM outputs. The north American Regional Climate Change Assessment Program (NARCCAP) and Canadian Regional Climate Model (CRCM) provide the required data to address the assessment of climate change signal. It produces some simulations generated by a set of regional climate models on a common period and domain. Researchers have been analyzed annual maximum rainfall from multi-model NARCCAP ensemble simulations over Canada and northern part of United States. Results from GCM-future and GCM-historical groups evidently indicates a widespread increase with median relative changes across all grid points ranging from 12 to 18 % depending on duration and return period (Mailhot et al., 2012). In this methodology, according to the location of the study area, future changes in the intensity of rainfall is increased based on predicted climate change simulation models (18 % increase in this case as an assumption based on pervious researches) for all durations and return periods of rainfall in the model.

In addition, in order to reflect the overloaded storm pipes and flooding risks. Future prediction models can be developed base on urbanization factor by increasing rate of impervious areas as well. Transforming some land covers such as green area, agricultural area, bare soil etc. in which runoff coefficient is low, into impervious area in urban environments because of population increase and the need for more various urban infrastructures such as pavements and buildings make urban catchments more impermeable and consequently more runoff.

In other words, prediction models can be performed based on different scenarios. In this study, a combination of climate change and urbanization is generated based on changing urbanization indicator and the intensity and frequency of the future rainfalls. In order to achieve this goal, future Master plan of the interested case study and future IDF curves based on climatic simulations are employed to detect probable changes in the surface runoff and finally transported demand for the storm water drainage network.

3.4.5 Development of demand-performance curves

Estimation of runoff water flow can be used to determine the demand arriving at each pipe within the network, this element provides an assessment of current circumstances, however expected changes on the system should be modeled to support decision making. Demand curves based on expected rates of change (from urbanization and climate change) should be developed from hydrological modeling. They are used by the decision maker in order to have perfect foresight of the future today. This allow him/her to allocate resources to comply with targets of service at the network level.

Typical allocation of resources is based upon pipes deterioration which can also be included in the decision making system (Jacobs et al., 1993, Micevski et al., 2002, Tran et al., 2010).

This study proposes an extended approach for an optimal allocation of pipe's replacements in which the capacity of pipes is involved as a primary indicator of functional failure (to avoid flooding) and its deterioration follows the classical definition based on accumulation of damage (preventing the pipe to break). Functional failure is more likely to occur with catchments experiencing land cover changes. The effect of changes in climate are incorporated for all areas under study. Deterioration of pipes is defined in terms of aging. This definition could be further revised upon Nondestructive evaluation (NDE) and Structural Health Monitoring (SHM) techniques for pipe line inspections (Rizzo, 2010) (Sinha, 2003). Other elements that leads to hydraulic failure such as the number of blockage occurrences are not considered in this research and could be incorporated as well.

In this methodology, current and future capacity of each pipe segment are employed for creating capacity-based performance curves. Three performance curves were used to model demand-capacity and one performance curve was used for deterioration. Future research could create a more detailed set of curves per material and demand-capacity intervals.

3.4.6 Classical Optimization Framework for Condition-based allocation

The main goal of any storm pipe system is to find the best way to employ available resources (time, money, and etcetera) to maximized levels of service of such infrastructure while constrained by budget and other limitations.

The main objective of this research is to plan actions to be applied on storm pipes during their lifecycle in order to achieve increasing capacity (to avoid flooding) and condition (to prevent breaks) with a reasonable budget. After predicting capacity-based performance of the network, the decision making system will answer the main questions regarding long term plans, that is: how much should the capacity be increased (selecting replacement pipe's size), which pipe segments and in what period of time replaced such that the system affords the optimum combination with the least costs and the highest level of service.

The classical approach, however, utilizes linear programming as a tool for long term planning with only one objective which is classically the condition. The objective functions are to maximize the level of service (primal) as restricted to a given budget or to minimize costs subject to a performance requirement (dual) (Varian, 1992). The mathematical algorithms for the primal problem are shown in Equations 3-5 through 3-8.

$$\text{MINIMIZE } Z = \sum_{t=1}^{T} \sum_{i=1}^{b} \sum_{j=1}^{J} \mathbf{C}_{\mathbf{t,j}}\, \mathbf{x}_{\mathbf{t,i,j}}\ \mathbf{L}_{\mathbf{i}} \tag{3-5}$$

Subject to:

$$\sum_{t=1}^{T} \sum_{i=1}^{a} \mathbf{Q}_{\mathbf{t,i}}\, \mathbf{L}_{\mathbf{i}} \leq \sum_{t=1}^{T} \sum_{i=1}^{a} \mathbf{Q}_{\mathbf{t-1,i}} \mathbf{L}_{\mathbf{i}} \tag{3-6}$$

$$\sum_{j \in J_{t,i}} \mathbf{X}_{\mathbf{t,i,j}} \leq \mathbf{1} \qquad \text{\{For all times T and for each asset i…\}} \tag{3-7}$$

$$\boldsymbol{Q_t} = \boldsymbol{X_{t,i}}\left(\boldsymbol{Q_{t-1}} + \boldsymbol{I}\right) + \left(\mathbf{1} - \boldsymbol{X_{t,i}}\right)\left(\boldsymbol{Q_{t-1}} - \boldsymbol{D}\right) \qquad \text{(Transfer Function)} \tag{3-8}$$

Where:

$X_{t,i,j}$= {0, 1}; “1” if treatment j is applied on asset i on year t, “0” if no action is applied

$Q_{i,t}$ = Level of service (condition) of asset i on time t,

$C_{t,j}$ = Monetary cost ($) of treatment j on year t

Li = length of pipe segment *i* (m)

B_t= planning budget on time t

I= Improvement

D= Decay

The dual or alternative problem is defined by replacing objectives with constraints. Equations 3-9 and 3-10 present such mathematical formulation:

$$\text{MAXIMIZE } Z = \sum_{t=1}^{T} \sum_{i=1}^{b} \boldsymbol{Q_{i,t}}\, \boldsymbol{L_i} \tag{3-9}$$

$$\text{Subject to: } \sum_{t=1}^{T} \sum_{i=1}^{b} \sum_{j=1}^{J} \boldsymbol{C_{t,j}} \boldsymbol{X_{i,t,j}}\, \boldsymbol{L_i} \leq \boldsymbol{B_t} \tag{3-10}$$

With the same definition of variables

3.4.7 Extending optimization to consider Storm water pipes demand-capacity

In order to incorporate pipe's capacity into storm pipe network management systems, a capacity index must be developed and integrated along with a condition objective (and in more complete modeling with other assets). This requires a multi-objective optimization which is difficult to model in a linear programming environment, typically solved by the use of an aggregation of objectives through a weighted method or a goal programming. In this study, pipes capacity is also part of the optimization's problem objective. Demand capacity ratio (*F)* of each pipe is used to add such indicator into the classical mathematical formulation of section 3.4.6. The same procedure is applicable for other objectives that could be brought in the future. When integrating conflicting objectives one needs to identify the sense of each to define its sign on the global objective and, its overall magnitude (sometimes based on the extensiveness of the network *L*) to pick a weight that corresponds to the required level of attention that it will be paid. For example, pipes condition (*Q*) should be maximised for the network (+ sign) while the indicator for capacity ratios (*F)* should be minimized (- sign). After this, an analysis of reallocation of funds between objectives known as trade off analysis should be conducted to identify the most suitable scenario capable of achieving optimal global along with good progression results (Equation 3-11)

$$MAXIMIZE\ Z= \boldsymbol{\alpha} \sum_{t=1}^{T} \sum_{i=1}^{a} \boldsymbol{L_i}\, \boldsymbol{Q_{i,t}} - \boldsymbol{\beta} \sum_{t=1}^{T} \sum_{i=1}^{b} (\boldsymbol{F})_{\,i,t} \boldsymbol{L_i} \tag{3-11}$$

Where α and β are relative weights, *L* and *Q* as previously defined, *F* is the ratio of flow water demand arriving on the pipe divided by pipe's given capacity (fixed). The minus sign in front of the second term implies a minimization in which the decision maker must confront dynamical increases in Flow (from changes in land use and climate) with upgrading of Capacity (Pipe diameter) during the lifespan of the system.

Allowing weights to vary is a technique to form various scenarios based on relative importance given to each objective. According to the degree of importance for the interventions, weights are arbitrarily selected on a percentage scale from zero to one hundred percent. Finally, the most optimum solution is chosen by a comparison process in which various scenarios are assessed, compared and the final solution is selected. Progression of annual mean values per objective per scenario are evaluated for the entire network, to select the optimal combination of weights that complies with minimum required annual performance. Generally, the highest values for storm pipe conditions and pipe capacity index lead to the most appropriate solutions.

3.4.8 A Multi-objective optimization process and trade-off analysis

The multi objective optimization approach used in this study contains two phases. First the system identifies the necessary resources required to achieve non-declining levels of service (Equation 3-12 to 3-14), this does not mean that such levels of service are acceptable. Alternatively, a goal programming approach could have been used.

$$\boldsymbol{MINIMIZE} = \sum_{t=1}^{T} \sum_{i=1}^{n} C_{i,t} X_{i,t}\, L_i \qquad (3\text{-}12)$$

Subject to:

$$\sum_{i=1}^{n} L_i\, Q_{i,t} \ \geq\ \sum_{i=1}^{n} L_i\, Q_{i,\,t-1} \qquad (3\text{-}13)$$

$$\forall\, t$$

$$\sum_{i=1}^{n} F_{i,t}\, L_i \leq\ \sum_{i=1}^{n} F_{t-1}\, L_i \qquad (3\text{-}14)$$

$\sum_{j \in J_{i,t}} X_{i,t,j} \leq 1$ {For all times t and for each asset i…}

Where: $X_{i,\,jet}$ = {0, 1}; if treatment *j* is applied on asset *i* on year *t*, "*0*" otherwise

$Q_{i,\,t}$ = Condition Index for asset i on year t

$(F)_{i,t}$ = capacity Improvement for pipe i on year t

$C_{j,t}$ = Unitary cost ($) of treatment j on year t

L_i = length of road segment i (m)

Previously identified budget is allocated for the maintenance of deteriorated pipes and to seek improvements on pipes demand-capacity ratios, then budget is increased until desired performance results are observed. This process required various fine tuning of the corresponding weights as the analysis progress.

$$\boldsymbol{MAXIMIZE = \alpha \sum_{t=1}^{T} \sum_{i=1}^{n} L_i\, Q_{i,t} - \beta \sum_{t=1}^{T} \sum_{i=1}^{n} F_{i,t}\, L_i} \tag{3-15}$$

$$\boldsymbol{\sum_{i=1}^{b} \sum_{j=1}^{J} C_{t,j}\, X_{i,j}\, L_i \leq B_t \qquad \forall\, t} \tag{3-16}$$

Where: α and β are variable weights for the analysis for pipe condition and pipe capacity (correspondingly)

$X_{i,\,j,\,t}$ = binary decision variables; pipe segment i to receive treatment j, on year t

$Q_{i,\,j,\,t}$ = Condition of pipe i on period t after receiving treatment j

$(F)_{i,t}$ = ratio of flow water demand arriving on the pipe i on period t after receiving treatment j

L_i = length of road segment i (m).

B_t = Annual Budget on year t

$C_{t,\,j}$ = Unitary cost ($) of treatment j on year t

Figure 3-3 indicates the process employed in order to find minimum required budget to attain optimal level of service.

