Mapping Urban Surface Infiltration Capacity

Segment-based land cover classification with VHR imagery for urban water management and design.

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MSc. Geomatics Final Thesis Report
Danbi Lee
Mapping Urban Surface Infiltration Capacity

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Danbi Lee (4180941)
Delft University of Technology
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TU Delft
Graduation Committee:
Prof. Dr. Massimo Menenti, Graduation Professor
Dr. Ir. Ben Gorte, Main Tutor
Dr. Ir. Frans van de Ven, Tutor
Dr. Ir. Stefan van der Spek, Chair
Dr. Marianne de Vries, Co-reader
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I believe that faith is a precursor of all our ideas. Without faith, there never could have evolved hypothesis, theory, science or mathematics. I believe that faith is an extension of the mind. It is the key that negates the impossible. ~ Charlie Chaplin

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Abstract

Effective urban water management requires certainty about surface conditions such as the surface infiltration capacity (SIC). A SIC map of an urban catchment area could be a useful input for evidence-based urban design of water-sensitive/low-impact neighbourhoods and multi-tiered water management schemes for reducing flood vulnerability. Methods for mapping SIC are underdeveloped. Typically, infiltration rates are derived from topographic or urban extent maps. Instead, if a land cover map can precisely identify hydrologically relevant land cover classes, then a more accurate SIC map can be derived.

The research explored whether an accurate SIC map could be derived from VHR multi-spectral imagery of Amersfoort, Netherlands, using specific hydrologically relevant land cover classes and segment-based land cover classifiers to achieve meaningful object resolution. The impact of different similarity metrics, rule sets, and data types on classification accuracy were explored. In particular, the impact of lower class specificity (generic classes) was tested. The SIC map was assessed based on impact in a pluvial flood model.

Results indicate a high degree of spectral and textural confusion between impermeable and semi-permeable surface types in land cover classification. The analysis of the SIC and land cover maps illustrates that with generic classes the SIC is under-predicted for the catchment area despite a higher overall accuracy in land cover classification. Generic classes also reduce object resolution (detail). Using specific classes produces a less accurate land cover map but improves SIC prediction. In a pluvial flood model, the generic classes increased runoff volume and reduced peak runoff time, validating the conclusion that class specificity and object resolution plays an important role in mapping SIC.
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1. INTRODUCTION

Water is every part of the Dutch urban landscape as the rusty bicycle that leans on a brick house alongside a brick road (Figure 1). It is no surprise that for every Dutch city, where over 80% of the Dutch population lives, effective urban water management is a top priority. Nearly 800mm of precipitation fall annually over the urban areas which are already kept safely dry under sea level by distant but trustworthy pumps. Urban water plays a part in city recreation, beauty, landscape and transport of goods and wastes. It also has an environmental hand in urban heat reduction, pollution transport, vegetation health, and ground subsidence. Without effective management, it can be as destructive as it is supportive of urban life.

Effective urban water management requires an understanding of water behaviour in the urban environment. To link urban design interventions, to infrastructure works, and to urban climatology, a proper and certain description of the urban water landscape is needed. Knowing how much water enters (by rain or canals), where and how fast it flows through, and where and how it exits the city can help evaluate and improve water management policies and practices.
1.1 Problem statement

This thesis work aspires to be a contribution to the ways in which the urban water landscape is described. Besides the technical subsurface drawings of drainage inlets and pipelines for water engineers, topographic land use maps for urban designers, and urban heat maps for climatologists, a new type of input is considered here that can be of interest to all and describes the urban surface infiltration capacity to rainwater (SIC, or capacity for water to infiltrate through the surface).

Considering that the process of urbanization seals surfaces with impermeable materials (such that rainwater can no longer be slowed, retained, and filtered by a naturally vegetated and permeable ground) knowing where and how much sealing and infiltration occurs becomes meaningful. Uncertainties from generalizations could mean the mismanagement of the volume and movement of surface runoff, unaddressed vulnerability to pluvial flooding and non-point source surface water pollution.

Evidence-based urban design interventions for water-sensitive/low-impact neighbourhoods, environmental management, and pluvial flood modeling could benefit from a detailed surface description tailored for urban hydrology. Work by pavement scientists, urban designers, and water engineers point out that SIC is more spatially fragmented and varied across the urban landscape than topographic maps would suggest (Figure 2).

Land cover and land use (LULC) maps (Figure 3), and soil maps can only describe the urban water landscape in a generic way because the maps use classes that often have generic hydrological meaning. Topographic maps are
tailored to measure urban extent or general land use at small scales (broadly speaking, determining between urban/impermeable and non-urban/permeable). Class specificity rather generic and the object resolution is low (only parcel boundaries). This likely has an implication on urban flood models, for example, where surface area plays a role. Otherwise the water-sensitive design interventions and pavement technology developments would be in vain.

One uncertainty in urban hydrology models may be from poor model calibration of urban catchments in terms of the ability to store, infiltrate, and evaporate rainwater. Detailed SIC mapping is a meaningful response to work like Canters et al. (2011) who showed more precise mapping of ‘imperviousness’ (urban areas) increased the peak discharge rate of urban runoff compared to lower resolution imperviousness maps. In other words, spatial detail matters. Currently, knowledge about urban SIC is thin and true values must be determined by expensive in-situ measurement campaigns or otherwise inferred from topographic maps (explaining its common use).

Attention to urban soils and subsurface conditions has only surfaced in the past two decades. Methods for mapping surface infiltration capacity at the appropriate object resolution are underdeveloped, and few, if none, are found in practice. This research explored whether an accurate SIC map could be derived from VHR multi-spectral imagery of Amersfoort, Netherlands, using specific hydrologically relevant land cover classes and segment-based land cover classifiers to achieve meaningful object resolution. The impact of different similarity metrics, rule sets, and data types on classification accuracy were explored. In particular, the impact of lower class specificity (generic classes) was tested. The SIC map was assessed based on impact in a pluvial flood model.

![Figure 3. General urban land cover or land use map may show urban extent, but no details about surface cover or material type.](image-credit: University of Minnesota, 2011)
1.2 Research approach

The research presented in this report explored whether hydrologically relevant land covers could be accurately mapped through segment-based land cover classification of very high spatial resolution (VHR) multi-spectral imagery of Amersfoort, Netherlands (0.25m NIR/R/G and 0.035m RGB), in order to derive a more detailed SIC map than if derived from topographic data. The impact of class specificity and object resolution were assessed based on the SIC maps produced.

A literature scan established the class specificity by identifying the hydrologically relevant land cover classes. Following suggestions in land cover classification research, spectral and textural features were tried in object classification, and using a digital elevation model (AHN-2) only in image segmentation. Moreover, the SIC maps were assessed on effect of class generalization in a pluvial flood model to conclude whether the higher object resolution and class specificity is at all meaningful to achieve.

The study was completed in three phases over the course of nine months (Figure 4). Since the application of the map could span across disciplines, the research approach was advised by researchers and practitioners in urban design, water management, remote sensing, and urban hydrology. The results give a first impression into the feasibility of automatically generating a SIC map through translating VHR imagery into a meaningful hydrological concept.

1.3 Research questions

The required work involved evaluating the performance of various image classifiers to generate a land cover map tailored for urban hydrology. Then to assess whether a SIC derived from such a map has any implication on design and water management. To do so, the class specificity and necessary object resolution of the map had to be established from the needs identified in the literature. The classification experiments and the mapping product assessment were structured under the research questions described herein.
1.3.1 Positioning the research within a theoretical framework

It is well known that sealed surfaces occupy a significant portion of the urban fabric (Figure 5). Akbari et al. (2003) mapped the metropolitan region of Sacramento, California and showed that paved surfaces (roads, sidewalks, and parking lots) account for nearly 39-70% of the urban fabric depending on the land use. The total paved surface area of the entire study site was roughly 310 km², which is nearly equal to the metropolitan area of Rotterdam. A land use mapping study of a residential neighbourhood in Leuven showed that roughly 56% of the study area was considered sealed (Verbeeck et al. 2011).

Water-sensitive/low-impact developments include design interventions that purportedly address surface impermeability by improving SIC. Bioswales and semi-permeable pavements are commonly used design tools to address this concern and are wrapped under the concept of ‘green infrastructure’ for cities (Figure 6). But what is surface infiltration capacity and how is it affected by soil sealing and urbanization? Therefore, what are the hydrologically relevant land cover classes in urban areas and why?

Surface and subsurface conditions (e.g. sealing material, subsoil type, compaction, antecedent moisture, siltation, crusting and age) are known to affect SIC. This study suggests that sealing type (e.g. brick, asphalt, concrete) as a class could predict well the SIC. Pavement technologies and installation procedures are known, and in-situ SIC rates can be retrieved from literature (see Chapter 2). Thus, the specific sealing type as a class can give a better prediction of SIC than generic land cover classes. At the same time, no two seals may actually have the same SIC due to constraints like compaction and siltation. This challenges this premise and is discussed later.

1.3.2 Mapping experiments

The mapping of surface sealing in urban areas is not a trivial exercise. The performance of an object-oriented approach to generating a SIC map compared to a manually classified one is unclear. The experiments were intended to elucidate how well hydrologically relevant land cover classes (as
objects) can be mapped using VHR multi-spectral data while meeting object resolution requirements. Moreover, classification experiments were intended to document the impact of segmentation on map readability, and the impact of using texture features on classification accuracy.

LULC mapping methods usually classify image pixels into urban/non-urban (or sealed/non-sealed, or pervious/impervious classification) classes with medium spatial resolution multispectral imagery where small urban objects like detached houses or parking lots are not easily identified. While this has been useful for illustrating the 2D extent, morphology, and dynamic nature of regional urbanization, this generic class specificity and low object resolution poorly describes the magnitude, distribution, and connectivity of SIC (Jacobson 2011).

Using VHR images enables precise object recognition but introduces additional mapping challenges such as within-class spectral confusion, shading, and surface occlusion by leaning structures and tall objects (Figure 7). It is uncertain how standard classifiers perform in distinguishing between hydrologically relevant land cover classes, and whether it is even necessary for precisely mapping SIC.

1.3.3 Demonstrating map impact and identifying new questions

Using the land cover map product from the classification experiments, a SIC map was derived and assessed to understand the impact of class specificity and object resolution on accurately predicting SIC in an urban catchment. Advantages and limitations to the SIC map application are discussed.

Potential applications of a SIC map are:

1. **Context benchmarking for driving investment**: Where there is political will to mitigate the hydrological effects of soil sealing during lighter rainstorms, a SIC map can provide benchmark conditions of the water landscape, as an holistic and quick overview.
2. Monitoring and evaluating design performance: Small to large design interventions and infrastructure works are continuously underway that change the water landscape. A SIC map can be one way of monitoring the impact of these works in an urban catchment.

3. Improved parameterization and modeling: Urban water catchments depend on the drainage infrastructure, SIC, elevation, and other losses. Spatial analyses using a SIC map in combination with elevation and inlet data can better parameterize local water catchments (anticipated sinks and underground flow direction) for added precision in urban heat, drought, and flood modeling.

1.4 Purpose and structure of the report

This report details the framework and evolution of the research by first elaborating on the research questions (this Chapter) and theoretical framework (Chapter 2). The methodology (Chapter 3), results (Chapter 4), and conclusions including further research questions (Chapter 5) make explicit the challenges and findings of the work. Rather than drawing any hard and fast conclusions about mapping SIC, the research unearths more research directions regarding the confusion between the hydrologically relevant land cover classes, use of texture features and DEMs in classification, and its application.
2. THEORETICAL FRAMEWORK

The first part of the research was intended to build a rationale for mapping SIC (see Section 1.3.1). In this Chapter, an overview of concepts in urbanization, soil sealing effects, and water-sensitive design are reviewed to establish a practical purpose for a SIC map. This leads into a discussion on surface infiltration concepts and urban hydrology, in order to understand the physical nature of the surfaces to detect from the VHR imagery. Most importantly, the review identifies the hydrologically relevant land cover classes using the differences in measured SIC and thus the necessary object resolution. Finally, methods to detect these specific classes are reviewed, establishing the methodological benchmark for the mapping experiments.

2.1 Urbanization and water-sensitive urban design

Urbanization is a human settlement process that drastically modifies the vadose zone (unsaturated soil matrix) and seals soil surfaces (Figure 8). According to the European Commission (2013), soil sealing is when the ground is covered by an impermeable material. This alters the composition and ecological function of naturally undisturbed soils below.
Soil disturbances in the urban fabric (also known as the ‘urban area’, or ‘built-up area’) can be explained by the process of site preparation for land development. On undisturbed soil, traditional site preparation involves the removal of vegetation and topsoil, and a leveling of the exposed subsoil below (the sub-grade). In order to stabilize and sometimes elevate a foundation fit for building construction, layers of compacted gravel and/or sand mixes are overlain (the sub-base) on top of a geotextile and is called integral filling. The thickness of the sub-base could be at least 50cm, but depends on the pre-existing drainage capacity and the soil compressibility of the sub-grade below. Subsurface infrastructure can also be installed before the area is back-filled and sealed with concrete slabs, bitumen (asphalt), brick pavement, tiles, or top soil for gardening (Figure 9). Various pavement installation techniques are known, thus the shallow subsurface composition can be implied by the sealing type.

Site preparation demonstrably impacts the natural SIC of the ground, especially in the natural root zone (around 1m), because sealing reduces the availability of water to infiltrate into the surface (Scalenghe and Marsan 2009), and the site preparation process reduces the overall permeability of the underlying soil through removal of vegetation, organic material, and compaction (Gregory et al. 2006).

A scientific discourse is growing around describing new classes of ‘anthropogenic’ soils that play an important role in urban ecology (Rossiter 2007, Hazelton and Murphy 2011). Urban soils found in parks, sports fields, and residential lawns, have distinctively different characteristics from undisturbed or agricultural soils because they have significant contamination and material mixing, and an underdeveloped soil profile (Figure 10). They are characterized by a high bulk density (indicating low porosity), high temperature and high pH (Hazelton and Murphy 2011, Pitt et al. 2002,
Lehmann 2010, Scheyer and Hipple 2005). While global, national, and regional soil maps are available, urban soils are rarely mapped at meaningful spatial resolutions for local overviews and the degree of variability and fragmentation is under-determined.

The urban fabric is a heterogeneous mix of exposed disturbed soils, sealed surfaces, vegetated surfaces and built structures. From a hydrological perspective, the urban fabric can be considered a constrained physical ‘membrane’ for the flux of rainwater affecting its behaviour (Figure 11, Zoppou 2001, Akan and Houghtalen 2003, UCAR 2010) including:

» Increased runoff volume (due to decreased interception by vegetated surfaces and reduced surface infiltration).

» Modified runoff networks (due to modified and canalized surface drainage networks).

» Increased non-point source water pollution, especially in canalized urban rivers (due to detachment and transport of debris, minerals and soils by high runoff velocities).

» Reduced groundwater recharge and subsequent subsidence of land (due to reduced infiltration capacity and distribution over the urban fabric).

» Increased demand on water supplies (exacerbated by reduced groundwater recharge and leading to water supply issues).

» Other chemical, microbiological, and ecological effects on water quality.

» Increased vulnerability to pluvial floods.
Other environmental effects of soil sealing as outlined in a review by Scalenghe and Marsan (2009) and Wessolek (2008) are:

» Contribution to the diurnal urban heat island effect at the urban boundary layer (warming of impervious surface materials and reduced surface cooling ability as researched by Oke (1982) and O’Donohue et al. (2008)).

» Sinking of carbon gas in urban soils, affecting gas exchange in urban environments.

» Changes in plant phenology due to urban heat, increased air pollution, and concentration of heavy metals (complete shifts in biodiversity and abundance of native species).

These impacts are what trigger urban designers, planners, and water managers to advocate for resilient cities. Substantial attention is being placed on improving surface permeability to rainwater (Pötz and Bleuzé 2012, Zevenbergen et al. 2011). Several names have been given to this interventionist design approach such as ‘best management practices’ (BMP), ‘low-impact development’ (LOD), water-sensitive design (WSD), sustainable urban drainage systems (SUDS) and ‘green-blue’ design. These methods purportedly increase the adaptability (and thus resilience) of a city to rainfall events because they allow space for rainwater to reside in the ground, dampening the peak discharge of water to the conventional drainage system (see White 2010).
Thinking of the urban fabric as a permeable membrane adds another dimension to conventional drainage-driven, single-tier, water management schemes. Water-sensitive designs support a multi-tiered decentralized approach (Figure 12, Genus and Coles 2008, Burnett and Blaschke 2003). Rainwater is no longer seen as waste to drain out of the city, but a resource by which to irrigate urban gardens, recharge groundwater, re-hydrate and regulate micro-climates. It aims to improve the infiltration, retention and detention of rainwater (concept of retain-store-delay of rainwater) at the surface before any excess enters the sewer drainage system (Zevenbergen et al. 2011).

Water-sensitive designs typically have five key objectives:

» Reduce runoff velocity (slow down and store rainwater, thereby reducing detachment energy leading to soil erosion).

» Reduce runoff volume that enters the drainage system.

» Reduce runoff pollutants (in-situ treatment of soluble and particulate pollutants).

» Strengthen urban catchment areas (connecting stores and sinks of rainwater).

» Add aesthetic and cultural value to the urban landscape (landscape design).

Urban designs that include ‘semi-permeable’ pavements are popular surface treatments to meet the above objectives (Figure 13). They can be easily installed over a large surface such as a parking lot (normally treated with bitumen, asphalt, or concrete) to create surface infiltration zones. Other interventions include bioswales and urban ponds or wetlands. The re-introduction of SIC is a concept that is supported by contemporary urban water management practices (Zevenbergen et al. 2011).

Infiltrated water quality is improved by semi-permeable pavements since the increased SIC allows in-situ pollution treatment. The presence of geo-textiles in permeable pavements systems can reduce suspended solids, biochemical oxygen demand and ammonia-nitrogen by 80-90% (Maharaj-Tota and Scholz 2010).

Improved SIC also increases the potential exfiltration of rainwater to the groundwater or losses by evaporation. Semi-permeable pavements better retain rainfall, and continue to show evaporative cooling behaviour (increased latent heat exchange), thereby reducing surface temperature when compared to traditional concrete and asphalt surfaces (Starke et al. 2010, Nakayama and Fujita 2010, Li et al. 2013). A glance through the book of Pötz and Bleuzé (2012) will illustrate several case studies of water-sensitive designs.
2.2 Surface infiltration and runoff concepts

The complex and artificial urban environment for water movement gives rise to the field of urban hydrology. Here the urban water cycle is divided into four parts that account for the movement of rainwater:

1. Rainfall (incoming volume of water)
2. Losses
3. Excess (surface runoff)
4. Recharge (exfiltration into ground and surface water)

Losses of rainfall volume (part 2 above) is also termed ‘hydrologic abstractions’ by water managers (Figure 14). The proportion of each abstraction to the total loss varies over the urban fabric because of spatial heterogeneity and fragmentation of the urban fabric. These are time dependent processes and are described as:

1. Interception (by the urban forest canopy and green roofs).
2. Evaporation and transpiration (from built-surfaces, soil, and vegetation).
3. Infiltration (by the urban surface).
4. Storage (by depressions in the urban surface, subsurface, or other designed storage areas).

Infiltration accounts for the majority of rainfall loss. Akan and Houghtalen (2003) define infiltration to be “…the process by which rainwater passes through the ground surface and fills the pores of the underlying soil”. After infiltration, water moves through the shallow subsurface towards the ground-
water (from a point of high water potential to low water potential). The capacity of rainwater to flux through the ground is the SIC and is measured as a time-dependent velocity, or surface infiltration rate (SIR). This is not exactly ‘permeability’, which from a geotechnical definition is a coefficient, \( K \), that describes the ease of fluid passing through a porous medium. The SIR is dynamic and dependent on several factors including \( K \).

Conceptually speaking, the SIR is determined by water availability at the surface and ability to infiltrate into the subsurface (Figure 15). The availability is considered to be the volume of rain available (\( \partial \theta \)) that generates an overlying water pressure (\( \psi \), the pressure head, due to gravity). However, in urban areas the various degrees of sealing and surface roughness will reduce the actual availability (Collins et al. 2008). Not to mention the effect of slopes on rainfall velocity horizontally across a surface. So, not all rain that falls can penetrate the surface.

With enough available water over a surface to create a pressure gradient, water begins to infiltrate (transmit through) the surface. The transmitability is a function of the shallow subsurface conditions where the effect of \( K \) (coefficient of permeability) of the medium is observed. \( K \), in turn, depends on the fluid viscosity and density, and subsurface pore geometry. The hydraulic gradient, \( z \), created by the distance between the wetting front (above) and the groundwater (below) and is impacted by vertical flows and the antecedent subsurface moisture (ASM) condition (Akan and Houghtalen, 2003).

These relations are captured by the Richards equation (1931, Equation 1) which describes the unidirectional flow of water through unsaturated porous media and is based on Darcy’s Law for vertical flow in saturated porous media.

\[
\frac{\partial \theta}{\partial t} = \frac{\partial}{\partial z} \left[ K(\theta) \left( \frac{\partial \psi}{\partial z} + 1 \right) \right] \tag{1}
\]

The Richards equation describes a non-linear and continuous model of infiltration based on subsurface geometry and antecedent moisture. It is considered the most accurate model but it is somewhat impractical to compute for engineering applications. Simpler models have been used and
include the physically-based Philips equation (1953), the empirically-based Kostiakov equation (1932), the most popular Horton equation (1933), and Holtan equation (1961). The Green and Ampt model (1911) is a non-linear physical model that can produce quite realistic estimates of SIR as it considers the dependence of SIR on ASM. On the other hand, the Horton model (Equation 2) assumes SIR is independent of ASM but is fast to compute.

