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**Remote Sensing of Wetlands in the Lake Whangape Catchment,
Waikato, New Zealand.**

A thesis
submitted **in partial fulfilment**
of the requirements for the degree
of
Master of Social Science in Geography
at
The University of Waikato
by
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Abstract

Wetlands are among the world's most valuable ecosystems. They provide numerous ecological and socio-economic benefits. However, wetlands continue to disappear due to the increasing demand for wetland resources. In New Zealand, more than 90% of the original extent of wetlands has been lost since the mid-eighteenth century. Therefore, legislation has been identified for the protection of wetlands as a matter of national importance.

Geographic Information System (GIS) and Remote Sensing (RS) techniques have proven helpful for mapping and monitoring wetland resources. This study aims to understand how RS techniques can classify wetlands in the Lake Whangape catchment, Waikato. The parameters that can be extracted from available data and their effectiveness in the classification process are also studied.

Four types of input data are collectively employed in the study. The data types are optical RS data, Synthetic Aperture Radar (SAR) data, a Digital Elevation Model (DEM), and wetland polygons provided by the Waikato Regional Council (WRC). All the steps including, accessing satellite scenes and data processing were performed within Google Earth Engine (GEE) computing platform using JavaScript language. The classification process for this study includes feature extraction, feature selection, model training, classification, and validation. Finally, the accuracy of the classification results is checked visually and statistically.

The classification was carried out in two stages. In Stage one, open water, wetland, and non-wetland areas are classified (simple classification). The combined wetlands class is separated into marsh and swamp in the second stage (detailed classification). Based on the results, the Topographic Position Index (TPI) is the most influential parameter in identifying wetlands, while the Modified Normalized Water Index (MNDWI) successfully identifies open water. The overall accuracy reached 91% at the simple classification stage. However, the detailed classification results received comparatively low classification accuracies (the overall accuracy is 76%).

Keywords: Wetlands, GIS, Remote sensing, Classification, Lake Whangape, Google Earth Engine

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Abbreviations

ANN	Artificial Neural Networks
DVI	Difference Vegetation Index
DEM	Digital Elevation Model
EM	Electromagnetic
Esri	Environmental Systems Research Institute
EVI	Enhanced Vegetation Index
GDVI	Generalized Difference Vegetation Index
GIS	Geographic Information System
GEE	Google Earth Engine
GNDVI	Green Normalized Difference Vegetation Index
GOSAVI	Green Optimized Soil-Adjusted Index
GSAVI	Green Soil-Adjusted Vegetation Index
GRVI	Green-Red Vegetation Index
IHS	Intensity-Hue Saturation
LiDAR	Light Detection and Ranging
ML	Machine Learning
MODIS	Moderate Resolution Imaging Spectroradiometer
MNDWI	Modified Normalized Water Index
NASA	National Aeronautics and Space Administration
NIR	Near Infrared
NDVI	Normalized Difference Vegetation Index
NDWI	Normalized Difference Water Index
OBIA	Object-based Image Analysis
OLI	Operational Land Imager
OSAVI	Optimized Soil-Adjusted Index
PALSAR	The Phased Array type L-band Synthetic Aperture Radar
Radar	Radio Detection and Ranging
RF	Random Forest
RS	Remote Sensing
SPOT	Satellite Pour l'Observation de la Terre
SWIR	Shortwave Infrared
SAVI	Soil-Adjusted Vegetation Index
SVM	Support Vector Machine
SAR	Synthetic Aperture Radar
TPI	Topographic Position Index
WRC	Waikato Regional Council

Chapter 1: Introduction

1.1. The structure of the thesis

The focus of this study is to understand how Geographic Information System (GIS) and Remote Sensing (RS) techniques can be employed in identifying wetlands in the Lake Whangape catchment, Waikato, New Zealand. The thesis comprises five Chapters: Introduction, Knowledge from the previous studies, Materials and methods, Results, Discussion and Conclusion. The introductory Chapter provides an overview of wetlands, their importance, the current situation, and trends of wetlands across the world. Wetland restoration efforts, monitoring of existing wetlands, and restoration success are described, followed by GIS and RS solutions for wetland monitoring. The chapter concludes with rationale for the study followed by the details on the study location.

Chapter 2 is a comprehensive literature review of previous research findings on the topic. This Chapter also explains the RS process implemented to achieve the study purpose in detail. The third Chapter includes the materials and methods used in the study and the details of the workflow of the project. The results of each classification step are presented in Chapter 4. Chapter 5 discusses the results and presents the conclusions. As the final classification map is small in scale, a series of 12 enlarged maps were created and are presented in the appendix.

1.2. Wetlands

The most widely used and accepted definition of wetlands is adopted by the Convention on Wetlands of International Importance usually referred to as the Ramsar Convention (Matthews 1993). According to the Ramsar Convention, "Wetlands are areas of marsh, fen, peatland or water, whether natural or artificial, permanent or temporary, with water that is static or flowing, fresh, brackish or salt, including areas of marine water the depth of which at low tide does not exceed six meters" (Ramsar Convention Secretariat 2016, 1).

Wetlands are among the world's most productive and valuable ecosystems (Burton et al. 2009; B.R. Clarkson, Ausseil, and Gerbeaux 2013). They offer many ecological and socio-economic benefits including habitats for fish and plant communities, storing flood water, recharging groundwater, reducing peak runoff, filtering water, sinking nutrient and sediment, safeguarding shorelines from erosion and providing recreational opportunities (Burton et al. 2009; B.R. Clarkson, Ausseil, and Gerbeaux 2013; Mitsch and Gosselink 2000; Zedler and Kercher 2005).

In New Zealand, wetlands have special significance for Māori for many cultural and spiritual values and uses. These include mahinga kai (cultural harvest sites), cultural identity, and decision-making through Te Mana o Te Wai. In addition, wetlands are traditional gathering sites for food, rongoā (medicines), and many taonga species (such as fish, birds, and plants for weaving) for Māori (Taura, Van, and Clarkson 2017).

1.2.1. Status and trends of wetlands

Human demand for wetland resources for agricultural expansion and urban development continues to grow due to the increase of the world population (Mitsch and Gosselink 2000; Zedler and Kercher 2005). In addition, global climate change has pronounced impacts on wetland ecosystems through alterations in hydrological regimes (Erwin 2009). It has been estimated that 64% of the world's wetlands have disappeared since 1900 (Ramsar Convention Secretariat 2010). Therefore, the conservation of wetlands is identified as an urgent need.

In New Zealand, 90% of the original extent of wetlands has been lost in the last 150 years (Ausseil et al. 2008). The South Island has 16% of its original wetland area remaining; the more populated and intensively developed North Island has only 4.9% (Ausseil et al. 2011). According to Robertson (2016), only 10% of pre-European palustrine wetlands remain, with 63% currently located within protected areas. The lost historical wetlands in New Zealand are significant in comparison with global reductions. The Ministry for the Environment has reported a loss of 1,247 ha of wetlands in New Zealand between 2001 and 2016.

1.2.2. The conservation efforts and monitoring needs

The Convention on Wetlands (Ramsar Convention, 1971) is playing a key role with a mission of “the conservation and wise use of all wetlands through local, regional and national actions and international cooperation, as a contribution towards achieving sustainable development throughout the world”. As of 2016, the convention comprises 169 nations, known as Contracting Parties, and protects more than 2,220 wetlands around the world. Many countries have adopted the wetland definition by the Ramsar Convention to promote wetland conservation in their lands and to designate “wetlands of international importance” in accordance with the terms of the Ramsar Convention (Tiner 2016).

New Zealand is also obliged to monitor the health and condition of wetlands as a signatory to two international conventions namely Convention on Biological Diversity and the Ramsar Convention on Wetlands. The responsibility for meeting the obligations of these conventions is shared between several central government agencies, in particular the Department of Conservation and the Ministry for the Environment (Clarkson et al. 2003).

Many wetlands are invaded by pests and remaining wetland areas continue to be degraded (Zedler and Kercher 2005). Effective, accurate and robust tools for monitoring wetlands are urgently needed following their destruction and degradation (Ozesmi and Bauer 2002). The health or condition of remaining wetlands can further decline due to a range of external pressures such as changes in hydrology, water pollution, and impaired wetland functioning. Monitoring is important for detecting these negative changes and preventing further loss of wetlands. Monitoring is also essential for assessing the effectiveness of restoration efforts (Clarkson et al. 2003). Accurate wetland mapping is an important tool for understanding wetland functions and monitoring their response to natural and anthropogenic actions (Baker et al. 2006).

1.3. GIS and RS for monitoring of wetlands

GIS and RS technologies have proven helpful for mapping and monitoring wetland resources (Lang et al. 2012; Ozesmi and Bauer 2002). There are many advantages of using RS in wetland monitoring. RS is a cost-efficient method that can cover larger areas and inaccessible locations such as wetlands. RS is a convenient and non-destructive tool for wetland mapping over a range of spatial scales. RS data can easily integrate with GIS. It is less time-consuming than traditional field surveys for large geographic areas (Ozesmi and Bauer 2002). They are also allowing researchers to take a broader view of ecological patterns and processes (Malthus and Mumby 2003; Ozesmi and Bauer 2002).

Wetland classification using remote sensing data has been performed for more than 50 years (Guo et al. 2017). Many types of remote sensing including aerial photography have been used to study wetlands, but the time-consuming nature of manual visual interpretation-based wetland delineation makes it impractical to monitor on a regional scale. Earth observation satellites provide a more reliable and standardized source of environmental data (Allan 2016).

Computerized classification methods conquered the drawbacks of manual and early artificial visual image interpretation. Computerized classification methods include supervised, unsupervised, and hybrid approaches. In supervised classification approach, the user can choose sample pixels in an image that represent specific classes and then tell the image processing software to learn from them. Supervised classification uses training samples to recognize the difference. The advantage of this method is the ability to specify the desired classes (Ozesmi and Bauer 2002; Schowengerdt 2006). In unsupervised classification approach, the clusters are formed based on similar spectral characteristics in the image. The computer program classifies each cluster without training samples (Goncalves et al. 2008). Hybrid classification methods combine the supervised and unsupervised approaches to expedite the identification of classes and the acquisition of training samples (Lillesand, Kiefer, and Chipman 2015).

The spectral signature is used to identify the objects using RS data. Spectral signatures are patterns of reflectance that varies as a function of wavelength for various targets. There are four principal characteristics of spectral signature: spectral variations, spatial variations, temporal variations, and polarization variations. Spectral variations are identified as a function of wavelength while spatial variations are determined by the shape, size, and texture of the target. Temporal variations refer to seasonal changes in reflectance while polarization variations are caused by the degree of polarization (Sharma et al. 2015). All these variations are used in the study to identify the objects in the study area.

1.4. Rationale for the study

Wetlands have a complex and rich vegetation composition, which makes mapping them difficult with traditional optical sensors (Ozesmi and Bauer 2002). RS with finer spatial resolution is preferred for detailed classification because of their better spatial characteristics (Cao and Zhang 2020). The red edge and near-infrared bands in optical imagery are the most useful bands for wetland classification, according to the literature (Mahdavi et al. 2018). Longer wavelengths are also more appropriate for separating forested or densely vegetated wetlands from non-flooded ones, according to several studies (Amani, Salehi, et al. 2019). Some scholars argue that the use of multi-season RS data could increase classification accuracy (Amani, Mahdavi, et al. 2019; Q. Wu 2018).

In New Zealand, GIS and RS are widely used for wetland classification (Allan 2016). One of the recent studies (Dymond et al. 2021) revised the extent of New Zealand wetlands from an explicit combination of national databases Waters of National Importance (WONI) and the New Zealand Landcover Database (LCDB). Regarding the regional level, Allan (2016) has prepared a literature review on RS of Waikato wetlands and recommended a minimum of 10 m Digital Elevation Model (DEM), image segmentation, the inclusion of ancillary data, and combining spatial data from multiple sources. The literature review of Allan (2016) further suggested Synthetic Aperture Radar (SAR) Sentinel-1, Advanced Land Observing Satellite-the Phased Array type L-band Synthetic Aperture Radar (ALOS-PALSAR), or Light Detection and Ranging (LIDAR) for differentiation of wooded wetlands from other forest land covers.

The study presented in this thesis uses optical, SAR, and elevation data with a DEM (10 m cell size) to classify wetlands. In addition, two types of satellite data are used in the study from Sentinel-1 and Sentinel-2.

Sentinel-1 has two polar-orbiting satellites that are operating day and night. It provides SAR which acquires imagery regardless of the weather. The Sentinel-1 data are used in maritime monitoring, land monitoring, emergency management, and mapping applications (The European Space Agency 2012).

Sentinel-2 provides continuity of Satellite Pour l'Observation de la Terre (SPOT) and Landsat-type image data. Sentinel-2 data can be used for applications such as land management, agriculture and forestry, disaster control, humanitarian relief operations, risk mapping, and security concerns (The European Space Agency 2015).

1.5. Study location

There are three internationally significant wetlands in the Waikato region namely Whangamarino, Kopouatai, and the Firth of Thames. The Waikato Regional Council (WRC) monitors and reports on the region's wetlands regularly. The Lake Whangape catchment is also a vital wetland area in the region. Therefore, it was selected as the study location.

Lake Whangape is hydrologically linked to the Waikato River and is physically, chemically, and biologically influenced by the river. Water levels fluctuate seasonally, and large swamp areas dry out during summer when rainfall and river levels are low. Lake Whangape is the only lake in the area which still has a natural connection with the Waikato River. It is a government purpose (Wildlife Management) reserve gazetted in 1986 with an extent of 1,330 hectares, and it is the second-largest lake in the lower Waikato River basin.

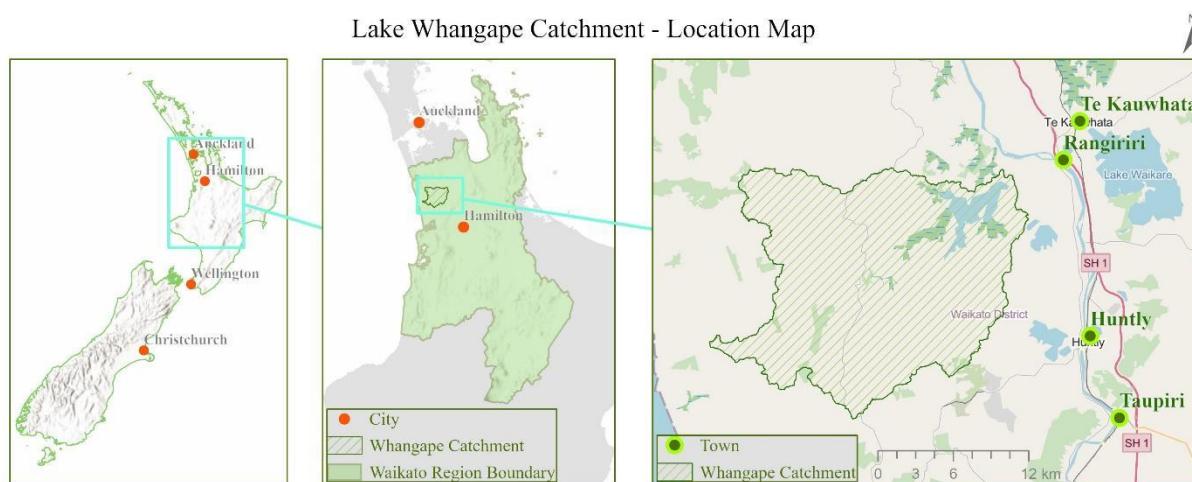


Figure 1. Location Map-Lake Wahagape Catchment

Map data: Open Street map contributors, Microsoft, Environmental Systems Research Institute (Esri) Community Maps contributors, Esri, United States Geological Survey (USGS) and Koordinates.com (NationalMap 2020).

There are large areas of willow forest around the lake and much of the lake margin is dominated by pasture. The wetland plant zone has a diverse native plant community (Williamson et al. 2016). According to LCDB, two main wetland classes are identified in the area: Swamps and Marshes.

Chapter 2: Knowledge from previous studies

This Chapter provides a comprehensive summary of previous studies on wetlands and remotely sensed wetland classification. The first part of the Chapter is devoted to the literature on definitions of wetlands and the wetland classification system in New Zealand. Important literature on RS principles, various image enhancement approaches, and RS data types are described in the middle of this Chapter. The latter part of the Chapter explains the classification method, various classifiers, and details on accuracy testing. The last section of Chapter 2 gives details on the application of RS in identifying wetlands and previous studies carried out using the Google Earth Engine (GEE) platform.

2.1. Wetlands

There is no general definition of wetlands due to the diverse nature of wetlands. Some wetland definitions include open-water habitats as wetlands, while others exclude permanent deepwater and focus on shallow-water habitats (Cowardin 1979). In general, wetland is a broad term that encompasses a wide range of wet habitats such as marshes, swamps, bogs, fens, and seasonally waterlogged areas (Tiner 2016). The most widely used and accepted definition is adopted by the Convention on Wetlands of International Importance (Ramsar Convention), as explained in the introduction.

In New Zealand, the Resource Management Act (1991) provides a wetland definition for New Zealand purposes. According to the act, wetland includes permanently or intermittently wet areas, shallow water, and land water margins that support a natural ecosystem of plants and animals adapted to wet conditions.

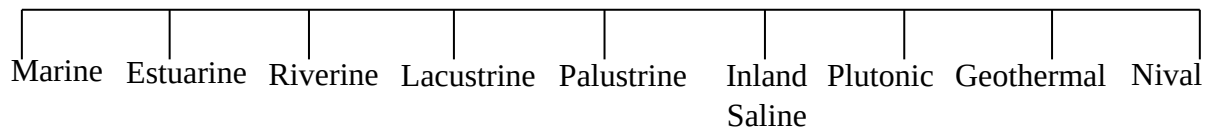
2.1.1 New Zealand wetland classification system

Experts subsequently developed a national classification system for wetlands in New Zealand. The information from two leading publications is used to determine the difference between wetland classes for this study. These two publications are wetland types in New Zealand by Johnson and Gerbeaux (2004) and *Wetland Restoration: A Handbook For New Zealand Freshwater Systems* by Clarkson and Peters (2010).

Wetland classes are governed by distinctive combinations of substrate factors, water regime, and the consequent factors of nutrient status and pH. The ten recognized wetland classes are bog, fen, swamp, marsh, seepage, shallow water, ephemeral wetland, pakihi, gumland, and saltmarsh (Johnson and Gerbeaux 2004). The semi-hierarchical classification system for New Zealand wetlands described in "Wetland Types in New Zealand" is given below.

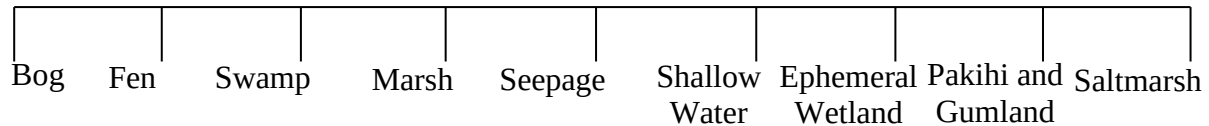
I. Hydrosystem

(Based on broad hydrological and landform setting, salinity, temperature)



IIA. Subsystem

(Based on substrate, water regime, nutrients, pH)



IIB. Wetland Form

- Landforms which wetlands occupy (e.g., slope, basin)
- Forms which wetlands create (e.g., domed bog, string, fen)
- Forms or features which wetlands contain (e.g., pool, rand)

III. Structural class

- Structure of the vegetation (e.g., forest, rushland, herbifield)
- Predominant ground surface (e.g., rockfield, mudflat)

IV. Composition of vegetation

- One or more dominant plants (e.g., bog pine, wire rush)

(Johnson and Gerbeaux 2004)

In 2004, the Department of Conservation (DOC) published wetland types in New Zealand that provided a detailed description of wetland types and characteristic features of wetlands. The following information on swamps and marshes are gathered from the book, *Wetland types in New Zealand* (Johnson and Gerbeaux 2004).

Marshes

Marshes are fed by groundwater or surface water and have fluctuating water levels. Marshes are often flooded by standing or slowly moving water. Marshes have mainly mineral soil and have reasonable drainage. They have medium to high fertility and are slightly acidic to neutral. Marshes mainly occur on gentle slopes, especially on valley margins and floors, beside rivers and lakes. Vegetation is most often rush land, grassland, sedgeland, or herb field (Johnson and Gerbeaux 2004).