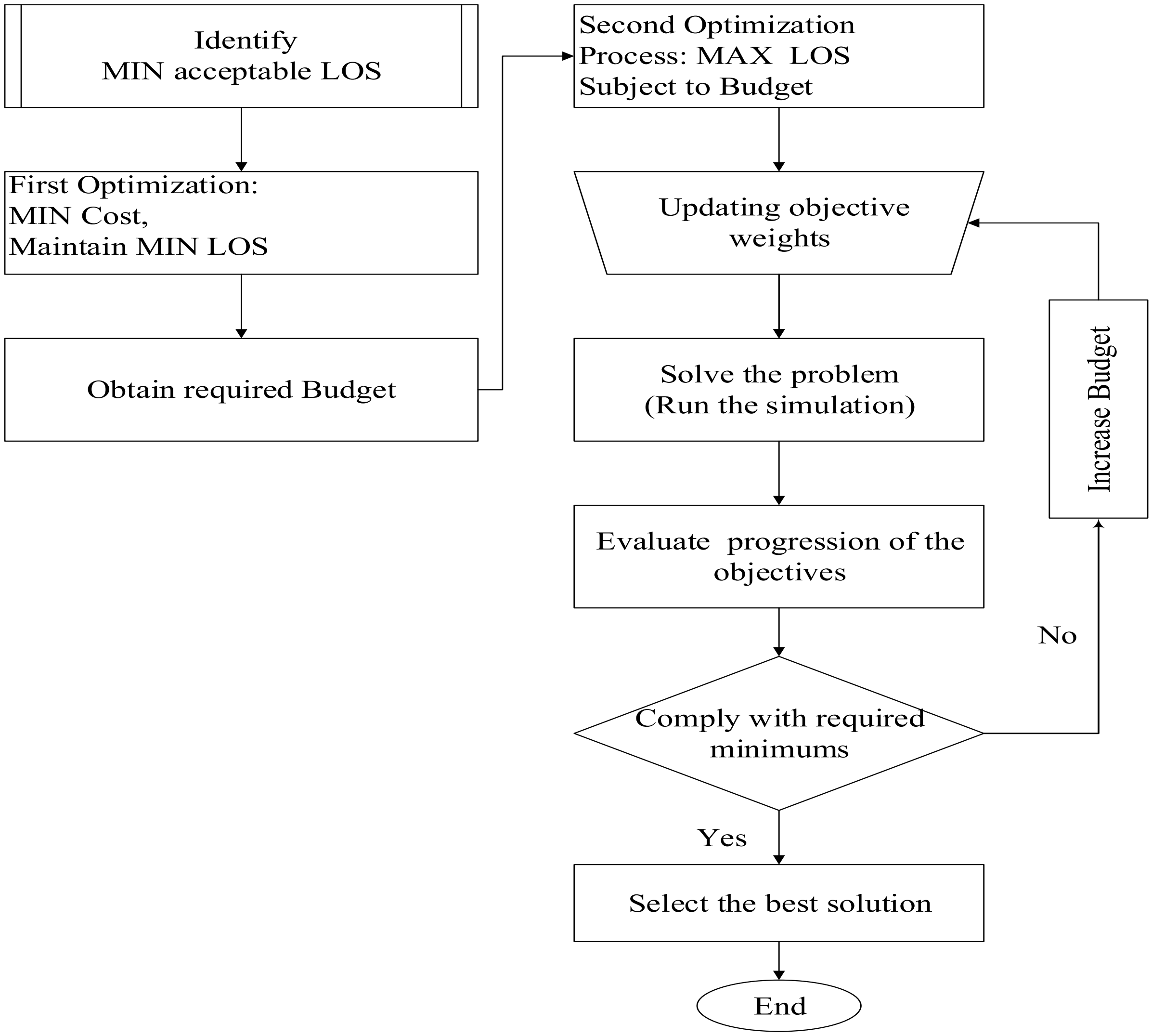


Figure 3-3: Multi-objective optimization process

LOS = Level of Service (Capacity and Condition)

Chapter 4 Case study

4.1 Introduction

In this chapter a case study was used to apply the proposed method to a real life situation. The Town of Kindersley, in the province of Saskatchewan (Canada) was selected because of data availability required. This Chapter is divided into three sections. First, an introduction of the study area, second, for a period of twenty five years, changes of the Kindersley land cover were detected by using remote sensing technology in GIS environment. In the last section, impacts of climate change and urbanization on storm water drainage system were evaluated by hydrological models and a long term (40 years) multi-objective decision making process was proposed based on the capacity and condition of the storm water pipes. A budget of $100,000 and weights of α= 0.45 for capacity and β=0.55 for condition showed improvements on capacity and condition level for the pipe network.

4.2 Geographic location of the study area

The town of Kindersley is located in west- central Saskatchewan, (58° 28’ 04”, 109° 09’ 24” W) Canada, along highway 7, a primary road linking Calgary, with Saskatoon. Town of Kindersley is considered as a major business and recreation center for the surrounded areas. It has an established industrial base that has supported the exploitation of natural resources such as agriculture, oil and gas.

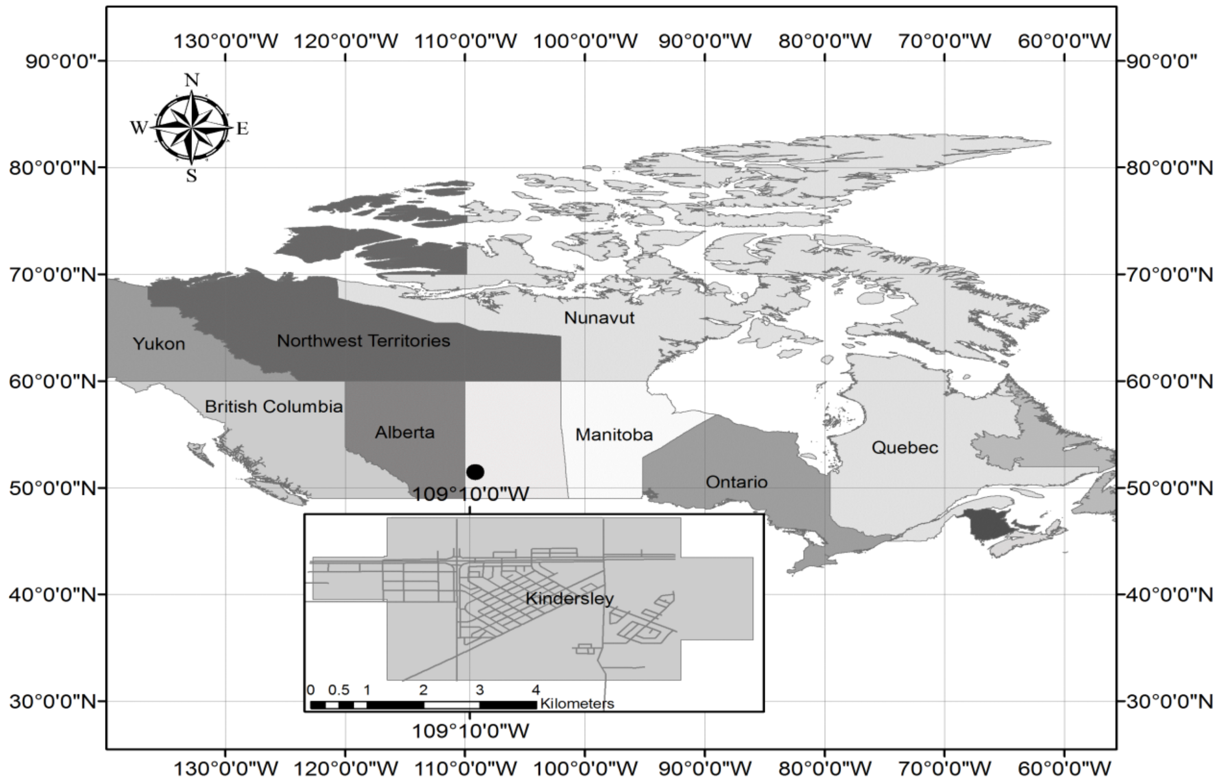


Figure 4-1: Location of the study area, Town of Kindersley, Saskatchewan, Canada

4.3 Kindersley Change Detection

Spatial data from the USGS`s Landsat was used in order to analyze the imperviousness and vegetation changes from 1988 to 2013 in Kindersley, Saskatchewan. Six remote sensed images of Kindersley were selected from the USGS remote sensed data. This information was analyzed in order to detect plausible, irregular development volume and direction and, its probable destruction of green space due to new constructions for the past 25 years. The available sensors for the GIS data derived from USGS are MSS, TM, ETM+-SLC-off and ETM+ where the ETM+ images were corrected automatically for atmospheric effects and they did not required any extra atmospheric correction due to external impacts. The DOS method was used only for three TM images. The images were selected (table 2) with the following assumptions: (1) a 5-year interval is sufficient to record significant land cover changes; (2) in Kindersley, summer images (July- September) maximize spectral variability among different land cover classes (3) images must maximize the coverage of the watershed and minimize cloud covering. Table 4-1 shows the characteristics of different systems and sensors, according to the acquired images (Table4-2). To facilitate comparison, all images were acquired during summer (July-September) which presented similar vegetation cover conditions over the town of Kindersley with minimized cloud coverage (clear sky conditions).

Table 4-1: Image and sensor characteristics

Sensor	Spectral (µm)	Band Resolution (m)
Landsat-5 TM	Band 1 (0.45-0.52)	30
	Band 2 (0.52-0.60)	
	Band 3 (0.63- 0.69)	
	Band 4 (0.76- 0.90)	
	Band 5 (1.55-1.75)	
	Band7 (2.08- 2.35)	
	Band 6 (10.40-12.50)	120
Landsat 7-ETM+	Band 1 (0.45–0.52)	30
	Band 2 (0.52–0.60)	
	Band 3 (0.63–0.69)	
	Band 4 (0.76–0.90)	
	Band 5 (1.55–1.75)	
	Band 7 (2.08–2.35)	
	Band 6 Th (10.40–12.50)	120
	Band 8 Pan (0.59–0.80)	13×15

Table 4-2: Acquired Landsat Images and characteristics on town of Kindersley Catchment

Date of acquisition	22 July 1988	9 Jun 1993	18 July 1998
Sensor Type	TM	TM	TM
WRS Path	38	39	38
WRS Row	24	24	24
Cloud Cover	0%	0%	0%
Sun Elevation	52.72	55.15	54.26
Sun Azimuth	138.13	135.7	140.46
Receiving Station	Null	Null	Null
Scene Start Time	17:35:30 GMT	17:33:30 GMT	17:43:04 GMT

Date of acquisition	13 July 2003	21 July 2008	10 July 2013
Sensor Type	ETM-SLC-off	ETM-SLC-off	ETM-SLC-off
WRS Path	38	38	39
WRS Row	24	24	24
Cloud Cover	0%	0%	0%
Sun Elevation	54.14	57.60	57.009
Sun Azimuth	144.77	144.68	146.44
Receiving Station	EDC	EDC	EDC
Scene Start Time	17:53:18 GMT	17:54:06 GMT	18:06:22 GMT

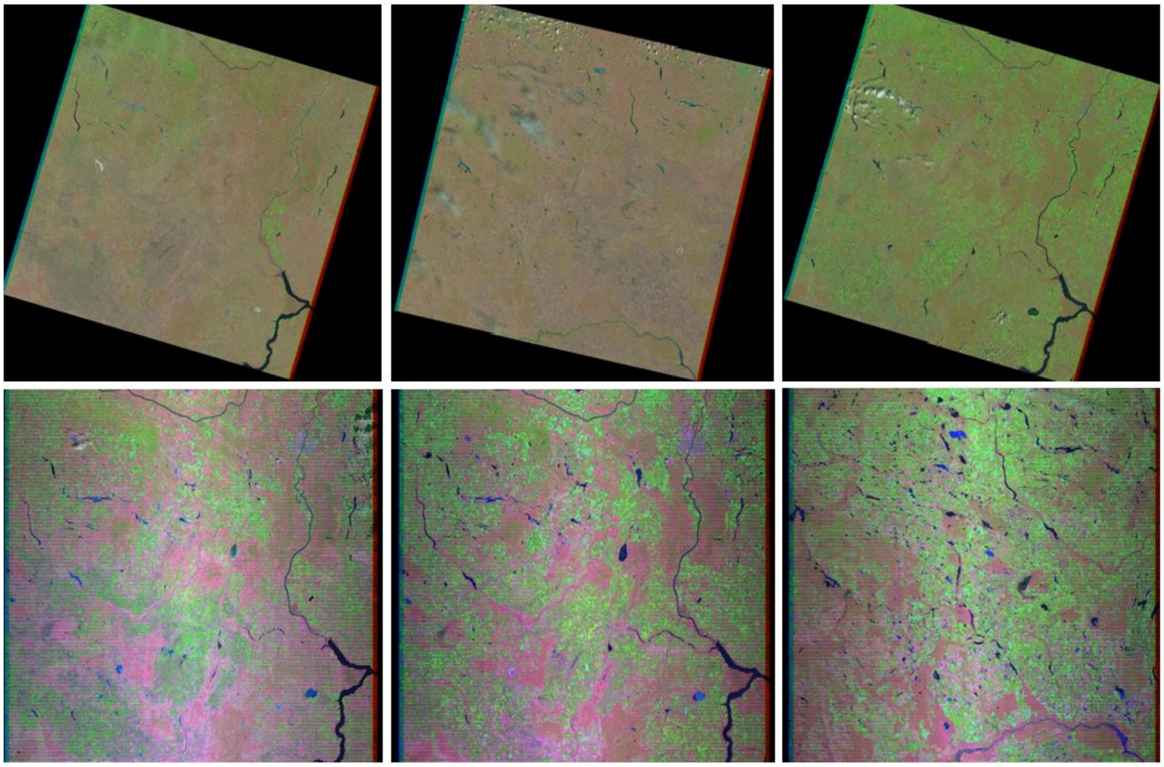


Figure 4-2: Raw data related to 1988, 1993,1998,2003,2008 and 2013 years (left to right)

Selecting data from the summer season (preferably during July) in most cases, resulted in minimum cloud coverage (between 0% to maximum 5%) which aided to improve the reliability of the results significantly. The effects of elevation and azimuth variation in this study are negligible. The scene processing time for all cases has been done between 17:30 and 18:10 GMT to minimize the effect of time of the day on the results. In summary, the effects of these factors in the selected images can be neglected and obtained results reflect land coverage changes.