Equation 2 models the rate of vertical infiltration as an exponential decay over the rainstorm duration, where $f_o$ is the initial infiltration rate of the unsaturated ground and $f_f$ the final infiltration rate, and $k$ a decay constant depending on the media. This gives $f_p$, the SIR at time $t$, and explains the general exponential decay behaviour of infiltration capacity over time (Figure 16).

$$f_p = f_f + (f_0 - f_f)e^{-kt} \quad (2)$$

Vertical infiltration rates ($f_o$) are highest at the beginning when the subsurface is dry and the process is driven predominantly by suction forces of the subsurface. As the ground saturates, infiltration rate declines and is driven by gravitational forces and energy potentials until the final SIR ($f_f$) is reached. The final SIR is a good indicator of saturated hydraulic conductivity, $K_s$ (Hsu et al. 2002), which can also be determined in-situ over pavements by measuring the flux of water through a pavement using a constant or falling head of water (infiltrometer tests). The final SIR seems to be independent of ASM (Yang and Zhang 2011). However, ASM does affect the time to reach final SIR since water is already present in the subsurface voids, reducing the hydraulic gradient. ASM also reduces pore suction forces thereby reducing initial infiltration rates (Akan and Houghtalen, 2003). An increasing hydraulic gradient increases the infiltration rates overall (Figure 17).
Many studies have demonstrated that an exponential function for infiltration is generally true and explains its popular application (Akan and Houghtalen 2003). However, Hsu et al. (2002) and Turner (2006) shown that the simplicity of Horton’s equation leads to the least accurate estimates of infiltration rates, especially in the unsaturated (early) and saturated (late) measurement periods as it does not consider effects of ASM. The exponential decay rate in the Horton equation was unstable and sensitive to rainfall intensity, initial soil moisture, and rainfall duration (Hsu et al. 2002).

During a rainfall event, runoff will occur when the rate of incoming rainfall exceeds the SIR and is named infiltration excess or Hortonian flow (UCAR 2010). When the ground becomes saturated the SIR equals the exfiltration rate (to the groundwater), any rainfall rate exceeding this will become saturation overland flow (Figure 18). Saturation flow is quickly reached during intense and/or long rainfall events, where subsurfaces are partially saturated, or over impermeable surfaces. Water-sensitive urban design aims to reduce both runoff velocity, volume and peak discharge lag time by affecting SIR and overland flow processes.

Figure 19 compares the final vertical SIR of various undisturbed bare soils (sandy soil for Amersfoort) and semi-permeable surfaces measured in-situ and reported in the literature. It illustrates a wide range of SIR even within
the same sealing type, and that semi-permeable surfaces have exceptional SIR. These sealing types are therefore hydrologically meaningful and should be the considered land cover classes from which to derive SIC. The following sub-sections explain the specific processes that determine the effective SIR of tested surfaces.

2.2.1 Surface effects on SIR

The previous Section presented different SIR for various urban surface types. To explain, the concept of availability and ability for infiltration is examined further. Availability was previously described as the total amount of falling rain. However, this assumes that any surface can transmit water. In reality, only a fraction of the rain hitting the surface is actually able to penetrate into the subsurface due to losses by surface geometry and material adsorption.

To roughly model this loss, final rainwater availability could be based on the surface void ratio resulting from the gaps introduced between paving units or within the pavement material itself (Figure 20). They have been shown to increase SIR that matches or exceeds pre-development rates, such as with gridded concrete pavers (CGP). For example, matrix void ratio for porous concrete (PC, Figure 21) ranges between 25-40%, depending on the mixture. A PC final SIR can be from 170mm/hr, which is comparable to

Figure 18.
Runoff occurs when the rainfall rate exceeds the SIR. The goal of water-sensitive design is to reduce the runoff volume and delay peak discharge lag time (below).
the final SIR for old compacted residential lawns (Yang and Jiang 2003), to over 50,000mm/hr. On the other hand, Collins et al. (2008) suggested that the linearly shaped voids of permeable concrete interlocking pavers (CIP) tends to channel water away from the surface and could explain a lower SIR between two similar pavements.

Pavement materials can also adsorb rainfall, thereby reducing available water for infiltration and buffering the peak runoff discharge rate. For lighter rainfall events (<50mm), the adsorption losses can be high (>60%) and sometimes result in no peak flow due to total retention during the rainfall event (Collins et al. 2008). Fassman and Blackbourn (2010) report up to 6mm of rainwater retention for CIP, slowing the runoff discharge peak time for rainstorms under 55mm. Experiments on the SIR of various semi-permeable surfaces concluded that the buffering capacity became less relevant with increasing storm intensity and duration, because the rainfall rate becomes suddenly greater than the highest infiltration rate (Collins et al. 2008).

Aside from void ratios, the texture of surfaces may also affect availability. The horizontal overland flow over impermeable smooth and flat surfaces are considered to be laminar, but in urban areas the variety of surface
textures, permeabilities, and slopes results in rather turbulent flows. Surface roughness indices (like the Manning roughness factor, $n$) is a measure of surface roughness. The roughness concept captures flow resistance over a surface and has an implication on overland flow velocity ($Q$). Based on the manning formula for normal open channel flow, an increasing roughness factor should decrease overland flow velocity, thereby increasing availability (Equation 3).

$$Q = \frac{A}{n} R^{2/3} S_f^{1/2}$$  \hspace{1cm} (3)

In Equation 3, $A$ is the cross-sectional area of the channel (for urban runoff, consider a very wide and shallow channel), $R$ the channel hydraulic radius, and $S$ the channel friction slope. Established Manning coefficients used in engineering practice for hydrologically relevant land cover classes are shown in Table 1.
Surface depressions add flow resistance, and increase the potential pressure head at the surface. Agricultural soil studies have extensively investigated the relationship of surface roughness on SIR for exposed soils that could shed light on behaviour on urban surfaces (Figure 22, ASCE 2009). Crusted soils behave like many sealed surfaces, having a negative impact on SIR and having reduced surface roughness. A 10 - 85% reduction in SIR was found on crusted soils in southern France (de Jong et al 2011).

Pluvial flood models use the surface wave equations (conservation of mass and momentum), vertical infiltration models (e.g. Green and Ampt or Horton), and surface roughness to determine flow extent, velocity and volume at specified time steps. Roughness and SIR are taken as independent variables. Results of such models can be compared against in-situ measurements of SIR (most offer vertical infiltration rates) and calibrated accordingly. Horizontal flows are less frequently determined in-situ, but vertical flow calibration may achieve additional accuracy (Bronstert and Plate 1997).

<table>
<thead>
<tr>
<th>material</th>
<th>$n$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ceramic tile</td>
<td>0.014</td>
</tr>
<tr>
<td>Asphalt</td>
<td>0.015</td>
</tr>
<tr>
<td>Brick Interlocking</td>
<td>0.015</td>
</tr>
<tr>
<td>Concrete</td>
<td>0.016</td>
</tr>
<tr>
<td>Bare soil</td>
<td>0.025</td>
</tr>
<tr>
<td>Gravel</td>
<td>0.028</td>
</tr>
<tr>
<td>CGP</td>
<td>0.030</td>
</tr>
<tr>
<td>CIP</td>
<td>0.030</td>
</tr>
<tr>
<td>PC</td>
<td>0.030</td>
</tr>
<tr>
<td>Woody Veg</td>
<td>0.150</td>
</tr>
<tr>
<td>Synthetic turf</td>
<td>0.200</td>
</tr>
<tr>
<td>Grass lawn</td>
<td>0.425</td>
</tr>
</tbody>
</table>

Figure 22. Increased surface roughness improves SIR over agricultural soils (A) (From ASCE 2009). The same relationship could be expected of urban surfaces as demonstrated by Schmidt and Michael (2004) which shows increased simulated infiltration rate when sandy soils are covered with semi-permeable seal (B).
2.2.2 Shallow subsurface effects on SIR

The ranges of $K_s$ is well known for undisturbed soil types. Soil grain size, porosity, and chemistry affect the behaviour of infiltrating water and therefore the SIR curves (Figure 23). For example, clayey soils hold water more tenaciously than a sandy soil due to the particle charges and smaller pore structures. Clays swell by water adsorption so their SIC is reduced. Loamy soils have finer texture than sandy soils, but SIC can be high due to macro-pore formation (better clumping of soil and root formation). However, it is unclear to which extent these relationships are held for disturbed urban soils which exhibit varying degrees of mixing and compaction. Sandy soils underneath semi-permeable seals do seem to positively affect SIR (Bean et al. 2007) meaning that SIC could be negatively impacted by subsoils like clay. Dreelin et al. (2006) concluded that for light rainfall events, porous pavement with clay sub-grade produced 93% less runoff than an asphalt seal over clay. This suggests that the porous pavement is still effective over clay, but still says little about the impact of clay on SIR.

Infiltration rates are expected to decrease overall with increasing compaction. But the effect of compaction on infiltration is a consideration often overlooked in surface infiltration models (Pitt et al. 2008, Pitt et al. 2002). Instead, land use class (e.g. ‘agriculture’) is commonly used to derive SIC (e.g. Herath et al. 2003). However, compaction caused by trampling, grazing, or other overburdens reduces soil porosity and macro-pore structure and has consequences on $K_s$ (Figure 24), water holding capacity, soil quality, and vegetative health. Compaction is measured by bulk density (BD, weight per unit volume) or resistance force to a penetrometer (units of kPa). Typically, around 1.6 g/cm$^3$ is considered the maximum threshold for root penetration of plants in sandy soils and 1.14 – 2.16 g/cm$^3$ has been documented for urban soils (Jim 1998).

In a penetrometer study on sandy soils in North Central Florida, a 70-99% reduction in overall infiltration rate was recorded when comparing non-compacted (pre-development) to compacted (post-development) soils, and compaction tended to increase with depth (Gregory, et al. 2006). A final SIR of 10-20mm/hr was recorded for a BD around 1.8 g/cm$^3$ for a sandy soil.

Figure 23.
Saturated hydraulic conductivity varies by soil texture. Sandy soils exhibit higher $K_s$ compared to silty soils because they hold onto water less tenaciously (A). Infiltration rates of different soils (B).
Compaction may be a more practical indicator of SIR than ASM. For clayey soils, compaction and ASM have a notable impact on final SIR but not nearly for sandy soils (Figure 25, Gregory et al. 2006, Pitt et al. 2008). Compaction can be used to explain the relationship between land use and infiltration rates in urban soils. When comparing residential lawns to other open green spaces, Yang and Zhang (2011) showed that residential lawns had a final SIR 3 to 5 times greater than urban parks (240mm/h for residential lawns versus 40-90mm/h for patronized parks, Figure 26).

2.2.3 Age effects on SIR

Age (or time) and land use has been related to compaction and siltation. Urban soils in newly developed residential areas appear to have lower infiltration rates than older residential areas (Figure 27). Newly imported soils are deficient in organic matter, nutrients, and structure and often experience additional compaction due to equipment from the construction process. The impacts of newly disturbed soils seem to be attenuated over time as microbial biomass, organic material, and soil structure improves, especially in the presence of deepening roots from maturing trees and bushes (Yang and Zhang 2011, Scharenbroch et al. 2005, Woltemade 2010). Contrarily, the duration of patronization for urban parks and sports fields in Hong Kong tended to increase soil compaction when measured up to 100cm depth (Jim 1998). Thus, age effects depend on the land use in question.

Figure 24.
Saturated hydraulic conductivity is generally reduced by increasing bulk density. These USDA $K_{s}$ soil triangles show the $K_{s}$ curves for high, medium, and low BDs for all soil textures.

Figure 25.
Compaction and antecedent soil moisture has a sizable effect on SIR for clay soils but only compaction affects SIR for sandy soils.
Figure 26.
Yang and Zhang (2011) showed SIR was 3-5 times greater for residential lawns (RA) than for urban parks (P), campus lawns (C), and roadside green (RG). Image below of compacted informal pedestrian path of an urban park in Amersfoort, NL.

Figure 27.
Yang and Zhang (2011) also compared old and newly laid residential soils and found that older soils had greater SIR. Bulk densities of typical soil types are compared to that found in patronized urban parks of Hong Kong and residential lawns (from Brady and Weil, 2009 and Jim 1998).
Research also shows that the age of a semi-permeable surface matters, which can also explain why two similar pavers might have different SIR. Eventual clogging and siltation of surface voids, compaction, and crusting of geotextiles can negatively impact SIR (Fassman and Blackbourn 2010, Schmidt and Michael 2004). Proximity to fines (erodible fine soils and sands) exacerbates the age effect. Bean et al. (2007) demonstrated that final SIR for CIP in proximity to fines was significantly lower (80 cm/h) than maintained landscapes (2000 cm/h), a reduction of 96%. Other factors affecting SIC include the seasonal impacts on infiltration and storage (effect of soil freezing, crustling, surface temperature and moisture), and the impact of vertical flow forces on infiltration.

2.3 Mapping land cover and surface infiltration capacity

Few studies have been published on automatic mapping of urban SIC with concerns to level of detail, except for where flood models have been tested and a characterization of the water catchment area was needed. In the ‘quick and dirty’ first approach, classic air-photo interpretation (API) and ground-truthing can be done to identify land cover. Pauleit and Duhme (2000) employed this method to map infiltration and sealed surface per ‘land cover unit’ (map partitions according to land use). With this, urban design interventions could not be evaluated for infiltration potential based on the mapping units (Figure 28). The percent ‘infiltration’ class here has ambiguous meaning. However, the mapping units are useful for citywide overviews.

API requires expert knowledge in order to identify meaningful objects to classify. However, it introduces human error and can be time consuming. A recent comparative study using 0.125m resolution aerial photography concluded that an object-based classification approach using eCognition image segmentation software could effectively replace API methods in high-resolution land use mapping since objects are delineated more quickly and objectively. Any erroneously classified objects could be mitigated by using fuzzy classifiers (IF, AND, OR, NOT conditions), other spatial data types, or manual correction (Kampouraki et al. 2008). From a cartographic perspective, this yields more readable land cover maps over per-pixel mapping. From a cognitive perspective, however, a meaningful object should be up to the intended map user. Surface objects of hydrological relevance would include the different surface treatment areas as discussed in the previous subsections.

2.3.1. Early methods of automated urban land cover mapping

In this study, ‘land use’ mapping describes how the land is used (e.g. residential, industrial, park, mixed-urban etc.) whereas ‘land cover’ mapping illustrates patterns of detectable surface cover of general classes (e.g. water, vegetation, bare soil, and urban). Many urban extent maps mix land use and land cover (LULC) in a map, depending on the purpose. Often for determining urban extent and morphology. These maps have then been applied to urban water models, but not yet adapted.
Until recently, research in urban remote sensing focused on automated detection of urban growth with multi-spectral data of medium spatial resolution (around 10-100m or more, Weng 2012). The map produced by Myeong et al. (2001) shows just five land cover classes with 0.61m resolution multispectral imagery (Figure 29). General land use covers were distinguishable from only a few spectral bands because of their high separability in spectral signatures even within the visible spectrum (Figure 30). These were generated by both supervised and unsupervised pixel-based classification methods.

Using medium resolution images for per-pixel urban surface mapping introduces classification challenges. Unlike vast homogeneous agricultural fields or forested areas, the urban fabric is a complex heterogeneous mixture of materials, with relatively small object sizes and irregular object shapes (Blaschke 2010). For example, the average width of a concrete sidewalk in North America is 1.5m and can be even narrower in European city centers. Coarse resolutions cannot adequately discriminate small urban objects of interest like sidewalks or trees (Figure 31). This relates to a well-documented problem of the mixed-pixel (Weng 2012). A single image pixel might include signal reflections of multiple materials thereby increasing confusion of ‘pure’ spectra of known materials (also called spectral end-members, EM). Materials that are often confused are roof materials, road materials, bare soils, parking lots, and non-photosynthetic vegetation (Herold and Roberts 2010).

Membership of a pixel to the ‘urban’ class requires the detection of material other than vegetation, water, or bare soil, or a majority detection of several man-made materials. The latter option is a form of sub-pixel analysis (or spectral un-mixing). For example, when the threshold of percent impervious cover is used as a classification rule. Confusingly, ‘impermeability’ or ‘im-
Figure 29.
High-resolution data used for general land cover classification of Syracuse, New York (Myeong et al. 2001).

Figure 30.
Spectral signatures of general land cover classes are separable by few bands.

Figure 31.
Increasing spatial resolution reduces the mixed-pixel problem by containing more 'pure' spectral responses, and enables better object shape recognition.
perviousness’ is synonymously used with a class called ‘urban’ (e.g. Canters et al. 2011, Leinenkugel et al. 2011) although any urbanist or hydrologist may easily reject this typification. Few attempts have been made to standardize land use classes that have hydrological applicability (Golden et al. 2009). The previous sections established that it is inaccurate to assume that all urban areas are completely impervious nor that two lawns have equal SIR. Such assumptions could lead to inaccurate or imprecise hydrological models.

Linear spectral unmixing techniques have been developed by using EM extracted from hyperspectral data. This expands the spectral libraries of urban materials for sub-pixel analysis (Heiden et al. 2007, Heiden et al. 2012, Weng 2012). But, too many EM choices could re-introduce spectral confusion. Furthermore, the problem will persist as the objects of interest continue to decrease in size. Even with the increasing availability of VHR optical data for urban areas from airborne (e.g. AVIRIS and HyMap) and satellite sensors (e.g. QuickBird or IKONOS), object edges become more complex introducing within-class spectral confusion (Weidner 2006).

Within-class separability can be achieved by using spectral data between 1350-1600nm (Figure 32), the spectral range where urban surfaces are most separable (Herold et al. 2003). Heiden et al. (2007) argue that up to eleven spectral shape features determined from hyperspectral data can be used to separate spectral signatures of urban materials (Figure 33). The required wavelengths for analysis depend on the material under examination.

Segl et al. (2003) used a 6.1m resolution hyperspectral image (DAIS 7915) of Dresden, Germany to improve EM selection by first using shape rules to identify buildings in the scene, and using these pixels to point to EM seeds. Band ratios with thermal data (short-wave infrared or SWIR) were used to improve rooftop distinction from other surfaces since they were assumed less capable of holding moisture.

Airborne data acquisition geometry introduces the problem of ground shading and occlusion by erected structures like buildings and trees (Lu et al. 2011, Shackelford and Davis 2003, Figure 34). Classification errors can be greatly influenced by the view geometry to the received spectral response. The off-nadir regions of images accounted for up to 21% classification error of the ‘built-up’ class using 4m resolution imagery and up to 16% of the overall classification errors (Van der Linden and Hostert 2009). Object-based image analysis (OBIA), data fusion and hybrid data processing techniques are being explored to overcome shadow effects, but occlusion by leaning objects remains a challenge. There is little knowledge on the impact of leaf-on and leaf-off imagery on classification accuracy.

The considered classes for object assignment has an impact on classification accuracy. Verbeeck et al. (2011) used two class levels and nearest-neighbour classification from 2.44m multispectral QuickBird-2 imagery (Figure 35). Level 1 was land cover (pervious, impervious, and shadow), and Level 2 land use (roof, pathway, garden, shadow). The results showed lower accuracy with the land use classes. This could also mean that discrimination of super-class ‘impermeable’ into sub-classes could also reduce classification accuracy.
Figure 32. Spectral range of 1350-1600nm can be used to resolve within-class spectral confusion of many urban land covers (Herold et al. 2003).

Figure 33. Other numerical descriptions of spectral signatures could be used to separate spectral signatures (Heiden et al. 2007).

Figure 34. The view geometry of VHR imagery introduces the problem of shadow and ground occlusion by leaning objects as seen in the urban scene used by Shackelford and Davis (2003).
Van der Sande et al. (2003) used a 1m resolution IKONOS-2 pan-sharpened imagery of Borgharen, Netherlands, to map land covers for flood risk assessment in a regional floodplain area. A region-growing segmentation using eCognition software and a knowledge based (topographic information) classification approach was applied with an overall mapping accuracy of 74%. However, the classes used (like ‘deciduous forest’, ‘mixed forest’, ‘sand’, ‘road’, ‘pavement’, ‘factory’) were intended to rationalize a floodplain friction map, rather than SIC. More importantly, a flood model sensitivity test showed that the higher resolution map, and distinguishing specific surface types related to friction (roughness), led to more accurate modeling results.

2.3.2. Data fusion and hybrid techniques

Mapping urban SIC should identify meaningful objects for both the urban designer and urban hydrologist. It was already suggested that for general urban LULC mapping, image segmentation approaches result in more readable maps. OBIA is an automated mapping technique involving the recognition of meaningful spatial objects in an image scene by segmentation and subsequent classification of each object based on spectral (or other) signatures (Blaschke 2010). Objects are recognized by segmenting the image into relatively homogeneous groups of pixels. Object edges can be detected where differences in spectral response are maximized. Several segmentation approaches (region-growing, edge detection, watershed) have been developed but are not explained in this review. Segmentation algorithms have been recently offered as packages of various commercial image processing software (IDRISI Selva and eCognition for example).