Swamps

Swamps receive a relatively rich supply of nutrients, and often sediment, through surface runoff and groundwater from nearby land. Swamps usually lie on a mixture of mineral and peat substrates. Channels of water are common, and the water table is often above the ground in places. Swamps usually occur in basins and on valley floors, deltas, and plains. The plant

species typically found in swamps are sedge, rush, reed, flax, tall herbs, scrub, often intermingled, and forest (Johnson and Gerbeaux 2004).

The following table presents the main distinguishing features of Swamps and Marshes in New Zealand.

Table 1. Distinguishing features of Swamps and Marshes in New Zealand.

Wetland Class	Water origin (predominant)	Water flow	Drainage	Water table position of ground	Water fluctuation	Periodicity	Substrate	Nutrient status	pH
Swamp	Mainly surface water and ground water	Moderate	Poor	Usually, above surfaces in places	Moderate to high	Wetness permanent	Peat and/or mineral	Moderate to high	4.8 – 6.3
Marsh	Ground water and surface water	Slow to moderate	Moderate to good	Usually below surface	Moderate to high	May have temporary wetness of dryness	Usually, mineral	Moderate to high	6-7

Source: (Johnson and Gerbeaux 2004).

Table 2. Landforms, vegetation, and key indicator plants associated with wetland classes.

Wetland class	Predominant landforms	Common vegetation structural class	Some key indicator plants
Swamp	Mainly on valley floors, plains, deltas	Usually sedge, rush reed, tall herb, and scrub type, often intermingled, and including forest	<i>Phormium, Carex, Coprosma, Gahnia, Typha, Cordyline, Dacrycarpus, Laurelia, Syzygium</i>
Marsh	Slight to moderate slopes, valley margins, edges of water bodies	Typically, rush, grass, sedge, or shrub types	<i>Juncus, Carex, Agrostis, Cortaderia</i>

Source: (Johnson and Gerbeaux 2004).

Later in 2010, *Wetland restoration: a handbook for New Zealand freshwater systems*, illustrates wetland types of New Zealand. The publication suggests a simple gumboot test for distinguishing wetland classes. Short gumboots are usually adequate for keeping feet dry in bogs because of the vegetation and peat. Taller gumboots will be needed for fens, and thigh waders are recommended for swamps, which have large areas of open water. Waist waders may be required for marshes when water levels are high, and a dry suit or wetsuit will help traverse shallow water. The critical environment characteristics of wetland types according to the publication are given below.

Wetland Type	BogFenSwampMarsh Shallow water			
Water Source	Rainfall → Groundwater → Surface water			
Waterflow and fluctuation	Low → Medium → High			
Nutrient availability	Low → Medium → High			
pH	Low/acidic → Medium → High/neutral			
Peat content	High → Medium → Low/none			

Figure 2. Environment characteristics of wetland type (Clarkson and Peters 2010).

2.2.Remote sensing

The central concept of these definitions is gathering information at a distance (Campbell and Wynne 2011). Musk (1979) suggests that RS is the acquisition of physical data of an object without touch or contact. "RS is the science (and to some extent, art) of acquiring information about the Earth's surface without actually being in contact with it. The information gathering is done by sensing and recording reflected or emitted energy and processing, analysing, and applying that information"(Joseph 2005, 1).

This section includes knowledge and understanding of RS instruments, data acquisition, pre-processing, image enhancement, dimensionality reduction, model training and validation, and accuracy testing. The RS process incorporated with GIS followed by the study is presented in Figure 3.

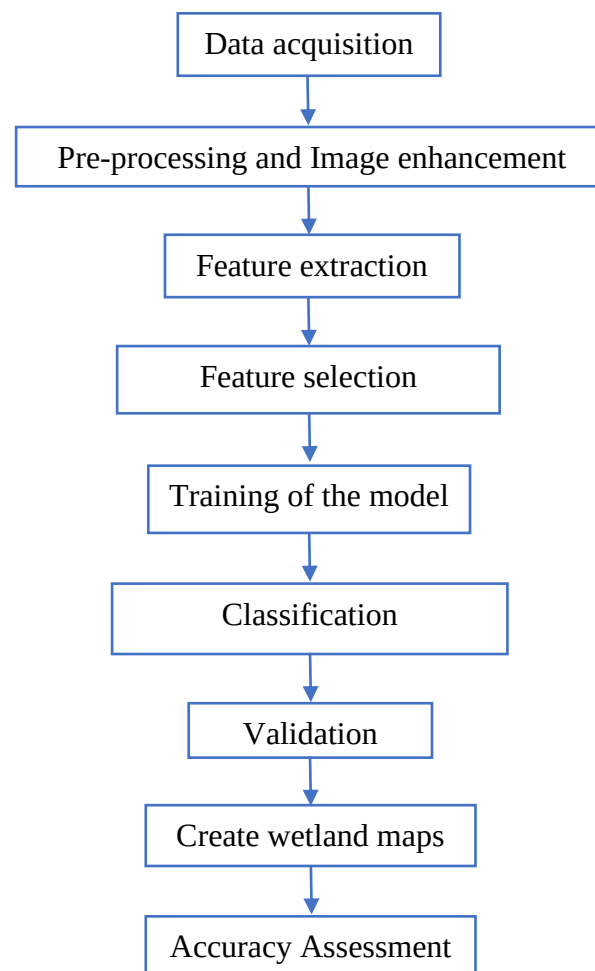


Figure 3. Simplified process followed by the study.

2.2.1. Data acquisition

In remote sensing, the sensing and sensors are broadly classified into two categories based on the source of energy used to record the information. The classes are known as active and passive (Gupta 2018). Active and passive RS data acquisition are described below.

Active remote sensing

Active remote sensing involves transmitting coherent electromagnetic wave at the target. The active RS sensor measures the time for the transmitted electromagnetic (EM) wave to return and the phase information of the returned EM wave (Lee and Wong 2018). According to Hassebo (2012), widely used active RS data include Radar, LiDAR and Sound Navigation and Ranging (SONAR).

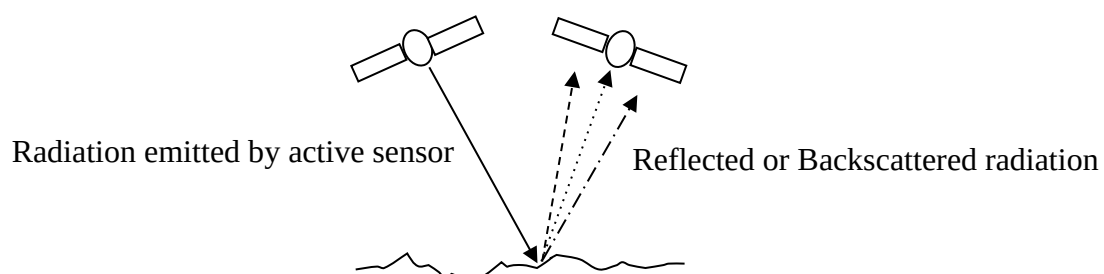


Figure 4. The simplified diagram to demonstrate active remote sensing.
The diagram is adopted from National Aeronautics and Space Administration (NASA) Applied RS Training Program training materials (2017).

The surface scale relative to the wavelength determines how rough or smooth they appear and how bright or dark they will appear on the image. Figure 5. shows how the backscattered radiation behaves when facing different surfaces.

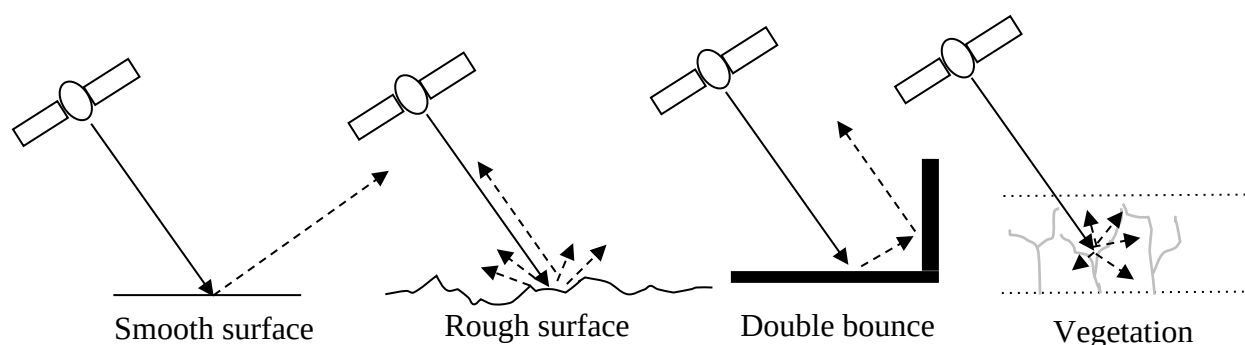


Figure 5. Backscattering mechanisms

The diagram is adapted from NASA Applied RS Training Program materials (Podest 2017).

SAR data

SAR provides high-resolution, two-dimensional images independent from daylight, cloud coverage, and weather conditions. The Radar system transmits EM pulses with high power and receives the echoes of the backscattered signal sequentially. Therefore, more penetration of the EM pulses in media will occur for Radar systems using longer wavelengths which usually have an accentuated volume contribution in the backscattered signal (The European Space Agency 2012). Commonly used frequency bands in SAR systems and the associated wavelength ranges are given in the following table.

Table 3. SAR systems and the associated wavelength ranges.

Frequency Band	Ka	Ku	X	C	S	L	P
Frequency (GHz)	40–25	17.6–12	12–7.5	7.5–3.75	3.75–2	2–1	0.5–0.25
Wavelength (cm)	0.75–1.2	1.7–2.5	2.5–4	4–8	8–15	15–30	60–120

Source: Microwaves and Radar Institute of the German Aerospace Centre (DLR), Germany.

Sentinel-1 images

Sentinel-1 has two polar-orbiting satellites that are operating day and night. Its SAR sensors acquire data which acquires imagery regardless of the weather (Sentinel-1 SAR User Guide, 2012). Each scene contains either 1 or 2 out of 4 possible polarization bands, depending on the instrument's polarization settings. The possible combinations are given in Table 4.

Table 4. SAR bands.

VV	Single co-polarization, vertical transmit/vertical receive
HH	Single co-polarization, horizontal transmit/horizontal receive
VV + VH	Dual-band cross-polarization, vertical transmit/horizontal receive
HH + HV	Dual-band cross-polarization, horizontal transmit/vertical receive

Source: Sentinel-1 SAR User Guide (2012).

Passive RS

In passive remote sensing, the sensors detect natural energy (radiation) emitted or reflected by the object. The sun is the source of visible to shortwave infrared (SWIR) radiation collected by passive RS systems. Thermal radiation emitted directly by materials on the Earth combines with self-emitted thermal radiation in the atmosphere as it propagates upward in the thermal infrared (Schowengerdt 2006).

The following diagram (Figure 6) presents an overview of the process using information detected from a passive sensor.

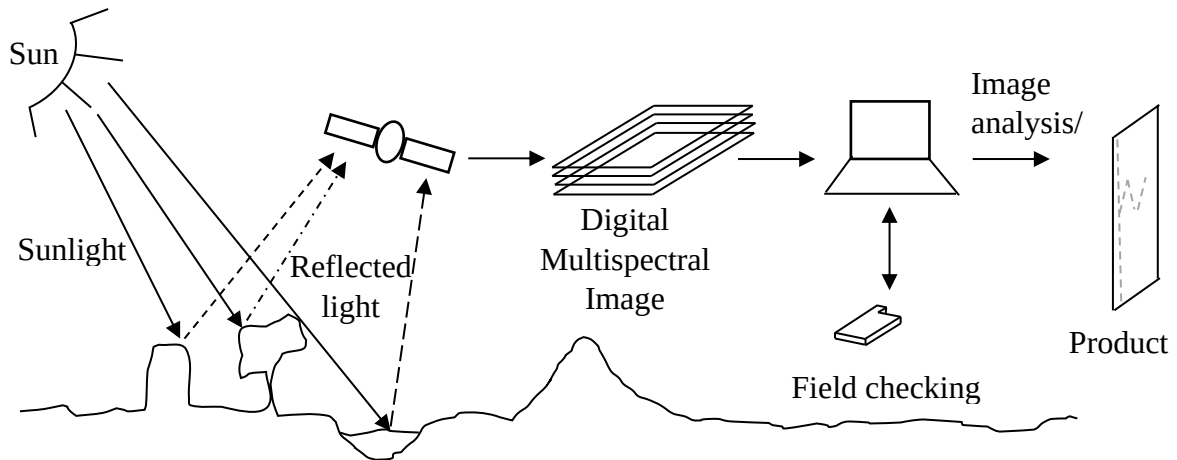


Figure 6. The general process of RS with passive sensor.

The diagram is adapted from (Aggarwal 2004).

Optical RS data

Optical RS uses visible, Near Infrared (NIR), and SWIR sensors to form images of the Earth's surface by detecting the solar radiation reflected from targets on the ground. Different materials reflect and absorb differently at different wavelengths. Therefore, the targets can be differentiated by spectral reflectance signatures in the remotely sensed images (Horning 2019). Since the first Earth Resources Technology Satellite (ERTS-1, later renamed as Landsat-1) launched in 1972, satellite-based optical sensors have demonstrated their potential to monitor large-scale land cover changes on the Earth's surface (Deutsch and Ruggles Jr 1978).

Sentinel-2 images

Sentinel-2 is a wide-swath, high-resolution, multispectral imaging mission that provides data continuity for data acquisitions previously performed by heritage missions such as Landsat and SPOT. The data is designed to be modified and adapted in thematic areas such as spatial planning, agro-environmental monitoring, water monitoring, forest and vegetation monitoring, land carbon, natural resource monitoring, and global crop monitoring (The European Space The European Space Agency 2015).

The Sentinel-2 satellites acquire data over islands greater than 100 km² in area, islands in the European Union, all other islands within 20 km of a coastline, the Mediterranean Sea, all inland water bodies, and all closed seas (The European Space The European Space Agency 2015).

There are thirteen spectral bands in the Visible and NIR and SWIR regions.

- Four bands at 10 m spatial resolution with different wavelengths 490 nm (B2), 560 nm (B3), 665 nm (B4), 842 nm (B8)
- Six bands at 20 m spatial resolution with different wavelengths 705 nm (B5), 740 nm (B6), 783 nm (B7), 865 nm (B8a), 1,610 nm (B11), 2 190 nm (B12)
- Three bands at 60 m spatial resolution with different wavelengths 443 nm (B1), 945 nm (B9) and 1 375 nm (B10)

(The European Space Agency 2015).

Image data characteristics

The characteristics of the sensor-platform system primarily determine the quality of image data. These characteristics include spatial coverage, spatial resolution, spectral resolution, dynamic range, radiometric resolution, temporal coverage, and revisit time (Kerle, Janssen, and Huurneman 2004).

Spatial resolution is one of the most considered parameters in this study, which refers to the area of ground observed within a pixel and determines the level of detail captured by the sensors. Therefore, spatial resolution is one of the most direct factors that control the usage of different sensors in the applications (Huang et al. 2017; Kerle, Janssen, and Huurneman 2004). The spatial resolution parameter derived from satellite data in the study is 10 m.

2.2.2. Image enhancement and pre-processing

Image pre-processing

The image pre-processing includes thermal noise removal, radiometric calibration, terrain correction, and atmospheric correction (The European Space The European Space Agency 2012, 2015). Usually, the images available for end-users are pre-processed. The image provider performs long series of processing to optimize the imagery for general use in a typical scenario (Green, Congalton, and Tukman 2017). For example, the Sentinel-2 Level-1C dataset is already a standard product, and no additional pre-processing is required (Deidda and Sanna 2012).

Atmospheric correction

Atmospheric correction is an optical image pre-processing step critical for multi-temporal analysis and digital classification processes (Sola et al. 2018). It removes the effects of active atmospheric elements such as molecular and aerosol scattering and absorption by water vapor, ozone, oxygen, and carbon dioxide (Gao et al. 2009). Consequently, the quality of reflectance depends on the atmospheric correction method, atmospheric-surface characteristics, and sensor design (Okin and Gu 2015). Two main algorithms, known as image-based and atmospheric radiative transfer codes, are available for atmospheric correction (Hadjimitsis, Clayton, and Hope 2004).

In the image-based approach, the effects are derived from the image and removed from the Top of Atmospheric (TOA) signal. The Sen2Cor processor is included in the Sentinel toolbox by European Space Agency (ESA) for atmospheric correction based on an image-based approach. The most used image-based atmospheric correction methods are Multi-Mission Atmospheric Correction and Cloud Screening (MACCS), and Joint Atmospheric Correction (Main-Knorn et al. 2017). In addition, the Second Simulation of a Satellite Signal in the Solar Spectrum (6s vector version) is a well-established radiative transfer code used in atmospheric correction (Vermote et al. 1997).

According to Baraldi and Tiede (2018), the atmospheric correction and land cover classification depend on an accurate cloud map. However, the cloud and shadow pixels need to be left from the analysis because the cloud does not represent the Earth's surface. Therefore, cloud screening is necessary for further processing steps. It can be done either by the atmospheric correction itself or higher-level processing such as compositing, time-series analysis, or estimation of bio-geophysical parameters (Zekoll et al. 2021). All the algorithms mentioned above under atmospheric correction can be used for cloud masking. The Cloud Masking Intercomparison Exercise is a set of algorithms designed for cloud masking the Sentinel-2 and Landsat-8 products (Zekoll et al. 2021).

Thermal noise removal

Thermal noise removal reduces noise effects by normalizing the backscatter signal within the entire Sentinel-1 scene. The thermal noise removal operator is available in SNAP (Sentinel toolbox) for Sentinel-1 data (Filipponi 2019).

Radiometric calibration

The radiometric correction techniques are based on the values of individual pixels within each band. The radiometric enhancement techniques are based on histograms (the number of pixels with a given brightness versus brightness values). The tonal or radiometric quality of an image can be assessed from these histograms using digital numbers. There are linear and non-linear radiometric techniques used in radiometric enhancement (Lasaponara and Masini 2012).

Terrain correction

The SAR data are generally characterized by viewing angles greater than zero degrees. Therefore, some distortion related to side-looking geometry can result during data acquisition. The terrain correction compensates for these distortions. The geometric distortions caused by topography can be corrected by range doppler terrain correction (Filipponi 2019).

Image enhancement

Image enhancement makes features more visible. Therefore, the image is more straightforward to interpret than raw data (Lasaponara and Masini 2012). The enhancement doesn't increase the inherent information content of the data, but it improves the dynamic range of the chosen features so that they can be detected easily by emphasizing or sharpening image features such as edges, boundaries, or contrast (Abidin, Sulochana, and Prabin 2020). There are many image

enhancement techniques available depending on the application, data availability, and analyst experience (Richards and Richards 1999). The enhancement can be categorized into two types called non-fusion-based and fusion-based image enhancement.

Data Fusion

Images with low spatial resolution are fused to generate high-resolution images in fusion-based image enhancement (Li, Jing, and Tang 2017). The fusion-based image enhancement methods include component substitution method, multi-resolution method, optimization-based method, and numerical and statistical-based approach (Ablin, Sulochana, and Prabin 2020).

Component substitution includes the Intensity-Hue Saturation (IHS) colour transformation, the most common component substitution approach. The true colour image in RGB space is converted into Hyperspectral Image Saturation (HIS) colour space. The auxiliary information is placed in the intensity band in this highly efficient algorithm. The method was introduced by (Malpica 2007).

In the Multi-Resolution method, the radiometric information present in a low-resolution image is combined with the spatial information present in a high-resolution image to sharpen the low-resolution image. There are many multi-resolution algorithms available for image enhancement (Ablin, Sulochana, and Prabin 2020).

Pan-sharpening

As described above, image fusion's objective is to combine the spatial information from the higher spatial resolution image and spectral information from a multispectral image with a lower spatial resolution (Li, Jing, and Tang 2017). Pan-sharpening is a branch of image fusion with multiple applications. The applications include pattern recognition, visual enhancement, classification, change detection, object detection, and area surveillance (Pohl and Van Genderen 1998). Pan-sharpening methods are based on many data fusion methods (Shrivastava and Miri 2020), and standard component substitution methods are Principal Component Analysis (PCA) and IHS pan-sharpening.

Sentinel-2 images cover 13 bands in the visible, NIR, and SWIR wavelengths with 10 m, 20 m, and 60 m spatial resolutions. Sentinel-2 does not offer a panchromatic band with high resolution. However, panchromatic bands can be created using the four fine spectral resolution bands and used in the Sentinel-2 image fusion to create ten fine spatial resolution bands (Selva et al. 2015).