4.3.1 Methodology

Some steps were done, in order to detect changes over the area of interest: image preprocessing, image processing and image classification. High quality preprocessed images ordered from USGS site. First order polynomial model and the nearest neighborhood method were employed for resampling. TM images were corrected based on Dark Object Subtraction (DOS) method in order to minimize the external atmospheric impacts in the primary images. Next, boundary of the Kindersley was extracted by a vector layer, using on-screen interpretation and digitization. Afterwards, images were evaluated by NDVI index. NDVI images were classified into green area, impervious area, bare soil, and water classes in order to detect the development of the Kindersley in the last 25 years. Figure 4-3 illustrates the flowchart of the change detection methodology.

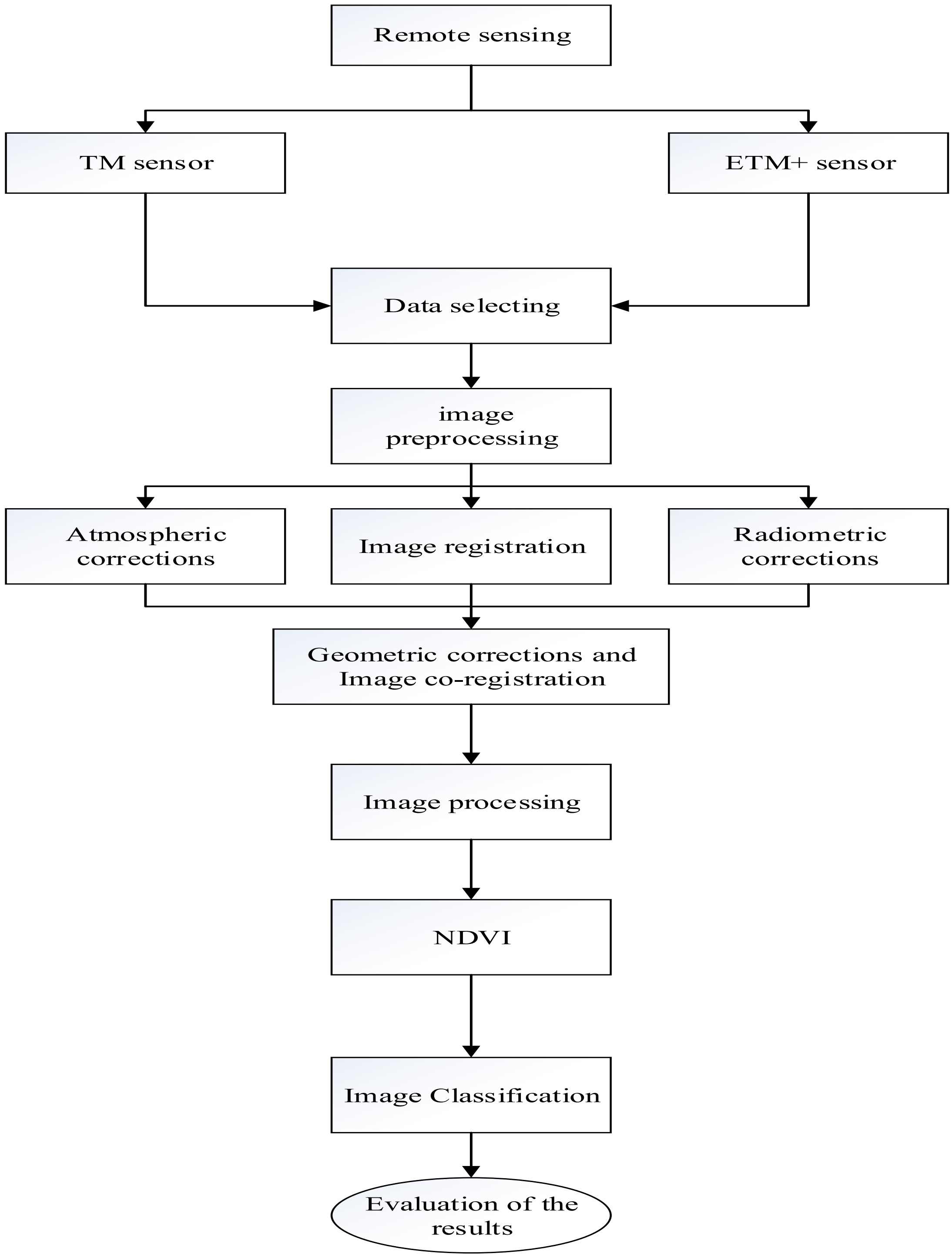


Figure 4-3: Change Detection Methodology (Adapted from Shahabi et al., 2012)

4.3.2 Preprocessing

Preprocessing step was done through a series of sequential operations including, radiometric corrections, image registration, and geometric corrections. Atmospheric effects were removed using Dark Object Method (DOS). ETM+ images were already corrected automatically by USGS. For correcting TM satellite images ENVI software was used. No other radiometric transformations were performed since 1: the acquisition period (June and July) reduced atmospheric effects 2; the classification process was applied separately and training sites were specific to each image and 3: temporal comparisons were conducted on the classified images instead of reflectance.

Furthermore, since the center of the images and the location of the sensors are not the same, images must be registered to the appropriate point and particular boundaries. Georefrencing and geometric transformations convert the geometry of the image into a cartographic planimetry. Based on 12 ground control points collected from throughout the scene, 2008 image was registered to the topographic map, Universal transverse Mercator (UTM) coordinate system zone 13N, and other images were registered to the 2008 image utilizing similar set of ground control points (GCPs). Geo-referencing of ground control points was done by first order transformation and nearest neighbor resampling.

4.3.3 Data Processing

In this study, NDVI images were used in order to classify the data into different tangible classes, such as impervious areas (roads, buildings), green space, bare soil and so on. This analysis conducted by using ArcGIS 10.2 which is a powerful tool in order to evaluate and analyze GIS data.

NDVI index was determined as the ratio of the measured intensities in the red (R) and near infrared (NIR) spectral bands.

$$\boldsymbol{NDVI = \frac{B_4 - B_3}{B_4 + B_3}} \tag{4-1}$$

Where:

NDVI: Normalized Difference Vegetation Index

B_3: *Available pixels in the third band of image (Representing Red spectral bands)*

B_4: *Available pixels in the fourth band of image (Representing near Infrared spectral bands)*

The NDVI images with a specific value for any one point on the image were extracted and employed for classifying the images into different required classes. The algorithm produced output values in the range of -1 to +1. Here, it should be mentioned that positive NDVI values have a direct relation by the amount of infiltration of the storm water into the ground, the higher the NDVI value on the image, the more water that infiltrates into the ground.

4.3.4 Image Classification

For the classification of the images, normalized difference vegetation index (NDVI) images were selected because of the land surface reflectance characteristics of the Red and near infrared bands. NDVI images were applied for the following reasons: 1: reduces heterogeneous spectral-radiometric characteristics within land cover surfaces and 2: normalized potential atmospheric effects within the image.

A supervised classification was used in order to evaluate the spatial distribution of the urban expansion. Supervised classification is the process of using samples of known informational classes (training sets) to classify pixels of unknown identity. In this study, a maximum likelihood classification was used. It utilized training data by means of estimating means and variance of the classes, which used to evaluate probabilities and also consider variability of brightness values in each class. In this research, more than 10 training sites were selected for each class (the more training data, the more accurate output). After digitizing training site area, statistical characterizations of information (signatures) were produced and finally, after classifying the images into the variety groups, changes of the land cover were analyzed based on image comparison in order to evaluate the urban development and green space changes during the last 25 years.

4.3.5 Results

The land use and land cover classified images of town of Kindersley for 1988, 1993, 1998, 2003, 2008 and 2013 are shown in figure 4-4. The total area (percentage) of each land use class in the total study region area from year 1988 to year 2013 were calculated and presented in table 4.3. According to the results obtained from the six classified images, over the past 25 years, impervious areas have increased considerably from 17 percent in 1988 to 40 percent in 2013. Water bodies have almost remained fix, bare lands have increased. Analysis of LULC changes revealed that green area have decreased significantly by more than 200 % which indicates development of the Kindersley from 1988 to 2013. Conversely, impervious area exhibit a significant growth by 235 % (Figure 4-4).

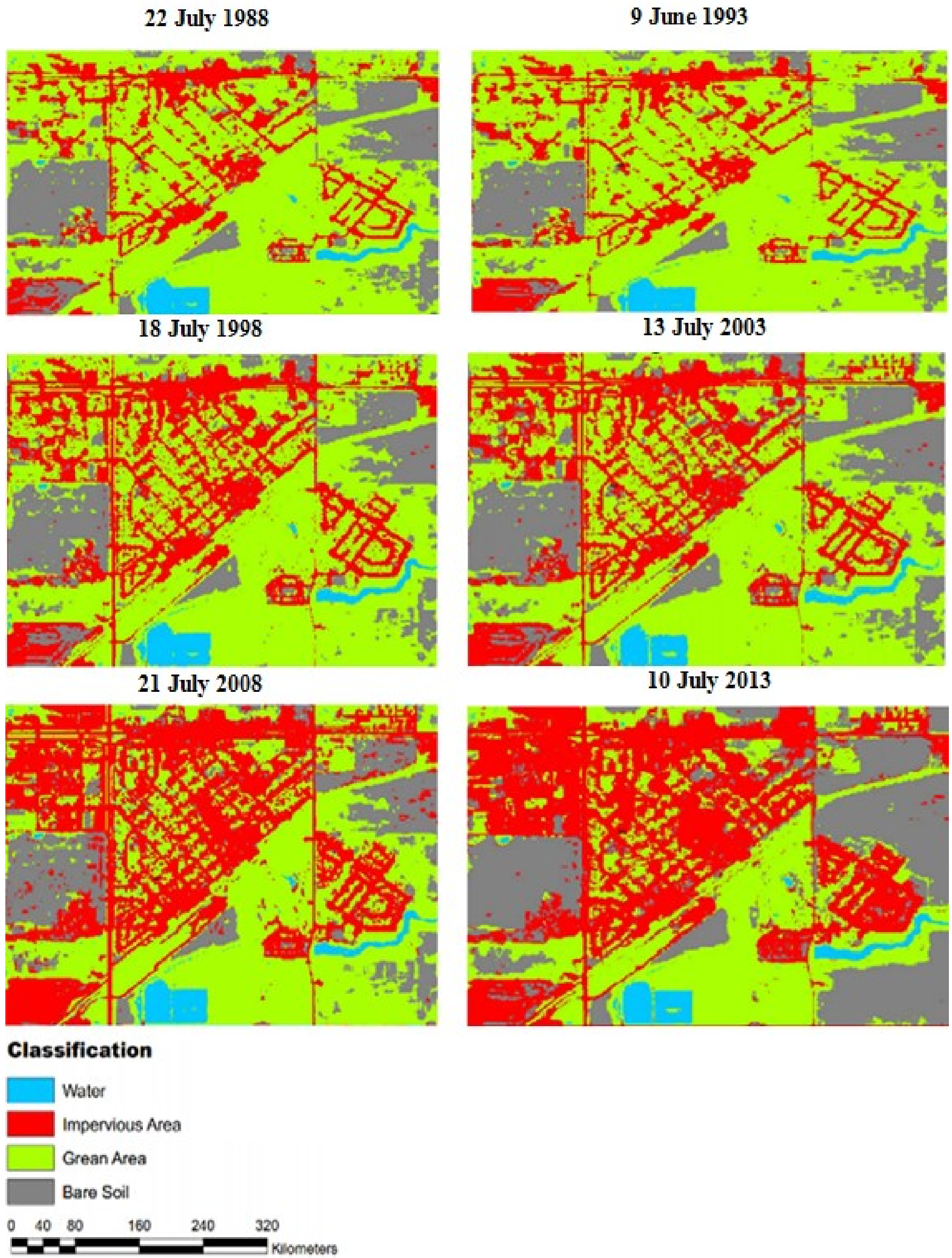


Figure 4-4: Land use Cover - Town of Kindersley

Ideally, this measured estimations of land cover changes should be used to extrapolate and predict future demand –capacity for every pipe in the system, by evaluating the amount of maximum flow for each sub catchment. However, lack of high resolution images prevented this research to proceed in such a manner. A simplified method was used to build a lifespan demand-capacity behavior of pipes by matching apparent ages to demanded capacity, three groups of pipes were used for this network, each group responded to faster/slower rates of demand. To validate this method, this research converted detected historical land use cover changes in demanded-capacity ratios and apparent ages. IDF average value was normalized to 1 but multiplied by a climate change expected increase of 18% (1.18) (Mailhot et al., 2012). Detected changes in land use were used to estimate normalized runoff. Runoff for the year 2013 was divided by a factor to match current observed average network pipe capacity (this was the 1st benchmark calibration). Apparent ages were estimated for the estimated capacity ratios, the historical observations were expected to fit a trend of apparent ages that projected back to zero (apparent age) would yield a zero demand ratio (y-axis). Therefore the slope of such trend was calculated as the required slope to produce apparent ages to obtain a zero intercept. Historical observations corresponded to average capacities between 46.44% and 74.28% with apparent ages between 38 and 63 years, which corresponded well with predicted trends for group G1 as shown on Figure 4-5.