In an earlier urban drainage mapping study, Elgy (2001) used high-resolution (1.5m) multispectral image (11 Bands of visible to NIR) of Black Country, UK to compare supervised and unsupervised classification both with and without segmentation (Figure 36). The study concluded that image segmentation yielded a more readable land use map than with a pixel-based approach since object polygons provided better supervision for classification. Although, ‘readable’ was not defined. Lu et al. (2011) used maximum-likelihood classification rules from object pixels and showed the marked reduction of speckling by an OBIA mapping approach. But neither method sufficiently addressed issues of spectral confusion between similar surface materials and the classification of shadowed areas.
A hybrid classification approach can help deal with spectral confusion by requiring conformance to additional rules. For example, Myeong, et al. (2001) used a normalized difference vegetation index (NDVI) to help discriminate between shadowed grasses and other materials. Texture analysis (the measure of greyscale intensity variation in a 15x15 window, for example) was used to distinguish between grass and tree/shrub land covers. Comparisons between unsupervised classification of a 3-band image, the combination of 3-band, NDVI and texture, and subsequent image smoothing showed 78.2%, 83.2%, and 84.8% accuracy respectively.

Shackelford and Davis (2003) used a multi-spectral, pan-sharpened IKONOS image of a dense urban area to compare an OBIA approach with pixel-based (maximum likelihood classifier) and concluded that OBIA combined with fuzzy classifiers using DEM (e.g. class ‘building’ when above specified height) improved accuracies from 10-20% (Figure 37). The classes were limited to: road, building, impermeable, grass, tree, bare soil, shadow. Road and impervious/impermeable class definitions are ambiguous for deriving realistic SIC.

The combination of spectral with geometric data like digital surface models (DSM) and/or digital elevation models (DEM) can help resolve spectrally confused objects or pixels. The work of Shackelford and Davis (2003) exemplify the classification challenge of shadowed surfaces. Shadow objects were somewhat resolved by Verbeek, et al. (2011) by guided classification using a reference image with less shadow. Overall accuracy of this method was a moderate 64% and could probably be improved by using hyperspectral data (Figure 38).
Figure 37.
Shackelford and Davis (2003) compared a pixel-based versus object-based fuzzy logic classifier of IKONOS multispectral data and reported up to 20% improvement in accuracy using object based classification.

Figure 38.
Verbeek et al. (2011) classified shadows using a reference image with less shadow.
Heiden, et al. (2012) used 120 bands of a hyperspectral (HyMap), 3.2 m resolution image of Munich city center to classify imperviousness by spectral un-mixing and pixel-based classification. A DSM was used for segment-based EM selection from the hyperspectral image (Figure 39). Certain height thresholds were used to differentiate between two spectrally similar objects. The ‘urban structure type’ mapping unit used is reminiscent of Pauleit and Duhme (2000) (Figure 40). This mapping unit is based on an agglomeration of urban ‘building blocks’ (boundary of developable land), a term derived from German urban planning policy. Greiwe and Ehlers (2005) used similar data types but calculated the spectral angle mapper (SAM) scores per pixel. SAM scores compare the spectral signatures to end-members by treating them as vectors and comparing vector direction. Accuracy jumped from 51.8% using only the 3-band orthophoto (0.125 m resolution) to 73.3% using also DSM data and SAM score classifiers (Figure 41).
Besides segment-based EM selection, surface geometry could also be used to directly improve object classification. Weidner (2006) used roof slope calculations from LiDAR data alongside HyMap hyperspectral data of an urban area in Karlsruhe, Germany to improve segmentation and classification of various roof types with fuzzy membership rules using 20 hyperspectral bands. A visual inspection of Figure 42 shows that roof slope improved the classification of buildings. Classification results of unsupervised classification using LiDAR intensity data showed roughly 10% improvements in accuracy following geometric and radiometric calibrations (Yan et al. 2012).

The use of dawn thermal infrared imagery was also suggested by Elgy (2001) as a way to identify permeable surfaces since dawn surface heat could be related to surface moisture. This makes sense since semi-permeable pavements tend to be cooler than pavements like asphalt and standard concrete due to their water holding capacity or high permeability (Nakayama and Fujita 2010). However, pavement type could easily be masked in the visible spectrum by coatings of paint and coolants (Haselback et al. 2011, Santamouris et al. 2011) so the use of thermal imagery could help distinguish special pavements. For example, a daily or hourly time series to see diurnal temperature changes might show that surfaces like lawns heat slower and cool faster than sealed surfaces. Correlating surface moisture and temperature over time could resolve some separability issues between the ‘impermeable’ sub-classes.

Surface temperatures and percent surface sealing was linearly correlated in a study of Berlin during July 1998 (Figure 43). An aerial measurement campaign was used to extrapolate diurnal surface temperatures over the entire city and correlated with several LULC classes - for example ‘water’, ‘green spaces’, ‘gardens’, ‘residential areas’, and ‘mixed areas’ (Kottmeier et al. 2007). A similar approach could be taken by correlating surface temperature and compaction. This could be complicated by the cooling effect of shading with VHR data but the average recorded surface temperatures might be useful in a probabilistic approach to land cover classification.
2.3.3. Notes on measuring surface roughness and compaction

Earlier discussion noted that siltation and roughness have an impact on water availability; and compaction can drastically reduce the overall SIR. Surface roughness is a property that can be analyzed using 0.2mm resolution DSM and hyperspectral data in the 1550-1750 nm range as was implemented by Croft and Kuhn (2009). This could be used to determine measures of roughness for semi-permeable surfaces. As an alternative, existing coefficients like Manning’s $n$ values can be used. It may be possible to quantify roughness by texture images (variations in grey levels).

Compaction, however, (as a function of age/time) is a more complicated story as it cannot yet be directly detected with remotely sensed data. Instead, it must be derived through other physical responses that can be directly detected. For instance, compaction has dire effects on vegetation health. The reduction of soil porosity make root penetration a challenge, reduce soil aeration and available water for nutrient transfer and uptake by roots. This manifests as decreased photosynthesis, abnormal leaf growth, leaf dryness, reduced nutrient uptake and photosynthesis, senescence, and the excessive production of ethylene gas (Kozlowski 1999).
To find the particular relationship between compaction and each of these biological responses is beyond the scope of this review, but it might be reasonable to use overall plant stress as an indicator of compaction. Healthy vegetation generally has higher NDVI values than stressed vegetation. For instance, Xiao and McPherson (2005) used an NDVI threshold to map healthy and unhealthy trees using multi-spectral high-resolution aerial photos (Figure 44). Appropriate NDVI thresholds for different plant species must first be established. Plant ethylene production, which is a stress-induced plant hormone, has been detected from closer range laser detection (Cristescu et al. 2013) but it seems not yet for larger urban areas.

Unfortunately, assuming that plant stress is only a factor of compaction is a gross assumption and ignores other possible causes like fungal or bacterial diseases, heat stress, or drought, to name a few. To reduce the uncertainty, surface moisture conditions might also provide an indication of plant water availability due to compaction. Plants undergoing water stress can be detected by indices like the normalized difference water index (NDWI, Gao 1996). But chlorophyll fluorescence (indicating levels of photosynthesis) by using a reflectance index of wavelengths 685 and 740nm has been suggested as a more reliable method for establishing health. This is independent of NDVI and can be confirmed by comparing temperature trends since dryer plants are expected to be warmer (Zarco-Tejada et al. 2009). A combined information set of plant temperature, dryness, and fluorescence could help indicate compacted areas within an image.

2.3.4. Notes on vegetation detection and mapping

NDVI thresholding has also been used to assist with tree crown object detection (Figure 45). Ardila et al. (2012) used an NDVI threshold on QuickBird imagery to identify vegetation objects, then located the brightness centers of objects to extract candidate tree crowns from various contexts (tree clusters, geometric shape and adjacency to shadow, region-growing segmentation of vegetation objects). This multi-scale, multi-attribute extraction approach uses both spectral and spatial information which is interesting for SIC mapping.
Urban treed areas have also been detected in a refined way by a mix of texture and spectral features and fuzzy classification rules. Zhang (2001) intersected a treed/non-treed image derived on texture features with a vegetated/non-vegetated image using an NDVI threshold to identify treed areas. Using texture features increased user’s accuracy by almost 30% when using 0.25m near-infrared, red, and green bands (Figure 46). Texture measures also yield good results. By using a texture image with spectral information, Zhang (2001) was able to increase tree detection accuracy by about 30% (97% accuracy). The potential application of a textural-spectral approach to surface type detection is obvious.

Figure 45. Tree crown pixels from Ardila et al. [2012] were detected by NDVI thresholding and context-sensitive decision rules. Subset (a) original false color composite, (b) vegetation pixels with NDVI threshold, (c) NDVI distribution of pixels in (b), and (d) final set of pixels (yellow) representing the tree crown after a further NDVI thresholding.

Figure 46. Zhang (2001) used both texture feature images and multi-spectral images to detect urban treed areas. Accuracy increased 30% by adding texture information. Subset (a) shows the original image, (b) treed area regions (grey) using multi-spectral data and (c) treed area regions using texture and spectral features.
2.4 Summary

The purpose of the literature review was to position this study within the multi-disciplinary context of urban water management, linking the societal, environmental, and practical reasons behind water-sensitive urban design interventions to a SIC map that might inform them. The physical nature of the objects to detect (surface types) were also described to rationalize the specific land cover classes to be detected from the VHR imagery of Amersfoort. Finally, a methodological benchmark was established by a review of tried methods using VHR multi- and hyper-spectral data.

Basic concepts in urban hydrology were explained. SIC describes the potential of a rainwater to infiltrate into the surface and is measured by the SIR. Figure 47 illustrates the six key variables affecting SIR and are listed below:

1. Surface cover void ratio (water-penetrable surface area reduced by siltation over time).
2. Surface material (affecting adsorption).
3. Surface roughness (including soil crusting, affecting flow resistance and overall SIR).
4. Subsurface hydraulic conductivity, $K$ (or the sub-grade permeability/transmissivity) where the sub-grade layer with the lowest $K$ is limiting, and can be approximated by empirically determined final SIR.
5. Subsurface compaction (measured by bulk density or void ratio and indicated by use and age relationships).

Particular surface seals or pavement types are hydrologically meaningful because the SIR magnitude and range vary. This is explained by the physical nature of urban surfaces (affecting water availability and ability to transmit), dictated by the site preparation process.

The research presumed that, rather than deriving SIC from generic land covers used in many topographic maps (like the GBKN), a SIC map should be derived from hydrologically relevant land cover classes (Table 2). Final SIRs (equivalent to the saturated hydraulic conductivity, $K_s$) have been measured in situ from various pavement studies and SIRs show some amount of separation within and between classes. A SIC map would provide a visual and numerical estimation of the infiltration potential in an urban catchment, which can be useful for urban heat, drought, and flood modeling, as well as urban design.

The SIC map would essentially show the minimum or maximum documented final SIR of each class (ignoring the effects of horizontal flows). The more realistic and conservative scenario would be to use the minimum SIRs. Maximum SIRs are likely observed for new maintained pavements only. In this respect, even further precision could be achieved by using information on pavement age, compaction, or siltation parameters, to more precisely predict SIC.
Table 2. Hydrologically relevant land cover classes with min and max final SIR and \( n \)-coefficients

<table>
<thead>
<tr>
<th>class</th>
<th>min SIR (mm/hr)</th>
<th>max SIR (mm/hr)</th>
<th>( n )</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. asphalt concrete (AC)</td>
<td>0</td>
<td>0</td>
<td>0.015</td>
</tr>
<tr>
<td>2. concrete aggregate (CA)</td>
<td>0</td>
<td>0</td>
<td>0.016</td>
</tr>
<tr>
<td>3. stone tile (ST)</td>
<td>0</td>
<td>0</td>
<td>0.014</td>
</tr>
<tr>
<td>4. brick interlocking paver (BIP)</td>
<td>6</td>
<td>15</td>
<td>0.015</td>
</tr>
<tr>
<td>5. concrete interlocking paver (CIP)</td>
<td>20</td>
<td>200</td>
<td>0.030</td>
</tr>
<tr>
<td>6. concrete grid paver (CGP)</td>
<td>70</td>
<td>130</td>
<td>0.030</td>
</tr>
<tr>
<td>7. porous concrete (PC)</td>
<td>110</td>
<td>50,000</td>
<td>0.030</td>
</tr>
<tr>
<td>8. natural gravel (NG)</td>
<td>50</td>
<td>90</td>
<td>0.028</td>
</tr>
<tr>
<td>9. stone gravel (SG)</td>
<td>50</td>
<td>160</td>
<td>0.035</td>
</tr>
<tr>
<td>10. synthetic turf (STT)</td>
<td>30</td>
<td>190</td>
<td>0.200</td>
</tr>
<tr>
<td>11. lawn and short grass (LN)</td>
<td>40</td>
<td>240</td>
<td>0.425</td>
</tr>
<tr>
<td>12. shrub and woody vegetation (SH)</td>
<td>200</td>
<td>620</td>
<td>0.150</td>
</tr>
<tr>
<td>13. bare soil (BS) - sandy</td>
<td>50</td>
<td>700</td>
<td>0.025</td>
</tr>
<tr>
<td>14. water and canal (WA)</td>
<td>n/a</td>
<td>n/a</td>
<td>n/a</td>
</tr>
</tbody>
</table>

*Refer to Figure 19 for sources. Values in italics are adjusted based on expert knowledge.

Figure 47. Six variables affecting surface infiltration capacity.
Even without considering the added precision from detecting compaction and siltation, the class specificity should add more information compared to topographic data. Thus, if a land cover map of the hydrologically relevant land covers could be derived from VHR multi-spectral imagery at the right object resolution, a more realistic SIC map could be derived.

The previous land cover classification studies showed difficulties in detecting far fewer classes with lower image resolutions. The problem may lie in the considered classes (e.g. ‘road’ class is spectrally impure). No examples of using remotely sensed imagery to detect particular semi-permeable land covers were found, nor for distinguishing between brick and concrete aggregate roads, for example. It seems that subdividing the ‘impermeable’ land cover class may reduce classification accuracy.

For applications like urban design, map readability (from a cognitive standpoint) is important and affected by the object resolution and shape. To improve object recognition in a classified map, segment-based approaches are favoured over per-pixel, yet it is unclear what the effect of image resolution has on the accuracy of segment-based approaches given the same classification rules, and especially classes for the hydrologically relevant land cover classes.

Image classification challenges remain with multi-spectral images due to spectral confusion of urban materials, which are best discriminated with hyperspectral data, especially in the 1350 to 1600 nm range. A time series of thermal data (hours or days) could provide added information to discriminate between sealed surfaces. But few expectations on classification accuracy can be made for the classes in Table 2 using only 3-band imagery.

Fuzzy classifiers using indices like NDVI and segment-guided classification training show promising results in resolving spectral confusion. Texture, height, and thermal information can overcome some classification errors caused by spectral confusion from lower-resolution imagery. However, thermal data was unavailable for this research.

Classifying shadowed objects and occluded surfaces remain a significant challenge since spectral signatures are compromised in shadowed objects. Shadow object classification might be improved by geometric rules (e.g. shape and adjacency) in addition to spectral signatures or more practical methods such as images taken with different illumination angles or using NDVI.
There are indeed multiple dimensions to land cover mapping, from choosing pixel or segment-based, crisp or fuzzy rules, rule statistics, number of data types, and data resolution. The ‘best’ mapping workflow depends on the application of the generated map. Figure 48 illustrates the exploratory approach to the research, spanning across classification methods in order to gain a first impression on mapping SIC with VHR imagery.

Data available for this study included a 0.25m NIR/R/G image of Amersfoort, Netherlands, a 0.035m RGB image, a 0.5m resolution DEM (AHN-2), and topographic maps (TOP10NL, GBKN). Considering that the studies producing the most interesting maps used hyperspectral data, the classification experiments in this research explore if comparable accuracies could be achieved with lower -spectral but higher -spatial resolution data.

Chapter 3 details the land cover mapping experiments conducted in order to compare approaches (pixel versus segment-based), to crisp metrics (spectral angle mapper, minimum euclidean distance, and maximum likelihood), to modified crisp decision rules (region classifiers and NDVI) to try to deal with spectral confusion, shadowed image pixels, and occluded image pixels. It also explains how the SIC maps were derived and applied in a pluvial flood model.

![Figure 48](image.png)

Three dimensions to land cover mapping based on the literature review. The objective of the study is to gain a first impression of mapping SIC using VHR and DEM data with various classifiers.
If a land cover map can identify hydrologically relevant surface covers at the necessary object resolution, then a more detailed SIC map can be derived from it than from topographic or urban extent maps. The literature review provided indefinite insight into the feasibility of detecting the hydrologically relevant land covers using VHR multi-spectral imagery. Thus this research took a more exploratory look into the performance of various classifiers to map the specific land cover classes at the needed object resolution. To assess the derived SIC maps from this data, the impact of class specificity was analyzed and demonstrated in a pluvial flood model.

The research was undertaken in three parts: segmentation of the NIR/R/G image using a DEM, establishing a definition of readability as a function of object resolution; land cover classification with the NIR/R/G image data (manually and automatically based on spectral and textural information, and using crisp and fuzzy classifiers with area/adjacency rules); and finally derivation and evaluation of the SIC map based on in-situ SIRs reported in literature. To demonstrate if mapping the hydrologically relevant land cover classes has any bearing in water management, the SIC maps were input into a pluvial flood model.
3.1 Case Study - Amersfoort, Netherlands

Amersfoort is a Dutch city in the province of Utrecht (52.1°N 5.4°E). Today, it is home to a population of 150,000 with a population density around 2300 inhabitants per km² (half that of nearby Amsterdam). The medieval center, covering nearly 1 km², is its main tourist attraction but the surrounding urbanized extent reaches more than 60 km² (Figure 49). The residential forms are like most Dutch cities with mid-rise, street-facing, row housing and detached houses arranged along curvilinear two-lane residential streets. Two meter sidewalk widths and bike lanes sealed with interlocking brick or concrete pavers are typical. Various colours of concrete mixes and asphalt can be found in addition to natural gravel, crushed stones, and short grasses, bushes, synthetic turf, metals (i.e. railway) and open water are the main surface classes (Figure 50). Annual precipitation charts show that on average Amersfoort experiences 24 days of rain per month, with monthly rainfall ranging from 56 to 83mm. Usually this is sustained light rain, rather than sudden downpours.

In August of 2011, Amersfoort was selected as one of nine case studies for a public-private innovation venture called HydroCity. HydroCity was an innovation project funded by the Netherlands Ministry of Infrastructure and Environment, to demonstrate the benefits of an ‘open-innovation’ framework for urban water management and policy-making. The core objective
of the project was to collect and combine a variety of geographic and spatial data for flood risk analysis, in order for cities to identify opportunities for increasing resilience to excessive rainfall events. The strategic deliverable of this project was an online portal that would offer a common operational picture about vulnerabilities, infrastructure, and flood predictions to water managers. Nine case studies were chosen where the framework was evaluated for feasibility in collecting, streamlining, analyzing and sharing the data.

For Amersfoort, a small area was chosen which covered six urban blocks, or approximately 0.7 km². Aerial imagery and topographic data was combined to produce a land cover map using relevant Basic Registration Large Scale Topography (BGT) classes. This was used as an input into a developing 2D pluvial flood model (PriceXD) to demonstrate the possibilities of combining the datasets. This study builds upon this work by testing a methodology to generate a more informative and realistic land cover map of sealing type that can be utilized in models like PriceXD in addition to the thematic map of SIC that can be used to identify urban design opportunities. Other uses are suggested in Chapter 4.

### 3.2 Data

The multispectral imagery and DEM were the primary data sets for this research. The data was delivered radiometrically corrected and orthorectified to a UTM31N projection on a WGS84 reference system, and converted to 256-greyscale 3-band GeoTiff images. Table 3 lists the data specifications.

<table>
<thead>
<tr>
<th>composite</th>
<th>resolution</th>
<th>year</th>
<th>extent</th>
</tr>
</thead>
<tbody>
<tr>
<td>NIR/R/G</td>
<td>0.25m</td>
<td>2011</td>
<td>LAI</td>
</tr>
<tr>
<td>R/G/B</td>
<td>0.035m</td>
<td>2011</td>
<td>LAI</td>
</tr>
<tr>
<td>R/G/B</td>
<td>0.25m</td>
<td>2009</td>
<td>SAI</td>
</tr>
<tr>
<td>DEM [AHN-2]</td>
<td>0.5m</td>
<td>2013</td>
<td>LAI</td>
</tr>
<tr>
<td>TOP10NL</td>
<td>n/a</td>
<td>2013</td>
<td>LAI</td>
</tr>
<tr>
<td>GBKN</td>
<td>n/a</td>
<td>2011</td>
<td>SAI</td>
</tr>
</tbody>
</table>

### 3.2.1 Aerial imagery

Three sets of aerial images were available for processing. The main dataset was the 2011 orthorectified images provided at a resolution of 0.25m in the NIR/R/G bands for the large area of interest (LAI, 12.6km², 13180 x 15320 pixels). An image with the RGB channels was also available at 0.25m resolution but captured in 2009 and only for the small area of interest (SAI, 3438 x 3390 pixels). Figure 51 shows the SAI extent within LAI. The two images did not register exactly since the view angles for the two acquisi-
Figure 51.
[Above] The 2009 RGB colour-composite showing the extent of the SAI. [Right] Views of NIR/R/G colour composite of the SAI.
tions were inconsistent causing different leaning effects of tall objects. A 2011 0.035m resolution RGB image of the LAI was available, but also with registration issues to the NIR/R/G image, at a leaf-off moment. The 0.25m NIR/R/G and 0.035m RGB composite was used for the classification experiments.