Kaplan (2018) compared three methods for producing a panchromatic band from Sentinel-2 bands. The results revealed that using a single panchromatic band is less time-consuming and more practical. Since, Green and SWIR bands of Sentinel-2 have different spatial resolutions of 10 m and 20 m, Modified Normalized Water Index (MNDWI) can be produced from Sentinel-2 at the spatial resolution of 20 m by upscaling the 10 m green band to 20 m correspondingly. This scheme, however, wastes the detailed information available at the 10 m resolution (Du et al. 2016). Therefore, in this study, the pan-sharpening is applied to downscale

the 20 m SWIR band to 10 m by using the 10 m NIR band as the pan-like band to take full advantage of the Sentinel-2 image that has four 10 m bands.

As mentioned above, the image provider performs long series of processing to optimize the imagery for general use in a typical scenario. However, there are times when additional image enhancement can highlight, or pull-out features of interest based on the analyst's need. Raster filters are the most common application that can enhance the image gravely. There are two groups of filters called high-pass filters and low-pass filters. High-pass (smoothing) filters help identify edges in an image or sharpen an image. Low-pass filters (edge filters) help remove noisy pixels from an image and create smoother, visually appealing images (Green, Congalton, and Tukman 2017). Image filters work by assigning a new value to each pixel in an image based on that pixel's value and the values of neighbouring pixels. Thus, each pixel in the image is considered one at a time during the filtering (Green, Congalton, and Tukman 2017).

2.2.3. Feature extraction

According to Baatz et al. (2004), feature extraction can be defined as an image processing technique for identifying and classifying mutual relationships or meaning between image regions. Therefore, feature extraction is essential in extracting meaningful information in RS (Karim et al. 2017). According to Amani, Mahdavi, et al. (2019), a common approach is to extract more features from the RS data to increase image classification accuracy. For example, sentinel-2 features and SAR ratio features such as co-polarizations could be helpful in the identification of wetlands. The co-polarizations are important for the detection of flooded wetlands.

As noted in the introduction section, GIS and RS techniques can facilitate wetland identification and delineation by analysing a combination of wetland indicators such as hydrology, vegetation, soil types, and topographic position (i.e., Potential wetlands) (Q. Wu 2018).

Hydrology is probably the most important factor that affects the formation and functions as it influences plant communities, animal species, soil properties, and human use. Lands must remain 'wet' for an extended period during the growing season to be designated as wetlands. The prolonged wetness of wetlands results from water received from various sources, including precipitation, snowmelt, surface water runoff, and groundwater discharge. Wetlands can generally be classified as ephemeral, temporary, seasonal, semipermanent, and permanent wetlands based on the frequency and duration of inundation or soil saturation. In general, wetlands with high wetness are relatively easier to identify than dried wetlands through remote sensing. Apart from cloud shadows, a dark tone in multispectral RS imagery often indicates water or high soil moisture areas where wetlands are likely to occur. McFeeters (1996) Normalized Difference Water Index (NDWI) is a commonly used index to detect and delineate water-like features and high soil moisture areas.

The main limitation of (McFeeters) NDWI is that it cannot suppress the signal noise coming from the land cover features of built-up areas efficiently. Xu (2006) noticed that the water body has a stronger absorbability in the Short-Wave SWIR band than in the NIR band, and the built-up class has greater radiation in the SWIR band than that in the NIR band. Therefore, Xu (2006) introduced the MNDWI that uses green and SWIR bands for the enhancement of open water features. It also diminishes built-up area features that are often correlated with open water in other indices.

The formula for calculating MNDWI is $MNDWI = \frac{(GREEN - SWIR)}{(GREEN + SWIR)}$
(Xu 2006)

Various vegetation indices have been used to identify macrophytic vegetation and hydrophytic vegetation while wetland mapping. The importance of macrophytic vegetation in wetland identification is described in the New Zealand wetland classification section. In addition, (Burton et al. 2009) has mentioned in their book, *Ecology of Wetlands*, that the "macrophytic plants (plants visible without magnification) growing in wetlands are referred to as hydrophytes (water-loving plants) or hydrophytic vegetation." These species have adapted to the frequent and prolonged flooding events that occur in wetlands.

Difference Vegetation Index (DVI) is one of the simplest vegetation index (Tucker 1979). According to Tucker, DVI is sensitive to the amount of vegetation, distinguishes between soil and vegetation, and does not deal with the difference between reflectance and radiance caused by the atmosphere or shadows.

Further, Tucker (1979) stated that remotely sensed data are frequently used to identify specific plant species or vegetation types that are indicative of wetlands. The most commonly used index to detect green vegetation from multispectral RS data is Normalized Difference Vegetation Index (NDVI). NIR and red bands represent the spectral reflectance values acquired in the NIR and red portions of the EM spectrum, respectively. NDVI values range from (−1) to (+1) theoretically. Thus, an NDVI value that is negative or close to zero means no vegetation, whereas an NDVI value close to (+1) indicates the highest concentration of green vegetation.

Mahdianpari, Jafarzadeh, et al. (2020) used DVI, NDVI, Generalized Difference Vegetation Index (GDVI), Green Normalized Difference Vegetation Index (GNDVI), Green-Red Vegetation Index (GRVI), Green Soil-Adjusted Vegetation Index (GSAVI), Green Optimized Soil-Adjusted Index (GOSAVI), Soil-Adjusted Vegetation Index (SAVI), Optimized Soil-Adjusted Index (OSAVI) and Enhanced Vegetation Index (EVI) indices in their study on *a large-scale change monitoring of wetlands using time-series Landsat imagery on Google Earth Engine: a case study in Newfoundland*. In the same year, Mahdianpari, Granger, et al. (2020) employed NDVI and SAVI in their study on *a Meta-analysis of wetland classification using remote sensing: A Systematic Review of a 40-Year Trend in North America*.

There are many vegetation indices employed in previous studies to map and monitor wetlands. Therefore, this study tested the most suitable indices to effectively perform the remotely sensed classification of wetlands in the Lake Whangape catchment. The formula for vegetation indices used in the study are given below.

Table 5. Formula of vegetation Indices used in the study.

$NDVI = \frac{(NIR - RED)}{(NIR + RED)}$	(Rouse et al. 1974)
$DVI = (NIR) - (Red)$	(Tucker 1979)
$SAVI = \frac{1.5 * (NIR - RED)}{(NIR + RED + 0.5)}$	(Huete 1988)
$OSAVI = \frac{(NIR - RED)}{(NIR + RED + 1.6)}$	(Rondeaux, Steven, and Baret 1996)
$GNDVI = \frac{(NIR - GREEN)}{(NIR + GREEN)}$	(Gitelson and Merzlyak 1998)
$EVI = \frac{1.5 * (NIR - RED)}{(NIR + 6 + RED - 7.5 * BLUE + 1)}$	(Huete 1988)
$GDVI = (NIR) - (GREEN)$	(Sripada 2005)
$GSAVI = \frac{1.5 * (NIR - GREEN)}{(NIR + GREEN + 0.5)}$	(Sripada 2005)
$GRVI = \frac{(NIR)}{(GREEN)}$	(Sripada et al. 2006)

In addition to the vegetation indices, the SAR feature is useful in the classification of wetlands. The backscattering coefficient and polarization coefficient are among the most common parameters that are extracted from SAR data.

The non-flooded cypress-tupelo and hardwood forests can be distinguished using increased polarization ratios (S. Wu and Sader 1987). Later Bourgeau-Chavez et al. (2009) revealed that the Sentinel-1 VV polarized band is sensitive to soil moisture and flood conditions, and the dual-polarization ratios discriminate between herbaceous and woody wetlands. In addition, the polarization ratios between vertical transmit/vertical receive and horizontal transmit/horizontal receive bands are extracted.

SAR backscatter changes are linked with water level changes of wetlands, phenological changes, and soil moisture (Kim et al. 2013). According to Mohammadimanesh et al. (2018), swamp and marsh separate easily using the backscattering coefficient (σ^0). The swamp class can be easily distinguished from other wetland classes using intensity observations associated with backscattering.

The backscattering coefficient (sigma nought or σ^0) is usually given in decibels (dB). The σ^0 is calculated using the following equation.

$$\sigma^0_{(dB)} = 10 * \log_{10} \sigma^0$$

(Laur et.al., 2004)

2.2.4. Integration of RS and GIS data

RS is generally restricted to methods that utilize EM energy in detecting and measuring target characteristics (Sabins Jr 1986). However, Ancillary information needs to be included in the process of RS data interpretation (Campbell and Wynne 2011; Lillesand, Kiefer, and Chipman 2015). The ancillary data usually have various value distributions and may be highly correlated (Jensen 2005). Remotely sensed data are available digitally and the results of remote sensing analysis allow for rapid integration into a GIS (Eastman 2001). Many studies can be found in developing Machine Learning (ML) methods for integrating RS data and ancillary GIS data.

The DEM data can be incorporated in the RS studies in this context. DEM data can be used to derive topographic factors such as slopes, aspects, hill shading, slope curvature, slope roughness, slope area, and qualitative classification of landforms. The DEMs can also be used to derive important parameters such as flow direction, flow accumulation (Fernández et al. 2003) and indices such as Topographic Position Index (TPI)(Weiss 2001).

Modeling of environmental systems needs terrain analysis (Moore, Grayson, and Ladson 1991). The elevation is linked to terrestrial temperature, vegetation type, and potential energy accumulated on a slope. In addition, the aspect, and derived products, such as Northernness and Easternness attributes, can be linked to the potential solar irradiation on terrain. The slope gradient, for example, controls the overland and subsurface flow velocity and runoff rate. Similarly, curvatures are associated with acceleration and dispersion of water and sediment flows that impact erosion and soil water content (I. Florinsky 2016).

The public availability of elevation data with global coverage, such as the DEM derived from NASA's Shuttle Radar Topography Mission (SRTM) and the digital surface model from the Advanced Land Observing Satellite, has promoted the exploration of topographic features in different contexts using processing tools available in several geographic information systems (Liu et al. 2018).

Safanelli et al. (2020), in their study on *Terrain Analysis in Google Earth Engine: A Method Adapted for High-Performance Global-Scale Analysis*, aimed at describing and making available a user-friendly processing algorithm for performing terrain analysis in GEE. This algorithm takes advantage of GEE's high-performance architecture for making the computational analysis scalable, adapted to customized needs, and requiring minimal user input.

GEE provides three algorithms for calculating slope, illumination, and aspect of terrain but lacks calculation methods for other terrain information, such as the curvatures and landscape characterization. In addition, a common obstacle of global terrain analysis in common GIS is the need for projecting DEMs onto projected coordinate systems, which ensures the elevation data is equally spaced on a plane square grid (I.V. Florinsky 2017).

2.2.5. Feature selection

The goal of most ML tasks is to find the most accurate model of the response and determine which input variables are most important in making predictions (Louppe 2014). Random Forest (RF) has the advantage of calculating the relative importance of parameters. The relative importance of the explanatory variables can be assessed using the RF algorithm to select the most important ones. Therefore, it reduces dimensionality (Ouedraogo, Defourny, and Vanclooster 2019). Furthermore, the feature importance can be used for feature selection by removing low importance features (Koehrsen 2018). Since this study uses many parameters, such as vegetation indices and coefficient terrain features, the classifier is asked to describe the relative importance of the parameters. The parameters with above average importance based on the results are progressed to the final classification.

2.2.6. Classification methods

Common classification methods can be divided into two broad categories, namely supervised classification and unsupervised classification. In supervised classification, the analyst first selects training samples (i.e., homogeneous and representative image areas) for each land cover class and then uses them to guide the computer to identify spectrally similar areas for each class. The selection of training samples can be based on field data collection or expert knowledge.

Pixel-based and object-based approaches

The pixel-based classification methods are based on spectral information (i.e., Digital Number values). Individual image pixels are analysed by the spectral information that they contain (Richards and Richards 1999). Many researchers, including Van de Voorde et al. (2004), found that each pixel in the pixel-based paradigm is treated separately from its neighbours when pixel-based methods are applied to high-resolution images. Therefore, neighbours often have different classes, despite their similarities. This effect is known as the "salt and pepper" effect. Object-based classifiers use the spatial context around a pixel to aid in its classification, while pixel-based classifiers use only the spectral signature of a single pixel (Weiss 2001).

The object-based classification aggregates image pixels into spectrally homogeneous image objects that are then classified individually using an image segmentation algorithm (Liu, 2010). There are advantages and disadvantages of using Object-Based Image Analysis (OBIA) over the pixel-based approach. The advantages are that OBIA removes the salt pepper effect and spatial, textural, contextual properties can be derived as complementary information to the direct spectral observations, improving classification accuracy (Guo et al. 2017). The OBIA has its own limitations such as over segmentation and under segmentation (Blaschke et al. 2014; Kampouraki, Wood, and Brewer 2008; Möller, Lymburner, and Volk 2007).

In addition to multi-spectral satellite data, researchers use other data to improve classification results. The other data includes radar and ancillary data. Radar data provide different information than optical data. (Ozesmi and Bauer 2002). Elevation data are among the most

common ancillary data that have been used in wetland identification (Sader, Ahl, and Liou 1995). Change detection is one of the other ways improve wetland classification accuracy. In this method, use the dates of imagery to study whether wetlands are in the same phenological state from year to year (Ozesmi and Bauer 2002).

The study is based on a pixel-based, supervised classification approach. The first step in supervised classification is to identify examples of the information classes. The classes assigned in this study are described in the Materials and methods section. These classes are called training sites, and the software system is used to develop a statistical characterization of the reflectance for each information class. This stage is often called signature analysis. After each information class has been statistically characterized, the image is classified by examining the reflectance of each pixel and deciding which of the signatures it most closely resembles. Classifiers are a group of techniques for making these decisions (Eastman 2001).

2.2.7. ML classifiers

There are many methods for ML classifiers, including Support-vector machine (SVM), Artificial Neural Network (ANN), RF, Fuzzy Adaptive Resonance Theory-Supervised Predictive Mapping, Mahalanobis Distance, Decision Tree. RF is the classifier selected for the study.

SVM is a non-parametric supervised machine learning technique and initially aimed to solve the binary classification problems (Maxwell, Warner, and Fang 2018). It is based on the concept of structural risk minimization, which maximizes and separates the hyper-plane and data points nearest the spectral angle mapper of the hyper-plane. It separates data points into various classes using a hyper-spectral plane. In this process, the vectors ensure that the width of the margin will be maximized (Bouaziz, Eisold, and Guermazi 2017).

The ANN is a widely applied machine-learning technique, which can be efficiently used in non-linear phenomena such as parameter retrieval (Atkinson and Tatnall 1997). It does not depend on any assumption of generally distributed data (Liou, Tzeng, and Chen 1999).

Fuzzy Adaptive Resonance Theory-Supervised Predictive Mapping refers to a group of neural network models that employ both supervised and unsupervised learning techniques to solve problems like pattern recognition and prediction (Song et al. 1998).

Mahalanobis distance is a measure of the distance between a point and a distribution. It's a multi-dimensional generalisation of the concept of determining how many standard deviations differs from distribution's mean (McLachlan 1999).

In decision Tree classifier, a population is divided into branch-like segments that form an inverted tree with a root node, internal nodes, and leaf nodes using the Decision Tree method. The algorithm is non-parametric, which means it can handle large, complex datasets without imposing a complex parametric structure (Sun et al. 2013).

RF algorithm

A meta-analysis of peer-reviewed articles over the last ten years shows that the RF algorithm is the most frequently used classification algorithm for satellite imagery (Gorelick et al. 2017). The RF classifier consists of a combination of tree classifiers where each classifier is generated using a random vector sampled independently from the input vector, and each tree casts a unit vote for the most popular class to classify an input vector (Breiman 2001). One of the advantages of RF is that it produces an estimation of classification accuracy based on the out-of-bag cross-validation method. The method out-of-bag cross-validation measures the prediction error of RF boosted decision trees and other machine learning models utilizing bootstrap aggregation (James et al. 2013). The conceptual diagram of the RF algorithm given below describes how training and testing functions. The diagram is adapted from Mennitt, Sherrill, and Frstrup (2014).

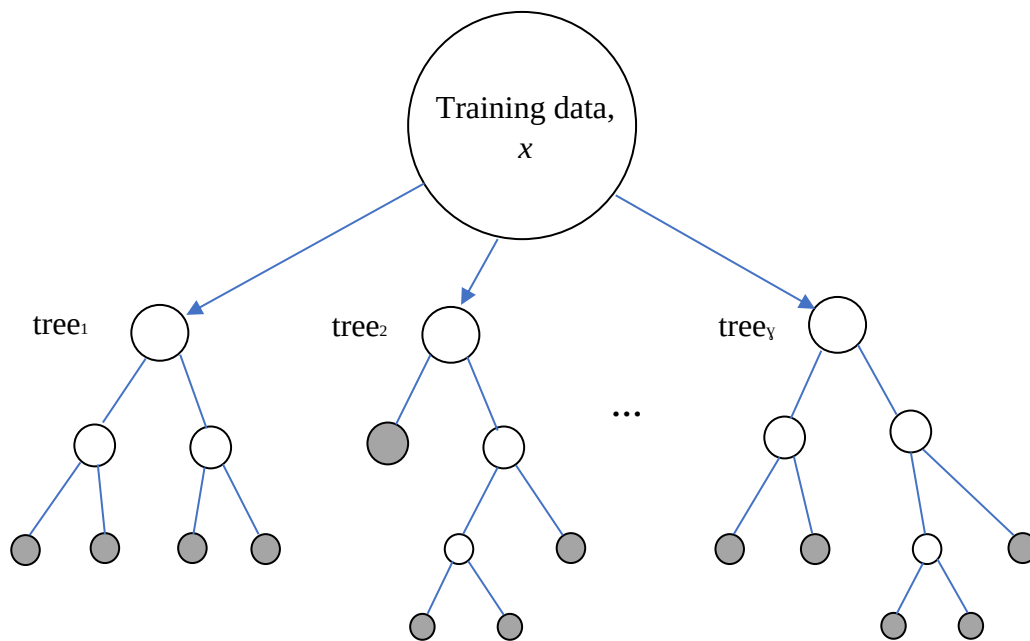


Figure 7. The trees are trained independently by recursive binary partitioning of a bootstrapped sample of the input data, X .

The diagram is adapted from (Mennitt, Sherrill, and Frstrup 2014).

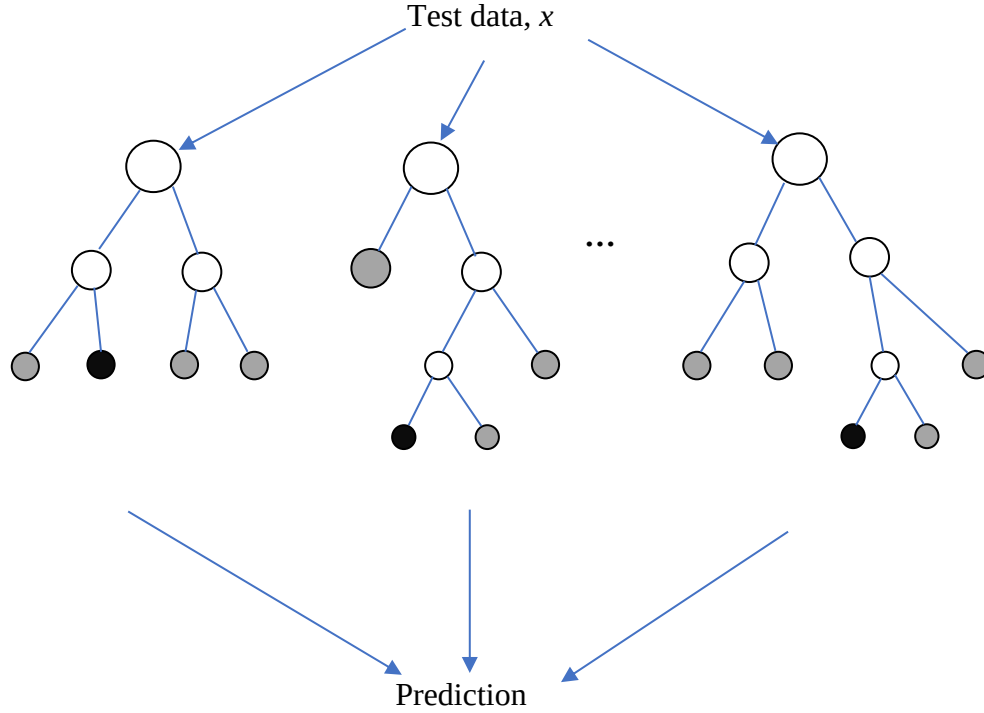


Figure 8. The test data is dropped down through each tree, and the response estimate is the average over all the individual predictions in the forest.