Table 4-3: Kindersley Land use/cover statistics from 1988 to 2013

Apparent ages	Land Use changes					Runoff - capacity	
predicted apparent age	year	impervious	green	Bare soil	water	normalized runoff	Capacity %
38	1988	17	60.5	20	2.5	38.70	46.44
43	1993	19	60.3	18	2.7	40.45	48.54
48	1998	27	53.4	17	2.6	47.68	57.21
53	2003	29	46.7	22	2.3	49.55	59.46
58	2008	38	42.4	17	2.6	57.58	69.09
63	2013	40	29.6	28	2.4	59.42	***74.28***

It was found that the required slope was 1.16 which is very close to the predicted slope for group G1. Therefore, historically observed trends increased by a factor of 1.18 (to match assumption of climate change impact as explained ahead in this section) matched very well predicted apparent age- capacity lifespan behaviour (of the simplified analysis) based on future expected land use, instead of extrapolation of historical trends. Groups G2 and G3 showed faster rates of reduction of capacity which corresponded to possibly faster rates of expected urbanization than the ones historically observed.

The conclusion is that the simplified method based on perfect foresight and realization of expected future land use, does matches well historical observations in their ability to capture changes during the lifespan capacity of pipes, and that it could be used as upper boundary of an initial demand-capacity prediction to support the optimal allocation of pipe replacement. In the worst case, pipe replacement under this method maybe assuming rates of capacity reduction slightly faster than the actual ones.

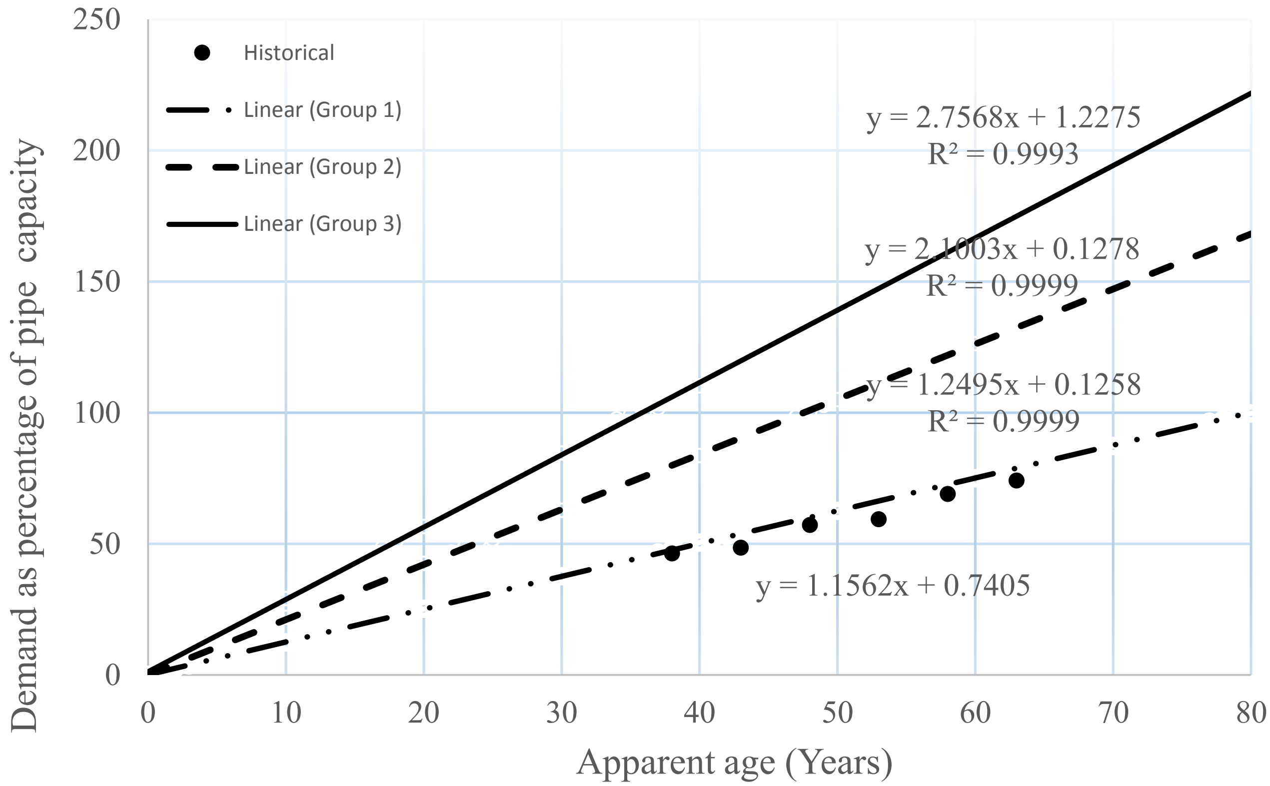


Figure 4-5: Fitting of Historical Observations on predicted demand-capacity

4.4 Impact of Climate Change and Urbanization on Kindersley' Storm System

4.4.1 Database

Storm pipe network data was facilitated by the Town of Kindersley, such data contained the spatial location of pipes, the age of each pipe and its corresponding characteristics such as material type and diameter. Table 4-5 presents the information available for the first storm pipe network and table 4-6 for the second one as illustrated on figure 4-6.

Figure 4-6: Storm Pipe network One and Two

Table 4-4: Storm water system data for the first network

Pipe Number	From Catch basin	To catch basin	Length(m)	Diameter(mm)	Age(year)	Material
1	A	B	84.6	300	48	VCT
2	B	C	85	300	48	VCT
3	C	D	116.2	375	48	Concrete
4	J	D	101.2	300	48	VCT
5	I	D	116.2	375	48	Concrete
6	G	I	41.7	300	48	VCT
7	F	G	43.7	375	48	PVC

8	H	G	51	300	48	VCT
9	X	L	108.8	300	48	VCT
10	M	N	44.1	350	48	VCT
11	N	O	98.6	525	48	Concrete
12	O	P	102.6	525	48	Concrete
13	Q	P	101	300	48	VCT
14	P	R	61.4	600	48	Concrete
15	R	S	90.7	610	48	Concrete
16	S	T	47.3	610	48	Concrete
17	U	T	62.6	300	48	VCT
18	V	U	45.2	300	48	Concrete
19	D	K	107.5	450	48	Concrete
20	K	L	107.3	450	48	Concrete
21	L	N	86.6	525	48	VCT
22	T	OUTFALL	134.7	750	48	Concrete

Table 4-5: Storm water system data for the second network of pipes

Pipe Number	From Catch basin	To Catch basin	Length(m)	Diameter(mm)	Age(year)	Material
23	1	2	102	300	48	VCT
24	2	3	102.4	300	48	VCT
25	3	4	102.3	375	48	Concrete
26	4	5	102.7	375	48	Concrete
27	5	6	102.3	375	48	Concrete
28	6	7	108.1	375	48	Concrete
29	7	8	106.9	450	48	Concrete
30	8	9	87.3	600	48	Concrete
31	9	10	97.3	600	48	Concrete
32	11	12	98.5	300	48	VCT
33	12	13	102.7	300	48	VCT
34	13	14	94.6	300	48	VCT
35	14	15	102.8	300	48	VCT
36	15	16	102.5	300	48	VCT
37	16	17	103	375	48	Concrete
38	17	18	81.7	375	48	Concrete
39	18	10	106.5	450	48	Concrete
40	10	19	90.6	750	48	Concrete
41	19	20	90.7	750	48	Concrete
42	23	24	8.2	300	24	PVC
43	24	25	103.2	300	48	VCT
44	25	26	94.7	300	48	VCT

Pipe Number	From Catch basin	To Catch basin	Length(m)	Diameter(mm)	Age(year)	Material
45	26	27	102.4	300	48	Concrete
46	27	28	102.6	450	48	Concrete
47	28	29	102.1	525	50	Concrete
48	29	30	108.2	525	50	Concrete
49	30	20	108.3	750	50	Concrete
50	20	OUTFALL	156.7	750	50	CSP
51	31	20	88.1	750	50	Concrete
52	32	31	88.3	750	50	Concrete
53	34	35	102.3	300	50	Concrete
54	35	36	91.8	375	50	Concrete
55	37	39	102.4	525	50	Concrete
56	39	32	106.5	600	50	Concrete
57	40	41	102.7	300	48	VCT
58	41	42	102.2	300	49	Concrete
59	42	43	102.1	375	49	Concrete
60	43	44	102.4	450	50	Concrete
61	44	45	102.3	525	50	Concrete
62	45	46	83.6	525	50	Concrete
63	46	39	82.5	525	50	Concrete
64	47	48	101.9	300	48	VCT
65	48	49	100.8	300	48	VCT
66	49	50	96.3	300	59	VCT
67	50	51	102.6	300	48	VCT
68	51	52	102.1	300	48	VCT
69	52	53	91.9	375	48	Concrete
70	53	44	87.1	375	48	Concrete
71	21	23	121.5	300	24	PVC
72	33	54	92.1	300	50	Concrete
73	54	34	103.9	300	50	Concrete
74	36	37	104.5	450	50	Concrete

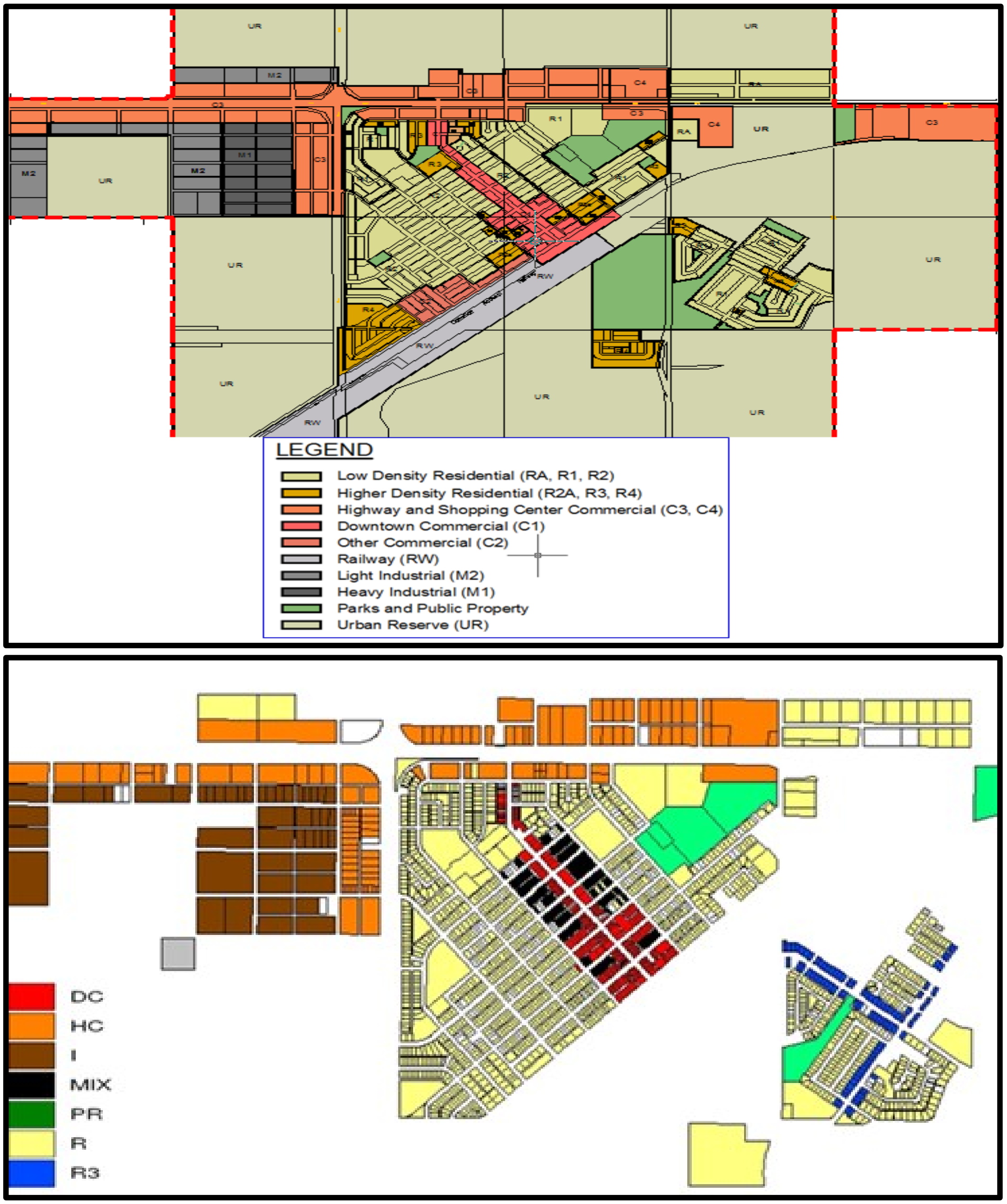


Figure 4-7: Current and Future Land Use

The estimation of current demand was based on the estimation of the flow of water from the rational method. Two networks were used because there were two separate networks with outfalls.