### 3.2.2 Elevation data (DEM)

Elevation data in the Netherlands is provided at a nominal fee from the Actueel Hoogtebestand Nederland (AHN). The second generation, AHN-2, is a model of elevation above sea level, provided at 0.5m cell resolution with 5cm elevation accuracy. It is classified from LiDAR measurements taken between the year 2007 to 2012. This model is filtered for buildings and the ground. The ground AHN-2 data for the LAI was acquired as an ASCII file and read into a raster image using GDAL in Python script (Figure 52).
3.2.3 Topographic data

Topographic data in the Netherlands is freely available. Official vector-based topographic data provided by the Dutch Cadaster includes the Top10NL, Top25NL, and as a raster, Top25raster (Figure 53), which is a part of the Basisregistratie Topografie (BRT), or the Basic Topographic Registry. These are base files that identify functional and geographic boundaries of basic infrastructure like roads, buildings, and relief at a scale of 1:5000 or 1:25000. The Grootschalige Basiskaart Nederland (GBKN) is a basic registry offered at the scale of 1:500 to 1:5000 also in vector format. In an effort to streamline the topographic data collected from various agencies, the Dutch government initiated the Bill for Basic Registration for Large Scale Topography (BGT), where all agencies will have access to topographic data at the same large scale. However, the BGT for Amersfoort was being compiled at the time of this study.

Figure 53. Top10NL topographic data of the LAI.
3.2.4 Soil and shallow subsurface

Soil data in the Netherlands is collected and mapped by Alterra, at Wageningen University and is available free of charge through an online portal. (Figure 54). Maps are available at scales of 1:50000 and 1:25000. However, soil data for urban areas are unspecified at the 1:25000 scale and shallow subsoil type can only be assumed from the 1:50000 scale. Shallow subsurface profiles in the SAI were obtained from the Data Informatie Nederlandse Ondergrond (DINO) free of charge, but was not analyzed.

3.3 Overview of experimental set-up

The experiments are explained below in three parts: segmentation, automatic classification, and finally thematic mapping of SIC and input into a pluvial flood model (Figure 55). In order to evaluate the performance of an automating a land cover map, some initial ground-work had to be completed including manually classifying the imagery. A segment-based classification approach was favoured for readability and accuracy, and was compared against a modified per-pixel classification. The effect of using texture features for classification was also explored before finally creating the thematic map of SIC.

3.3.1 Developing a segmentation workflow and reference map

A manually classified map of the SAI was created by API, and used as the reference map. Because image segmentation tools are now so readily available in image processing software packages, an assisted API was con-
ducted by first segmenting the 0.25m NIR/R/G image with and without DEM data, and subsequently classifying segments by-eye rather than tediously digitizing polygons or classifying pixel regions. This saved a significant amount of time and avoided possible digitization errors. It did mean that the map readability and accuracy depended largely on the segmentation quality since segment shapes were unaltered during the classification phase.

3.3.2. Experiments with automatic land cover classification rules

Subset-1 (SS1, Figure 56) was used for the supervised automatic classification experiments using only the NIR/R/G data. Two approaches, segment-based and per-pixel were compared and tested with three classification metrics - the spectral angle mapper (SAM), minimum euclidean distance to the class mean (MD), and maximum likelihood to class mean (ML) using equal prior probability and sampled prior probabilities from a training set. Crisp rules (one condition for decision) and fuzzy rules (more than one condition for decision) were also tested with spectral data. The impact of splitting the training set into illuminated and shadowed classes, and grouping the classes (generic classes) was also tested with every metric. This resulted in a total of 22 maps that were compared against the manual land cover map for accuracy (producer’s accuracy, user’s accuracy, and kappa coefficient).

Subset-2 (SS2, Figure 56) of the 0.035m RGB image was used to experiment with texture features in automated classification using the same segments.

Figure 55.
The experiment workflow for this study includes three main steps: image segmentation, segment classification, and map application in a pluvial flood model.
3.3.3. Land cover map application: deriving a SIC map and input into a pluvial flood model

Maps with the specific and generic classes by manual and ML classification were translated into a map of maximum and minimum final SIR and compared in terms of SIR distribution and extent. To assess the impact of lower class specificity and object resolution on SIR distribution within an urban catchment, the maps were input into a pluvial flood model. Peak runoff time and volume were compared.

3.4 Developing a segmentation workflow and reference map

Chapter 2 mentioned the advantages of segment-based land cover classification on accuracy and map readability. Image segmentation is a large field of research in itself and the objective of this study was not to develop new segmentation algorithm, but to gain an impression on the utility of segmentation generally as part of an overall workflow for mapping SIC with VHR imagery.
3.4.1 Image segmentation tests

This study acknowledges that there is no ‘perfect’ segmentation, and the quality of the segmented image is ultimately judged by the users’ criteria. The literature showed no clear method of robustly evaluating a segmented image in terms of readability. Thus an evaluation tool was developed to address this need from the perspective of urban design and hydrology.

The software package IDRISI Selva was used to segment the 0.25m NIR/R/G image. IDRISI Selva uses a watershed approach to segmentation in a three step process. First, the variance is calculated for each pixel within a user-specified kernel size (e.g 3x3) for each input channel (bands). Increasing kernel sizes covers a larger spatial extent thereby diluting the variance intensity. This might be useful for certain applications that require classification of very heterogeneous areas like urban gardens.

The result is a variance image, where higher variances indicate the probability of being an object edge. Each variance image is weighted by the user and summed to form a single variance image. Then, watershed lines are defined based on the catchment areas from the summed variance image (variance being treated as a topological surface). To be sure that the catchments are really separable objects, a third and final step is to merge watersheds based on similarity rules. In IDRISI Selva, similarity is determined by difference in the mean and variance between two adjacent watersheds up to a user defined threshold. Moreover, the user can weigh the importance of mean and variance (from 0 to 1) for a weighted sum of differences. Thus, increasing the threshold (more leniency) will increase the segment size (Clark Labs, 2009).

A segmentation workflow was developed using an arbitrary subset of the SAI. This area included a variety of textures and land covers representative of the SAI and had a dimension of 1100 x 1070 pixels (approximately 0.074 km²). An improved method was tested on a second arbitrary subset of the LAI (2362 x 2392 pixels, 0.35 km²), which included interesting covers such as sand, synthetic turf (football fields) and densely forested areas no present in the first subset (refer to red-lined regions in Figure 51). Given the results from these subsets, the selected workflow was implemented and verified on SAI.

It was unclear what the optimal window size or similarity threshold should be for images of 0.25m resolution. Thus, segmentation sensitivity tests to two kernel sizes (3x3 and 9x9), three tolerance values (default at 100, 70, and 50), and three data combinations were conducted.

Firstly, the objective was to determine which data combination yielded the best segmentation results. Each set was tested with the three tolerance values. The AHN-2 DEM was used to first remove all building pixels from the multi-spectral image, since only the surfaces were of interest. The side-effect was that leaning buildings were occluding some surfaces (Figure 57). This had to be ignored in the segmentation process, and manually resolved in the land cover classification step.
The data combinations were:

1. 3-band multispectral data (256-greyscale for three channels, NIR/R/G)
2. 3-band multispectral and DEM as fourth channel (resampled to 0.25m resolution cell size)
3. 3-band multispectral and the normalized vegetation difference index (NDVI, as fourth channel) calculated by the following formula:

\[
NDVI = \frac{(NIR - R)}{(NIR + R)}
\]  

A positive NDVI indicates the presence of photosynthetic vegetation. By placing a threshold of 0.15 on the NDVI image, vegetated areas were articulated (especially tree crowns and shrubs, Figure 58) while excluding most bare soil areas which tend to exhibit a low NDVI. This led to a fourth ‘separated’ method using data combination-2. In order to preserve the shapes of the vegetated areas, the vegetated pixels were segmented separately and intersected with a full image segmentation. This method was tested on all subsets and eventually to the SAI.

3.4.2 Segmentation evaluation and workflow refinement

The segmentation results were evaluated on readability. This means that evaluations pointed to the workflow that yielded the most readable map. Readability is a subjective notion dependent on the users’ needs but is an important notion in cartographic and map cognition. Here, the hydrologically relevant land covers (Table 2) and their spatial arrangements were the objects of interest and determined the required object resolution. Objects of interest should be identifiable from the resulting map. The number of segments, segment mean and median size, and number of segments below 1m² were counted to determine which object resolution corresponded to readability.
Readability was defined as the readers’ (in this case, the authors’) ability to identify the major organizing elements of the urban scene based on the segments alone, without any visible spectral information. High readability meant sufficient object resolution, as it created meaning to the reader.

The five features selected were buildings, roads, trees, lawns, and pedestrian paths. Shadow segmentation was a sixth non-feature category. Figure 59 conceptually illustrates this point on readability. Over-segmented or under-segmented features of interest hinder readability. Generally segments that were less than 6m² (96 pixels) were considered to be part of an over-segmented object. Sometimes this would be due to the segmentation method (e.g. separating the vegetation), but also obstructing objects, like small cars, boxes, or other objects and their shadows.

An evaluation scheme was developed to robustly quantify readability. Scores ranging from 0 (unreadable) to 5 (readable) were given to the readability of the six organizing features (Table 4). Scores were weighted based on the importance of proper and sufficient segmentation. It was more important that the segmentation sufficiently separated shadowed pixels from the object which cast it (e.g. tree shadows). The weighted average for each data set, threshold, and window size combination was calculated. The selected segmentation workflow had the highest readability score, while balancing object resolution. The selected workflow was validated on the SAI using the same three different thresholds and evaluated for readability.

Figure 58.
SAI pixels where NDVI \geq 0.15 reveals the vegetation areas (dark green).
Table 4. Readability evaluation criteria

<table>
<thead>
<tr>
<th>Feature</th>
<th>Qualitative question</th>
<th>Score of 5</th>
<th>Score of 0</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Buildings</td>
<td>Are building footprints clearly discriminated from the surface as one segment per building?</td>
<td>one segment per building</td>
<td>more than one segment per building</td>
</tr>
<tr>
<td>2. Roads</td>
<td>Are roads clearly distinguished in as few segments as possible?</td>
<td>representative shape and few segments</td>
<td>jigsaw puzzle pieces</td>
</tr>
<tr>
<td>3. Trees</td>
<td>Are tree crowns sufficiently segmented from their shadows into just a few segments?</td>
<td>one to three segments, not including shadows</td>
<td>segment includes shadow or other surface</td>
</tr>
<tr>
<td>4. Lawns</td>
<td>Are lawns clearly distinguished in just a few segments?</td>
<td>one to three segments</td>
<td>jigsaw puzzle pieces</td>
</tr>
<tr>
<td>5. Paths</td>
<td>Are pedestrian paths sufficiently segmented from nearby grasses or other surface materials?</td>
<td>representative shape and few segments</td>
<td>jigsaw puzzle pieces</td>
</tr>
<tr>
<td>6. Shadows</td>
<td>Are shadows sufficiently segmented from the objects which cast them, and into segments that can be classified as to the surface they are cast (indistinguishable)?</td>
<td>all shadows broken from object and by surface</td>
<td>most shadows merged with casting object</td>
</tr>
</tbody>
</table>

Figure 59. Segmentation A is more readable than segmentation B where objects are undersegmented (roads, lawns, buildings are unclear, for example).
3.4.3 Segment-based manual classification

The winning segmentation from the readability scores was used for manual and automatic land cover classification. Manual classification was done by knowledge-based API of the 0.25m NIR/R/G image in Quantum GIS (QGIS). QGIS is a powerful open source application for GDAL-based (Python) processing of spatial data, being able to translate various proprietary spatial data formats onto one interactive interface for spatial analysis. The first step in manual classification was a visit to the SAI. A walk-through identified major surface types, and the main land cover classes that should be detected from the image. Google Street View and the 0.035m RGB image provided invaluable insight where ground-truthing was lacking.

For efficiency, first the major organizing elements and very large segments were classified (water, roads, railways). This provided enough guidance for a more local, block-wise, classification process of the vegetation and local road surface types. A final site-visit was made to reconcile remaining classification uncertainties during API. The approximate time to complete the mapping was recorded.

3.5 Experiments with automatic land cover classification

Careful knowledge-based API can produce a reliable land cover map. The human brain can be quickly trained to identify image features based on local knowledge, image colour, texture, and spatial arrangements, and now aided by other unique views from products like Google Street View. Unfortunately, this is incredibly time consuming and relies on the judgment and impeccable performance of the interpreter. The time invested in a manually classified map may not be worth the value extracted. An automated approach is preferable, although accuracy may be compromised.

The literature gives little indication as to the accuracy that can be achieved in detecting specific land covers as in Table 2 using VHR and a segment-based approach. At best, the reported methods perform well with detecting four or five generic classes, that typically group the surface types into a category like ‘road’ or ‘impermeable surface’. To understand how such methods would perform for detecting hydrologically relevant land covers, several supervised classifiers were considered. For practical reasons, SS1 of the NIR/R/G data was used to test classification performance rather than the entire SAI.

3.5.1 Creating the training set for supervised classification

The process of manual segment classification identified segment candidates for a training set. Training segments were selected by simple random sampling of the SAI extent for 13 classes found in Table 2 (excluding porous concrete which was not found by API or ground-truthing). Given that the NIR reflectance was unaffected by shading, it was thought that representative signatures might be built for the same land covers in shadowed areas. Thus, the class samples were separated into illuminated samples and shadowed samples (Figure 60) for testing classification accuracy using a class mean from a full or separated grouping (i.e. illuminated asphalt and shadowed asphalt) and was anticipated to improve classification accuracy (Table 5).
Figure 60. Segments selected for the training samples included both illuminated and shadowed pixels for 13 of the 14 classes in Table 2.
### Table 5. Training pixels - counts and mean vector of NIR/R/G bands

<table>
<thead>
<tr>
<th>classes</th>
<th>Illuminated</th>
<th>Shadowed</th>
<th>Mean vector [NIR, R, G]</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. asphalt concrete (AC)</td>
<td>17934</td>
<td>2711</td>
<td>[132, 155, 162]</td>
</tr>
<tr>
<td>2. concrete aggregate (CA)</td>
<td>7936</td>
<td>2372</td>
<td>[164, 183, 190]</td>
</tr>
<tr>
<td>3. stone tile (STT)</td>
<td>1210</td>
<td>1376</td>
<td>[132, 152, 148]</td>
</tr>
<tr>
<td>4. brick interlocking paver (BIP)</td>
<td>18256</td>
<td>9889</td>
<td>[151, 169, 170]</td>
</tr>
<tr>
<td>4. concrete interlocking paver (CIP)</td>
<td>11450</td>
<td>1741</td>
<td>[170, 188, 192]</td>
</tr>
<tr>
<td>6. concrete grid paver (CGP)</td>
<td>1962</td>
<td>765</td>
<td>[161, 152, 154]</td>
</tr>
<tr>
<td>7. porous concrete (PC)</td>
<td>no count</td>
<td>no count</td>
<td>no count</td>
</tr>
<tr>
<td>8. natural gravel (NG)</td>
<td>5372</td>
<td>1619</td>
<td>[185, 190, 193]</td>
</tr>
<tr>
<td>9. stone gravel (SG)</td>
<td>20866</td>
<td>4364</td>
<td>[118, 131, 135]</td>
</tr>
<tr>
<td>10. synthetic turf (ST)</td>
<td>999</td>
<td>633</td>
<td>[123, 131, 135]</td>
</tr>
<tr>
<td>11. lawn and short grass (LN)</td>
<td>5957</td>
<td>2648</td>
<td>[191, 129, 145]</td>
</tr>
<tr>
<td>12. shrub and woody vegetation (SH)</td>
<td>19097</td>
<td>10539</td>
<td>[195, 104, 131]</td>
</tr>
<tr>
<td>13. bare soil (BS)</td>
<td>12188</td>
<td>748</td>
<td>[188, 205, 203]</td>
</tr>
<tr>
<td>14. water and canal (WA)</td>
<td>6863</td>
<td>1482</td>
<td>[74, 89, 103]</td>
</tr>
<tr>
<td>15. sand (SA)</td>
<td>no count</td>
<td>no count</td>
<td>no count</td>
</tr>
</tbody>
</table>

#### 3.5.2 Per-pixel automatic classification

In urban scenes that are spectrally mixed and spatially heterogeneous, a per-pixel approach likely results in a noisy map. It is likely that if the considered classes cannot be easily separated by spectral properties alone, even the best training sets cannot improve accuracy. For some applications (mapping urban extent, for example), this might be a sufficient ‘quick and dirty’ approach but is not considered ideal for SIC mapping.

To demonstrate, supervised pixel-based classification was implemented in IDRISI Selva using three different metrics on the NIR/R/G SS1 image and the combined set of training pixels (illuminated with shadowed). In supervised classification, the metrics assess similarity of a pixel vector \( x = (x_1, x_2, \ldots, x_{nb})^T \) of \( nb \)-bands to a reference vector of \( nb \)-bands for class \( C_i \), where \( i = 1, 2, \ldots, w \) and \( w \) = number of classes. Similarity is measured by distance, \( d(x; C_i) \) of vector \( x \) to class \( C_i \). The vector \( x \) is assigned to class \( C_i \) which minimizes the distance:

\[
C = \arg\min_{C_i} (d(x; C_1), d(x; C_2), \ldots, d(x; C_w))
\]

Distance was calculated by three metrics:

1. minimum euclidean distance to class mean (MD)
2. maximum likelihood with posterior probabilities (ML)
3. spectral angle mapper (SAM)
The MD classifier is by far the fastest to compute but the crudest estimation when considering urban land covers. In MD, class distributions are assumed to be normal, thus mean is a valid metric. The reference vector is taken to be the mean of the class training set, \( \mu_i \), or the central tendency of the class,

\[
\mu_i = \frac{1}{N_i} \sum_{x \in C_i} x \quad \text{for} \quad i = 1, 2, \ldots w
\]

where \( N_i \) is the total number of pixels in a class sample. Distance is calculated as the euclidean norm between vector \( x \) and \( \mu_{C_i} \), and expressed in matrix form is,

\[
d_e = \sqrt{(x - \mu_i)^T (x - \mu_i)} \quad \text{for} \quad i = 1, 2, \ldots w
\]

or in numerical form,

\[
d_e = \sqrt{\sum_{j=1}^{nb} (x_j - \mu_{j(C_i)})^2} \quad \text{for} \quad i = 1, 2, \ldots w
\]

The vector \( x \) is assigned to class \( C_i \) where distance to \( d_i \) is minimized (Figure 61). The disadvantage to a MD classifier is when class spread is not normal or they overlap in feature space. This method is most robust when sample means are well distanced from each other since variance is not taken into consideration.

An improved method is by using distance in probability space, to give the maximum likelihood of a vector belonging to a certain class by comparing probabilities. This takes into consideration the mean and covariance of the sample data (Figure 62). Variance is assumed to be normally distributed about the mean, and equal or a-priori probabilities can be applied to define the probability space.

The euclidean distance in probability space is calculated by the quadratic,

\[
d_p = \ln|V_i| + (x - \mu_i)^T V_i (x - \mu_i) - 2 \ln P(C_i | x)
\]

where \( V_i \) is the covariance matrix of \( nb \) by \( nb \) dimensions and \( P(C_i) \) is the a-priori probability that class \( C_i \) exists in the image, and is calculated by,

\[
P(C_i | x) = \frac{m_i}{m} \quad \text{for} \quad i = 1, 2, \ldots w
\]

where \( m \) is the total number of training pixels, and \( m_i \) the number of pixels in class \( C_i \). Assuming equal prior probabilities for each class, this quadratic can be simplified to,

\[
d_p = \ln|V_i| + (x - \mu_i)^T V_i (x - \mu_i)
\]

The vector \( x \) is assigned to class \( C_i \) where \( d_p \) is minimized (where class probability is maximized). ML is a special variant of MD (uses variance/covariance and can use a-priori probabilities as weights). IDRISI Selva uses probabilities of each class from the sample distributions (Clark Labs, 2009).
The SAM score gives a measure of angular distance (Figure 63) instead of the euclidean distance, between the specular angle of the pixel vector to the class mean vector $\mu_i$.

The angular distance, $\alpha_i$, is calculated by,

$$\alpha_i = \cos^{-1}\left(\frac{x \cdot \mu_i}{\|x\| \|\mu_i\|}\right) \quad (12)$$

This measure nullifies the effect of brightness changes within an image since the magnitude of the vector is ignored. However, this is another form of the minimum-distance classifier (minimum angle in this case) and can yield mis-classifications where class vectors are not angularly separable. Typically SAM is used with hyperspectral data. The vector $x$ is assigned to class $C_i$ where $\alpha_i$ is minimized.
After per-pixel classification of the NIR/R/G SS1 image, pixel noise was reduced by forcing the classified map to take the segment shapes. This was better for comparing per-pixel classifiers to the per-segment classifiers. This was implemented by two methods: (i) a frequency rule which assigned each segment pixel to the most frequently occurring class from the per-pixel classifier, and (ii) the majority rule where the segment was assigned to one class if the class occupied more than 75% of the segment pixels. The frequency and majority algorithms were, respectively:

```plaintext
>>for every segment:
    >>for every class:
        >>count number of pixels from pixel-based map
        >>take class with max(count) and assign to all pixels in segment

>>for every segment:
    >>for every class:
        >>count number of pixels from pixel-based map
        >>if class of max(count) >= 75% of total segment pixels
        >>assign this class to all pixels in segment
        >>else:
            >>do not force pixels to segment
```

### 3.5.3 Segment-based automatic classification

As with the per-pixel crisp automatic classification, the three metrics (MD, ML, SAM) were used in a segment-based classification on the segmented SS1 NIR/R/G image using GDAL and numpy tools in Python. The distances were calculated by taking $x$ to be the mean vector of pixel values in each segment, such that one vector represented each segment (Figure 64). Using segment mean values assumed that the segment spectral distribution was normal.
The algorithm was:

```python
for every segment:
    get mean value of all pixels in NIR, Red, and Green bands
    make segMeanVector = [meanNIR, meanR, meanG]
    calculate distance(segMeanVector, classVector)
    append (class, distance) to a distanceList
    assign class to segment where class = argmin(distanceList)
```

The effect of splitting the training set into illuminated and shadowed pixels was compared against using the full training set, for all three metrics.