The diagram is adapted from (Mennitt, Sherrill, and Frstrup 2014).

2.2.8. Training and validation

According to the GEE developer's website, supervised classification is handled using traditional ML algorithms by the GEE classifier package. Therefore, collecting training data and estimating classification errors with independent validation data are essential.

Breiman (2001) revealed that a significant improvement in classification accuracy has resulted from growing an ensemble (a group of individual decision trees) of trees and letting them vote for the most popular class. Furthermore, each tree grows with a different bootstrapped sample of the training data. Thus, training data establishes a relationship between remotely sensed data and field-determined data to produce the classification (Harken and Sugumaran 2005).

Supervised image classification needs both training and validation data to produce accurate classification maps. The ML algorithms may be biased if the training data or validation data are unequally distributed (Foody and Mathur 2004). The selection of training samples can be based on field data collection or expert knowledge (Tiner, Lang, and Klemas 2015). Amani, Mahdavi, et al. (2019) found the optimal values by trial-and-error method considering the computational efficiency of the method. The training-validation sample ratio used in this study is 70:30; 70% of the data is allocated for training while the remaining 30% is reserved for validation.

The stratified sampling method was applied in the study due to the following advantages. Stratified sampling provides more precise population parameters compared to simple random sampling. As a result, stratified random sampling produces more homogeneous strata; the sampling error of the estimates is reduced. The stratified random sampling allows the choice of the number of strata and the allocation of the sampling units to the strata (Cochran and William 1977).

2.2.9. Accuracy assessments

According to Congalton (2001), a variety of techniques can be used to assess or validate maps derived from remotely sensed and other spatial data. The paper describes that the accuracy assessment/validation is a key component of any project employing spatial data. There are three reasons mentioned in the article:

- The author can learn from your mistakes by knowing the accuracy
- The ability to quantitatively compare methods
- The ability to use the information resulting from spatial data analysis in some decision-making process

According to Congalton (2001), the first step in any evaluation should be a visual inspection of the map derived from spatial data. Visual inspection is a necessary but insufficient first step. It is critical to assess the map visually and be confident that it looks correct. Another method is the non-site-specific analysis of a map derived from spatial data. It involves only the comparison of overall amounts of various areas regardless of any locational component. Difference image creation is one of the other methods that can be used in validation. The creation of a difference image is the first step in evaluating the spatial component of the map error. A difference image is a direct comparison of any two registered images/maps of the same area. It is produced by comparing the two images/maps, pixel by pixel, representing areas of agreement and disagreement.

Error budgeting is the other method of validating a project. Many papers have been written about the quantification of error associated with remotely sensed and other spatial data (Congalton 2001). The ability to quantify the total error in a spatial data set has developed substantially. However, little has been done to partition this error into its components and construct an error budget. As a result, it is impossible to determine which components contribute the most error and which are easily corrected. Some work has been begun in this area in a paper by Lunetta et al. (1991).

2.2.10. Quantitative accuracy assessment

An error matrix is used to assess the classification accuracy quantitatively. It is a square array of numbers organized in rows and columns which express the number of sample units (i.e., pixels, clusters of pixels, or polygons) assigned to a particular category relative to the actual category as indicated by the reference data. The columns usually represent the reference data, while the rows indicate the classification generated from the remotely sensed data. Reference

data are assumed correct and can be collected from various sources, including photo interpretation, videography, ground observation, and ground measurement. An error matrix is a very effective way to represent accuracy in that the accuracies of each category are described along with both the errors of inclusion (commission errors) and errors of exclusion (omission errors) present in the classification (Congalton 2001).

Confusion matrix

Errors occur when the pixels in a category are incorrectly labelled. Building a $k \times k$ array (where k represents the number of categories) is the most common way of representing the degree of accuracy of classification. Confusion matrix is useful for determining overall errors for each category and misclassifications by category (Anand 2017).

Overall accuracy

The sum of the entries that form the major diagonal (i.e., the number of correct classifications) is then divided by the total number of samples taken to calculate overall accuracy for a particular classified image (Story and Congalton 1986).

Producer's accuracy

Producer's accuracy is defined as the probability that any pixel in that category has been correctly classified (Anand 2017). Therefore, the producer's accuracy is calculated as follows.

$$\text{Producer's accuracy} = \frac{\text{Total number of correct pixels in a category}}{\text{Total number of pixels of that category derived from the reference data (i.e., row total)}}$$

User's accuracy

User's accuracy is defined as the probability that a pixel classified on the image represents that category on the ground (Anand 2017).

$$\text{User's accuracy} = \frac{\text{Total number of correct pixels in a category}}{\text{Total number of pixels of that category derived from the reference data (i.e., column total)}}$$

2.3. RS of wetlands

A comprehensive review of commonly used satellite sensors for wetland mapping by Ozesmi and Bauer (2002) stated that the most widely used multispectral satellite sensors for wetland mapping include Landsat Multispectral Scanner (MSS), Thematic Mapper (TM), Enhanced Thematic Mapper Plus (ETM+), Operational Land Imager (OLI), Moderate Resolution Imaging Spectroradiometer (MODIS), Advanced Very High-Resolution Radiometer (AVHRR), SPOT- 4/5/6/7, IKONOS, QuickBird, GeoEye-1, RapidEye, Sentinel-2 and WorldView-1/2/3/4.

A recent study by Q. Wu (2018) on GIS and RS applications for wetland mapping and monitoring denoted that the technological advances have led to the increasing availability of remotely sensed imagery with better and more satisfactory spatial, temporal, and spectral resolution. In the meantime, image analysis and processing methods have improved, enabling us to map wetlands and monitor changes with unprecedented accuracy. In particular, the availability of high-resolution LiDAR, SAR, hyperspectral, and multispectral data, and the introduction of multi-sensor and multiscale data fusion techniques hold great potential for improving large-scale wetland mapping and monitoring. Q. Wu (2018, 6) further stated, "compared to aerial photography, satellite sensors can provide multispectral imagery with finer spectral and better temporal resolutions, which are essential for classifying wetland vegetation types and analysing wetland water dynamics".

2.4. GEE

GEE consists of a multi-petabyte, analysis-ready data catalog co-located with a high-performance, intrinsically parallel computation service (Gorelick et al. 2017). It is accessed and controlled through an internet-accessible Application Programming Interface (API) and associated web-based Interactive Development Environment (IDE) that enables rapid prototyping and visualization of results.

Processing big data is one of the challenges when considering remote sensing at the provincial or national level. Common image classification software packages are not efficient when classifying numerous satellite images over a large area. One of the key advantages of GEE is its ability to process large geospatial datasets and classify land cover over large areas (Gorelick et al. 2017).

Users can access free satellite datasets, such as those acquired by Landsat-8, Sentinel-1, Sentinel -2, and MODIS. There is no need to download these terabyte-scale, large-sized datasets to local computers since they can be directly and efficiently processed within GEE. Many products have also been pre-processed and can be easily inserted into user-defined algorithms. In addition, many algorithms, image classifiers, and cloud masking methods have been previously implemented, can be imported, and modified by users (Gorelick et al. 2017; Kumar and Mutanga 2018).

2.4.1. Previous studies on wetland classification using GEE

GEE was introduced in 2010, and several studies on wetland classification were carried out using the GEE computing platform thereafter. The researchers employed several datasets, processing algorithms, and classifiers in the remotely sensed classification of wetlands. The details of a few studies related to the topic are given in this section.

Hird et al. (2017) used GEE, open-access satellite data, and ML in support of large-area probabilistic wetland mapping. They used optical and SAR images and LiDAR data. Amani, Mahdavi, et al. (2019) created the first Canada-wide wetland inventory using Landsat-8

imagery and innovative image processing techniques available within GEE. RF algorithm was applied to classify the images for the entire country to produce Canadian wetland maps. Five wetland classes were defined (i.e., bog, fen, marsh, swamp, and shallow water).

Mahdianpari et al. (2019) created Newfoundland's first wetland inventory map at a spatial resolution of 10 m using Sentinel-1 and Sentinel-2 data on the GEE cloud computing platform. Mahdianpari et al. carried out another study in 2020 to elucidate patterns of wetland class change across Newfoundland from 1985 to 2015. It demonstrates the potential of the GEE and Landsat historical imagery to assess change at provincial and national scales. The study was a large-scale change monitoring of wetlands using time-series Landsat imagery on GEE. They compared different classifiers in the classification, and RF produced the highest overall accuracy results.

LaRocque et al. (2020) published an article on Wetland Mapping with Landsat-8, OLI, Sentinel-1, ALOS-1, PALSAR, and LiDAR data for Southern New Brunswick, Canada. The study has demonstrated the potential of applying the RF classifier to freely available Landsat-8 OLI, ALOS-1 PALSAR, and Sentinel-1 images combined with LiDAR-derived topographic metrics to produce a highly accurate wetland map of Southern New Brunswick.

Cai et al. (2020) proposed a method for wetland mapping using the object-based stacked generalization method based on multi-temporal and multi-source RS images. The proposed method mainly consists of four steps.

- Data collection, including the Sentinel-2 NDVI time series, the phenology data derived from the Sentinel-2 NDVI time series, the vegetation indices derived from Sentinel-2 multispectral images, and the time series SAR backscatters data generated from Sentinel-1
- Segmentation based on multi-temporal Sentinel-2 multispectral images
- Separability analysis of land cover types and optimal feature combination identification at the object level using the RF algorithm
- Mapping wetland using the stacked generalization method and optimal feature combination at the object level

Table 6. Some of the parameters used in GEE based wetland mapping in previous studies.

Reference	Data set	Bands/ Derived Variables
Hird et al. (2017)	LiDAR	TPI, Topographic Wetness Index (TWI)
	Sentinel-2	B2, B3, B4, B8, NDVI, NDWI
	Sentinel-1	Normalized Polarization index, VV, VV Standard Deviation
Mahdianpari et al. (2018)	Sentinel-2	B2, B3, B4, B8, NDVI, NDWI, Modified SAVI
	Sentinel-1	vertically transmitted, vertically received SAR backscattering coefficient
		Vertically transmitted, horizontally received SAR backscattering coefficient
		Horizontally transmitted, horizontally received SAR backscattering coefficient
		Horizontally transmitted, vertically received SAR backscattering coefficient
		Span or total scattering power
Amani, Mahdavi, et al. (2019)	Landsat-8	Difference between co- and cross-polarized observations
		Visible, NIR, SWIR
Mahdianpari, Jafarzadeh, et al. (2020)	Landsat-5,7,8	DVI, NDVI, GDVI, GNDVI, GRVI, SAVI, GSAVI, OSAVI, GOSAVI, EVI, NDWI, TCW, TCW
		TCV
Cai et al. (2020)	Sentinel-2	NDMI, Red-edge Chlorophyll Index, NDVI, Red-edge Normalized Difference Vegetation Index, Modified red-edge Simple Ratio, Wide Dynamic Range Vegetation Index
	Sentinel-1	Backscattering coefficient

Figure 9 given below presents a potential method to identify previously unclassified New Zealand wetlands using a combination of state-of-the-art (height level of general development) methods identified in the previous literature review by Allan (2016). This method combines previously developed New Zealand wetland identification methods with image segmentation methods. According to Allan (2016), "image segmentation and classification could be developed solely using Sentinel-2A satellite imagery. Depending on the accuracy of results, previously unidentified wetland polygons could be added to the current Waikato Wetlands Probability Layer (WWPL). For the identification of wetlands that may have been drained within farmland, terrain analysis may be used to derive TWI or other wetness indexes. This could be used in conjunction with land cover databases to identify potentially drained wetlands" (Allan 2016, 20).

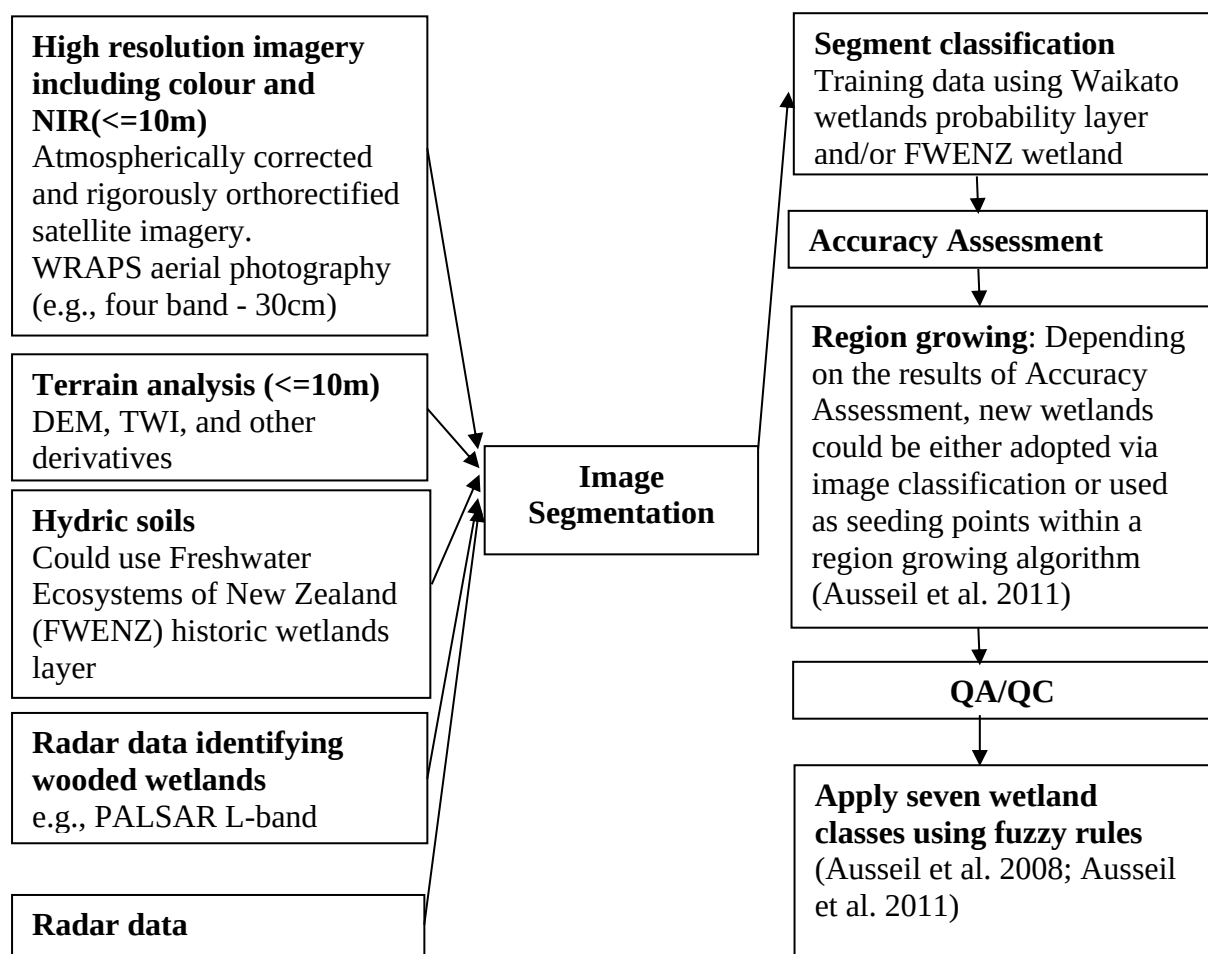


Figure 9. Outline of the proposed method for the identification of previously unclassified wetlands using GIS and RS data.

The method was adapted by (Brooks et al. 2013) and modified by Allan (2016).

Chapter 3: Material and methods

3.1. Working environment

All the steps, including processing, classification, and accuracy assessment, were performed within the GEE computing platform using JavaScript programming language. The GEE Code Editor and third-party applications use client libraries to send queries to the system through a Representational State Transfer (REST) API. Front End servers are handling the instant queries while forwarding the complex sub-queries to Compute Masters. This process manages computation distribution among a pool of Compute Servers. A Java library, FlumeJava manages the distribution of batch queries. The Asset Database provides efficient filtering capabilities. A cluster management software called Borg manages each component of the system and balances services over multiple workers. The following simplified system architecture diagram is provided by Gorelick et al. (2017).

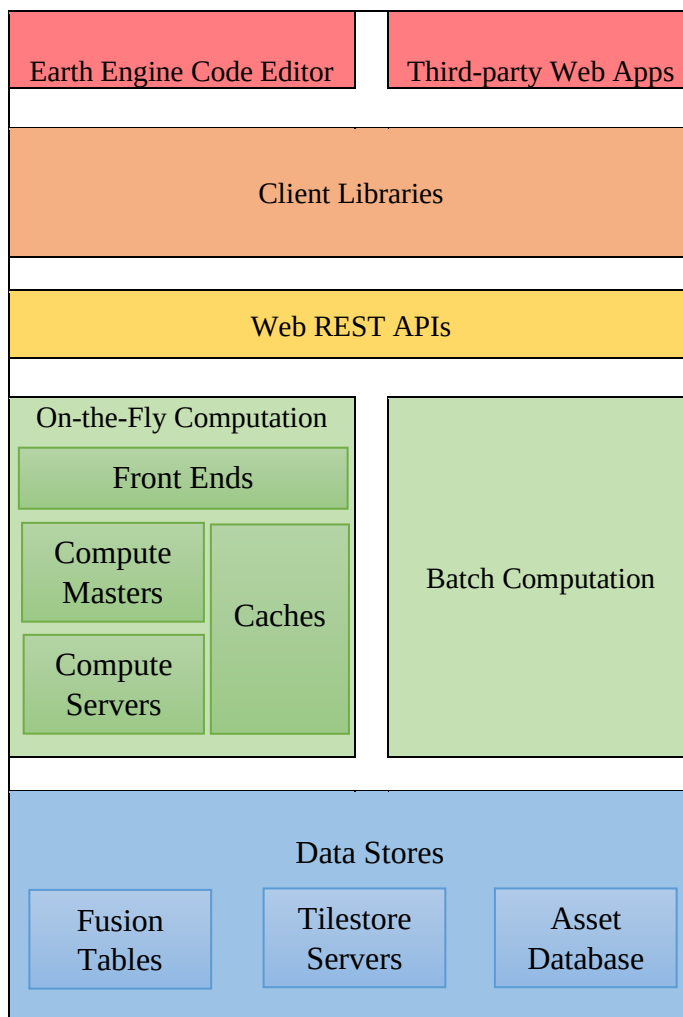


Figure 10. A simplified system architecture diagram.

The diagram is adapted from Gorelick et al., (2017).

3.2. Workflow of the study

According to the GEE developer's website, the supervised classification is handled using traditional ML algorithms by the GEE classifier package. The general workflow includes the following: collect training data, assemble features and properties, instantiate a classifier, set the parameters, train the classifier using the training data, classify an image or feature collection, and estimate the classification error with independent validation data. However, the workflow was modified towards achieving the best results.

Firstly, a set of parameters was extracted from three types of data: (1) satellite scenes were accessed from the GEE analysis-ready data catalog by using coding calls; (2) sampling data and (3) the DEM were uploaded as assets. Then, there were 10 parameters selected using a feature selection technique. The classification raster was created by adding the extracted features. Resulted classification image was classified by employing the tuned RF classifier. The classifier was trained and validated using stratified random samples of provided wetland polygons. Error matrices were generated to check the accuracy of the classification. Wetland classes were mapped accordingly. The workflow diagram of the study is given in Figure 11 below and explained later in this section.