A hydrological model in storm CAD (Figure 4-9) was used to assign flow to the pipes. Rainfall-runoff model was based on current land use and recommended intensity-duration-frequency of precipitation by environment Canada along with time of concentration for each sub catchment. Pipe diameter was used to estimate current capacity for every pipe which in addition to the predicted flow of water was used to obtain demand-capacity ratios expressed in percentage.

Table 4-6: IDF data for the town of Kindersley (Environment Canada 2014)

	Duration (Min)	Return Period (Year)					
		2	5	10	25	50	100
Intensity of Rainfall(mm/h)	5	81.3	130.7	164.6	209.3	242.3	275
	10	58.5	90.9	113.4	142.4	164	185.5
	15	47	71.8	89.1	111.2	127.8	144.2
	30	26.6	43.9	53.8	66.7	75.9	85.7
	60	17.5	25.7	31.5	38.9	44.4	49.8
	120	10.5	15	18.1	22.1	25.2	28.1
	360	4.4	6.4	7.6	9.3	10.6	11.9
	720	2.6	3.8	4.7	5.8	6.6	7.4
	1440	1.6	2.5	3	3.8	4.3	4.8

4.4.2 Modeling of current and future demand-capacity

Current demand was estimated through hydrological model on storm CAD based on the current land use map (Figure 4-8). A similar method was employed for future capacity with two variations. Future land use was used instead of current land use. Impact of climate change was incorporated through the IDF values. Table 4-9 shows current and future Flow/Capacity of each pipe segment to the first network (from Conduit 1 to 22) and table 4-9 shows the Flow/Capacity of each pipe segment for the second network.

Future capacity was modeled using an 18% increase on the intensity of rainfall based on previous research (Mailhot et al., 2012). The corresponding values of 2 years return period intensity were multiplied by 1.2 to obtain future expected flow demand on the pipe system and curves were develop as explain in the following section.

As, there are various types of land cover within each sub catchment, composite runoff index formula (equation) was used in order to investigate the value of runoff coefficient for the whole sub catchment.

$$\mathbf{RI_c} = \sum[\boldsymbol{f_{j/A}} \times \boldsymbol{RI_j}] \qquad (4\text{-}2)$$

Runoff coefficients were selected based on each types of land cover from table 4-8 for both models.

Table 4-7: Runoff Coefficient for Urban Areas (Saskatchwan Storm Water Guidelines, 2014)

Type of drainage area	Runoff Coefficient
Business:	
Downtown areas	0.70-0.95
Neighborhood areas	0.5-0.70
Residential:	
Single-family areas	0.30-0.50
Multi-units, detached	0.40-0.60
Multi-units, attached	0.60-0.75
Suburban	0.25-0.40
Apartment dwelling areas	0.50-0.70
Industrial:	
Light areas	0.50-0.80
Heavy areas	0.60-0.90
Parks, Cemeteries	0.10-0.25
Playgrounds	0.20-0.40
Railroad yard areas	0.20-0.40
Unimproved areas	0.10-0.30
Lawns:	
Sandy soil, flat, 2%	0.05-0.10
Sandy soil, average, 2 to 7%	0.10-0.15
Sandy soil, steep, 7%	0.15-0.20
Heavy soil, flat, 2%	0.13-0.17
Heavy soil, average, 2 to 7%	0.18-0.25
Heavy soil, steep, 7%	0.25-0.35
Streets:	
Asphaltic	0.70-0.95
Concrete	0.80-0.95
Brick	0.70-0.85
Drives and walks	0.75-0.85
Roofs:	0.75-0.95

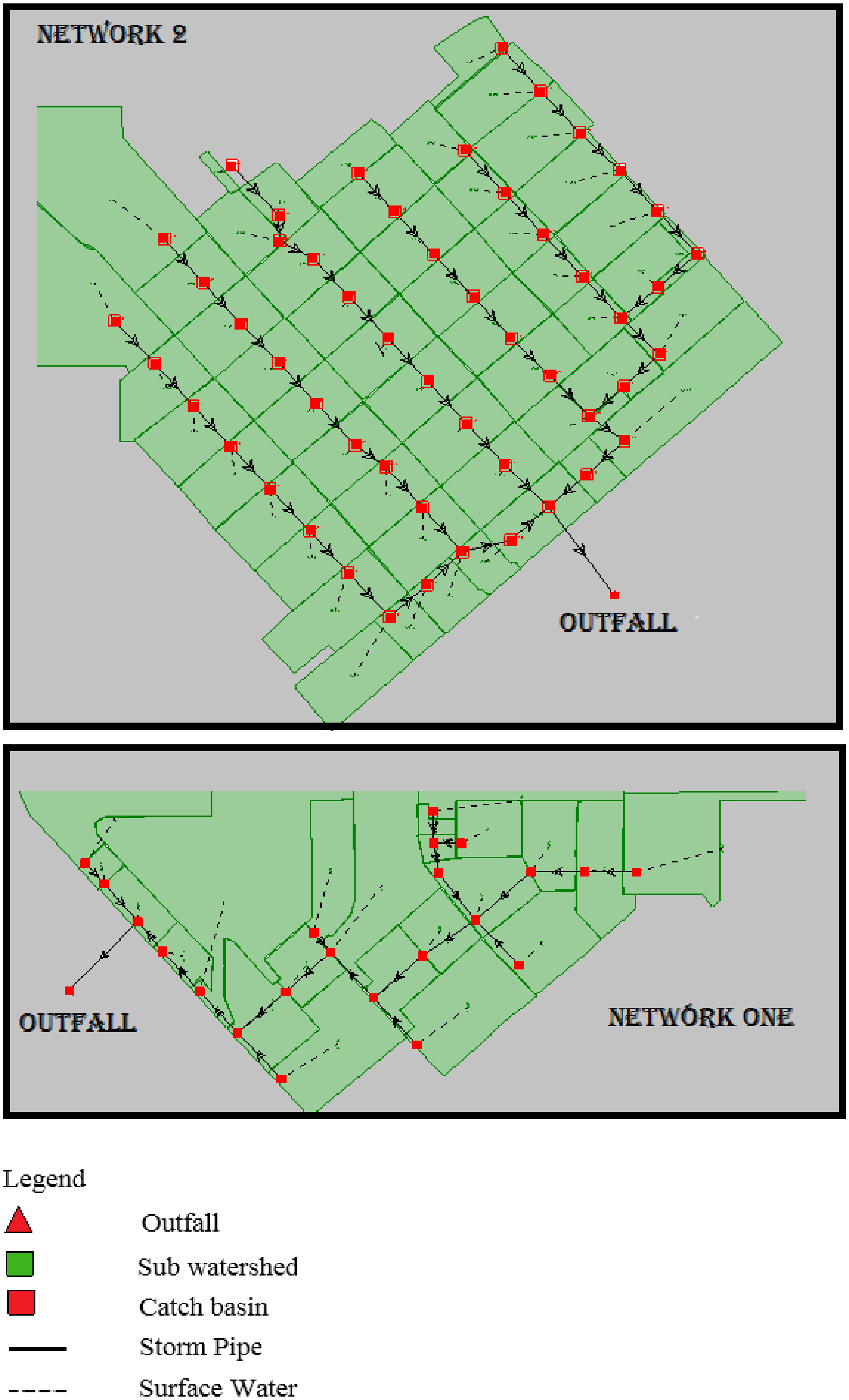


Figure 4-8: Storm CAD hydrological model for the two pipe networks

Table 4-8: Current and Future Flow / Capacity for each pipe segment for Network One

Link	Length (m)	Diameter (mm)	Current Flow/Capacity (%)	Future Flow/Capacity (%)
CO 1	84.6	300	99.8	162
CO 2	85	300	93.5	161.8
CO 3	116.2	375	90.8	161.6
CO 4	101.2	300	56.5	88.9
CO 5	116.2	375	51.9	71.1
CO 6	41.7	300	74.9	105.9
CO 7	43.7	375	13.1	25.7
CO 8	51	300	51.1	63.2
CO 9	108.8	300	67.3	106.5
CO 10	44.1	350	24.1	45.8
CO 11	98.6	525	90.3	147.9
CO 12	102.6	525	93.6	154.1
CO 13	101	300	95.1	148.2
CO 14	61.4	600	74.2	120.7
CO 15	90.7	610	99.3	155.7
CO 16	47.3	610	84.4	132.7
CO 17	62.6	300	51.4	67.9
CO 18	45.2	300	111.2	144.1
CO 19	107.5	450	109.2	169.5
CO 20	107.3	450	99.4	157.4
CO 21	86.6	525	101.2	161.6
CO 22	134.7	750	86.3	133.7

Table 4-9: Current and Future Flow/Capacity for each pipe segment in network Two

Link	Length (m)	Diameter (mm)	Current Flow/Capacity (%)	Future Flow/Capacity (%)
CO 23	102	300	28.6	52.6
CO 24	102.4	300	76	136.7
CO 25	102.3	375	56.6	99.2
CO 26	102.7	375	59.7	102
CO 27	102.3	375	93	156.8
CO 28	108.1	375	157.6	267.7
CO 29	106.9	450	82.4	140.9
CO 30	87.3	600	56.9	96.7
CO 31	97.3	600	38.3	65.1

CO 32	98.5	300	75.6	124.9
CO 33	102.7	300	97.8	163.7
CO 34	94.6	300	99.5	168.5
CO 35	102.8	300	127	216.9
CO 36	102.5	300	130.6	225.2
CO 37	103	375	80.5	139.9
CO 38	81.7	375	87.3	152.4
CO 39	106.5	450	98	169.6
CO 40	90.6	750	59.2	100
CO 41	90.7	750	53.4	90.3
CO 42	8.2	300	21.2	28.4
CO 43	103.2	300	54.7	76.7
CO 44	94.7	300	67	100.8
CO 45	102.4	300	93	144.8
CO 46	102.6	450	42	67.1
CO 47	102.1	525	29.9	45.6
CO 48	108.2	525	40.4	59.3
CO 49	108.3	750	16.1	23.1
CO 50	156.7	750	109.1	144.8
CO 51	88.1	750	105.2	191.1
CO 52	88.3	750	89.2	162.9
CO 53	102.3	300	105.6	222.5
CO 54	91.8	375	105.4	159.4
CO 55	102.4	525	64.1	99.1
CO 56	106.5	600	76.7	137.5
CO 57	102.7	300	20.8	24.5
CO 58	102.2	300	31.7	47.2
CO 59	102.1	375	26.8	42.6
CO 60	102.4	450	26.8	44.1
CO 61	102.3	525	66.9	128.7
CO 62	83.6	525	88.9	169.2
CO 63	82.5	525	102.7	192.8
CO 64	101.9	300	29	56.4
CO 65	100.8	300	35.2	68.7
CO 66	96.3	300	91	175.9
CO 67	102.6	300	109.1	211.7
CO 68	102.1	300	150.6	294.5
CO 69	91.9	375	90	176.2
CO 70	87.1	375	138.5	275
CO 71	121.5	300	10.7	12.6
CO72	92.1	300	45.9	54

CO73	103.9	300	89.4	125.5
CO74	104.5	450	61.7	94.9

4.4.4 Development of Condition and Demand-Capacity Prediction Curves

Two types of performance curves were required: (1) condition deterioration and (2) demand-capacity changes. Figure 4-9 shows condition deterioration changes for Kindersley. The condition curve was based on historical observations of pipe replacement and pipe breaks at the city of Kindersley, a linear trend was assumed and is perhaps an oversimplification of reality that can be improved in future research. For this case study we use such a curve in the absences of a better method to estimate condition performance and it is stressed the fact that this is only for academic purposes and needs to be revised for practical applications.