A modification to the crisp classifier was to use area and adjacency rules to improve readability and accuracy. Segmented objects like cars and small plants were occluding surfaces below (kind of object-noise). These objects tended to be less than 6m². In a manual classification process, the local knowledge by the interpreter could resolve these occluded surfaces and make the correct classification based on shape, colour and surroundings of the irrelevant object (Figure 65). To automate this decision process, first the segments greater than or equal to an area threshold of 6m² were classified by crisp rules using the three metrics (as above). Then, the segments below the threshold were classified by taking the most frequently occurring surrounding class.
The algorithm was:

```
>>for every segment >= area:
    >>classify by crisp metric
>>for every segment < area:
    >>count class occurrences for surrounding pixels (distance=1)
    >>take class with max(count) and assign to segment
```

For the segment-based classifications, it was still plausible that the specific classes were still spectrally confused by the tested classifiers. To compare, pavement classes were grouped according to similarity in SIR. This resulted in classes of ‘impermeable’ and ‘semi-permeable’ pavements in addition to classes less confused (vegetation and water). SIRs of these classes were also combined (Table 6)

### Table 6. Specific classes grouped to generic classes

<table>
<thead>
<tr>
<th>super-class</th>
<th>sub-class</th>
<th>min SIR (mm/hr)</th>
<th>max SIR (mm/hr)</th>
</tr>
</thead>
<tbody>
<tr>
<td>impermeable</td>
<td>AC</td>
<td>0</td>
<td>15</td>
</tr>
<tr>
<td></td>
<td>CA</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>ST</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>BIP</td>
<td></td>
<td></td>
</tr>
<tr>
<td>semi-permeable</td>
<td>CIP</td>
<td>20</td>
<td>200</td>
</tr>
<tr>
<td></td>
<td>CGP</td>
<td></td>
<td></td>
</tr>
<tr>
<td>gravel</td>
<td>NG</td>
<td>50</td>
<td>160</td>
</tr>
<tr>
<td></td>
<td>SG</td>
<td></td>
<td></td>
</tr>
<tr>
<td>lawn</td>
<td>LN</td>
<td>30</td>
<td>240</td>
</tr>
<tr>
<td></td>
<td>STT</td>
<td></td>
<td></td>
</tr>
<tr>
<td>shrub</td>
<td>SH</td>
<td>200</td>
<td>620</td>
</tr>
<tr>
<td>bare soil (sandy)</td>
<td>BS</td>
<td>50</td>
<td>700</td>
</tr>
<tr>
<td>water</td>
<td>WA</td>
<td>n/a</td>
<td>n/a</td>
</tr>
</tbody>
</table>

*Refer to Figure 19 for sources. Values in italics are adjusted based on expert knowledge.*
In total, 22 classifiers were tested with the specific classes and analyzed for producer and user accuracy, overall accuracy and KHAT statistic (PA/UA/OA/KHAT). Producer’s accuracy (omission errors) measures the agreement per class of the classified map to the reference map (how many pixels were correctly classified per class) where as the user’s agreement (commission errors) measures the reliability of the classified pixels (as in, the likelihood that the classifications are correct). This identifies which classes are confused (classes with low PA and UA). Overall accuracy, or overall agreement, measures the total number of correctly classified pixels over the entire image (the sum of the diagonals in a confusion matrix over the total number of pixels).

The KHAT statistic is a standard statistic of overall agreement between two images, by taking into consideration the probability of agreement between the two maps. That is, KHAT would indicate the classification performance compared to a randomly classified map.

KHAT is calculated by the following equation:

$$\hat{K} = \frac{\sum_{i=1}^{N} x_{ii} - \sum_{i=1}^{r} \sum_{j=1}^{c} x_{ij} x_{ji}}{N^2 - \sum_{i=1}^{r} \sum_{j=1}^{c} x_{ij} x_{ji}}$$

(13)

where $N$ is the total number of observations, $r$ the rows in the matrix, and $x_{ii}$ the observations in row and column $i$, $x_{i.}$ and $x_{.i}$ are the totals of the column and rows respectively.

### 3.5.3 Segment-based automatic classification with texture features

The previous two classification methods determined the class assignment for a pixel or segment using only the spectral information (mean values of NIR/R/G). But some research has shown interesting results for urban mapping by adding texture information to classifiers (e.g. Puissant et al. 2005, Dekker 2003). Thus, a small classification experiment with using texture and spectral responses was conducted on SS2 to evaluate classification performance.

Texture, generally the repetition of spatial pattern or variation, captures object geometry and arrangement differently than spectral information and could enable further separation between classes (e.g. synthetic turf and real grass, or water and shadow). It can be described by edge density (ED), which is a single value texture descriptor of the ‘busyness’ of an image region. To determine ED, an edge detection algorithm is used (e.g. Sobel) to create an edge gradient image. A Sobel edge detector uses a 3x3 convolution kernel to calculate the gradient change in greyscale values in the horizontal ($G_x$) and vertical ($G_y$) direction. The edge magnitude is given by,

$$|G| = \sqrt{G_x^2 + G_y^2}$$

(14)
and the ED would then be the average magnitude of edge pixels over the total region of $N$ pixels. However, this is still a very loose description of texture as it does not consider spatial arrangement of edges, only abundance (Figure 66).

Haralick et al. (1973) wrote a seminal paper on 14 texture-features for image classification (Table 7). The texture features are second order metrics based on greylevel co-occurrence matrices (GLCM), which means they capture spatial relationships between two neighbouring pixels (Hall-Beyer 1997), although the definition could be extended to take more distanced pixel pairs.

A GLCM is a matrix of all possible greylevel values in an image region $I$, which holds a count of all co-occurring greyscale value pairs $(i,j)$ of pixel distance=1 in a $0^\circ$, $45^\circ$, $90^\circ$, and $135^\circ$ direction (Figure 67). A GLCM must be normalized and made symmetric to become a matrix of co-occurrences probabilities.

Table 7. Haralick’s Texture Features

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>1.</td>
<td>Angular Second Moment (Energy$^2$)</td>
</tr>
<tr>
<td>2.</td>
<td>Contrast</td>
</tr>
<tr>
<td>3.</td>
<td>Correlation</td>
</tr>
<tr>
<td>4.</td>
<td>Sum of Squares (Dissimilarity)</td>
</tr>
<tr>
<td>5.</td>
<td>Inverse Difference Moment (Homogeneity)</td>
</tr>
<tr>
<td>6.</td>
<td>Sum Average</td>
</tr>
<tr>
<td>7.</td>
<td>Sum Variance</td>
</tr>
<tr>
<td>8.</td>
<td>Sum Entropy</td>
</tr>
<tr>
<td>9.</td>
<td>Entropy</td>
</tr>
<tr>
<td>10.</td>
<td>Difference Variance</td>
</tr>
<tr>
<td>11.</td>
<td>Difference Entropy</td>
</tr>
<tr>
<td>12.</td>
<td>Information Measures of Correlation</td>
</tr>
<tr>
<td>13.</td>
<td>Information Measures of Correlation</td>
</tr>
<tr>
<td>14.</td>
<td>Maximal Correlation Coefficient</td>
</tr>
</tbody>
</table>

Figure 66. Edge density gives information about the abundance of edges in a region, but not the edge distribution or arrangement. Pixel regions A, B, and C have the same edge density, but clearly a different pattern.
The GLCM is normalized by,

\[
f(i,j) = \frac{M(i,j)}{\sum_i \sum_j M(i,j)}
\]  

(15)

where \(M(i,j)\) is the GLCM from each direction. The 14 texture features can then be calculated using the normalized and symmetric GLCM, or \(f(i,j)\). In this way, an image region of interest (e.g. image of a brick surface) can be assigned a texture feature value. In this study, two features describing contrast (local variation in greylevel) and one describing orderliness were used.

These are homogeneity (HOM), contrast (CONT), and angular second moment (ASM) respectively and are calculated by,

\[
HOM = \sum_{i=0}^{n-1} \sum_{j=0}^{n-1} \left\{ \frac{f(i,j)}{1+|i-j|} \right\}
\]  

(16)

\[
CONT = \sum_{i=0}^{n-1} \sum_{j=0}^{n-1} (i-j)^2 f(i,j)
\]  

(17)
\[ ASM = \sum_{i=0}^{n-1} \sum_{j=0}^{n-1} f(i, j)^2 \]  

Since there are GLCMs from four directions, four values per texture feature arise. Haralick (1973) suggested that taking an average should sufficiently represent the texture feature for the image region. For images of urban scenes, the image region \( I \) needs to be defined by a moving window (9x9, 12x12, for example) passing over a greylevel image. Then, a texture feature image can be generated by using \( I \) to calculate a single texture feature value per pixel. For this experiment, a 9x9 window was used to calculate ASM, HOM, and CONT per pixel of SS2 (Appendix A).

Two methods were tested to calculate texture features per segment (Figure 68). The first was a ‘native’ processing method whereby the segment was used as image region \( I \) to calculate the GLCM from the 0.035m red-band image (Figure 69), then calculating texture features directly. The second ‘biased’ method uses the texture feature images to calculate a mean feature value per segment (biased because feature values depend on a fixed 9x9 window).

The disadvantage of the first method is that a segment might insufficiently include pattern repetition whereas the second method guarantees a 9x9 image region. As segment size decreases, texture information is lost. Moreover, if a segment included different surfaces, the texture feature calculated would be unreliable. On the other hand, a 9x9 window may still be insufficient for some textures, and a larger window may be required.
A training set of texture feature vectors were calculated for all classes found in the subset. Using the 0.035m red-band greyscale image of the subset, a sample image region of the classes were taken from illuminated and shadowed areas (if possible). After calculating the GLCM of all four pair directions, mean ASM, HOM, and CONT were calculated for each reference class.

To classify with texture, the three texture features were added to the segment vector $x$ ($x = \text{NIR}, \text{R}, \text{G}, \text{ASM}, \text{HOM}, \text{CONT}$) for MD and ML classifiers using the two methods described previously, such that a total of 4 maps were produced. To test the effect of the segmentation quality, a second classification was implemented using manually defined segments. The results are visualized and discussed in Chapter 4.

### 3.6 Effect of object resolution and class specificity on SIC mapping

The manually classified map acts as a benchmark for the desired object resolution and class specificity for characterizing the urban landscape. It was hypothesized that a land cover map tailored for urban hydrology would yield a more accurate SIC map due to class specificity and object resolution. Therefore, the manually classified map with specific and generic classes were used to derive SIC, and compared against that derived from the ML classifier.

#### 3.6.1 Mapping SIC

Minimum and maximum values of final SIR represented the worst and best known final SIR for the hydrologically relevant land cover classes. The values for the full list of considered classes was in Table 2. The best SIR was observed when pavement was newly laid, and worst when compaction, siltation, and aging effects had taken their toll on SIC. The two SIC maps per land cover map were derived by simply converting the class to the respective documented SIR. This illustrated the range of SIR for the land covers. The SIC maps were compared for OA and total surface coverage per SIR, to understand the impact of using generic classes versus specific ones.
3.6.2 Hydrological land cover maps in a pluvial flood model

To demonstrate the impact of lower class specificity and object resolution the manually classified map with specific classes and generic classes were input into a pluvial flood model, HydroNET PriceXD by Hydrologic BV. The input maps were modeled to include a total of 7 catch basins on three main roads (Stationstraat, Utrechtseweg, and Arnhemseweg) and were modeled as surfaces with extreme infiltration capacity (180,000mm/h) and with no catchment limit.

PriceXD is a pluvial flood model designed to estimate runoff in both urban and rural areas caused by regular rainstorms, by taking into consideration ground slope, land cover and associated surface roughness (and optionally soil type). The model is unsuitable for storms which cause high runoff velocities (like tsunamis). The user may scale up the resolution of the results of runoff flow and velocity over each grid cell of the ground. At every time step, runoff velocity is determined by the slope and roughness of the cell (specifying the water available to infiltrate), while the volume is determined by the incoming water less the volume lost through infiltration in that time step. Infiltration is modeled as a Hortonian flow (see Chapter 2). The surface wave equation is used to model the runoff flow and velocity over the entire catchment area.

Table 8 lists the land cover classes and corresponding infiltration and roughness values for the three input maps, alongside visualizations of the SIC of the catchment area. Final infiltration rates for Hortonian flow were taken from the minimum final SIRs as they were more realistic. The initial infiltration rate was assumed to be twice the final. Since infiltration curves per land cover were not available from the literature, the decay constant was calculated by assuming a 4-hour period to reach constant saturated flow and is plotted against the rainfall rate of two design storms used (Figure 70).

The two design storms were a light but long rainstorm (peaking at 40mm/h) and a flash rainstorm (peaking at 100mm/hr) with a total of 15,000 cubic meters of rain designed to fall on 470,610m² surface area. Initial water levels were set to zero (no negative initial depths), soil moisture levels assumed to be dry, and a flat surface was assumed. For analysis, the total runoff volume in the catchment was calculated per epoch or every time step. This subsequently meant that total infiltration volume could also be calculated per epoch. The results were also compared against a topographic map (GBKN) as an input as it had even lower class specificity and object resolution. Given that the generic classes led to an under-prediction of minimum final SIR, it was expected that as an input, it would affect peak runoff time while increasing volume.
Figure 70.
The infiltration curves were simulated using Hortonian flow and assuming final SIR is half the initial rate plotted with the two design storms (light and flash).
Table 8. Infiltration and roughness parameters of input files

(i) Manual classification, specific classes

<table>
<thead>
<tr>
<th>class</th>
<th>( n )</th>
<th>( f_n )</th>
<th>( f_c )</th>
<th>( k )</th>
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<tbody>
<tr>
<td>AC</td>
<td>0.015</td>
<td>0.0</td>
<td>0.0</td>
<td>2.305</td>
</tr>
<tr>
<td>CA</td>
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<td>0.0</td>
<td>0.0</td>
<td>2.305</td>
</tr>
<tr>
<td>ST</td>
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<td>0.0</td>
<td>2.305</td>
</tr>
<tr>
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<td>12.0</td>
<td>6.0</td>
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</tr>
<tr>
<td>CIP</td>
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<td>20.0</td>
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</tr>
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</tr>
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</tr>
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</tr>
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<td>50.0</td>
<td>3.281</td>
</tr>
<tr>
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<td>30.0</td>
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</tr>
<tr>
<td>LN</td>
<td>0.425</td>
<td>80.0</td>
<td>40.0</td>
<td>3.225</td>
</tr>
<tr>
<td>SH</td>
<td>0.150</td>
<td>400.0</td>
<td>200.0</td>
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</tr>
<tr>
<td>BS</td>
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(ii) Manual classification, generic classes

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<tr>
<td>semi-permeable</td>
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<tr>
<td>gravel</td>
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<tr>
<td>lawn</td>
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<td>60.0</td>
<td>30.0</td>
<td>3.225</td>
</tr>
<tr>
<td>shrub</td>
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<td>400.0</td>
<td>200.0</td>
<td>3.627</td>
</tr>
<tr>
<td>bare soil</td>
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<td>100.0</td>
<td>50.0</td>
<td>3.280</td>
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</table>

GBKN, equivalent classes to map (i) or (ii)

<table>
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<tr>
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<th>( f_n )</th>
<th>( f_c )</th>
<th>( k )</th>
</tr>
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<tr>
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<td>0.0</td>
<td>0.0</td>
<td>2.305</td>
</tr>
<tr>
<td>Cement [CA]</td>
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<td>0.0</td>
<td>0.0</td>
<td>2.305</td>
</tr>
<tr>
<td>closed pavement [impermeable]</td>
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<td>0.0</td>
<td>0.0</td>
<td>2.305</td>
</tr>
<tr>
<td>open pavement [semi-permeable]</td>
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<td>40.0</td>
<td>20.0</td>
<td>3.052</td>
</tr>
<tr>
<td>coverage [lawn]</td>
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<td>50.0</td>
<td>3.281</td>
</tr>
<tr>
<td>ground cover [lawn]</td>
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<td>80.0</td>
<td>40.0</td>
<td>3.225</td>
</tr>
<tr>
<td>grass [lawn]</td>
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<td>80.0</td>
<td>40.0</td>
<td>3.225</td>
</tr>
<tr>
<td>road veg [lawn]</td>
<td>0.425</td>
<td>80.0</td>
<td>40.0</td>
<td>3.225</td>
</tr>
<tr>
<td>plantation [lawn]</td>
<td>0.150</td>
<td>400.0</td>
<td>200.0</td>
<td>3.627</td>
</tr>
<tr>
<td>shrub</td>
<td>0.150</td>
<td>400.0</td>
<td>200.0</td>
<td>3.627</td>
</tr>
</tbody>
</table>

GBKN - SIR map generic classes
4. RESULTS and ANALYSIS

The research took an exploratory approach in evaluating how VHR multi-spectral imagery could be used to create a map of SIC based on a land cover map of hydrologically relevant land cover classes at the needed object resolution. In Chapter 2, the theoretical background to selecting the hydrologically relevant land cover classes was established as well as a methodological benchmark for land cover classification. Chapter 3 explained the methodology of the land cover classification experiments using the 0.25m NIR/R/G and 0.035m RGB images of central Amersfoort (Figure 71) and the SIC mapping and subsequent assessment. The results of the research are discussed in this Chapter in the same order as in Chapter 3.

Broadly speaking, the results show that segment-based land cover classification of the hydrologically relevant land cover classes faces challenges already reported in literature for far fewer classes and object resolutions. The results show moderate classification accuracy with common crisp classifiers, and the performance of a simple spectral/textural approach are discussed. The importance of finding an accurate classifier should not be taken for granted. The resulting land cover maps are tailored to have specific hydrological meaning, and could add precision to flood models and water-sensitive urban design.

Figure 71.
The 0.035m RGB image of Amersfoort city center.
4.1. Image segmentation workflow and reference map

To ensure the needed object resolution resulted from segmentation, a readability evaluation scheme was developed. Readability was defined as the readers’ (in this case, the authors’) ability to identify the major organizing features of urban fabric based on the segments alone, without any other visible spectral information. Good ‘mappable’ segments were geometrically shaped and spatially arranged in a way that created meaning to the reader, and should have discriminated between the objects of interest (relevant land cover classes). The readability criteria was weighted and segmentations scored out of 5 (1/12*buildings, 3/12*roads, 1/12*trees, 2/12*paths, 1/12*lawns, 4/12*shadow).

4.1.1 Overall readability of segmentation tests

Surface features such as trees, sidewalks, parking lots, and lawns were best segmented when the mean segment size was from 40-60m² (Figure 72). The mean, however, is greatly influenced by the very large building segments. The size of the objects of interest are closer to the median of 10-33m². The vegetation separated approach selected vegetation pixels by an NDVI threshold. These pixels were segmented separately with a tolerance of 50, kernel size 3, and intersected with a full image segmentation at tolerance 70, kernel size 3, both using data combination-2 (NIR/R/G/DEM). The method produced over-segmented vegetation edges (due to overlapping edges, Figure 73), but the advantage of the approach was that proper shapes lawns and rows of shrubs and separation of shadows was ensured. Over-segmented edges were resolved in the classification phase. The mean segment area was not noticeably affected. A table overview is provided in Appendix B.

4.1.2 Effect of data-types, kernel size, and threshold

Data combination-1 produced the least readable results because the segment shapes were consistently under-segmented. The highest readability score was observed with the addition of the 0.5m DEM. The DEM seemed to improve segmentation of islands from roads and grassed areas, which are often separated at grade anywhere between 5 to 10cm and is noticeable from a slope map (Figure 74). However, this was not considered particularly helpful with subsequent classification, as surface grade has weak relation to seal type. Figure 75 summarizes the readability results for the first tested subset.
Figure 72.
Segment sizes corresponding to the highest readability score was 40-60m². At this level of detail, road islands, cars, small trees can be distinguished.

Figure 73.
The vegetation-separated segmentation approach created over-segmented vegetation edges due to the intersection of two segmentation results.

Figure 74.
The slope image points out that elevation could help distinguish between surface features such as road islands and lawns.
Tests on a small subset indicated that data-combination 2, tolerance 70, produced the most readable results and was used in subsequent segmentation tests. While data combination-2 provided similar readability scores, the NDVI as a channel added only stronger homogeneity for vegetated areas, which could also be achieved by the separated approach, and was thus considered trivial.

The second arbitrary subset contained large sports fields and densely built residential housing. Increasing the kernel size on data combination-2 generated undesirable results in these areas. Although segment sizes were within the readability range, segment shapes were ‘blocky’ due to the smoothing of the variance image with a larger kernel size (Figure 76). The effect of over-segmented edges on readability was compensated by the kernel effect (Figure 77).
As expected, for all tests, increasing tolerance size also increased the segment size exponentially for all three data combinations, which corresponded to a decrease in the number of segments and readability.

The segmentation workflow which was finally used on the SAI was the separated approach using data combination-2, kernel size of 3x3, with vegetation segmented at tolerance 50 and intersected with a full segmentation at tolerance 70 (Figure 78). The segmentation of SAI took approximately 10 minutes and generated 66,162 segments of mean area 52.9m², median area 25.2m², and 24,431 single-pixel segments, with a readability score of 4.17. The number of single-pixel segments reflects the over-segmented vegetation edges from this method.