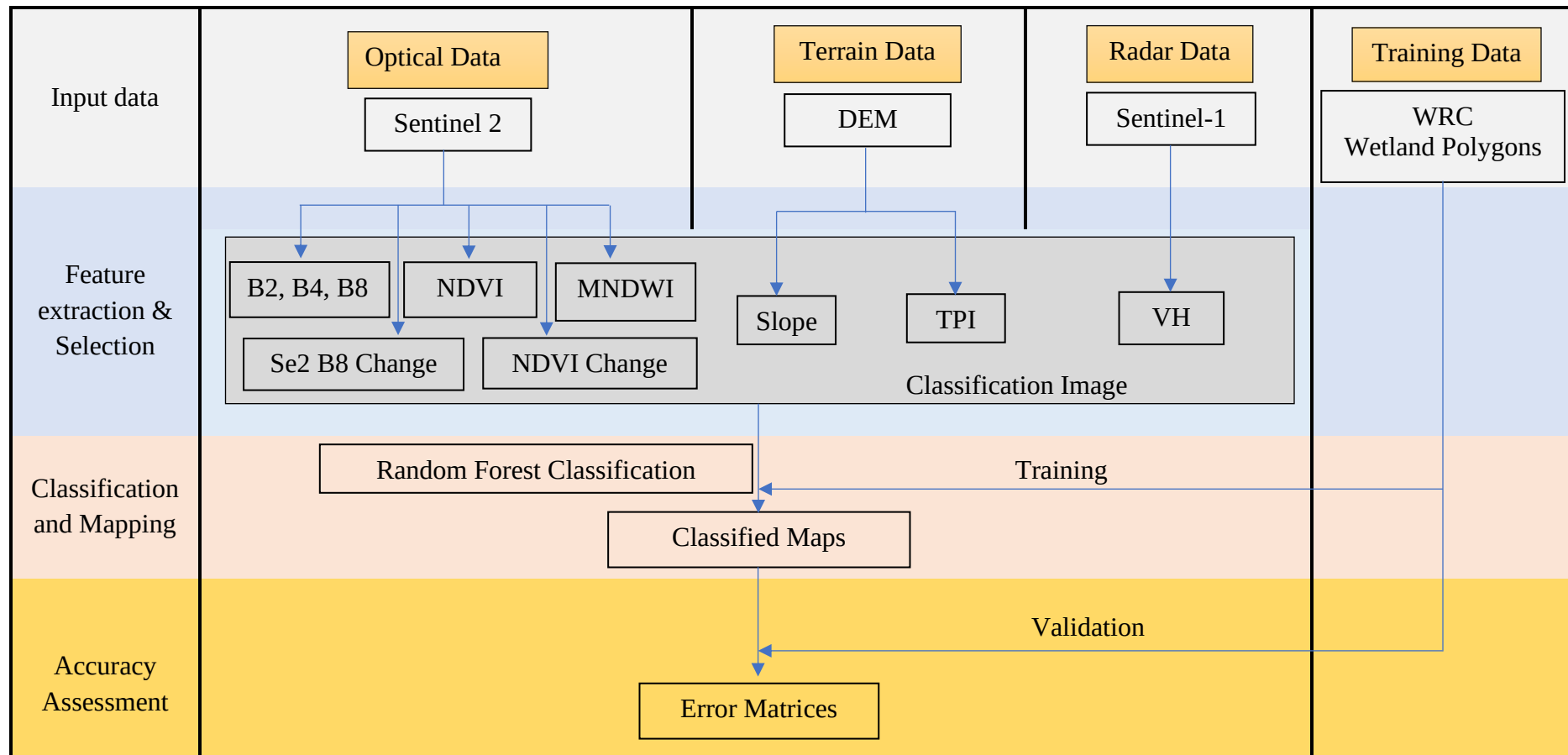


Figure 11. Workflow diagram.

3.3. Input data

3.3.1. Input data source

Optical RS data and SAR data were obtained for a period of one year from to 01/03/2020-28/02/2021. The elevation data used in the study was received from a DEM. Training and validation data are provided by the WRC. Table 7 below presents the data types and the sources used in the study.

Table 7. Data types and sets used.

Data type	Data source
Optical data	Sentinel-2
SAR data	Sentinel-1
Elevation data	DEM
Training and validation data	Wetland polygons from the WRC $\approx 70\%$ training polygons, $\approx 30\%$ validation polygons

3.3.2. Image availability

Sentinel-1 and 2 images that covered the area of interest from 2020 Autumn to 2021 summer are given in Table 8.

Table 8. Imagery selection.

Season	Dates of imagery selection	Number of images obtained	
		Sentinel-1	Sentinel-2
Autumn	2020-03-01 - 2020-05-30	5	5
Winter	2020-06-01 - 2020-08-31	0	3
Spring	2020-09-01 - 2020-11-30	4	4
Summer	2020-12-01 - 2021-02-28	4	4

3.3.3. Optical data

Sentinel-2, Multi-Spectral Instrument, Level-2A captured images were utilized in the study. Table 9 presents the bands selected for the preliminary stage of classification. The bands were selected based on the previous studies and the aim of achieving the results with the best spatial resolution.

Table 9. Sentinel-2 bands used in the study.

Band	Spatial resolution (m)
Blue (B2)	10
Green (B3)	
Red (B4)	
NIR (B8)	
SWIR 1 (B11)	20

3.3.4. SAR data

The images captured by Sentinel-1 satellite using its GRD sensor were downloaded for the one-year period mentioned above. The 10 m resolution VV and VH bands were used in the preliminary classification stage and the VH band was selected for the detailed classification.

3.3.5. Elevation data

A DEM with a 10 m cell size was used in the terrain analysis. The DEM was filled and utilized for calculating simple parameters like slope and aspect. The complex terrain indices such as TPI and TWI were also calculated in the GEE environment. The indices calculated for the study are given in the feature selection section.

3.3.6. Training and validation data

Training and validation data were provided by the WRC. The polygons were partitioned using a 70:30 split for training and testing, respectively. Polygons were assigned by considering the size and the number of polygons.

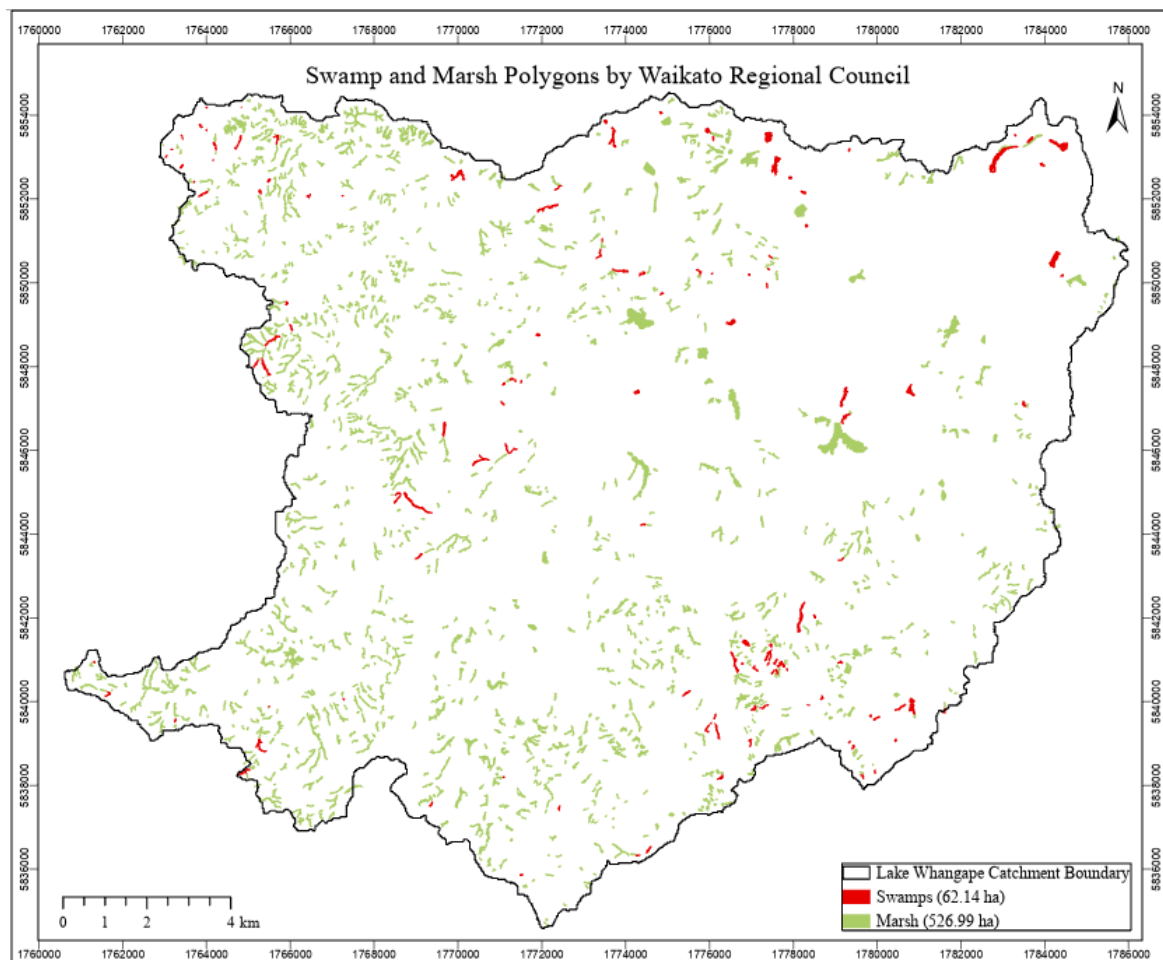


Figure 12. Swamp and Marsh polygons provided by Waikato Regional Council.

3.4. Feature extraction

The parameters were extracted from the RS data sources described in the input data section (3.3). The parameters for the preliminary stage were selected after the careful consideration of literature from the relevant studies and the data availability. All the features listed in Table 10 were subjected to undergo feature selection as described in section 3.5.

Table 10. Parameters extracted in the preliminary stage.

GIS/RS data source	Parameters extracted
Sentinel-2	<u>Bands</u>
	B2 (Green), B3(Blue), B4(Red), B8(NIR)
	<u>Vegetation Indices</u>
	NDVI, SAVI, DVI, GDVI, GNDVI, GOSAVI
	<u>Temporal changes</u>
Sentinel-1	Change of B8 over the time
	Change of NDVI over the time
	<u>Water Index</u>
	MNDWI
	<u>Bands</u>
DEM	VV
	VH
	<u>Backscattering</u>
	backscattering coefficient (Sigma nought)
	Normalized backscattering coefficient (Gamma nought)
	<u>Polarization</u>
	Polarization ratio (VV/VH)
	<u>Simple parameters</u>
	Slope
	Aspect
	<u>Complex indices</u>
	TPI
	TWI

The 10 parameters extracted from the feature selection step were used in the final classification. The parameters selected are given in Table 11. Please see section 3.6 for more details on feature selection.

Table 11. Parameters selected for the classification after feature selection.

GIS/RS data source	Band/parameter extracted
Sentinel-2 MSI	B2, B4, B8 Change of B8 over the time NDVI Change of NDVI over the time MNDWI
Sentinel-1 SAR	VH
DEM	Slope, TPI

3.4.1. Description of selected features

The parameters with above average relative importance were selected for the classification. The parameters extracted are described below.

I. Bands

The B2, B4, and B8 bands were directly extracted from Sentinel-2 images. The VH band was extracted from Sentinel-1 images.

II. MNDWI

MNDWI uses green and SWIR bands for the enhancement of open water features (Xu, 2018). It also diminishes built-up area features that are often correlated with open water in other indices (Ettehadi et al. 2019). The formula for calculating MNDWI is given Feature extraction section (2.2.3).

III. NDVI

The NDVI value for a given pixel is always in the range of minus one (-1) to plus one (+1). However, zero indicates no vegetation (Weier and Herring 2000). The formula for calculating MNDWI is given Feature extraction section (2.2.3).

NDVI and MNDWI calculated for the area of interest are given below in the Figure 13.

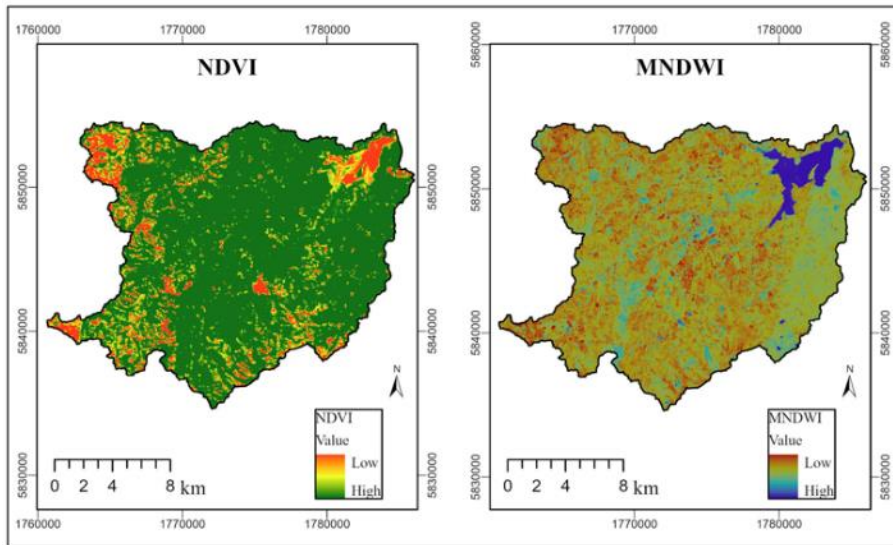


Figure 13. Calculated NDVI and MNDWI for the Lake Whangape catchment.

IV. Change detection

Some of the wetlands such as temporal water bodies and waterways or intertidal flats present a high temporal variability (Henderson, 2008). Satellite images for different seasons were sourced to identify the seasonal changes of wetlands in the Lake Whangape catchment.

Temporal changes of Sentinel-2 band B8 and NDVI are presented in the Figure 14.

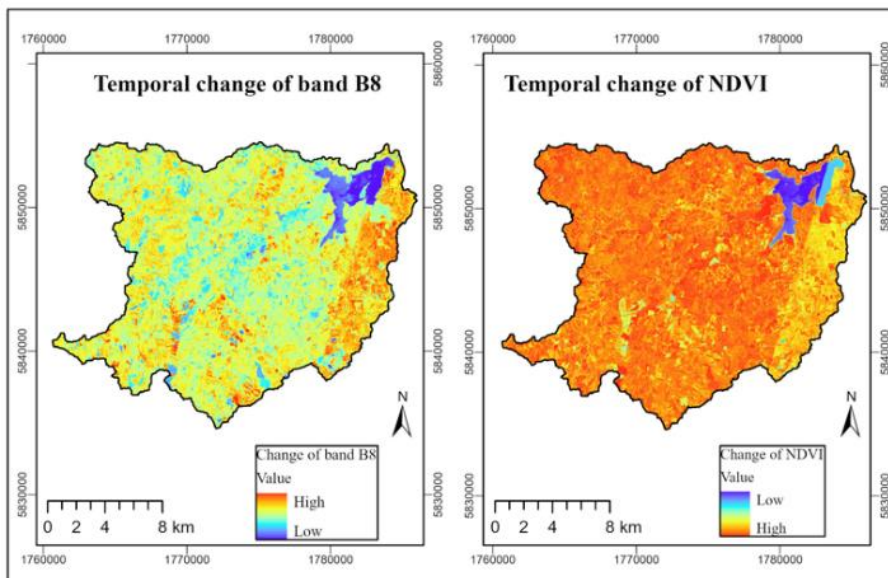


Figure 14. Temporal changes of Sentinel-2 band B8 and NDVI.

V. Parameters extracted using elevation data

Slope

Slope was calculated using the DEM and it is observed that the slope ranged from 0 to 19 degrees within the areas covered by wetland.

TPI

According to Weiss (2001), TPI compares the elevation of each cell in a DEM to the mean elevation of a specified neighbourhood around that cell. Since the only input required is a digital elevation model, TPI can be readily generated almost anywhere. Positive TPI values represent locations that are higher than the average of their surroundings, as defined by the neighbourhood (ridges). TPI was calculated based on (Weiss) method and annulus was used in the study. Negative TPI values represent locations that are lower than their surroundings (valleys). TPI values near zero are either flat areas (where the slope is near zero) or areas of constant slope (where the slope of the point is significantly greater than zero) (Weiss 2001).

Slope and TPI calculated for the area are presented in the Figure 15.

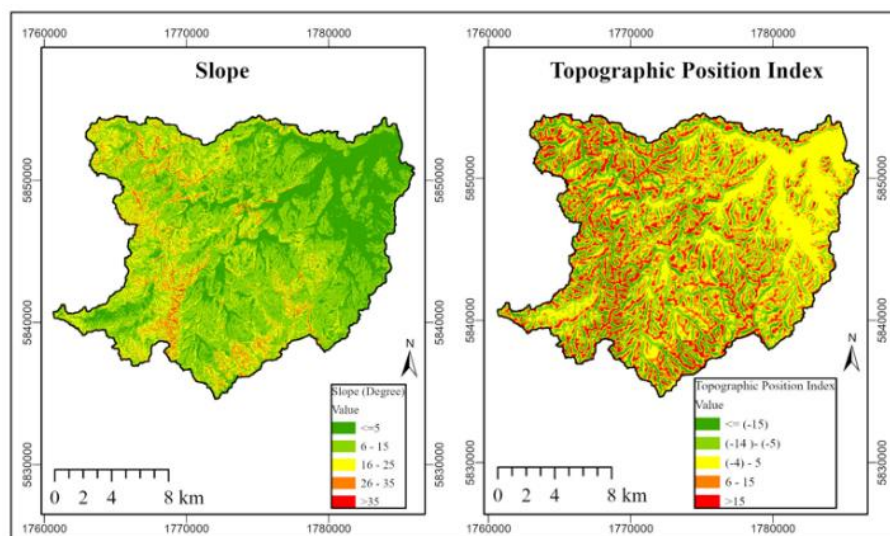


Figure 15. Slope and TPI calculated for the area

3.5.Feature selection

There were 22 parameters extracted and subjected to feature selection based on their relative importance. RF relative importance for each parameter was plotted and the parameters with above average relative importance were selected for the classification. The total number of bands selected for classification was ten. Figure 16 presents the RF variable importance for each parameter checked in the feature selection step.

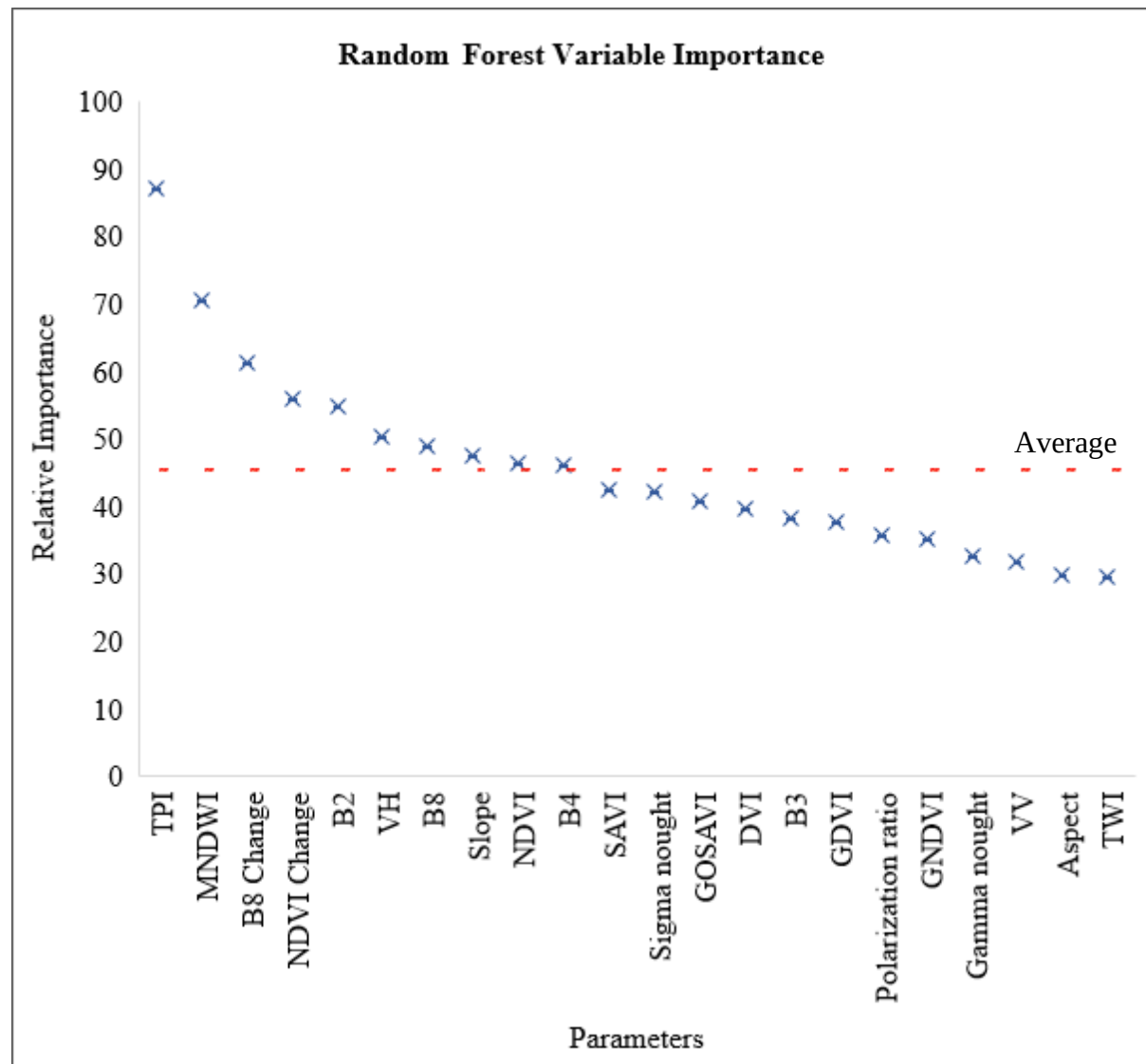


Figure 16. RF variable importance.