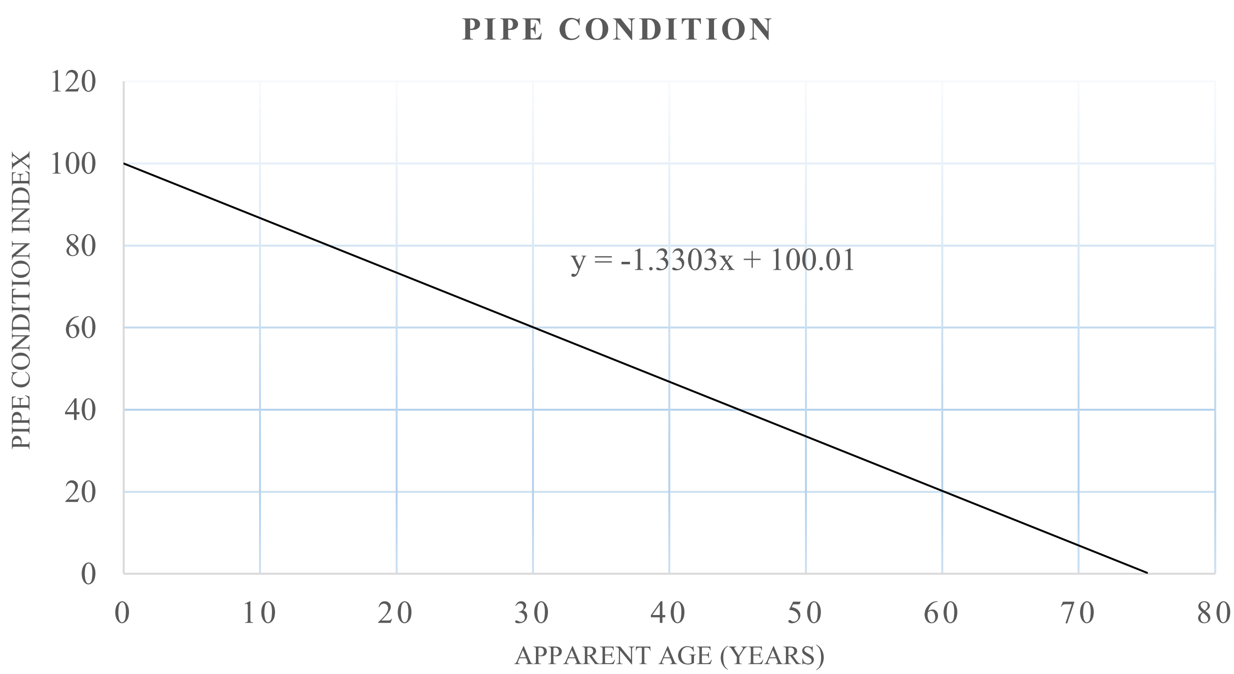


Figure 4-9: Condition deterioration assumed for this academic research

Demand capacity curves were created to rescale estimated values of current and future demand capacity of 3 groups of pipes such that pipes receiving very little flow (that is operating at almost zero demand capacity) were assigned apparent ages of near zero years and pipes at or beyond capacity were assigned higher values of ages. This was based on interpolation between observed average capacity and future expected capacity built on the previous sections. Figure 4-10 shows curves for three groups of apparent ages – demand/capacity curves. These curves were used to schedule pipe replacements as explained in the following section.

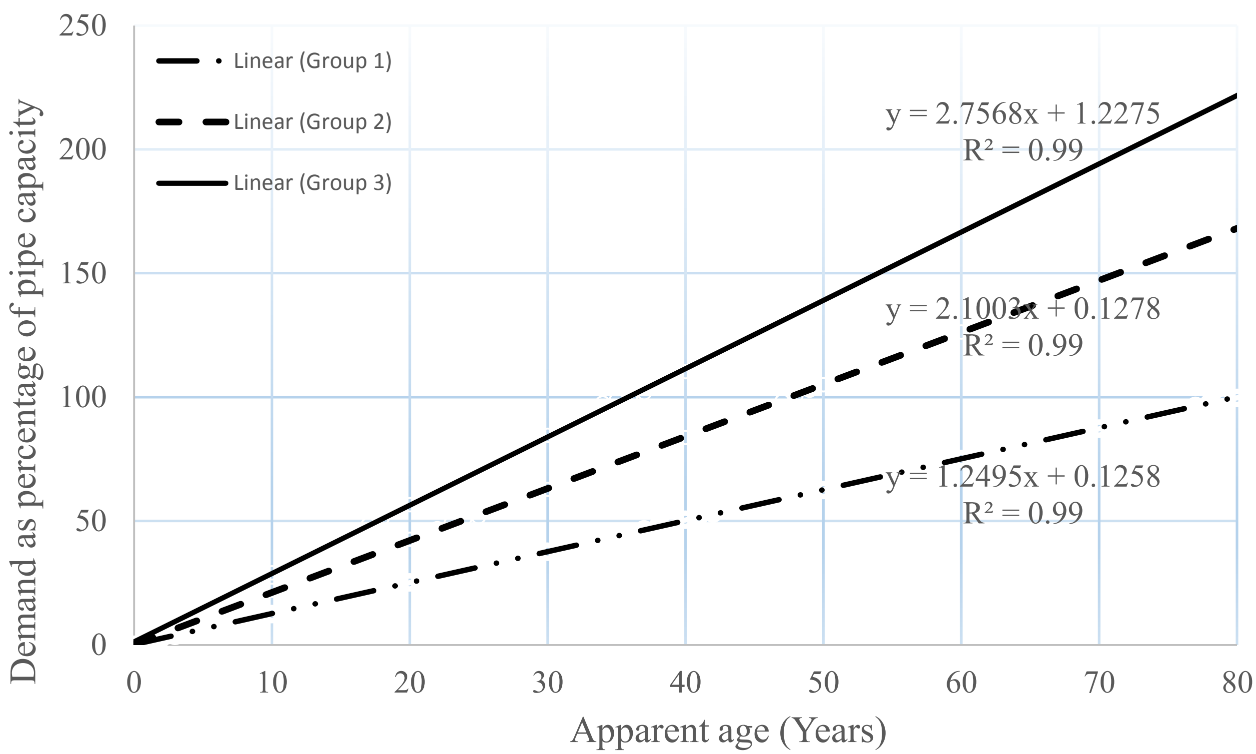


Figure 4-10: Apparent age of three different pipe groups

4.5 Optimizing storm pipe network' conditions and capacity

Allocation of pipe replacement was based on the maximization of total network pipe capacity, total network pipe condition with a budget constraint for total annual expenditure. This type of problem is dynamic in nature and recursive, each year's condition or capacity indicator depends on the previous year and on the predicted pipe condition degradation and changes in demanded capacity. Additionally, replacement of pipes has a nominal cost that is expected to increase following an expected 4% inflation rate.

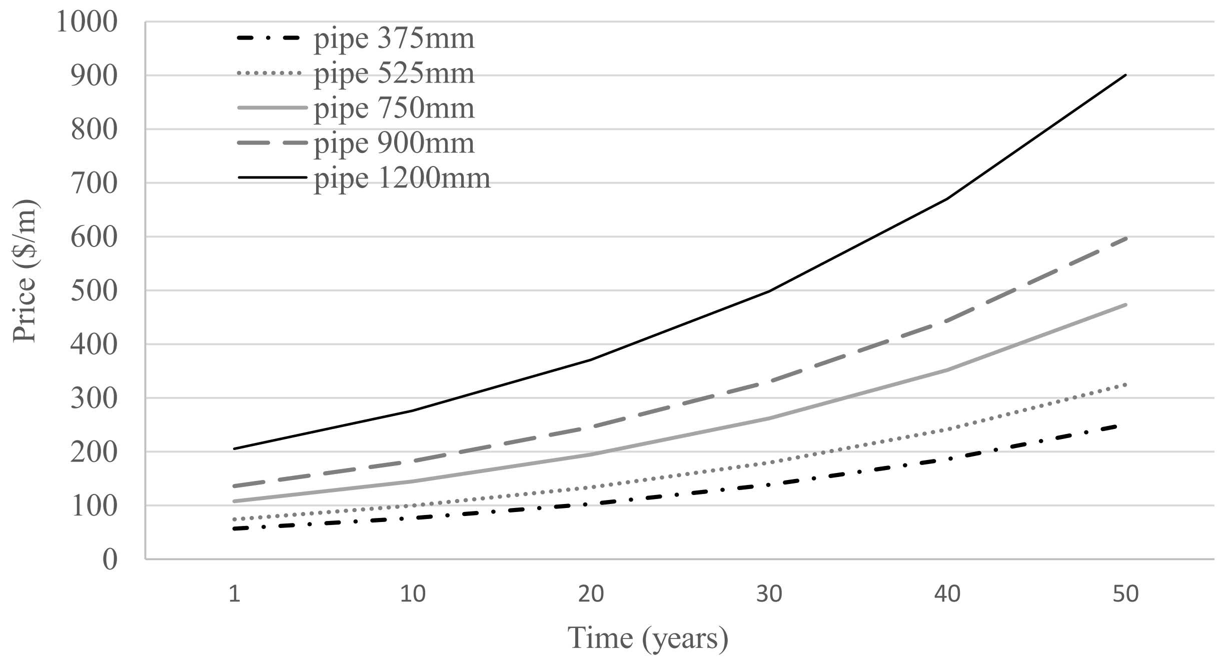


Figure 4-11: Current price and future based on 4% annual inflation

A rule set of was used to restrict pipe replacement in order to guarantee that a sufficiently large diameters will be provided in order to cope with future expected demand. Figure 4-12 show the rule set, for example pipe of 200mm could be replaced by a 275, 525 or 750mm pipe.

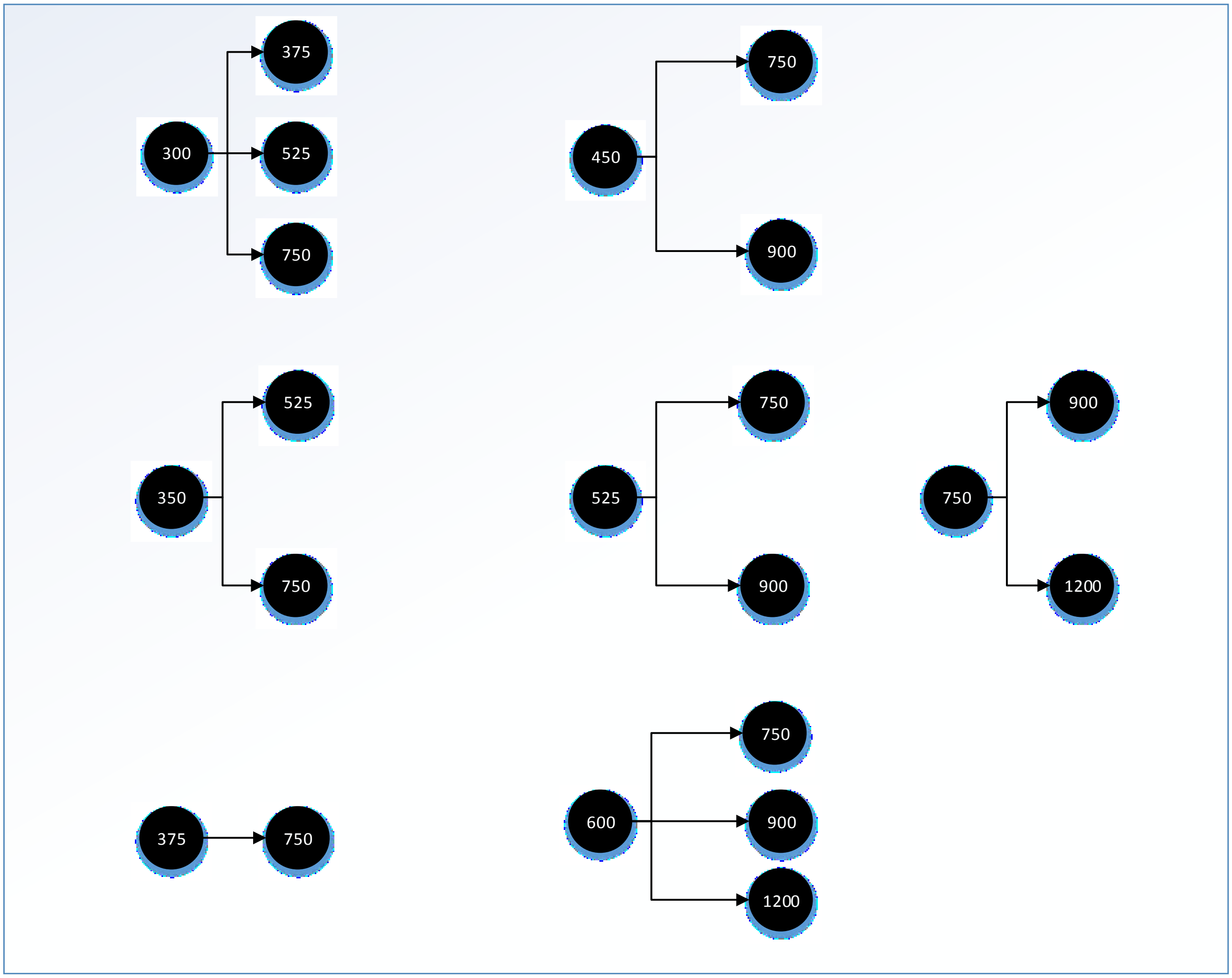


Figure 4-12: Rule set for pipe replacement

The mathematical formulation was set to optimize two goals, overall network condition which was given by each pipes size (L) and corresponding condition (Q) and each pipes flow-capacity ratios (F) times their length (L), two weights α and β were used and their role will be explained ahead.