### 4.1.3 Manual land cover classification of segments

The final segmentation result was manually classified using knowledge-based API of the 0.25m NIR/R/G image, 0.035m RGB composite image, Google Street View, and ground-truthing. To manually classify all 66,162 segments in QGIS took approximately 90 hours. Significant time was saved by using a segmented image rather manual segmentation or digitization (which could double or triple the time cost). This is certainly impractical, but the result was a validated knowledge-based surface cover map (Figure 79).

The manual classification process can be explained in four steps which provided inspiration for the fuzzy rule set during automatic classification (Figure 80). These were:

1. **Map first the major organizing features of the urban scene.** If a segment clearly included more than one class, the class occupying the majority of the segment was taken.
Figure 78.
The final segmentation of SAI using data combination-2, tolerance 70, and 3x3 kernel, intersected with vegetation segments at kernel 3x3, tolerance 50, using the same data combination.
Figure 79.
The resulting manually classified land cover map of SAI. 66,162 segments were classified in 90 hours.
2. Then map the vegetation objects found between the organizing features. This was more challenging since private gardens had highly mixed segments of vegetation, lawn, and indistinguishable sealed surfaces. Judgment had to be used to generate meaningful object shapes. Tree crowns were classified as woody rather than the expected land cover below.

3. Map the remaining surfaces. If a segment clearly included more than one class, the class occupying the majority of the segment was taken.

4. Resolve small and occluded segments like cars over brick roads and the over-segmented vegetation boundaries. These were classified based on an adjacency rule, where it was assigned the most frequent neighbouring class. In a tie, it was assigned the class resulting in the most meaningful shape.

4.1.4 A note on segmentation assisted API

To classify, the surface type assigned was first based on the interpretation from the segmented image (NIR/R/G composite), secondly on the 0.035m RGB composite, then on ground-truthing and Google Street View, when images could not provide a clear indication of class. It was not possible to identify porous concrete from the images or ground-truthing. Nevertheless, manual classification was the best method to generate an accurate reference map. The VHR images were invaluable for interpreting various surface materials where ground-truthing fell short (e.g. in private gardens). There were some drawbacks: (i) expensive time cost; (ii) imprecise segment shapes (iii) data sources did not register perfectly (different leaning and shadow effects, moving objects); but were mostly resolved using local knowledge.

Figure 80. Subset of SAI shows examples of manual classification rules applied. Instance 1 is the segment of a small tree occluding the surface. Instance 2 is of a segment containing two classes. Instance 3 shows the over-segmented feature boundaries.
4.2 Automatic land cover classification

The driver behind automating a classification process is to replace the hard and tedious work required in manual classification. The knowledge-based API can be simulated by various classification decision rule sets and different data sources. The results presented give a first impression of the performance of common land cover classifiers. A table summary of the classification results and large format visualizations are found in Appendix C and D respectively.

4.2.1 Classification with VHR spectral data

Overall accuracies (OA) for all per-pixel classifiers of the considered classes ranged between 17% (with MD) and 25% (with ML) with slightly better results using the frequency forcing rule. For SAM and MD metrics, the difference between forcing methods was almost negligible. Moreover, these metrics confused shadowed pixels with class: water. For readability, the majority rule for forcing produced a rather noisy map (68-74% of the segments forced, Table 9). Except for vegetation, all other surface classes were greatly confused, particularly BIP which was hardly present in the resulting maps (Figure 81). Small segments tended to be classified differently than larger adjacent segments. Thus, while pixel-noise was reduced, object-noise was not (Figure 82).

<table>
<thead>
<tr>
<th>per-pixel metric</th>
<th>count</th>
<th>area (m²)</th>
</tr>
</thead>
<tbody>
<tr>
<td>SAM</td>
<td>9886</td>
<td>79605.7500 (74%)</td>
</tr>
<tr>
<td>MD</td>
<td>9468</td>
<td>84040.8125 (53%)</td>
</tr>
<tr>
<td>ML</td>
<td>9170</td>
<td>66315.8750 (46%)</td>
</tr>
</tbody>
</table>

Method Recap:
Subset 1 was used for the supervised automatic classification experiments using only the spectral data. GDAL and numpy tools in Python were used to process the images.
Per-pixel classifications using SAM, MD, and ML were implemented and forced to take segment shapes by frequency and majority rules and compared to the manually classified segments.
Segment-based classifications using SAM, MD, and ML were also implemented. A modified approach used segment area and adjacency rule sets to classify again with SAM, MD, and ML to test for any improvements in accuracy.
The impact of splitting the training set into illuminated and shadowed classes as well as the impact of using a generic class grouping was also tested with all segment-based classifiers.
The use of three texture features (ASM, HOM, CONT) in automatic classification with the spectral data was also explored in a small experiment on subset 2.
Figure 81. Visualizations of per-pixel supervised classifications by three metrics forced by majority rule and frequency rule.
The OA for segment-based classifiers ranged from 17% (with SAM) to 45% (with ML) - better than per-pixel classifications. Excluding the SAM classifier, utilizing a split training set (illuminated and shadowed training sets) increased accuracies by 5-10%. The split training set dramatically suppressed the effect of shadows for the SAM and MD classifiers, and improved classification of shadowed vegetation.

Inspection of the spectral distribution of the split training set (Appendix E) showed modality, bi-modality, and skewness differences between classes but were similar between illuminated and shadowed sets, suggesting that other class descriptions besides the mean could be used (for example, if classes show bi-modality). Class CGP, water, and synthetic turf were over-classified while BIP was again under-classified for all except for the ML classifier using prior probabilities (45% overall accuracy). The gravel classes (stone and natural) were also poorly classified by SAM and MD (Figure 83).

Implementing the area/adjacency rule on small segments improved OA by <1% when using full and split training sets and was successful at reducing object-noise (from over-segmented edges). The larger segments were always classified by spectral features first. Thus the area/adjacency rule effect would probably be enhanced if class confusion is resolved first. Increasing the area threshold probably has little impact otherwise.

A summary of the OA and KHAT of all classifications with spectral data is shown from Figure 86 to Figure 85. Producer’s and user’s accuracies show that classification error of lawns and shrubs is low (thanks to NIR data) but high for pavement classes (low prediction and prediction accuracy of AC, CA, BIP, CIP, ST, STT, and CGP).

Given high levels of confusion between the classes, the classes were aggregated to generic classes and reassessed for OA. The average increase in OA was 11% which meant the confusion accounted for 11% of the error. In particular, this increased per-pixel ML classifier forced by frequency rule by nearly 20%, performing similarly to ML per segment with a split training set. Again, excluding the SAM classifier, a 4-11% increase in OA was observed by using the split training set but there were negligible impacts when using the adjacency rule set.
Figure 8.3.
Visualizations of segment-based classifications using SAM, MD, and ML with full and split training sets.
Figure 84.
User’s accuracy of all classified maps using the spectral data with all considered classes.

Figure 85.
Producer’s accuracy of all classified maps using the spectral data with all considered classes.
4.2.2 Segment-based automatic classification with texture features

The opportunity to use higher resolution imagery for automatic classification of the segments was explored. Using the red-band 0.035m RGB image, texture features were calculated for each segment (created from the 0.25m NIR/R/G image). Two methods were explored: (i) a native method whereby ASM, HOM, and CONT were calculated from greyscale values per segment and (ii) a biased method whereby the features were calculated per segment by averaging texture feature values from per-calculated texture images. The mean value for the texture features was calculated per class from the computed texture images (using the biased method), and is compared against the training set and a visualization of texture features (Table 10).

The analysis shows slight differentiation between vegetation and other classes for all three texture features but not amongst pavement classes, for example between AC and BIP (Figure 90). For ASM and HOM, a significant difference between shaded and illuminated grasses (0.05) may justify taking
a split sampling approach (as with the spectral data). Higher values for shaded areas may be attributed to the dampening of all greylevel variation thereby inducing order (everything is dark). Further analysis is needed with a larger number of samples and classes to see if this trend holds.

Interestingly, between the two approaches to obtain texture features, differences were observed for the orderliness feature ASM on non-vegetated segments (up to 0.17), but not for the contrast features HOM or CONT. For both approaches, very small segments did not capture enough pattern or texture, and resulting ASM values were very different from their surrounding segments (like the over-segmented vegetation object edges). This suggests dependency of this feature on segment geometry (size). Further analysis is required to determine any link between segment size and texture feature with native and biased calculations.
Table 10. Mean and variance of texture per class from texture images, compared to training samples

<table>
<thead>
<tr>
<th>Class</th>
<th>n</th>
<th>fo</th>
<th>fi</th>
<th>k</th>
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<td>0.2076</td>
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<td>451.8300</td>
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<td>194.2305</td>
<td>542777.8355</td>
<td>604.1313</td>
<td>10.4716</td>
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</table>
A simple approach to a spectral/textural classification was tested. The feature vector from the spectral data was appended with the three texture features per class and classified by MD and ML. The visual results show moderate agreement with the manual classification for all classifiers using both native and biased methods (Figure 91). This is probably due to the compounded confusion between hard surface covers in both the spectral and textural measures or by the segment shapes. Even by using manually determined segments, there was confusion between all classes (Figure 92).

In this experiment, texture images were created by using a 9x9 image region, and counting co-occurrences with pixel distance equal to one. Considering the VHR data, a 9x9 window may not actually capture the full representative texture or pattern of a class. Consider that a single CIP tile is 30x30cm, so 9x9 pixels at 3.5cm covers just one tile. This means patterns with largely distanced repetition would not be adequately captured so a larger image region could be used (say, 25x25) although this would increase computation time.

Another option would be to count co-occurrences of values of pixel distance greater than one in combination with the standard approach. This might better differentiate between very regular patterns (like BIP and CIP), but not necessarily for vegetation. Further investigation is required on how to use texture features to improve spectral classification results, such as in a neural network.

4.2.3 Summary of land cover classification results

The automatic land cover classification experiments were designed to show classifier performance for generating a hydrologically relevant land cover map from VHR imagery. The experimental results are summarized below:

1. **Per-pixel versus segment-based classifiers:** As already reported in many classification studies, the per-pixel classifiers generally produced more pixel-noise (speckling) than segment-based classifiers because of the signal spreading effect at object edges and mixed pixels, even after forcing to take segment shapes. Classification accuracy of per-pixel methods were lower (17-25% OA) than all segment-based classifiers (17-45% OA). Speckling diminishes visual clarity of the hydrologically relevant land covers (objects).

2. **Effect of metrics on classification accuracy:** The ML with prior probabilities produced the most accurate results of the considered classes (45% OA) whereas SAM produced the least (17% OA). A similar observation was made for ML in the per-pixel classifiers. There was confusion between pavement classes (AC, CA, BIP, CIP, CGP, STT) when using class means. It may be caused by aged, silted and compacted pavements that appeared smoother or darker in the composite images, giving a similar spectral response as asphalt roads, for example. Color differences in pavements may also play a role in spectral confusion as well as poor segmentation (causing more than one class per segment). This indicates that the of these classes in feature space is not normal. The ML classifier used covariance between spectral data, and better accounted for a non-normal distribution.
Figure 90. Boxplots of the texture features calculated per segment using the native (grey) and biased (orange) method shows low separability between paved surfaces.

Figure 91. Classification results using MD and ML with the extended feature vector (NIR, G, ASM, HOM, C) on automatically generated segments.
Figure 92. Classification results using MD and ML with the extended feature vector \([\text{NIR}, R, G, \text{ASM}, \text{HOM}, \text{CONT}]\) on a manually segmented image.
3. **Effect of splitting the training set on accuracy**: The impact of using a split training set showed promising results, increasing accuracies from 5-11% depending on the similarity metric used. In doing so, the confusion between water and shadowed segments was dramatically suppressed for the MD classifier, resulting in a 10-11% increase in OA which was comparable to ML classifiers without prior probabilities. The classification might be improved by using statistics other than the mean (when only a few spectral bands are available) as some classes showed bi-modality and skewness distributions.

4. **Effect of area/adjacency rule on accuracy**: The impact of using an adjacency rule to classify smaller (less important or over-segmented) objects increased OA by <1% since the classification of the larger segments was often incorrect (usually one of the confused pavement classes). The rule did improve visual readability by reducing object-noise. The rule had the unintended effect of removing relevant small objects (e.g. small lawns and shrubs). Additional rules could use NDVI to preserve these hydrologically relevant objects.

5. **Effect of class aggregation on accuracy**: By aggregating the confused pavement classes, OA of all classifications increased on average by 11% which means the class confusion accounted for at least 11% of the error. The effect was most pronounced with the per-pixel ML classifier (23 to 42% OA) and segment-based MD with split training set (28 to 39% OA). However, class specificity and object resolution was lost. An improved training set would probably not resolve the confusion. Instead, more spectral bands might be needed in specific ranges (see Chapter 2).

6. **Effect of adding texture features to spectral classifiers**: The initial hypothesis that combining texture from higher resolution imagery and spectral information from lower resolution imagery would improve accuracy could not be supported. Pavements like aged BIP and AC were texturally similar. There was no clear textural separability between pavement classes and using a single vector seemed to increase class confusion. Texture information used in a neural network and weighted against spectral information may yield better results than the single vector approach.
4.3 SIC mapping and pluvial flood modeling

**Method Recap:**
Maps with the specific and generic classes by manual and ML classification were translated into a map of maximum and minimum final SIC and compared in terms of SIR distribution and extent. The SIRs (Table 2) were obtained from various pavement studies and expert advice.

To assess the impact of lower class specificity and object resolution on SIR distribution within an urban catchment, the manually classified map with specific classes, generic classes, and the GBKN map with generic classes were input into a pluvial flood model. Peak runoff time and volume were compared between the three input maps.

The intent of classifying the VHR multi-spectral imagery was primarily to derive a more accurate SIC map than could be derived from topographic data. A segment-based approach was used to ensure that the required object resolution could be met, ensuring visual readability for urban designers and water managers, but also introducing precision to the surfaces to be classified. Since hydrologically relevant land cover classes were used, specific classes have numerical meaning.

### 4.3.1 Deriving SIC maps from hydrological land cover maps

Deriving a SIC thematic map from hydrological land cover maps was a matter of assigning minimum and maximum final SIR ($K_s$ or $f_f$) per land cover class (see Table 2) such that two thematic maps illustrated the range of documented SIC. The manual classification with specific classes was translated to establish a benchmark SIC map ($m$-specific and $m$-generic). A SIC map was also derived from the image classified by ML using prior probabilities and the split sample set ($ML$-specific and $ML$-generic).

Figure 93 points out that the agreement between $m$-specific and $m$-generic was around 68% for both minimum and maximum SIR maps whereas agreement was much lower when using a ML-classifier (below 50%). This
Figure 94. Minimum SIC maps from the manually classified land cover map and ML classifier [above] and a class distribution chart [right].

Figure 95. Maximum SIC maps from the manually classified land cover map and ML classifier [above] and a class distribution chart [right].
means that with manual classification of generic classes, the SIR prediction error was 32% and 48-62% when using the ML-classifier. This amounts to 46,208m² and 69,312 to 89,528m² of the total surface area respectively which were not mapped with the correct SIR. This is a meaningful number for physical models dependent on surface area (drought, heat, rainwater loss). Comparing \textit{m-generic} with \textit{ML-specific} shows comparable agreement in both the minimum and maximum rates to \textit{m-specific} with \textit{ML-specific} an \textit{ML-generic} maximum SIR (40-47%) and minimum SIR (38-52%), suggesting that the ML-classifier is an equally moderate predictor of SIC for both generic and specific classes.

The distribution of SIR over the urban catchment gives a meaningful spatial comparison (Figure 94 and Figure 95). Most of the surface affected by reducing class specificity was BIP (19% of the surface area) as it was grouped to an ‘impermeable’ class and accounts for most of the SIR prediction error between \textit{m-specific} and \textit{m-generic}. Grouping classes gave higher SIR to some areas and lower SIR to others. The reallocation of space to SIRs exaggerate overall SIC for the catchment area, and adds uncertainty to the urban water landscape. For example, BIP areas were forced to take a lower minimum final SIR such that completely impermeable areas rose from 11% to 35% in the catchment.

From an application perspective, the maximum SIR are highly unlikely in a city like Amersfoort. Maximum SIR are observed with newly laid pavements. After 10-20 years, surfaces experience compaction, siltation, and other age effects thereby reducing SIR in fragmented patterns so the minimum SIR should be considered in practice. Using generic classes with the same object resolution greatly under-predicts the (minimum) SIC. The class specificity appears to have opposite effects for land cover classification and SIC mapping which should be considered in practice. ML-generic comes from a higher land cover OA but lower SIC prediction compared to ML-specific (Figure 96).

![Class specificity and Overall Accuracy](image)

\textbf{Figure 96.} Class specificity appears to have opposite effects for land cover classification and SIC mapping which should be considered in practice.
4.3.2 Caveats to the SIC thematic maps

It has been previously discussed that SIR is a dynamic property which depends on the overlying water pressure (rainfall conditions) and shallow subsurface conditions, both of which vary to uncertain degrees in urban areas and depend on rainstorm intensity. To simplify, only the final SIR was mapped. This is the saturated hydraulic conductivity (after long or intense rainfalls, or if there is ASM). For typical rainstorms in Amersfoort, rainfall will be long but light, so final SIRs might not be reached. The following caveats should be noted before creating a SIC map:

» Strictly speaking, the map can only indicate one possible minimum and maximum final SIR at a given location, illustrating relative degrees of permeability ($K$).

» Actual conditions in Amersfoort might not be modeled correctly by maximum final SIRs. The observations from literature were at different geographic locations, where the subsurface conditions were not always reported and could have some influence (say, in terms of base soil types, or the presence of geotextiles). Areas experiencing compaction and siltation need to be observed carefully and SIRs adjusted accordingly either by actual in-situ measurements or by approximation from expert judgment.

» The SIRs reported in the literature were measured in-situ in controlled infiltration experiments, with constant pressure heads and flat surfaces, thus measuring only vertical flow rates. Even the minimum SIR should be considered under-conservative. Where slopes are present, there may be an influence of horizontal flows on SIRs.

» The SIC maps cannot clarify the possible areas of water adsorption to pavements and storage by small surface depressions. This may be significant if water losses in an urban area should be modeled accurately. An interesting by-product of the land cover map could be a total ‘loss’ map, where adsorption, storage, evaporation, and infiltration can be represented by assigning a value to each segment for each method of loss. The adsorptive capacity of the pavement materials could be taken into consideration when modeling light rainstorms. With a loss map, mapping tree crowns becomes very relevant. The rainfall intercepted by the tree reduces the intensity and volume of rain met at the surface.

» The map contains some ‘false surfaces’. These are segments which represent road and pedestrian overpasses or graded roofs but are classified as ground objects. The SIR rates taken from the literature supposed an underlying subsurface of soil which is not the case for the false surfaces. Thus, the SIRs are actually uncertain. Mapping might first use auxiliary data to single-out false surfaces.
4.3.3 Applications of the SIC maps

Few holistic descriptions of the urban water landscape are made in practice. In fact, monitoring of environmental conditions like urban heat, drought, hydrology, vegetative health, and soil properties on a city-wide scale are rare, infrequent, or localized because it is considered auxiliary information, or is too expensive to obtain.

Water-sensitive urban design for environmental change is a popularly adopted design principle. Designs that embrace water as a resource, rather than a waste to expel, are implemented locally and have a city-wide impact. Yet there has been little concerted effort by cities to monitor or document the impact of such efforts, not to mention developments by pavement and urban water engineers. These efforts combined surely have a measurable impact on the urban environment and are worthwhile to detect.

A SIC map is a response to the need for an holistic view of the urban water landscape by offering a sweeping view of infiltration potential across a city, while being based on local conditions. A SIC map enables more precise understanding of surface conditions for hydrological problems. Zones of infiltration potential can be connected with linear infrastructures and land uses bridging together engineers, designers, and planners. Caveats aside, such views of urban hydrology could be of interest to policy-makers who seek to mitigate the effects of soil sealing, and to water engineers and scientists interested in modeling urban heat, drought, and floods. The following points illustrate three potential applications of a SIC map, especially if predicted to a sufficient level of accuracy.

1. **Context benchmarking for driving investment**: Where there is political will to mitigate the hydrological effects of soil sealing during lighter rainstorms, a SIC map can provide benchmark conditions of the water landscape, as an holistic and quick overview. Specific sites or neighbourhoods with low SIC (such as industrial parks) may be targeted for strategic improvements. The map would also indicate where higher SIC are not desirable. SIR targets may be set for specific redevelopment areas, which can be used in incentive-based policies for improved urban water management.

2. **Monitoring and evaluating design performance**: Small to large design interventions and infrastructure works are continuously underway that change and fragment the already heterogeneous urban fabric. A SIC map can be one way of monitoring the impact of these works on area or neighbourhood SIC when there is a policy objective of meeting a specific SIC. Images taken at one or two year intervals can be subsequently classified and translated into SIC. Cities can compare the change over time by developing a ranking or scoring system for zonal-SIC (a ‘permeability index’, working similarly to a ‘green building’ score), thus allowing more robust evaluation of design proposals. Design proposals could be required to more objectively demonstrate the impact of their specific design materials and concepts to the total catchment SIC. In this way, the SIC may be involved in an iterative design process itself.
3. Improved parametrization and modeling: Urban water catchments depend on the drainage infrastructure, SIC, elevation, and other losses. Spatial analyses using a SIC map in combination with elevation and inlet information can better parameterize local water catchments (anticipated sinks and underground flow direction). The land cover map can be used directly as well, but only if the considered classes are hydrologically meaningful. Models that consider surface infiltration information can benefit by using more meaningful land cover classes, and higher object resolution (e.g., objectifying small patches of grass or individual concrete driveways). Urban heat models depend largely on the surface area of materials and it is suspected that the lower class specificity and object resolution of topographic maps has some impact on modeling urban hydrology or heat models.