TPI received an outstanding 86.9 relative importance value compared to the average value of 44.2 for the set of parameters. MNDWI, change of Sentinel-2 band B8 over the period, NDVI Change over the period, Sentinel-2 band B2, Sentinel-1 VH band, Sentinel-2 B8 band, Slope, NDVI and Sentinel-2 band B4 received above average relative importance values respectively. Therefore, TPI, MNDWI, Change of Sentinel-2 band B8 over the period, NDVI Change over the period, Sentinel-2 B2 band, Sentinel-1 VH band, Sentinel-2 B8 band, NDVI, Sentinel-2 B4 band, and slope were selected for the classification.

The parameters resulting from the feature extraction in the preliminary stage are listed on the left side while the parameters selected for the detailed classification stage are given on the right side of Figure 17.

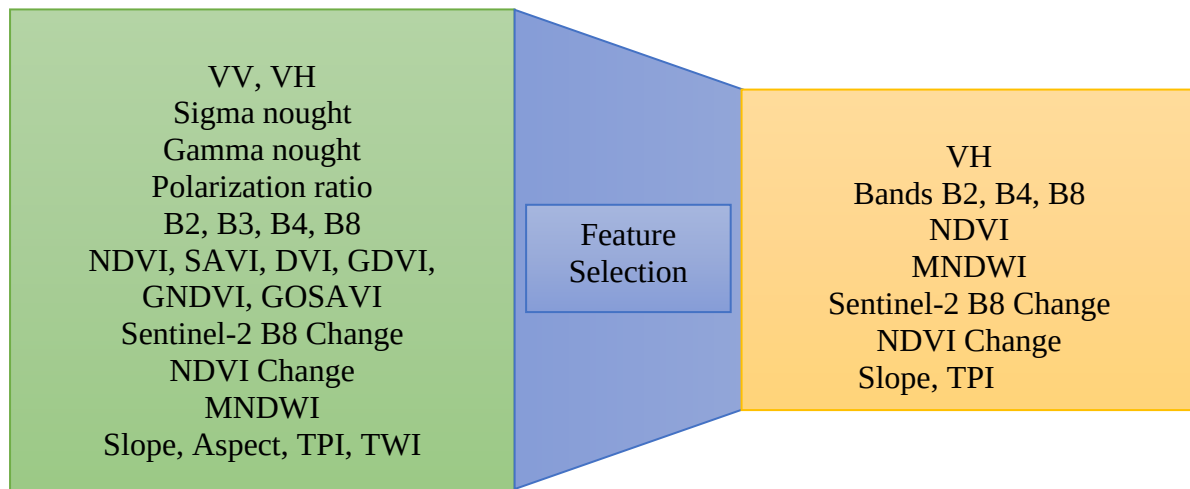


Figure 17. Parameters selected for classification after the feature selection.

3.6. Spatial resolution

Sentinel-2 B2 (Green), B3(Blue), B4 (Red), B8 (NIR) bands and Sentinel-1 VH band are at the spatial resolution of 10 m. The temporal change of NDVI parameter is at 10 m resolution because it was derived using 10 m resolution bands. Pan-sharpening was carried out using band B8 (NIR) as a pan-like band. The resulting MNDWI calculated using B2(Green) and pan-sharpened 10 m resolution bands is at 10 m spatial resolution. A DEM with 10 m cell size was used in the study to reach classification results with the best available resolution.

3.7. Classification

The classification was carried out using the RF algorithm with 400 decision trees. The study was carried out in two stages. Firstly, the study focused to classify Wetlands, Open water, and all other land use classes (simple classification). Then the study aimed to classify the combined wetland class further into two sub-classes (detailed classification), namely swamps and marshes as given in Figure 18.

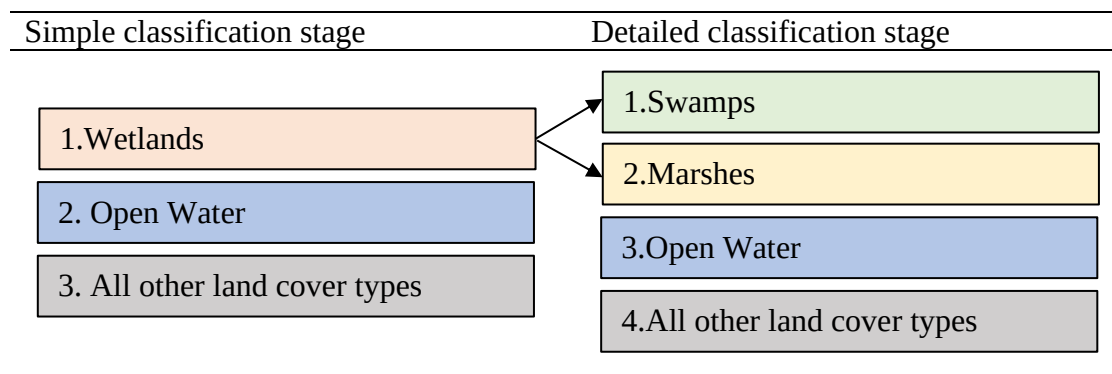


Figure 18. Classes.

Each stage of the classification was carried out in a stepwise manner. The results were studied visually and quantitatively. The bands/variables which received above average relative importance values were selected and employed from highest to lowest in the classification steps. Figure 19 illustrates the bands and variables used in each step; cells marked with a tick represent the band/variable used in each step of the classification.

Parameter	TPI	MNDWI	B8	NDVI	B2	VH	B8	Slope	NDVI	B4
Step			Change	Change						
Step 1	✓									
Step 2	✓	✓								
Step 3	✓	✓	✓							
Step 4	✓	✓	✓	✓						
Step 5	✓	✓	✓	✓	✓					
Step 6	✓	✓	✓	✓	✓	✓				
Step 7	✓	✓	✓	✓	✓	✓	✓			
Step 8	✓	✓	✓	✓	✓	✓	✓	✓		
Step 9	✓	✓	✓	✓	✓	✓	✓	✓	✓	
Step 10	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Figure 19. Classification steps.

3.8. Training and validation

The model was trained using the wetlands polygon provided by the WRC. Stratified random sampling is used to obtain a sample population that best represented the entire class polygons. One thousand training samples and 300 validation samples were generated from the training and validation rasters. Figure 20 presents the sample point distribution in the area of interest.

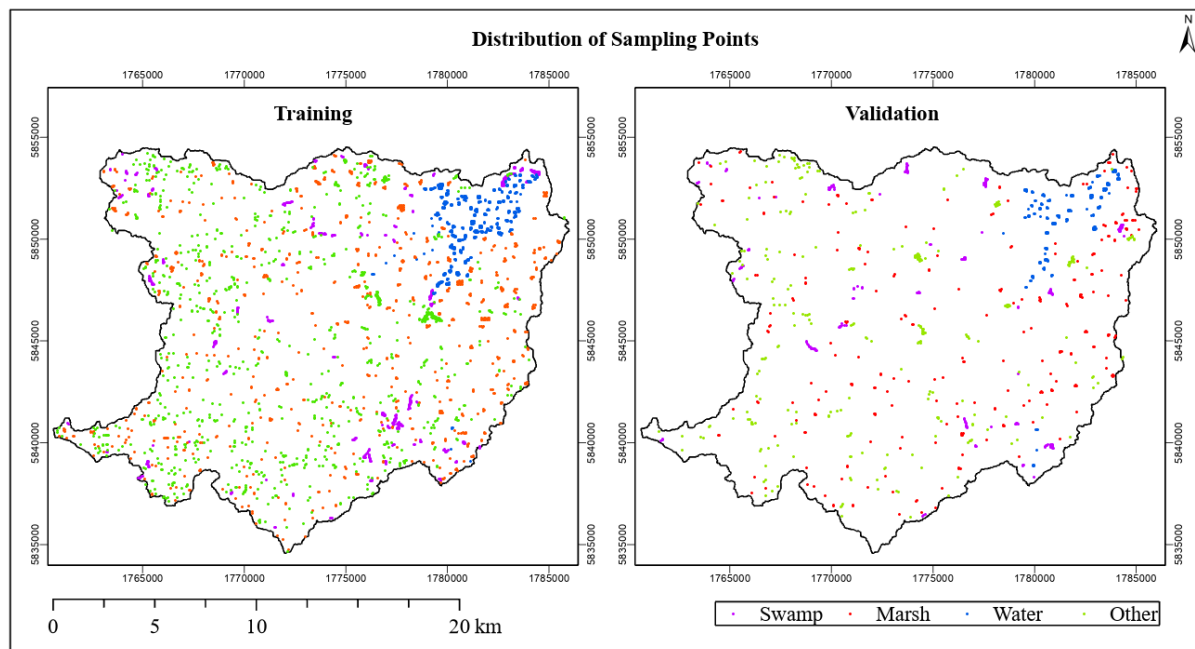


Figure 20. Distribution of stratified random sample points.

3.9.Accuracy

The accuracy was tested visually and statistically. All the classification step results were mapped and visually checked. Overall accuracy is commonly used methods as described in the literature review. The stratified sampling method provides precise estimates for user's and producer's accuracy (Sari et al. 2021). Confusion matrices produced to determine how errors occur when the pixels in a category are incorrectly labelled. The results are presented in Chapter 4.

Chapter 4: Results

The classification was carried out in two stages.

1. Simple classification stage

The simple classification focused on classifying wetland and non-wetland classes along with the open water class.

2. Detailed classification stage

The combined wetland class was separated into swamp and marsh classes in this stage and the classes determined the stage were Swamp, Marsh, Open water, and all other land use classes. Each stage of classification was carried out stepwise. The classification steps are given in Figure 19. The results obtained in each step of each stage are presented below.

4.1. Simple classification stage

4.1.1. Overall accuracy

Change of overall accuracy in each classification step is given in Table 12 below.

Table 12. Simple classification, change of validation overall accuracy.

Classification step	1	2	3	4	5	6	7	8	9	10
Overall accuracy (%)	61	87	89	86	87	88	90	91	91	91

Overall accuracy reached 80% value after running the classification step two. Figure 21 shows that the accuracy level did not change significantly after Step two. However, the confusion matrix made progress while carrying out Steps three to ten.

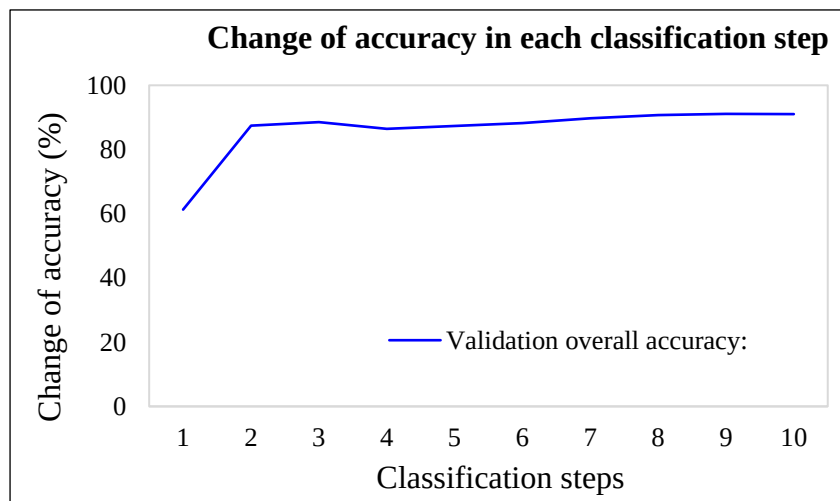


Figure 21. Simple classification stage, change of overall accuracy.

4.1.2. Validation error matrix

A confusion matrix was used to determine the degree of error in each classification step. The confusion matrix, user's accuracy, and producer's accuracy (%) for the final step of simple classification stage are given below (Figure 22).

		Classification result			Row total	Producer's accuracy (%)
		Wetlands	Water	Other		
Ground truth	Wetlands	270	0	29	299	90
	Open water	0	300	0	300	100
	Other	52	0	248	300	83
Column total		322	300	277	899	
User's accuracy (%)		84	100	90		

Figure 22. Simple classification stage, confusion matrix.

In the final step of the simple classification stage, all the samples were correctly classified for the open water class and 270 samples were correctly classified in the wetlands class. Twenty-nine samples of wetlands were misclassified among all other classes. Open water and wetland classes received 100%, 84% user's accuracy and 100%, 83% producer's accuracy, respectively.

4.1.3. Change of consumer's and producer's accuracy

Consumer's accuracy

Consumer's accuracy was checked in each classification step. The open water class received 100% accuracy while the wetland class reached 84% accuracy. Consumer's accuracy (%) figures received in each step of classification are given in Table 13.

Table 13. Simple classification stage, consumer's accuracy.

Classification step	1	2	3	4	5	6	7	8	9	10
Wetlands	63	78	80	77	79	80	82	83	84	84
Open water	61	100	100	99	100	100	100	100	100	100
Other	60	85	87	84	83	85	87	89	90	90

Producer's accuracy

The producer's accuracy is important to understand the probability that any pixel in that category has been correctly classified. The producer's accuracy (%) received after each step of classification are given in Table 14.

Table 14. Simple classification stage, producer's accuracy.

Classification step	1	2	3	4	5	6	7	8	9	10
Wetlands	66	87	89	86	85	87	88	90	90	90
Water	60	100	100	100	100	100	100	100	100	100
Other	58	75	77	73	77	78	81	82	83	83

The following two graphs (Figure 23) present the producer's and consumer's accuracy changing pattern in each classification step.

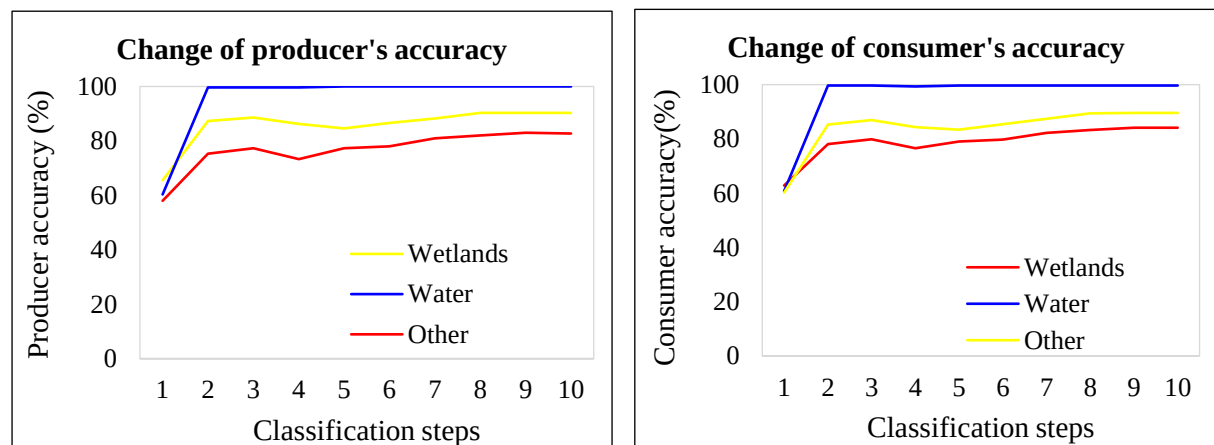


Figure 23. Simple classification stage, change of producer's and consumer's accuracy.

4.1.4. Visual accuracy

Each step of the classification was mapped and checked visually accordingly. Figure 24 presents how the classified image changes with each parameter.

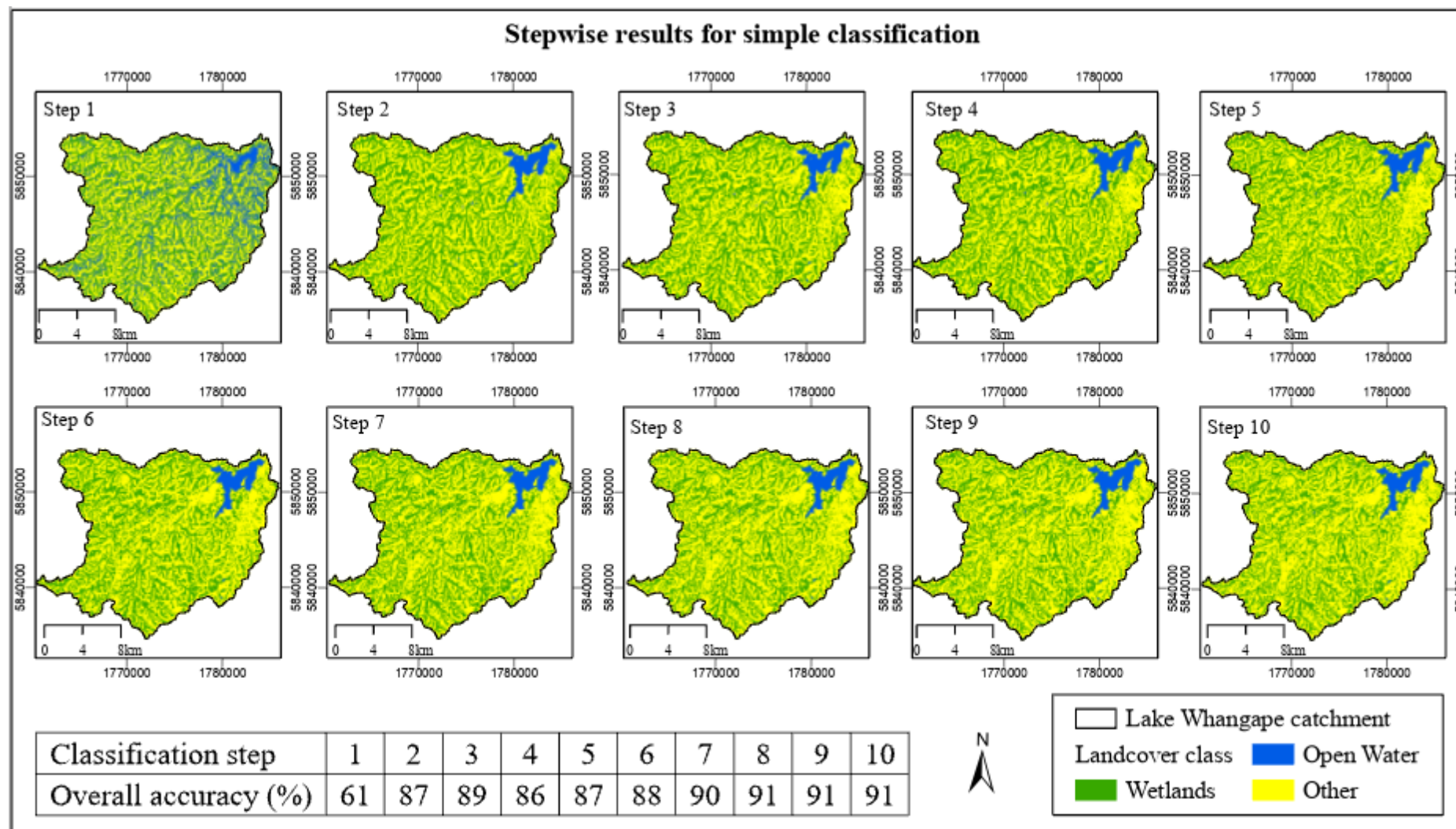


Figure 24. Simple classification stage, change of accuracy.