The unitary cost (C) of replacement per linear meter of pipe at any given point on time (t) was multiplied by each pipe's length (L) and by the binary decision variable (X) in order to estimate annual expenditure and was used as either a budget constraint or as an objective (Equation 4-3) to estimate the departure level of required budget to remain at current levels of service.

MINIMIZE Z= $\sum_{t=1}^{T}\sum_{i=1}^{b}\sum_{j=1}^{J}\boldsymbol{C_{i,t}X_{i,t,j}L_i}$ (4-3)

Constraints took the form of non-declining level of condition (Equation 4-4) or declining ratio flow/capacity as shown on Equation 4-5.

Other common constrains restrict pipe replacement frequency, take care of preventing non-negativity or maximum levels for the given indicators.

Subject to:

$$\sum_{t=1}^{T}\sum_{i=1}^{b}\boldsymbol{L_i\,Q_{i,t}} \geq \sum_{t=1}^{T}\quad\sum_{i=1}^{b}\boldsymbol{L_iQ_{i,t-1}} \quad (4\text{-}4)$$

$$\sum_{t=1}^{T}\sum_{i=1}^{a}\boldsymbol{(F)_{i,t}L_i} \leq \sum_{i=1}^{a}\sum_{t=1}^{T}\boldsymbol{(F)_{t-1}L_i} \quad (4\text{-}5\ )$$

$\sum_{j\in J_{i,t}} X_{i,t,j} \leq 1$ {For all times t and for each asset i…}

Where: $X_{i,\,jet}$ = {0, 1}; if treatment *j* is applied on asset *i* on year *t*, "*0*" otherwise

$Q_{i,\,t}$ = Condition Index for asset i on year t

$(F)_{i,t}$ = capacity Improvement for pipe i on year t

$C_{j,t}$ = Unitary cost ($) of treatment j on year t

L_i = length of road segment i (m)

In the next step, keeping the capacity and condition of the storm pipes in an acceptable level are considered as objectives, and constrained by the minimum budget obtained from the previous scenario (called status Quo). Here, different weights are assigned to objectives in order to generate an aggregated absolute objective. Mathematical formulations of this second stage are presented in following equations.

MAXIMIZE Z= $\alpha\sum_{t=1}^{T}\sum_{i=1}^{a}\boldsymbol{L_iQ_{i,t}}$- $\beta\sum_{t=1}^{T}\sum_{i=1}^{b}\boldsymbol{(F)_{i,t}L_i}$ (4-6)

Subject to: $\sum_{i=1}^{b}\sum_{j=1}^{J}\sum_{t=1}^{T} \boldsymbol{C_{t,j}X_{i,j,t}L_i} \leq \boldsymbol{B_t}$ (4-7)

Where: α and β are weights for the analysis for pipe condition and pipe capacity (correspondingly)

$X_{i,\,j,\,t}$ = binary decision variables; pipe segment i to receive treatment j, on year t

$Q_{i,\,j,\,t}$ = Condition of pipe i on period t after receiving treatment j

$(F)_{i,t}$ = ratio of flow water demand arriving on the pipe i on period t after receiving treatment j

L_i = length of road segment i (m).

B_t = Annual Budget on year t

$C_{t,\,j}$ = Unitary cost ($) of treatment j on year t

4.6 Results and discussion

Status Quo scenario identified a required level of funding of $40,000 per year to remain at current levels of condition as shown on Figure 4-13.

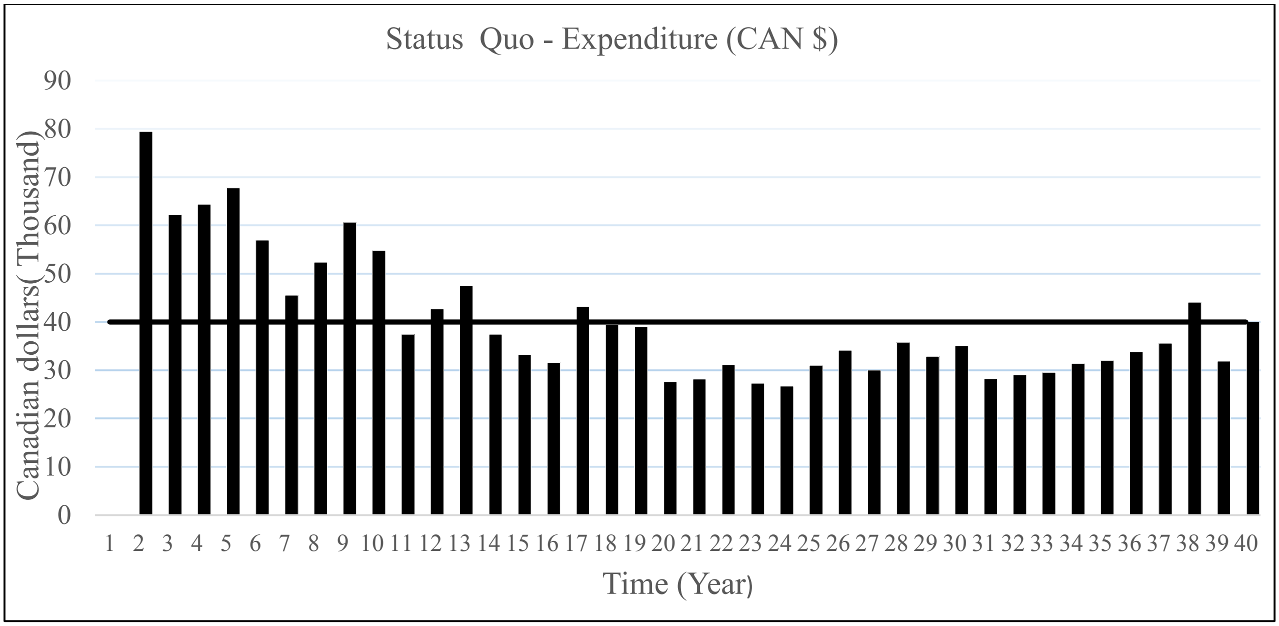


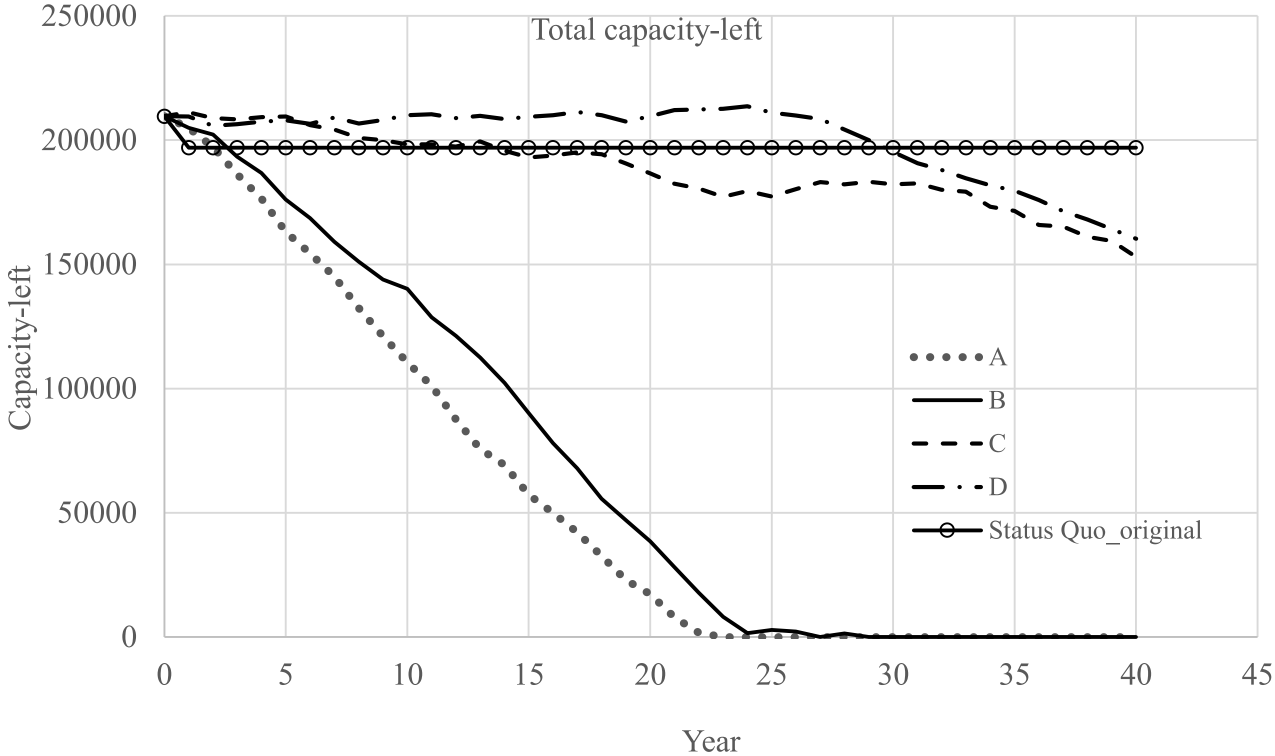
Figure 4-13: Level of expenditure for the status Quo scenario

Four scenarios called A, B, C and D were developed based on such level of funding to estimate the ideal weight on capacity and condition weights for the optimization. Scenario A used α = 0.1 (condition) and β = 0.9 (capacity), Scenario B used α = 0.3 and β=0.7 correspondingly, scenario C used α = 0.7 and β = 0.3 and finally scenario D used α = 0.9 (condition) and β= 0.1 (capacity). The ideal scenario is that capable of combining both objectives and obtaining at least non-declining levels of pipe condition and constant pipe capacity.

Progression of performance for a period of 40 years was used to select the best scenario in order to achieve non-declining average network capacity-left and condition. Four scenarios tested the impact of different weights in performance progression across time (Figure 4-14). After analysing the scenarios, it was found that scenario C (with weights of 0.3 for condition and 0.7 for capacity) produced the best results.