4.3.4 Impact of different SIC maps on pluvial flood model

Although the minimum SIR is lenient, it is more realistic than the maximum values and was used in the flood model experiments. The generic class set underestimated SIC for the catchment area. This was anticipated to result in greater runoff volume and earlier peak flow that with using the same object resolution but the specific class set. With even lower object resolution (GBKN, topographic map) but higher overall SIC, the accumulated runoff volume was expected to be under-predicted with an earlier peak runoff. This was validated by using the SIC maps in the PriceXD model under a light (gradual rise to 40mm/h) and flash (rapid peak to 100mm/h) rainstorm.

For each storm, a total of 15,000 cubic meters of rain was designed to fall on 470,610m² surface area of Amersfoort city center over a 3 hour period. Comparing the minimum SIC maps (Section 4.3.1) underscored the effect of class generalization on OA and SIR distribution in a pluvial flood model. The SIC of all maps showed good infiltrative performance with at least 84% of the rainfall being infiltrated (Table 11). With the light rainstorm, there was 30% more (544m³) runoff generated for the generic classes than specific classes but 18% less (327m³) by the GBKN map. A similar relationship is observed for the flash storm. This is explainable by the greater surface area of moderate SIC in the GBKN.

Table 11. Comparison of infiltration volume at 3 hours, by map

<table>
<thead>
<tr>
<th></th>
<th>specific</th>
<th>generic</th>
<th>GBKN</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Light Rainstorm, t=3hr</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>% infiltrated</td>
<td>88.15%</td>
<td>84.52%</td>
<td>90.33%</td>
</tr>
<tr>
<td>excess water [m³]</td>
<td>1775</td>
<td>2319</td>
<td>1448</td>
</tr>
<tr>
<td><strong>Flash Rainstorm, t=3hr</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>% infiltrated</td>
<td>87.46%</td>
<td>84.02%</td>
<td>89.53%</td>
</tr>
<tr>
<td>excess water [m³]</td>
<td>1889</td>
<td>2406</td>
<td>1576</td>
</tr>
</tbody>
</table>
The accumulated runoff volume was plotted with the total available water at each epoch. The difference between the runoff and the available water (incoming rain plus excess water from the previous time step) is effectively the accumulated infiltration and was also plotted for both rainstorms (Figure 97 and Figure 98). Generally, the cumulative runoff curves are in line with expectations. Excess water accumulates when the rate of rainfall exceeds the SIC (of the majority surfaces) and happens around 40min for the light storm. Total available water increases towards the rainfall peak, and reaches equilibrium with the total excess water when rainfall stops. In these results, the recovery of the surface (infiltration of excess after rainfall) is slow as too few inlets were modeled.

For both storm events, a distinct difference between the three maps was observed. With a light rainstorm, generic classes tended to reduce runoff peak time compared to the specific classes whereas runoff peak was earlier for the GBKN map and later for the specific classes in the flash rainstorm. This is
attributed to the over-allocation of moderate SIC in the GBKN compared to the manually classified maps. More water was able to infiltrate in the peak stages of the flash storm. Figure 99 visualizes this effect for the light storm.

In these experiments, a majority allocation to a moderate SIC always under-predicts runoff volume (GBKN), whereas better spatial allocation but generic classes over-predicts runoff volume. However, the runoff curve shapes did not deviate, which demonstrates that the input map has a significant implication on the accuracy of the flood model. Careful consideration should be given to class specificity and object resolution for surface parameterization. Using generic classes can both over and under-predict runoff depending on the object resolution.
Figure 99. Snapshots of rainfall excess over the 3 hour light rainstorm using the manually classified SIC map, specific classes, to the GBKN map, generic classes shows overall higher SIC at early stages of the rainfall with the GBKN map.
5. CONCLUSIONS

Effective urban water management requires certainty about the urban water landscape. A SIC map could be a useful input for evidence-based urban design of water-sensitive/low-impact neighbourhoods and multi-tiered water management schemes (Figure 100). However, methods for mapping SIC are underdeveloped. Typically, infiltration rates are derived from topographic or urban extent maps which are tailored to describe urban land use or extent. The classes used often have ambiguous or generic hydrological meaning and object resolution, and are used to derive SIC at the expense of accuracy and precision. This study responded to a need for better class specificity and object resolution by generating a land cover map tailored for applications in urban hydrology.

The research hypothesized that if a land cover map identifies hydrologically relevant land cover classes, then a more accurate SIC map can be derived. An exploratory approach was taken to land cover mapping for urban hydrology, using VHR multi-spectral imagery of Amersfoort, Netherlands (0.25m NIR/R/G and 0.035m RGB). A segment-based classification was implemented to obtain the needed level of object resolution and class specificity was determined by results of relevant pavement studies. The
impact of different image segmentation parameters and segment classifiers on classification accuracy was observed. The generated land cover maps were then translated into SIC and cross-examined with respect to its application in policy, design, and water management including a demonstration in a pluvial flood model (PriceXD). The implications of the results are packaged below.

5.1 Land cover classification tailored for urban hydrology

A land cover map with clear hydrological meaning requires proper class specification and meaningful object resolution. To identify the hydrologically relevant land cover classes to detect from VHR imagery, the first part of the research focussed on understanding the physical behaviour that determine SIC. The investigation shaped the premise that particular surface covers could sufficiently predict the SIC among other derivations.

5.1.1 Class specificity and object resolution

Values of final SIR of semi-permeable and permeable surfaces were gathered from various in-situ infiltration studies. By definition, final SIR represents vertical infiltration rates of saturated and flat grounds, and is effectively the lowest SIR measured from an infiltration curve (e.g. Hortonian flow) and is equivalent to the saturated hydraulic conductivity, $K_s$. The SIRs ranged widely depending on the ground condition. Highest SIRs were observed when pavement was newly laid, and lowest when compaction, age, and siltation had compromised SIC (refer back to Figure 19 and Table 2).

The surface covers determined the required object resolution. It was important that irregular objects like private driveways were distinguishable from a resulting map along with large parks, and were part of a definition of map readability (see Section 3.4.2, Table 4). A segment-based approach was favoured over per-pixel as the final mapping product would not be subject to speckling. Particularly, the size and shape of segments could be controlled by manipulating the segmentation parameters. Shadows could be separated from the object which cast them and segment-induced classification errors (i.e. by segments including more than one land cover) could be minimized.

Image segmentation guaranteed a basal level of map readability since segments were fixed for the classification experiments. Segmentation readability was quantified on a scale of 0-5 (refer back to Table 4). The SAI segments were generated using IDRISI Selva, using the 0.25m NIR/R/G dataset and the 0.5m DEM (resampled to 0.25m resolution) as the fourth input channel. Mean segment area (excluding buildings) corresponding to high readability scores ranged between 10-33m². The vegetation-separated method was used but resulted in over-segmented vegetation edges and were resolved during land cover classification with an area/adjacency rule.
5.1.2 Hydrological land cover classifications for mapping SIC

In retrospect, it might be questioned why land cover classification was implemented over SIC classification directly. Section 4.3.2 outlined the various caveats to using a SIC map that can be managed having land cover information. One of those was that SIRs from the literature were probably site specific, and only representing vertical infiltration rates. If site-specific SIRs can be measured, then improving the SIC map is a matter of updating the SIRs associated with each class. The rates could be adjusted for the effects of horizontal flows (the exact effect needs to be determined).

Having a land cover map also enables other by-products such as modeling rainfall loss. Moreover, information about land cover gives important insight to the designer about existing materiality and spatial arrangement of pavement types. SIC is thus a secondary product of an hydrological land cover map.

5.2 VHR multi-spectral data for SIC mapping

Segments of the SAI needed to be classified according to land cover. To establish a reference map, a knowledge-based API of the segments was conducted by ground-truthing, using Google Street View, and the 0.035m RGB image. Manual classification was the best method to generate an accurate reference map and the VHR images were invaluable for interpreting various surface materials where ground-truthing fell short (e.g. in private gardens).

Supervised classifications were conducted with the 0.25m NIR/R/G data. Classifiers testing two approaches (per-pixel vs. segment-based), three metrics (SAM, MD, and ML), crisp and modified crisp rules, two training sets (separating illuminated and shadowed pixels), and two class groupings (specific and generic) were tested. In total, 22 classifiers were tested per class grouping. Finally, three texture features (ASM,HOM,CONT) from the 0.035m RGB image were used to classify a smaller subset of the NIR/R/G image.

Evaluation of the image classifications revealed that the impermeable and semi-permeable pavement types were greatly confused (AC, CA, BIP, CIP, CGP, and gravels NG and SG). This was due to shadow but also the inseparability of classes using the NIR/R/G spectral bands. For example, ground-truthing revealed that many surfaces were mixed - weeds growing in gravel areas or sparse grass growing in a newly sowed lawn likely confused the feature vectors within segments. The best classifier was by segment-based ML using prior probabilities and a split sample set achieving a moderate 45% OA. A segment-based approach was able to maintain needed object resolution compared to pixel-base classifiers and using generic classes improved classification accuracy.
Comparisons of the derived SIC maps showed that using generic classes increased SIC prediction error and that the ML classifier with prior probabilities predicted equally well minimum and maximum SIC from specific and generic classes (38-52% OA). With respect to the SIR distribution, generic classes under-predicted the overall minimum SIC of the catchment because the BIP class (occupying a significant surface area) was forced to take a lower minimum. However, the maximum SIC distribution was comparable. These results have three key practical implications:

» The best performing classifier tested in this study (ML with prior probabilities and split training set) can predict equally well the SIC distribution for both minimum and maximum rates.

» Reducing class specificity, regardless of manual or automatic classification method, under-predicts the minimum SIC of the catchment due to reallocation of areas to greater or lesser SIRs. The impact of class specificity on maximum SIR distribution is not apparent. However, greater weight is placed on the minimum rates since they are more realistic.

» Using generic classes in land cover classification increased OA by 11% on average, but corresponded to lower SIC mapping accuracy due to re-distribution effects. The redistribution effect is dependent on the classes that are grouped. The subclasses varied little in SIR but occupied a large surface area. Thus classes with higher surface coverage should not be grouped even given land cover classification errors.

Using maps that under-predict SIC was expected to have an implication on a pluvial flood model (PriceXD), as it uses surface parameters to determine water loss during a rainfall event. The minimum SIR was used for specific classes, generic classes, and the GBKN topographic land cover map previously used in the HydroCity project.

The results of the flood model validated the expectation that using generic classes yields different results than when using specific classes and that the difference depends on the object resolution. With the same resolution, lowering class specificity increased runoff accumulation (23% or 544m³ more for the light storm). With both lower object resolution and class specificity, SIC was over-predicted and less runoff was accumulated (38% or 327m³ less). The research experiments and results are culminated in Table 12 (also refer back to Chapter 4).

The full roster of experimental results in this study indicate that the input map has a significant implication on the accuracy of the flood model and that proper SIC mapping is a meaningful exercise. Careful consideration should be given to class specificity and object resolution for surface parameterization. Using generic classes can both over and under-predict runoff depending based on object resolution and class specificity. Using VHR imagery for accurate land cover classification is challenging, but can produce a more realistic model of SIC, adding accuracy to pluvial flood models.
Table 12. Summary of land cover classification experiments and results

<table>
<thead>
<tr>
<th>experiment</th>
<th>image classification</th>
<th>SIC mapping</th>
<th>flood modeling</th>
</tr>
</thead>
<tbody>
<tr>
<td>pixel vs. segment</td>
<td>segments reduced speckling and have higher overall accuracy</td>
<td>not tested</td>
<td>not tested</td>
</tr>
<tr>
<td>metrics</td>
<td>ML-aprioi &gt; ML &gt; MD &gt; SAM</td>
<td>ML classifier: 32-50% agreement with specific and generic classes, for min. and max. SIC</td>
<td>not tested</td>
</tr>
<tr>
<td>splitting training set</td>
<td>split &gt; full</td>
<td>not tested</td>
<td>not tested</td>
</tr>
<tr>
<td>area/adjacency rule</td>
<td>reducing object-noise (dissolves segments &lt; 6m²)</td>
<td>not tested</td>
<td>not tested</td>
</tr>
<tr>
<td>adding texture features</td>
<td>compounded class confusion</td>
<td>not tested</td>
<td>not tested</td>
</tr>
<tr>
<td>class aggregation (generic classes)</td>
<td>increased accuracy and reduced object resolution</td>
<td>under-predicted min. SIR of catchment but marginal change on max. SIR.</td>
<td>increased runoff volume and decreased peak time with same object resolution, but decreased volume with lower object resolution.</td>
</tr>
<tr>
<td>object resolution</td>
<td>not tested</td>
<td>not tested</td>
<td>over-predicted SIC of catchment yielding lower runoff volume but increased peak runoff time</td>
</tr>
</tbody>
</table>
5.3 Recommendations for improved land cover and SIC mapping

Generating the SIC maps involved a series of land cover classification experiments to determine feasible methods. The impact of increasing object resolution and class specificity to SIC prediction was assessed. The analysis of the results supports the hypothesis that a better SIC map could be derived from VHR multi-spectral imagery using a segment-based classification approach than from a topographic map. The mapping process tested allows the user to establish a baseline object-resolution, enabling more precise land cover mapping of hydrologically relevant land covers. Nevertheless, the accuracy of the resulting map depends greatly on class specificity regardless of object resolution. Object resolution is more influential on map readability.

To improve the SIC mapping, segmentation and classification methods should be improved. The value of the improvements can be assessed by further application testing in other fields, such as urban design. Six key recommendations are made:

1. Assess the impact of adding texture feature images and slope for image segmentation. Consider adding additional spectral bands or use other thresholding techniques for colour and temperature in a separated segmentation approach (e.g. to better segment pavement types in shadowed areas).

2. Assess methods to resolve classification confusion between pavement types (AC, CA, BIP, CIP, CGP, STT) including:
   » improving segmentation (where each segment includes only one class).
   » using similarity statistics with the same classifier other than the mean to consider bi-modality and address the spectral confusion caused by poor segmentation,
   » using additional spectral bands into the far infrared with the same classifiers to curtail confusion caused by colour similarity of different pavement types,
   » further investigate the impact of different texture feature calculations on classification accuracy (experimenting with window size and directionality to reduce texture class confusion), and
   » modify the crisp classifier by adding fuzzy rules using texture or other data (e.g. elevation) for specific classes where distinct texture differences can be found by other methods of texture calculation.

3. Determine methods to estimate areas of compaction and siltation, thereby incorporating age into the determination of SIC and improving mapping precision (selecting a SIR within the documented ranges).

4. Determine methods to identify and remove false surfaces from land cover mapping to improve mapping accuracy. Accuracy could also be improved by taking in-situ measurements of SIR in the location to be mapped. SIC could also be correlated with measures like void spaces per segment (i.e. using texture) and values corrected with slope and thermal properties.
5. Further assess the value of improved SIC mapping by applying them in an iterative urban design process (i.e. quantifying design impacts by changes in SIC using topographic versus VHR-derived SIC). The map could also be assessed in policy applications as a communication tool.

6. Explore the development of other products from a hydrological land cover map, such as a loss or drought map and heat map and assess implications in existing urban hydrology or heat models.

5.4 Knowledge for cities, knowledge for design

Cities are the complex result of human settlement and innovation. Dwelling landscapes and cultural destinations are made from the manipulation, extraction, reconstitution, formation and installation of materials that make our cities. This activity is not without consequences to the urban water landscape. The natural SIC is greatly disturbed and must be otherwise re-engineered into urban surfaces to mitigate flood risk, among other effects of increasing surface runoff. Work by urban designers and pavement engineers have innovated ways to achieve SIRs sometimes better than the natural states. This coalesces with the effects of compaction, siltation, and other aging effects to induce a dynamically fragmenting pattern of SIC.

A map of SIC is a response to the need for clarity on the hydrology of cities. It offers an holistic snapshot to the urban designer and water manager about existing conditions and potential for an urban catchment to infiltrate rainwater. It also has numerical importance in terms of modeling pluvial floods, urban heat and drought. It can also be a tool to quantify the impact of proposed urban designs, facilitating an iterative design process, as well as a tool for policy communication and a means to measure environmental performance over time.

This study has demonstrated that classifying a land cover map with VHR multi-spectral imagery with a segment-based approach can achieve a more accurate SIC map than if derived from topographic data. Segmentation workflows enable control over the object resolution while typical automatic classifiers have shown promising results for classification of hydrologically relevant land cover classes. The impact of reducing class specificity and object resolution has been demonstrated in a pluvial flood model. Generic classes even with sufficient object detail (m-generic) under-predicts SIC whereas generic classes with lower object detail (GBKN) over-predicts SIC.

In the determination of flood risk, care should be taken to accurately parameterize the surface. Majority surface covers should not be subsumed under any generic superclass. Rather effort should be placed in improving classification of these surfaces by using spectral and textural data alongside other rules such as spectral thresholding and fuzzy rule sets that could differ per class. Further research has been identified toward this end with the expectation that growing interest in urban surface conditions, particularly urban hydrology, will propel the proposed SIC mapping methodology into widespread practice.
References and Bibliography


Clark Labs. “Segmentation and Segment-Based Classification.” IDRISI Focus Paper, 2009.


Glossary of Terms

agreement: similarity between two classified maps, measuring the percentage of the map which classified equal to the reference map.

AHN-2: Actueel Hoogtebestand Nederland-2, digital elevation model of the Netherlands.

API: Air Photo Interpretation

area/adjacency rule: a classification rule used to determine the class of small segments, like cars, that occluded the surface type underneath; a segment took the class of the most frequently occurring neighbouring class.

ASM: Angular Second Moment, one of 14 texture features proposed by Haralick in 1973.

biased method: method used to calculate texture features taking the mean value from pre-calculated texture feature images.

BRT: Basisregistratie Topografie, basic topographic data of the Netherlands which will streamline all other topographic products.

BIP: Brick Interlocking Paver; impermeable to semi-permeable pavement type.

CGP: Concrete Gridded Paver; semi-permeable pavement type.

CIP: Concrete Interlocking Paver; impermeable to semi-permeable pavement type.

class specificity: the number and type of considered classes.

compaction: in soil, the increasing of bulk density by a reduction in pore spaces and geometry; happening naturally through settlement but also by various overburdens; will decrease surface infiltration capacity.

CONT: Contrast, one of 14 texture features proposed by Haralick in 1973.

crisp classifier: classification rules that use one rule to decide class assignment.

data fusion: the combination of different data types and products.

DEM: Digital Elevation Model; Digital elevation model; the elevation of terrain including objects.

design intervention: an urban design that has been implemented to retrofit, improve, or shift some dynamic, flow, or process in an urban space.

DINO: Data Informatie Nederlandse Ondergrond, shallow subsurface profile information.

disturbed soil: soil that has been modified by mixing of materials, moved off-site, contaminated, or generally interrupted from developing naturally.

DSM: Digital surface model; the elevation of ground terrain.

ED: Edge density; a magnitude representing the likelihood that a pixel is the edge of an image object.

EM: End-member; pixels with ‘pure’ spectral responses used in supervised classification and spectral un-mixing.

frequency rule: using a per-pixel classified map, a segment was classified to the class that occurred most frequently within that segment.

fuzzy rules: classification rules that use more than one decision criteria to decide class assignment (AND, OR, and NOT statements).

GBKN: Grootschalige Basiskaart Nederland, large scale topographic data of the Netherlands.

GDAL: Geospatial Data Abstraction Library
GLCM: Grey-Level Co-occurrence Matrix; used to calculate Haralick’s texture features; measures co-occurrence of adjacent pixel value pairs.

ground-truthing: the act of visiting a real site, environment, place, to verify the existence of objects, features, and characteristics to be modeled.

HOM: Homogeneity, one of 14 texture features proposed by Haralick in 1973.

hydraulic conductivity: the ability of a material to conduct or transmit water in one direction; dependent on the material bulk density and geometry, and the fluid viscosity.

hydraulic gradient: the height difference between the groundwater and the wetting front of the surface; creates water potential that causes flux through the ground.

IDRISI Selva: a software package containing image processing tools, including segmentation and segment classification.

imperviousness: the inability of a material to transmit water (no or negligible hydraulic conductivity).

infiltration: a source of rainwater loss; the flux of water through a medium.

interception: a source of rainwater loss; the absorption or storage of water by objects occluding the surface.

KHAT: a statistic measuring similarity between two or more maps taking into consideration random chance.

LiDAR: Light Detection and Ranging

land use: the use or function of land; not the built form or materiality

land cover: the materiality of the land; the surface type regardless of use or function.

LULC: Land Use and Land Cover

majority rule: forcing classified pixels to change class if they lie within a segment area where more than 75% of the pixels belong to another class.

Manning’s n: a coefficient of roughness used to calculate flow velocity in an open channel.

MD: Minimum Distance; similarity metric in image classification that measures euclidean distances to class means.

ML: Maximum Likelihood; similarity metric in image classification that measures distance to probability, using class covariances.

native method: method to calculate texture features by taking the greyscale values in a segment to calculated a GLCM and subsequently the texture feature values.

NDVI: Normalized Difference Vegetation Index; taking advantage of the great difference in NIR and R bands to detect vegetation pixels.

NDWI: Normalized Difference Water Index; taking advantage of the great difference in NIR and SNIR bands to detect water in vegetation pixels.

neural network: establishing decision boundaries in classification by learning from new information based on biological neural network processes.

NIR/R/G: Near Infra-Red, Red, and Green spectral bands

OA: Overall Accuracy, the total number of pixels that have been correctly classified according to a reference image, for all considered classes.