4.1.5. Final map of the simple classification

The final classification map resulted by simple classification stage is given in Figure 25.

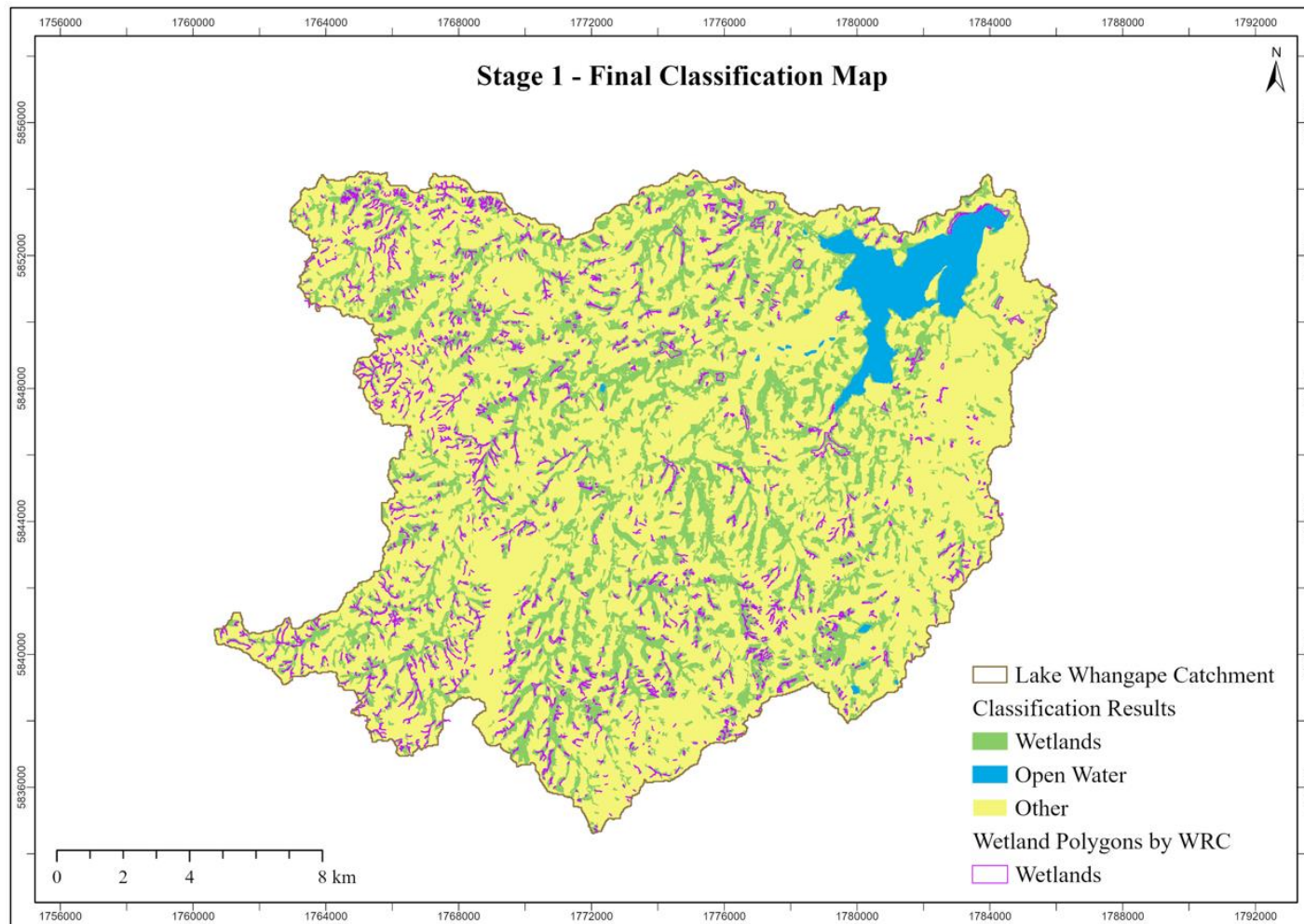


Figure 25. Final classification map resulted by simple classification.

4.2. Detailed classification stage

4.2.1. Overall accuracy

Change of validation overall accuracy in each classification step is given in Table 15 below.

Table 15. Stage 2, change of validation overall accuracy.

Classification step	1	2	3	4	5	6	7	8	9	10
Overall accuracy (%)	44	65	73	73	74	74	76	76	77	76

Validation overall accuracy reached only 76% after running all the classification steps. The following diagram shows that the accuracy level did not change significantly after Step three. However, the confusion matrix made progress while carrying out Steps four to ten (Figure 26).

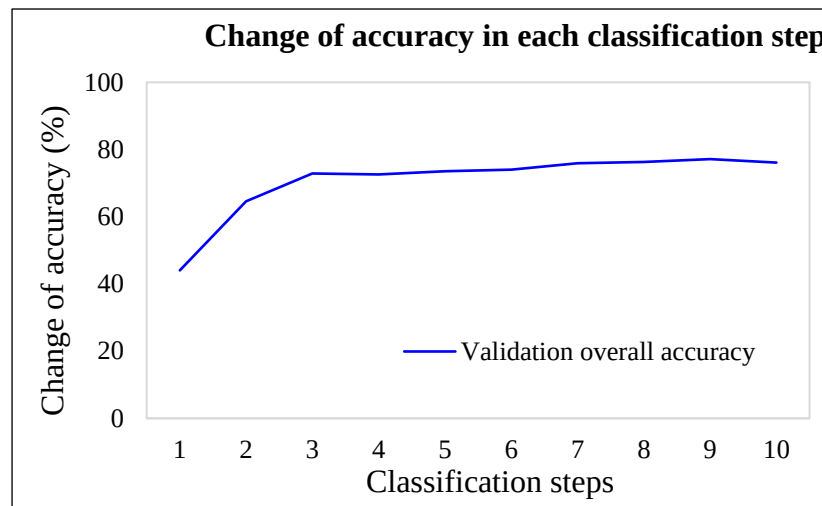


Figure 26. Detailed classification stage, change of overall accuracy.

4.2.2. Validation error matrix

A confusion matrix was used to determine the degree of error in each classification step. The confusion matrix, user's accuracy, and producer's accuracy for the final step of detailed classification stage are given below in Figure 27.

		Classification result				Row total	Producer's accuracy (%)
		Swamp	Marsh	Water	Other		
Ground truth	Swamp	159	124	4	13	300	53
	Marsh	41	217	0	41	299	73
	Water	1	0	299	0	300	100
	Other	13	37	0	250	300	83
Column total		214	378	303	304	1199	
User's accuracy (%)		74	57	99	82		

Figure 27. Detailed classification stage, confusion matrix.

In the final step of the detailed classification stage, 299 out of 300 samples were correctly classified for the open water class and only 159 samples were correctly classified for swamp class. There are only 217 samples were correctly classified for marsh class. Open water, swamp and marsh classes received 99%, 74%, 57% user's accuracy and 100%, 53% and 73% producer's accuracy, respectively.

4.2.3. Validation producer's and consumer's accuracy

Consumer's accuracy

Consumer's accuracy was checked in each classification step. Open water class received 100% accuracy while wetland class reached 84% accuracy. Consumer's accuracy (%) figures received in each step of classification are given in Table 16.

Table 16. Detailed classification, consumer's accuracy.

Classification step	1	2	3	4	5	6	7	8	9	10
Swamp	25	35	50	48	50	53	53	53	53	52
Marsh	32	49	65	67	67	68	68	69	73	70
Water	59	99	99	100	100	100	100	100	100	100
Other	59	75	77	75	78	77	84	83	83	83

Producer's accuracy

The producer's accuracy is important to understand the probability that any pixel in that category has been correctly classified. The producer's accuracy received after each step of classification are given in Table 17.

Table 17. Detailed classification stage, producer's accuracy.

Classification step	1	2	3	4	5	6	7	8	9	10
Swamp	37	47	67	70	67	69	70	71	74	73
Marsh	32	45	53	52	55	54	56	55	57	56
Water	50	98	99	99	98	98	99	99	99	98
Other	53	65	76	74	76	81	81	84	82	81

The following graphs (Figure 28) present the producer's and consumer's accuracy changing patterns in each classification step.

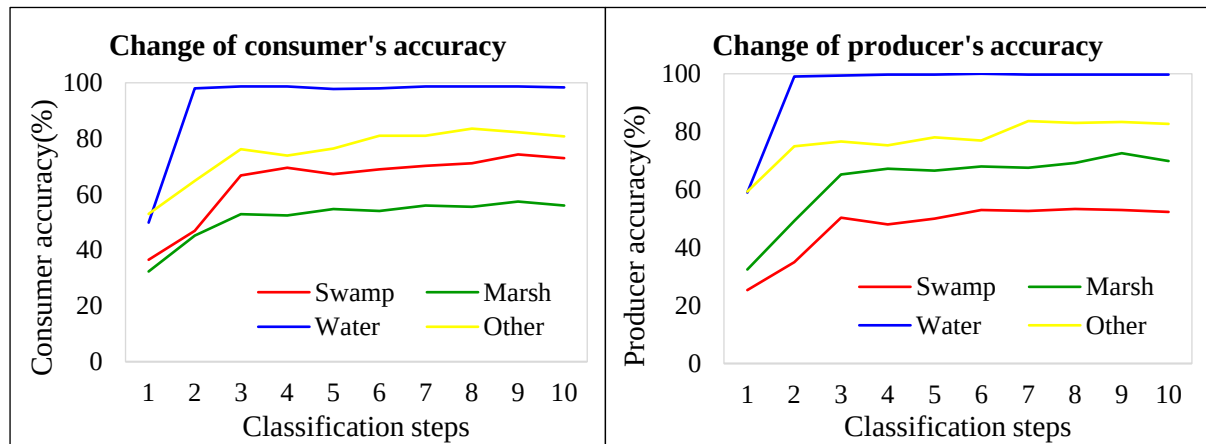


Figure 28. Detailed classification stage, change of producer's and consumer's accuracy.

4.2.4. Visual accuracy

Each step of the classification was mapped and checked visually accordingly. The following diagram (Figure 29) presents how the classified image changed with each parameter.

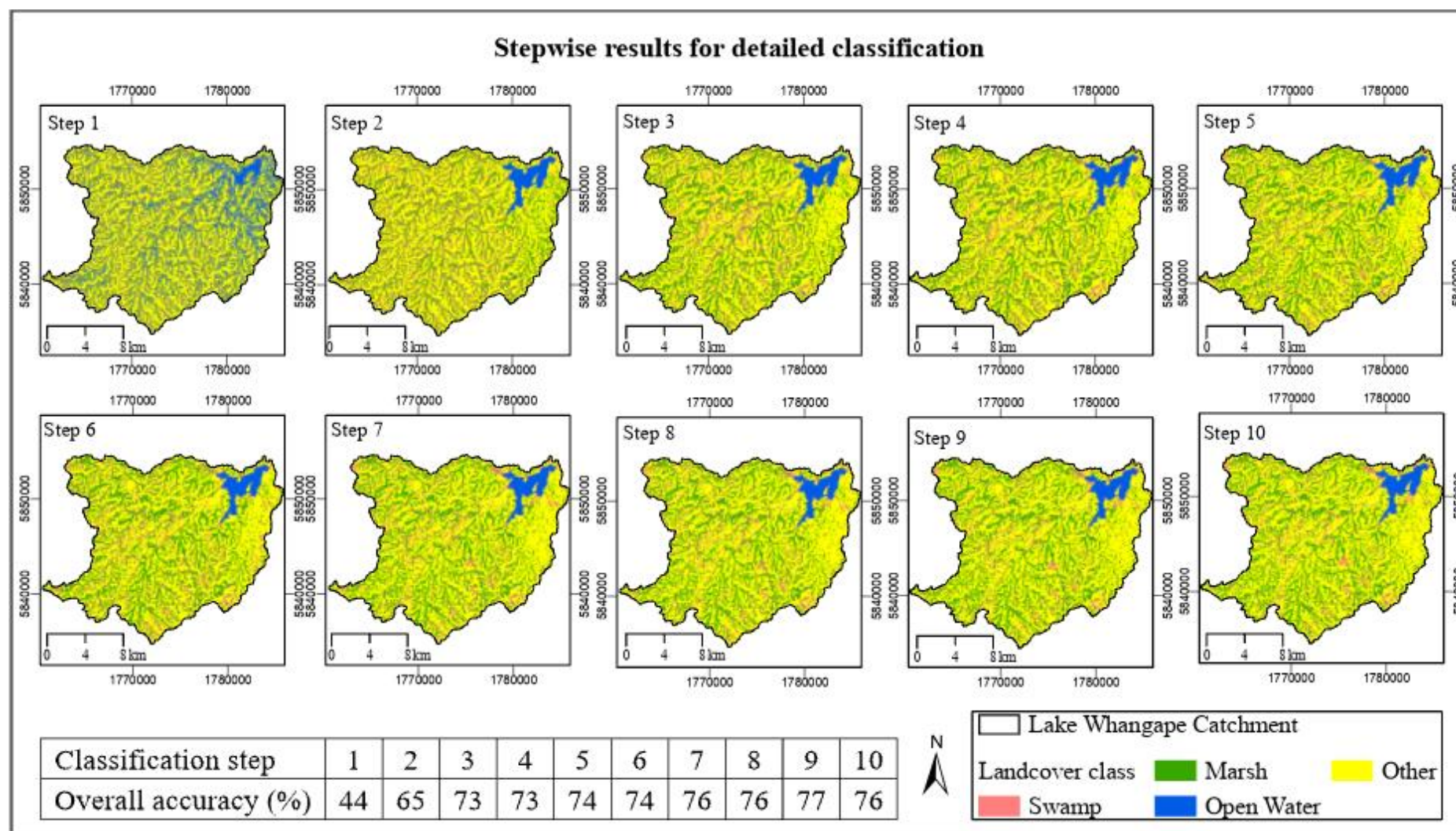


Figure 29. Detailed classification stage, change of accuracy

4.2.5. Final map of the detailed classification

The final classification map resulting from the simple classification stage is given Figure 30.

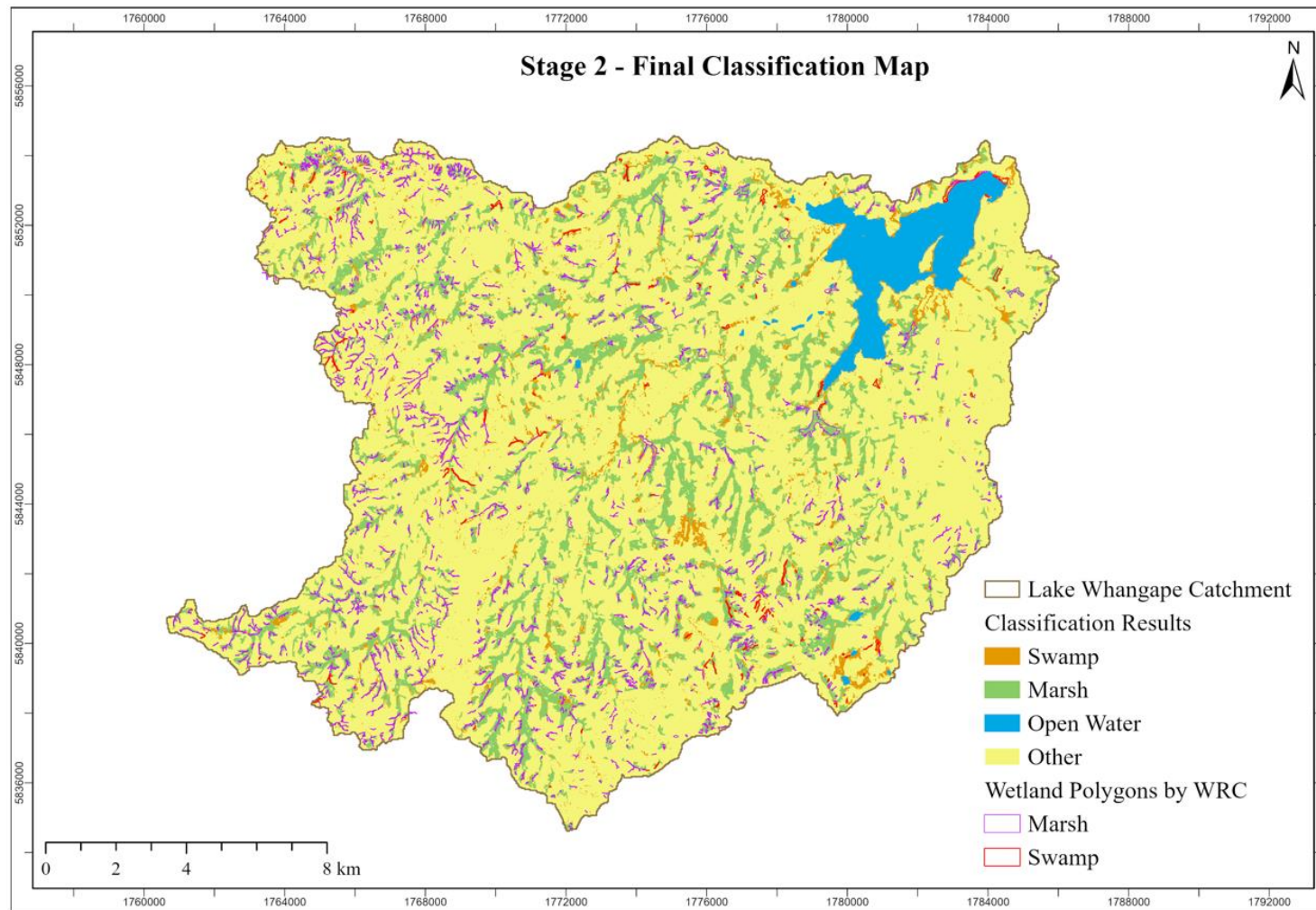


Figure 30. Final map of the detailed classification.

4.3. Wetland extents

The area covered by marsh within the catchment area is 5,508 ha, and the area covered by swamp is 751 ha out of 31,767 ha catchment area. The area covered by open water is 1,112 ha. The percentage of the area covered by marsh, swamp, and open water is 17%, 2%, and 4%, respectively.

4.4. Enlarged maps based on the detailed classification results

The classification map in Figure 30 is small in scale, hence, not detailed. Therefore, a series of 12 maps (see Appendix 1, Frames 1-12) were created to present ground information that can be used to visually determine the accuracy of the resulting wetland classes. The wetland polygons provided by the WRC were also mapped for comparison purposes. The twelve maps created are represented by the grid shown in Figure 31.

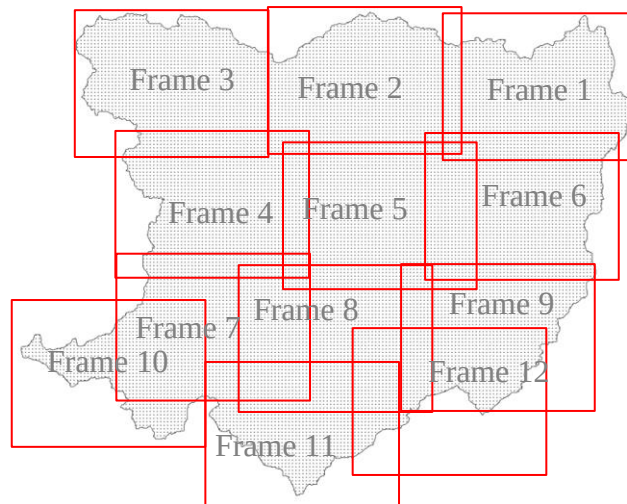


Figure 31. Detailed map guide.

Detailed classification results are provided in the appendix – 1, (Frame 1 to Frame 12).

Chapter 5: Discussion and conclusion

5.1. RS and GIS for wetland classifications

The overall finding of this study shows that RS and GIS techniques are effective for wetland classification. Wetlands in the Lake Whangape catchment were identified and separated into swamp and marsh classes. Possible areas of swamps, marsh and open water in the catchment were mapped and compared with wetland polygons provided by the WRC. According to the study, wetlands occupy a large portion of the Lake Whangape catchment.

5.2. Variable importance and assessment

Based on the results, the TPI is the most influential parameter in identifying wetlands of the area, and the MNDWI successfully identifies open water. TPI compares the elevation of each pixel to the mean elevation of a specified neighbourhood around that pixel (Weiss 2001). Therefore, it has the ability to subdivide landscape into morphological classes based on topography (Riley et al. 2017). Topography is one of the most significant factors for the surface and ground water movement (Winter 1999). Wetland ecosystems are usually depend on surrounding topography as driver of wetland hydrology (Los Huertos and Smith 2013). In this study, TPI received the highest RF relative importance value. The overall accuracy increased from 61% to 87%, when TPI applied in the classification.