Table 4-10: Relative weights for two defined objectives

	Scenario			
Relative weights	A	B	C	D
α	0.9	0.7	0.3	0.1
β	0.1	0.3	0.7	0.9



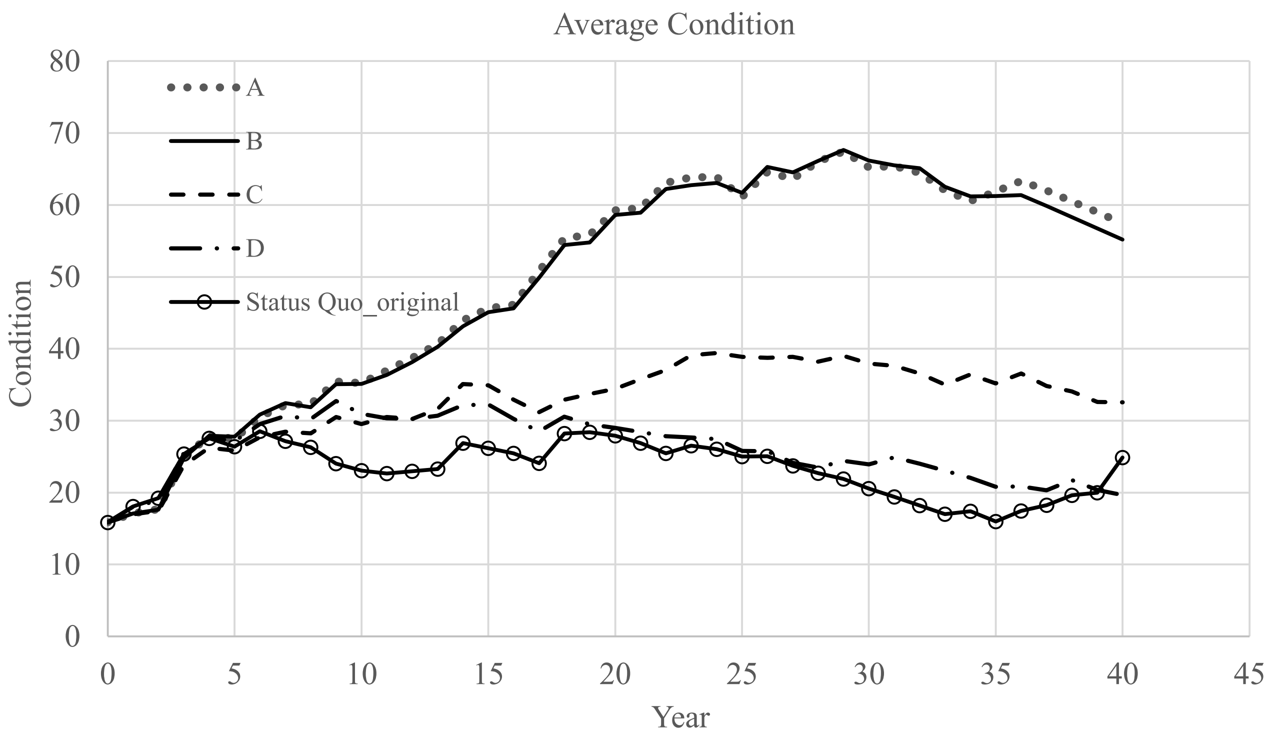


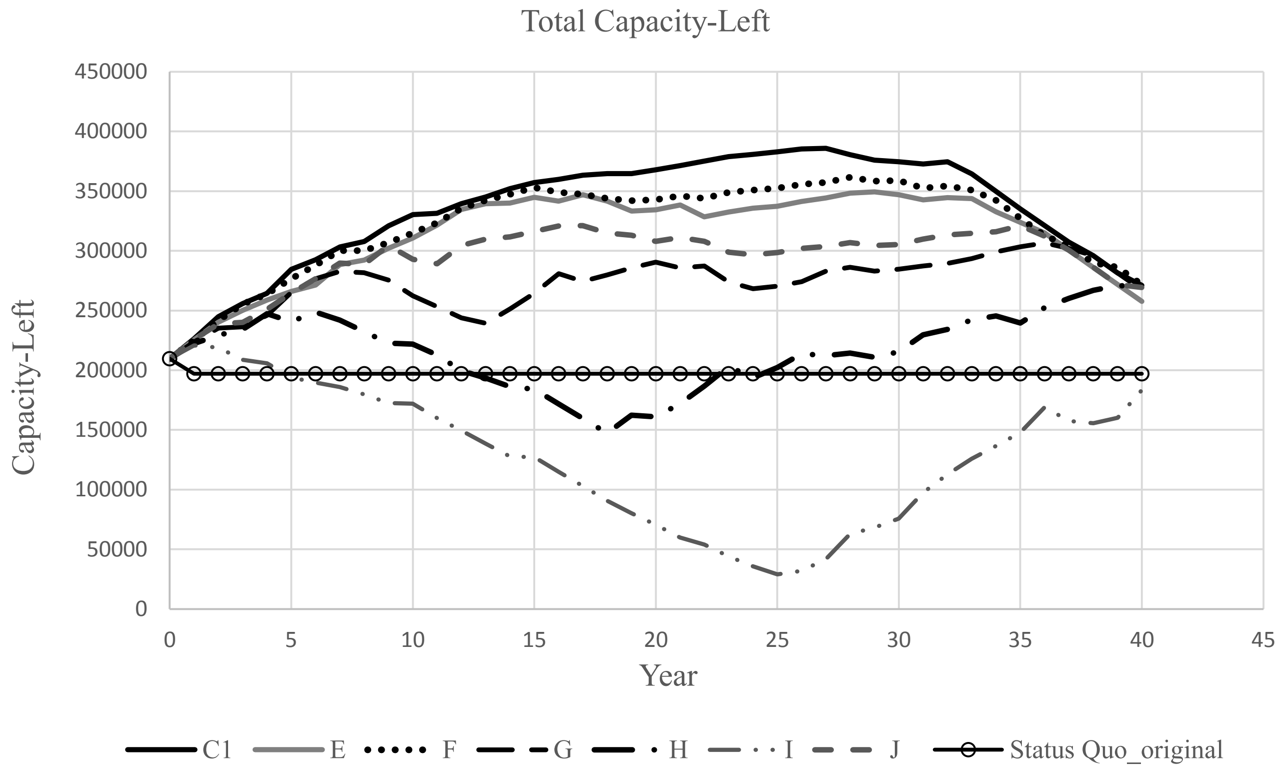
Figure 4-14: Total capacity–left and average condition

Even though scenario C was selected as the best scenario, it was noticed that after 13 years, capacity-left of the storm pipe network will decline. In other words, the amount of money destined to improve the capacity-left of the pipe network should increase. That is, current budget level of 40,000$ is not enough to keep the network in good condition while holding capacity fixed or achieving gains. Seven more scenarios were explored with the goal of reaching non-declining capacity left. Budget was raised to 100,000$ per year and the relative weights were re-examined. Table 4-12 shows the new weights for such scenarios. Among all these new scenarios, scenario H represents a more balanced solution (Figure 4-5) because it allocates interventions that improve the condition and increase the capacity of the storm pipe networks during the analysis period. Therefore, it is selected as the best optimal solution.

Table 4-11: Relative weights for defined objectives

		Scenario						
Indicator	Relative weights	C1	E	F	G	H	I	J
Condition	α	0.3	0.4	0.35	0.5	0.55	0.6	0.45
Capacity	β	0.7	0.6	0.65	0.5	0.45	0.4	0.55

Note: Scenario C1 is the same as scenario C but with a budget of $100,000 instead of $40,000



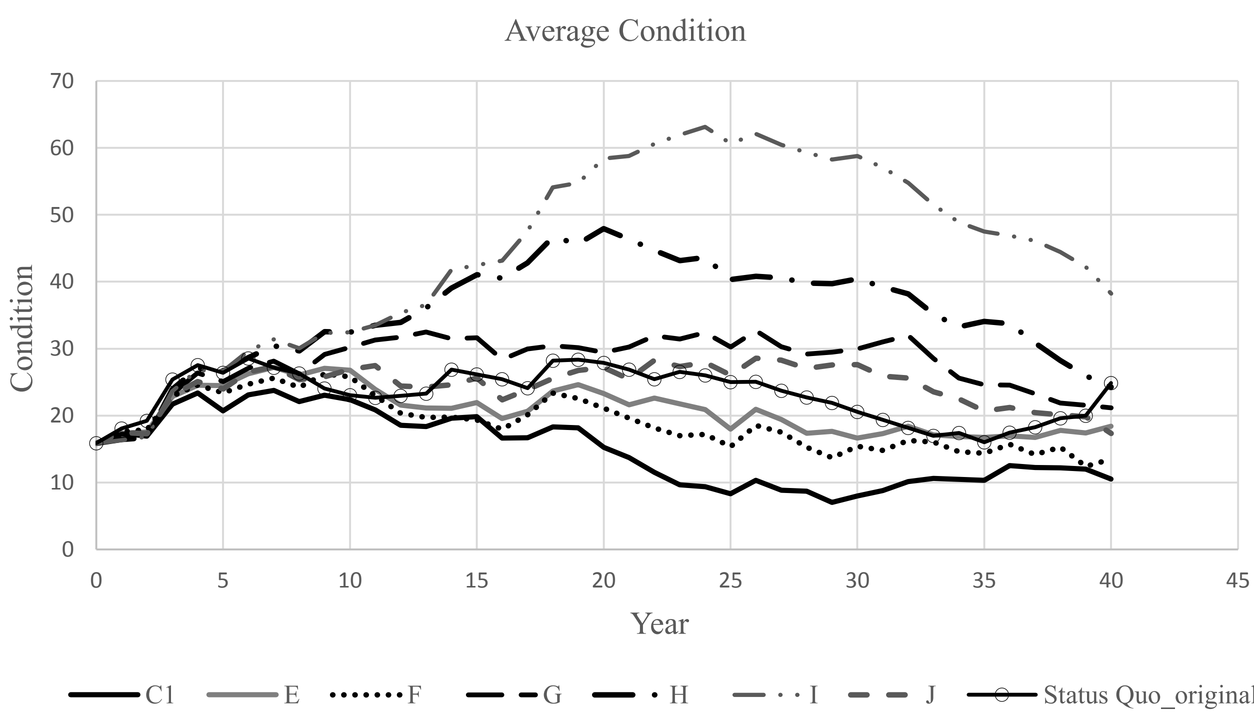


Figure 4-15: Total Capacity –Left and Average Condition of different scenarios for 40 years

Chapter 5 Conclusions and Recommendations

5.1 Concluding Comments

The overall goal of this thesis is to extend current decision making framework used to allocate storm pipe replacements by considering expected changes in pipe network demand capacity ratios, and/or condition.

As shown in the reviewed literature, many isolated studies have been done in the individual areas of remote sensing technology (RS) and Geographic Information System (GIS), urban hydrological modeling, storm pipe management optimization based on condition deterioration. However, there is no research that attempts to integrate all of the abovementioned fields in one framework in order to incorporate capacity of the storm pipes into management systems. Such a framework represents the possibility to explicitly consider changes in climate and urbanization for the optimal renewal and upgrading of storm pipes networks.

At the beginning, this research adopted a combined methodology of multi-temporal remotely sensed data and GIS spatial analysis to quantitatively characterize the dynamics of urban expansion and land use/land cover change. It was proposed that hydrological models using remotely sensed imagery and other spatial data (with a high degree of resolution) could be used when examining urbanized catchments. However, the determination of the runoff coefficient for each sub basin for the simulation of the maximum flow needs accurate land use information, in the form of very high resolution satellite imagery and such data was unavailable for this case study, hence, a simplified approach was proposed on the basis of current and future land uses.

A framework for optimal capacity and condition-based allocation of storm pipes by incorporating the demand-capacity ratio was proposed. Hydrological models were developed based on current and future trends in precipitation extremes and imperviousness of urban lands. Impacts of climate change and urbanization on the demand-capacity ratio of the storm water pipes were incorporated. The assessment of future stream flows, and the magnitudes of peak discharges, suggests that most of the pipes will reach maximum capacity at some point in the future (for the design storm) and runoff will spill off producing flooding, therefore considering capacity-based performance of pipes in management of this infrastructure is a vital task .

Storm pipe conditions were also considered as another objective and typified by a storm pipe condition index. Aging of the storm pipe networks, adversely affects their performance. Structural deterioration of the pipes is the common approach in order to assess depreciation, however loss of serviceability (i.e. blockage) of the pipes could be considered in future studies.

Actions to improve capacity and pipe conditions were applied on the network. The most optimum set of actions to sustain performance during the life cycle was selected using a multi objective optimization software. This was achieved through linear dynamic programming with the aid of the software WOODSTOCK. The optimization revised pipe's performance for various scenarios. Weights were given for the two objectives related to performance and an analysis of average pipe capacity and condition was conducted during the life cycle in order to choose the best solution among competing alternatives.

Four initial scenarios A, B, C and D constrained by a budget of CAN$40,000 identified relative weights of 0.7 for capacity and 0.3 for condition (scenario C) as the best one. However, it was found that level of budget was not enough to observed non declining available capacity for the analysis period while also improving in pipe condition.

Seven additional scenarios with weights close to those of scenario C were used to fine tune the analysis. Emphasis was paid to reaching non-declining capacity left. A budget of 100,000$ per year was used and relative weights were re-examined. It was noticed that, among all these new scenarios, scenario H with 0.55 for condition and 0.45 for capacity. Results from this scenario represents a more balanced solution, because it allocates interventions that improve the condition and increase the capacity of the storm pipe networks during the analysis period.

This research illustrated that it is possible to conduct an integrated strategic management of storm pipe infrastructure by fully considering pipe capacity and condition of pipe asset. It was found that it is possible to decrease the total capacity of the network and more importantly to achieve and sustain good levels of service in terms of capacity by first identifying capacity-deficient segments and then applying corrective measures. This will result in a network of storm pipes prone to flooding while minimizing costs in the long term. In overall, it was observed that using capacity-based performance based life cycle optimization saves money and achieves more sustainable results by looking at performance of the storm pipes during their life cycle in addition to the traditional sole use of costs or condition as the only objective. Looking at asset performance as the second criteria (in addition to costs) enhances selection of the optimum solutions by narrowing the final subset of alternatives in such a way that unsustainable (unbalanced) options are dominated and deemed out of the analysis.

5.2 Future research

There are several aspects of storm drainage pipes not considered in this research because of lack of data or time restriction. Such as the occurrences of blockage and their impact on network performance.

Future research should look into better means to model the impact of climate change on the intensity and duration of storms. Furthermore, for a more complete understanding of how precipitation extremes are likely to change in the future, downscaling of climatic GCMs and RCMs simulations for the favorable study area should be explored to develop precise intensity frequency duration curves for future hydrological modeling. Also future research should look into alternative simplified methods when high resolution data is unavailable.

Future research could incorporate other assets into the mix and address a more comprehensive urban infrastructure problem from a municipal perspective.

This study solely focused on storm-water network-management, however, water mains sanitary pipes as well as pavements, are also important components within the context of urban infrastructure. This research proposes an integrated management of the storm pipes for long term and future research could look into the coordination of their scheduling along with that of other urban infrastructure. Specially allocating pipe replacement following a corridor approach.

Future research could look into the operational scheduling of pipe replacements by considering constraints from working time, machinery and other physical resources required.

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