OBIA: Object-Based Image Analysis, also segment-based classification

object-noise: visual noise of a classified image created by differently classified neighbouring segments; reducing map readability.

object resolution: the size and shape of image objects, or segments; affects map readability.

over-classified: classes that have been assigned to pixels more often than they occur in the reference map.
**over-segmented**: objects that have a greater number of segments than required in order to be recognized.

**PA**: Producer's Accuracy; omission error, the degree to which the classified map matches the reference map, by class.

**PC**: Porous Concrete; permeable pavement type.

**permeability**: or coefficient of permeability; hydraulic conductivity.

**permeable**: infiltrative or transmissive, permitting flux of water.

**pixel-noise**: visual noise of a classified image created by mis-classifications of neighbouring or nearby pixels.

**pluvial flood**: flooding caused by excess rainfall.

**rainfall loss**: the infiltration, interception, evaporation or storage of rainwater.

**readability**: the ability to visually identify major organizing elements of an urban scene by arrangement and shape of image objects.

**RGB**: Red, Green, Blue spectral bands.

**runoff**: excess rainwater that is not infiltrated into the surface moving across the surface.

**SAM**: Spectral Angle Mapper; similarity metric measuring the angular distance between feature vector and reference vector.

**semi-permeable**: pavements that allow a greater volume of rainwater to infiltrate than impermeable pavements like asphalt and concrete aggregate materials.

**SIC**: Surface Infiltration Capacity; ability of the surface to allow rainwater flux measured by the surface infiltration rate.

**siltation**: clogging of surface void spaces (as with interlocking pavers) by fine sands and other particles, thereby reducing the surface infiltration capacity.

**SIR**: Surface Infiltration Rate; a rate at which rainwater infiltrates into the surface.

**site preparation**: process of drastically modifying and reforming the shallow subsurface in order to prepare ground for development and construction of buildings and other urban amenities.

**soil sealing**: prevention of natural infiltration capacity of soil by covering it with impermeable materials.

**spectral confusion**: similarity of spectral responses between classes due to the selection of bands used, pixel resolution, and mixed materials being detected.

**spectral separability**: ability to clearly distinguish between classes based on spectral responses.

**texture feature**: a compact measure of pattern and texture based on co-occurrences of pixel grey-levels in an image.

**UA**: User’s Accuracy; commission error, the degree to which the classified pixels are actually correct with respect to the reference map, per class.

**under-classified**: classes that have been assigned to pixels far less often than they occur in the reference map.

**under-segmented**: objects that have too few segments or improper segment shapes to be recognizable.

**urban catchment**: spatial zone or area which catches rainwater falling in that zone into a common point.

**VHR**: Very High Resolution, referring to images with submeter spatial resolutions.

**void ratio**: a ratio of the surface voids or gaps between interlocking bricks or aggregated materials to solid materials, for a given surface area.

**water-sensitive design**: urban design concepts intended to mitigate the negative effects of soil sealing (runoff, water pollution, reduced groundwater recharge) while adding cultural and aesthetic value.
APPENDIX A
Texture images of SS2 using red-band greyscale image

ASM texture image

HOM texture image

CONT texture image (filtered for values below 800)
## APPENDIX B

### Table overview of segmentation results

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Mapping Urban Surface Infiltration Capacity | Appendices
## APPENDIX C

### Table overview of SS1 land cover classification results with specific classes

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## Producer's Accuracy SS1

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## User’s Accuracy SS1

|                  | per-pixel |          |          | per-segment |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |
|------------------|-----------|----------|----------|-------------|----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|
|                  | SAM       | MD       | ML       | SAM         | MD       | ML       | ML-apriori |
| freq.            | major     | freq.    | major    | freq        | major    | full     | split    | full     | split    | full     | split    | full     | split    |
| asphalt conc     | 35.26     | 28.08    | 26.51    | 21.01       | 54.05    | 37.91    | 21.47    | 35.34    | 22.02    | 26.53    | 52.50    | 43.27    | 64.44    | 59.95    |
| conc aggregate   | 0.00      | 0.62     | 15.59    | 11.59       | 18.87    | 19.99    | 0.00     | 4.18     | 12.71    | 20.72    | 14.49    | 14.49    | 16.21    | 10.12    |
| BIP              | 0.24      | 1.84     | 1.25     | 2.30        | 4.90     | 7.27     | 2.84     | 9.28     | 2.23     | 25.40    | 10.80    | 24.97    | 34.61    | 51.30    |
| stone tile       | 0.00      | 3.50     | 0.00     | 2.97        | 0.00     | 5.60     | 0.00     | 0.00     | 0.00     | 0.00     | 0.00     | 0.00     | 0.00     | 0.00     |
| CGP              | 23.82     | 35.90    | 0.12     | 4.25        | 64.84    | 48.92    | 23.82    | 60.84    | 6.57     | 59.16    | 68.88    | 67.12    | 19.03    | 20.15    |
| stone gravel     | 3.46      | 10.68    | 6.08     | 8.98        | 5.93     | 11.92    | 16.35    | 31.91    | 15.04    | 27.97    | 10.22    | 33.45    | 7.01     | 24.16    |
| natural gravel   | 0.00      | 1.79     | 5.16     | 10.04       | 44.89    | 34.24    | 0.00     | 5.64     | 7.06     | 39.56    | 41.02    | 56.20    | 62.51    | 67.94    |
| lawn             | 27.94     | 30.52    | 36.95    | 35.31       | 39.98    | 41.14    | 28.94    | 39.33    | 35.88    | 32.02    | 43.72    | 46.03    | 20.29    | 22.75    |
| shrub/wood       | 60.40     | 57.14    | 34.95    | 36.25       | 55.79    | 50.83    | 58.27    | 31.53    | 36.85    | 48.23    | 44.35    | 48.75    | 85.43    | 77.06    |
| bare soil        | 32.23     | 30.52    | 29.84    | 29.69       | 28.77    | 27.73    | 32.23    | 30.26    | 29.06    | 26.35    | 28.77    | 28.35    | 28.77    | 28.16    |
| synth turf       | 0.00      | 5.59     | 0.00     | 5.26        | 0.00     | 4.73     | 0.00     | 0.00     | 0.00     | 0.00     | 0.00     | 0.00     | 0.00     | 0.00     |
| water            | 100.00    | 79.34    | 0.00     | 9.70        | 100.00   | 50.68    | 100.00   | 100.00   | 21.26    | 100.00   | 100.00   | 0.00     | 0.00     | 53.37    |
APPENDIX D

Large format land cover classification results with specific classes and SIR maps (specific and generic classes)

Manual classification
image dimensions: 1520x1520
segmentation cell size: 25cm
Per-pixel, SAM, forced to segment shape by majority rule
Per-pixel, SAM, forced to segment shape by frequency rule
Per-pixel, MD, forced to segment shape by majority rule
Per-pixel, MD, forced to segment shape by frequency rule
Per-pixel, ML, forced to segment shape by majority rule
Per-pixel, ML, forced to segment shape by frequency rule
Per-segment, SAM, full training set
Per-segment, SAM, split training set
Per-segment, MD, full training set
Per-segment, MD, split training set
Per-segment, ML, full training set
Per-segment, ML, split training set
Per-segment, ML using prior probabilities
full training set
Per-segment, ML using prior probabilities
split training set
Manual classification
minimum SIR
Manual classification minimum SIR

Generic
Manual classification

maximum SIR
Manual classification
maximum SIR

Generic
ML-apriori classifier
minimum SIR

Specific
ML-apriori classifier
minimum SIR

Generic
ML-apriori classifier
maximum SIR
ML-apriori classifier
maximum SIR

Generic
APPENDIX E
Histograms of illuminated and shadowed spectral samples

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<td></td>
<td>Full</td>
<td>Illuminated</td>
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<tr>
<td>shrub/woody</td>
<td><img src="image_url" alt="Graph" /></td>
<td><img src="image_url" alt="Graph" /></td>
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<tr>
<td>bare soil</td>
<td><img src="image_url" alt="Graph" /></td>
<td><img src="image_url" alt="Graph" /></td>
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<tr>
<td>synthetic turf</td>
<td><img src="image_url" alt="Graph" /></td>
<td><img src="image_url" alt="Graph" /></td>
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<tr>
<td>water</td>
<td><img src="image_url" alt="Graph" /></td>
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APPENDIX F
Python scripts for classification experiments

###--Final definitions for classification rules
###--Updated by Danbi Lee
###--Oct 2, 2013

```python
import os, sys, time, Image, random, finaldefs
import numpy as np
from matplotlib import pyplot as plt
from osgeo import gdal
from osgeo import gdalconst
import *
driver = gdal.GetDriverByName('GTiff')
driver.Register()
```

```python
##--Basic Functions

def readR(fn):
    ds = gdal.Open(fn, GA_ReadOnly)
    ds = ds.ReadAsArray()[1]
    return ds

def getRefs(array):
    rows = array.RasterYSize
    cols = array.RasterXSize
    Geo = array.GetGeoTransform()
    Proj = array.GetProjection()
    return rows, cols, Geo, Proj

def getNDVI(NIR, R):
    diff = np.subtract(NIR, R)
    s = np.add(NIR, R)
    s = np.where(s!=0, s, 0.0001)
    ndvi = diff/s
    return ndvi

def sam(vec1, vec2):
    a = np.arccos((np.vdot(vec1, vec2))/np.dot(np.linalg.norm(vec1),
    np.linalg.norm(vec2)))
    return a

def maxlike(segVec, sigs):
    Vi = sigs[1] # cov matrix
    detV = np.linalg.det(Vi)
    invV = np.linalg.inv(Vi)
    y = np.array(segVec) - np.array(sigs[0])
    yT = y[np.newaxis].T
    try:
        aP = sigs[2] # prior probability from training set
        d = np.log(detV) + np.dot(y, (np.dot(invV,yT))) -2*np.log(aP)
    except IndexError:
        aP = 0
        d = np.log(detV) + np.dot(y, (np.dot(invV,yT))) #ilwis
    return d

def saveTIFF(fn, ref, save):
    rows, cols, Geo, Proj = getRefs(ref)
    outDs = driver.Create(str(fn), cols, rows, 1, gdal.GDT_Float32)
    outDs.SetGeoTransform(Geo)
    outDs.SetProjection(Proj)
    outIm = outDs.GetRasterBand(1).WriteArray(save)
    outDs = None
    outIm = None
```

###--Getting Spectral Signatures

```python
def getSplitSigs(compim, ssIll, ssSh):
    '''This algorithm creates a list of the class reference vectors
    based on an illuminated and shadowed training set and returns
    a list of arrays (class ID, no. pix, mean NIR/R/G and covariance. The
    data set in compim should be arrays of NIR,R,G.''

    start = time.time()
    classes1 = np.unique(ssIll) # illuminated classes
    try:
        classes2 = np.unique(ssSh) # shadowed classes
        siglist = list()
        # count total number of training pixels
        m = len(np.where(ssIll>0)[1]) + len(np.where(ssSh>0)[1])
        for ID in classes1[1:]:
            loc = np.where(ssIll==ID)
            count = len(loc[1])
            NIR = (compim[0][loc])
            R = (compim[1][loc])
            G = (compim[2][loc])
            mVec = np.mean((NIR,R,G),axis=1) # mean vector
            Vi = np.cov((NIR,R,G)) # covariance
            aP = float(count)/m # prior prob
            classvec = (ID,count,mVec,Vi,aP)
            siglist.append(classvec)
        for ID in classes2[1:]:
            loc = np.where(ssSh==ID)
            count = len(loc[1])
            NIR = (compim[0][loc])
            R = (compim[1][loc])
            G = (compim[2][loc])
            mVec = np.mean((NIR,R,G),axis=1) # mean vector
            Vi = np.cov((NIR,R,G)) # covariance
            aP = float(count)/m # prior prob
            classvec = (ID,count,mVec,Vi,aP)
            siglist.append(classvec)
    except IndexError:
        pass
    end = time.time()
    print 'Got signatures in: ', (end - start), 'seconds'
    return siglist
```
def getTSigs(compim, ss):
    """This algorithm uses a composite image set of NIR/R/G and ASM/HOM/CONT to create a mean vector, covariance matrix, and prior probabilities for each class."""
    siglist = list()
    m = len(np.where(ss>0)[1])
    for ID in np.unique(ss)[1:]:
        loc = np.where(ss==ID)
        count = len(loc[1])
        NIR = compim[0][loc]
        R = compim[1][loc]
        G = compim[2][loc]
        asm = compim[4][loc]
        hom = compim[5][loc]
        cont = compim[6][loc]
        mVec = np.mean((NIR,R,G,asm,hom,cont),axis=1)
        Vi = np.cov((NIR,R,G,asm,hom,cont))
        aP = float(count)/m
        classvec = (ID,count,mVec,Vi,aP)
        siglist.append(classvec)
    return siglist

#--Functions for texture features

def GLCM(textim):
    """This function returns a normalized co-occurrence matrix for a 0-255 greyscale image region for each direction: 0, 45, 90, and 135 degrees."""
    imSh = np.shape(textim)
    MAX = np.max(textim)+1
    com0 = np.zeros((MAX,MAX))
    com45 = np.zeros((MAX,MAX))
    com90 = np.zeros((MAX,MAX))
    com135 = np.zeros((MAX,MAX))
    for m in range(imSh[0]):
        for n in range(imSh[1]):
            if (m+1)<imSh[0] and (n+1)<imSh[1]:
                GL0 = textim[m][n],textim[m+n+1][n]
                GL45 = textim[m][n],textim[m+n+1][n]
                GL90 = textim[m][n],textim[m+n+1][n]
                GL135 = textim[m][n],textim[m+n+1][n]
            else:
                GL0 = textim[m][n],textim[m+n+1][n]
                GL45 = textim[m][n],textim[m+n+1][n]
                GL90 = textim[m][n],textim[m+n+1][n]
                GL135 = textim[m][n],textim[m+n+1][n]
            R0,R45,R90,R135 = np.sum((com0,com45,com90,com135),axis=1)
            #normalize and make symmetric
            norm0 = (com0+com0.T)/R0
            norm45 = (com45+com45.T)/R45
            norm90 = (com90+com90.T)/R90
            norm135 = (com135+com135.T)/R135
    return norm0, norm45, norm90, norm135

def getASM(GLCM):
    asm0 = np.sum(np.square(glcm[0]))
    asm45 = np.sum(np.square(glcm[1]))
    asm90 = np.sum(np.square(glcm[2]))
    asm135 = np.sum(np.square(glcm[3]))
    asmavg = (asm0+asm45+asm90+asm135)/4
    return asm0,asm45,asm90,asm135,asmavg

def getHOM(GLCM):
    hom0 = np.sum((glcm[0]>0).sum(axis=1))
    hom45 = np.sum((glcm[1]>0).sum(axis=1))
    hom90 = np.sum((glcm[2]>0).sum(axis=1))
    hom135 = np.sum((glcm[3]>0).sum(axis=1))
    homavg = np.sum((hom0+hom45+hom90+hom135))/4
    return hom0,hom45,hom90,hom135,homavg
def getCONT(GLCM):
    diffmat = np.square(np.array(np.where(glcm[0] > -1)[0] - np.where(glcm[0] > -1)[1]))  # matrix of differences
    diffmat = diffmat.reshape(np.shape(glcm[0]))
    cont0 = np.sum(diffmat*glcm[0])
    cont45 = np.sum(diffmat*glcm[1])
    cont90 = np.sum(diffmat*glcm[2])
    cont135 = np.sum(diffmat*glcm[3])
    contavg = (cont0 + cont45 + cont90 + cont135) / 4
    return cont0, cont45, cont90, cont135, contavg

def textim(Red):
    '''Returns ASM/HOM/CONT texture feature images. Argument 'Red' must be the greyscale image called by gdal.''

    start = time.time()
    Redim = Red.ReadAsArray()[0]
    asmim = np.zeros(np.shape(Redim))
    homim = np.zeros(np.shape(Redim))
    contim = np.zeros(np.shape(Redim))
    vlist = list()
    imSh = np.shape(asmim)
    count = 0
    for m in range(imSh[0]):
        for n in range(imSh[1]):
            if ((m+9)<imSh[0] and (n+9)<imSh[1]):  # 9x9 window
                try:
                    view=Red.ReadAsArray(m,n,9,9)[0]  # take window
                    glcm = GLCM(view)  # get four glcms
                    asm = getASM(glcm)
                    hom = getHOM(glcm)
                    cont = getCONT(glcm)
                    asmim[m][n]=asm[4]  # take the avg
                    homim[m][n]=hom[4]  # take the avg
                    contim[m][n]=cont[4]  # take the avg
                    count +=1
                except ValueError : continue
            else:
                continue
    var = np.var((asmim, homim, contim),axis=1)
    Vi = np.cov((asmim.reshape(-1),homim.reshape(-1),contim.reshape(-1)))
    end = time.time()
    return (asmim, homim, contim), cov, (var[0],var[1],var[2])

def segTF(imreg):
    '''get a vector of average texture features per image region'''

    glcm = GLCM(imreg)
    asm = getASM(glcm)[4]
    hom = getHOM(glcm)[4]
    cont = getCONT(glcm)[4]
    return (asm, hom, cont)

# Classification Methods

def Force(oldim, segs, mode):
    '''This function forces a pixel-based classification to segment shapes by taking the majority class (mode 1) or most frequently occurring class in the segment (mode 2) and returns the new image.''

    start = time.time()
    newim = np.zeros(np.shape(segs))+99
    seglist = list()

    for ID in np.unique(segs):  # for every unique segment
        loc = np.where(segs==ID)  # list all classes in segment
        binc = np.bincount(classbin.astype(int))

        if mode == 1:
            highest = np.max(binc)
            majority = (float(highest)/len(classbin))

            if majority >=0.75:  # if >75% belong to one class
                winner = np.argmax(binc)
                newim[loc] = winner
            else:
                newim[loc] = oldim[loc]  # no change
        elif mode == 2:
            winner = np.argmax(binc)  # take most frequent class
            newim[loc] = winner

    end = time.time()
    return newim

def crisp(compim, RedArray, segs, sigs, tol, metric, mode):
    '''This classification function uses the a crisp metric to assign a class for segments. If an area tolerance >=0 is provided, the crisp classifier is used to classify segments greater than the tolerance. For the remaining segments, the most frequent neighbouring class is assigned to the segment.

metric 1 = Spectral Angle Mapper
metric 2 = Minimum euclidean distance to means
metric 3 = Maximum likelihood with prior probabilities'''

    start = time.time()
    tol = float(tol)
    firsts, lasts = list(), list()
    newim = np.zeros(np.shape(segs))+99
    segs = np.unique(segs)

    if tol !=0:
        for ID in segs:
            loc = np.where(segs==ID)
            area = np.shape(loc[1])*0.001225 # or 0.0625 if 25cm reso
            if area >= tol:
                firsts.append(ID)
            else:
                lasts.append(ID)
        if tol==0:
            firsts = seglist
            lasts = []

    return newim
```python
print 'Now classifying segments >= ',tol,'m.sq...'  
for i in firsts:
    loc = np.where(segs==i)
    NIR=np.mean(compim[0][loc])
    R = np.mean(compim[1][loc])
    G = np.mean(compim[2][loc])
    if mode == 1:
        try:
            asm = np.mean(comp[3][location])
            hom = np.mean(comp[4][location])
            cont = np.mean(comp[5][location])
            mVec = [NIR,R,G,asm,hom,cont]
        except IndexError:
            mVec = [NIR,R,G]
    elif mode == 2:
        try:
            dumpim = np.zeros(np.shape(segs))-1
            dumpim[loc]=redArray[loc]
            dumpim = trim(dumpim)
            asm,hom,cont = segTF(dumpim)
            mVec = [NIR,R,G,asm,hom,cont]
        except IndexError:
            mVec = [NIR,R,G]
    winner,scores = 0,list()
    if sum(mVec)>0:
        for j in range(len(sigs)):
            cl = sigs[j][0]
            rVec = sigs[j][2]
            if metric == 1:
                score = sam(mVec,rVec)
                scores.append((cl,score))
            elif metric == 2:
                score = np.linalg.norm(np.subtract(mVec,rVec))
                scores.append((cl,score))
            elif metric == 3:
                score = maxlike(mVec,sigs[j][2:5])
                scores.append((cl,score))
        winner = int([cl for (cl,score) in scores if score==np.min(scores, axis=0)[1]])
        newim[loc] = winner
    else:
        newim[loc]=0
while len(lasts)>0:
    print 'Now classifying the remaining segments...'  
    for k in lasts:
        loc = np.where(segs==k)
        x = loc[0]
        y = loc[1]
        xs = np.append(x, (x,x,x+1,x+1,x+1,x+1,x+1,x+1))
        ys = np.append(y, (y+1, y-1, y, y+1, y-1, y, y+1, y-1))
        (shape1,shape2) = np.shape(segs)
        xix=[ix for (ix,yi) in enumerate(xs) if yi in range(shape1)]
        yix=[iy for (ix,yi) in enumerate(ys) if ix in range(shape2)]
        prune=[val for val in xix if val in yix]
        xs = xs[prune]
        ys = ys[prune]
        classbin = newim[xs,ys]
        classbinn = [val for val in classbin if val<=14]
        if len(classbinn)==0:
            print k,'classbin zero!'  
            continue
        elif len(classbinn)>0:
            winner = np.argmax(np.bincount(classbinn))
            newim[x,y] = winner
            print k,'winner: ', winner
            lasts.remove(k)
            continue
    end = time.time()
    print 'Classified with crisp metric ','metric', 'and tolerance', tol,
    ' in ',(end - start)/60,'minutes.'
    return newim
```