MNDWI have been resulted greater accuracy in extracting water bodies (Du et al. 2016). The open water class was greatly delineated after employing MNDWI at Step two of both the simple and detailed classification stages. Figures 24 and 29 show that Open water class achieved a great improvement when MNDWI used in the classification. Open water class received over 99% of producer's and producer's accuracy in both classification stages.

5.3. Simple vs. Detailed classifications

Wetlands in the Lake Whangape catchment are identified in the simple classification stage. The results reached 91% overall accuracy. All the Open water pixels classified correctly. Wetlands class received 90% and 84% Producer's accuracy and User's accuracy respectively. However, the detailed classification resulted low overall accuracy of 76%. Out of 300 total samples, only 159 samples were correctly classified as swamp class while 217 samples correctly classified as marsh class in this stage. Swamp and marsh classes received 74%, 57% user's accuracy and 73% and 53% producer's accuracy, respectively.

Considering the previous wetland classification studies using machine learning such as RF, Amani, Mahdavi, et al. (2019) received 71% wetland class accuracy for all Canada. Mahdianpari et al. (2019) achieved 88% wetland class accuracy using an OBIA approach with RF algorithm across Newfoundland. Wetlands are naturally complex environments. Mahdianpari, Jafarzadeh, et al. (2020) mentioned that it is not easy to achieve higher classification accuracy for wetlands compared to the other land covers classes. For example,

wetland plant species have several spectral similarities due to their biophysical and biochemical characteristics

The previous studies suggests that wetland classification using deep learning achieved better results compared to machine learning methods (DeLancey et al. 2020). Mahdianpari et al. (2018) accomplished 96% wetland class accuracy in Newfoundland and Mohammadimanesh et al. (2019) received 93% in Newfoundland using convolutional neural network. However, they have used different data sets to achieve these results.

5.4. Limitations

Considering the wetland polygons resulting from detailed classification, some farm areas were confused with wetlands because of the spectral similarities. For example, polygons 1 and 2 overlap the WRC polygons with appropriate wetland class while the WRC does not identify the farm area covered by polygon number 3 as a marsh as shown in Figure 34.

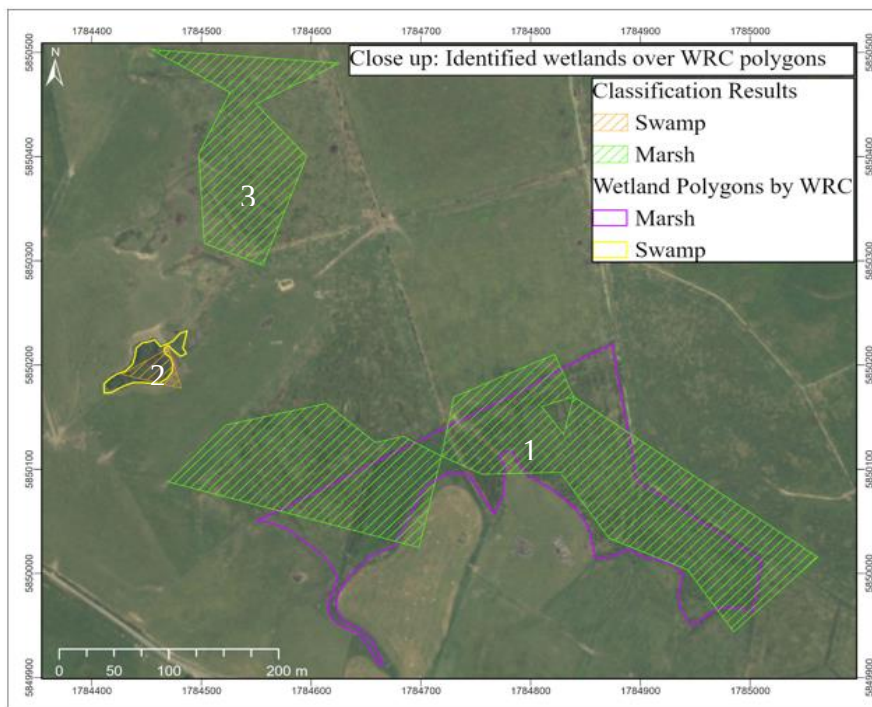


Figure 32. Areas classified as wetlands (Example 1).

Several areas of misclassification were observed. Example 2 in Figure 35 shows areas classified as marshes laid on farm roads. Therefore, these areas need to be further examined to increase classification accuracy.

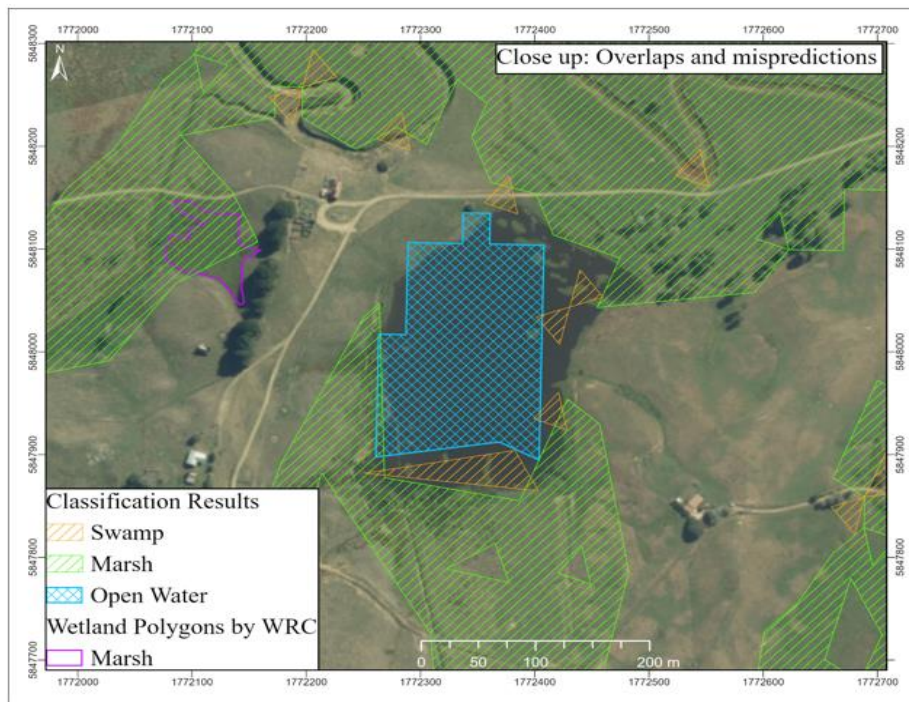


Figure 33. Areas classified as wetlands (Example 2).

Seasonal changes of the NIR band received from Sentinel-2 image and seasonal changes of calculated NDVI effectively identify the dynamic nature of wetlands in the area. Therefore, the spectral characteristics vary with their vegetation cycles. For example, wetlands in the summer (December to February) appear different from winter (June to August). Figure 32 compares visual changes of a wetland change in different seasons. The images represent the median of the images collection accessed for each season.

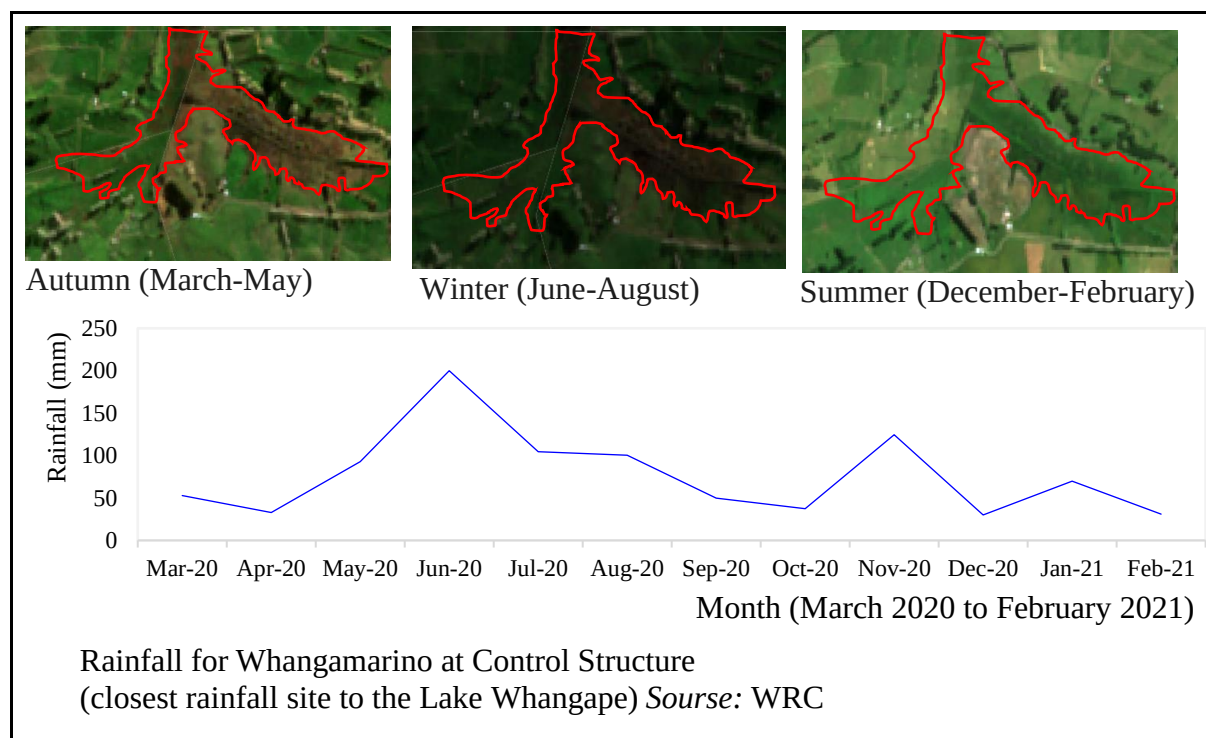


Figure 34. Change of wetlands over time.

The sensitivity of Radar backscatter to the moisture content of the terrain is one of the SAR strengths (Ulaby et al. 1986). As seen in Figure 33, the water surface appears dark in a SAR image because of low backscattering intensity. The dark area of the SAR image is distributed evenly as the lake's water surface is calm. In addition to identifying open water, SAR can distinguish areas saturated with water (Reschke et al. 2012) therefore, SAR supported to improve the classification.

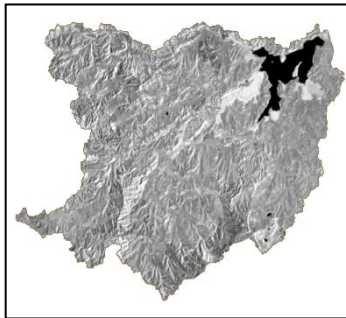


Figure 35. SAR backscattering.

5.5. GEE platform for wetland classification

Based on the study, employing GEE for wetland classification was very efficient. Accessing remote sensing data was straightforward due to the rich GEE data catalog. The data processing was efficient, and exporting results was easier in this environment. The only limitation that affected the classification was the per worker memory.

5.6. Future directions

The overall validation accuracy reached 91% at the simple classification stage. However, the accuracy of the detailed classification remains low (the overall accuracy is 76%), and a significant amount of confusion resulted among the wetland classes. Therefore, further research is needed to improve the classification accuracy.

A study using highly accurate data such as LiDAR could be helpful to gain more accurate classification results. The study area is not covered with LiDAR at the moment (2021), but LiDAR coverage will be available for future studies. SAR L-band (wavelength 15-30 cm) is often cited as the best wavelength for wetland classification in previous studies (Mahdavi et al. 2017). Also, Mohammadimanesh et al. (2018) suggest that swamp and marsh are easily separated using the backscattering coefficient (σ^0) of the L-band SAR data. However, C-band (wavelength 4-8 cm) SAR was used in this study instead of L-band due to the availability of RS data for the study. SAR ability to penetrate through the vegetation increase with increasing the wavelength (Tsyganskaya et al. 2018). Therefore, accessing L-band SAR data can be useful in the future studies.

One of the other future research interests could be studying the shallow water wetlands in the area. According to Johnson and Gerbeaux (2004), wetlands can exist in shallow water. The shallow water wetland class was not included in the study due to the unavailability of training data.

The results show that a combination of spectral, SAR, and terrain data is effective in identifying wetlands. In addition, employing complex terrain indices using GIS data enhanced the classification further. Overall, the areas classified in both simple and detailed classification stages were reasonably aligned with the locations of wetland polygons by the WRC. Therefore, the data, parameters, and classification method are potentially helpful for wetland identification in the region.

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Appendix

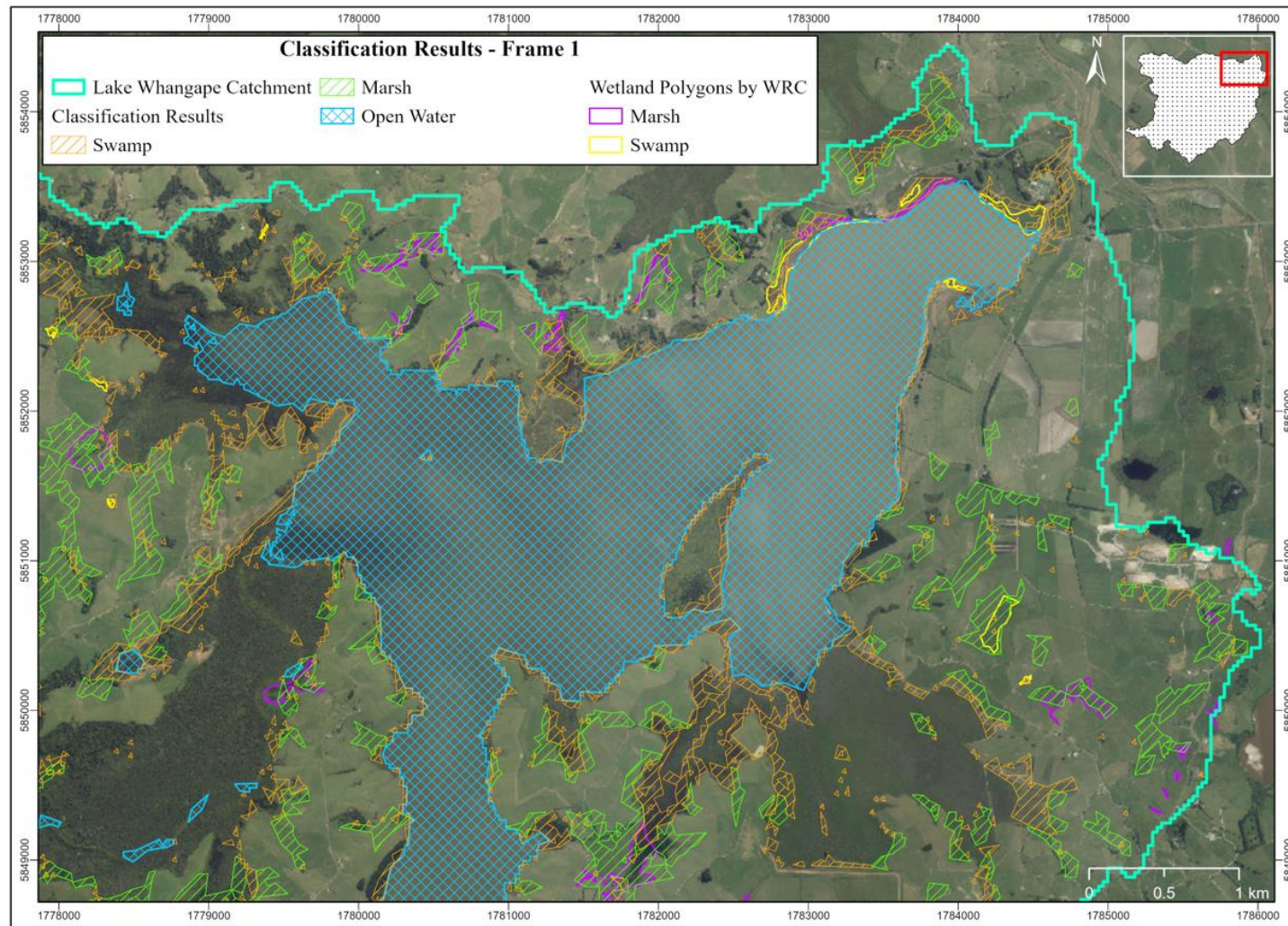


Figure 36. Frame1.

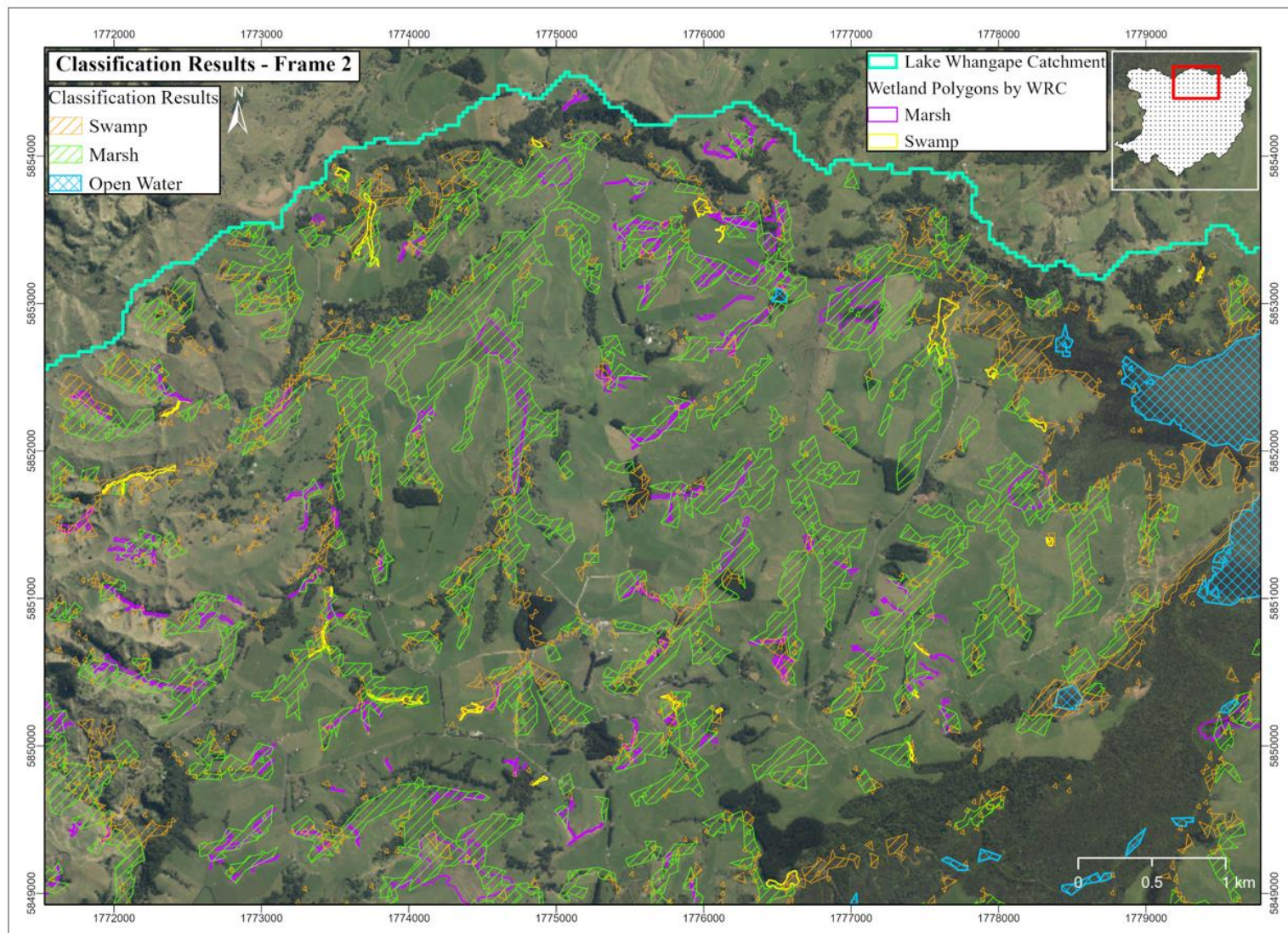


Figure 37. Frame 2.

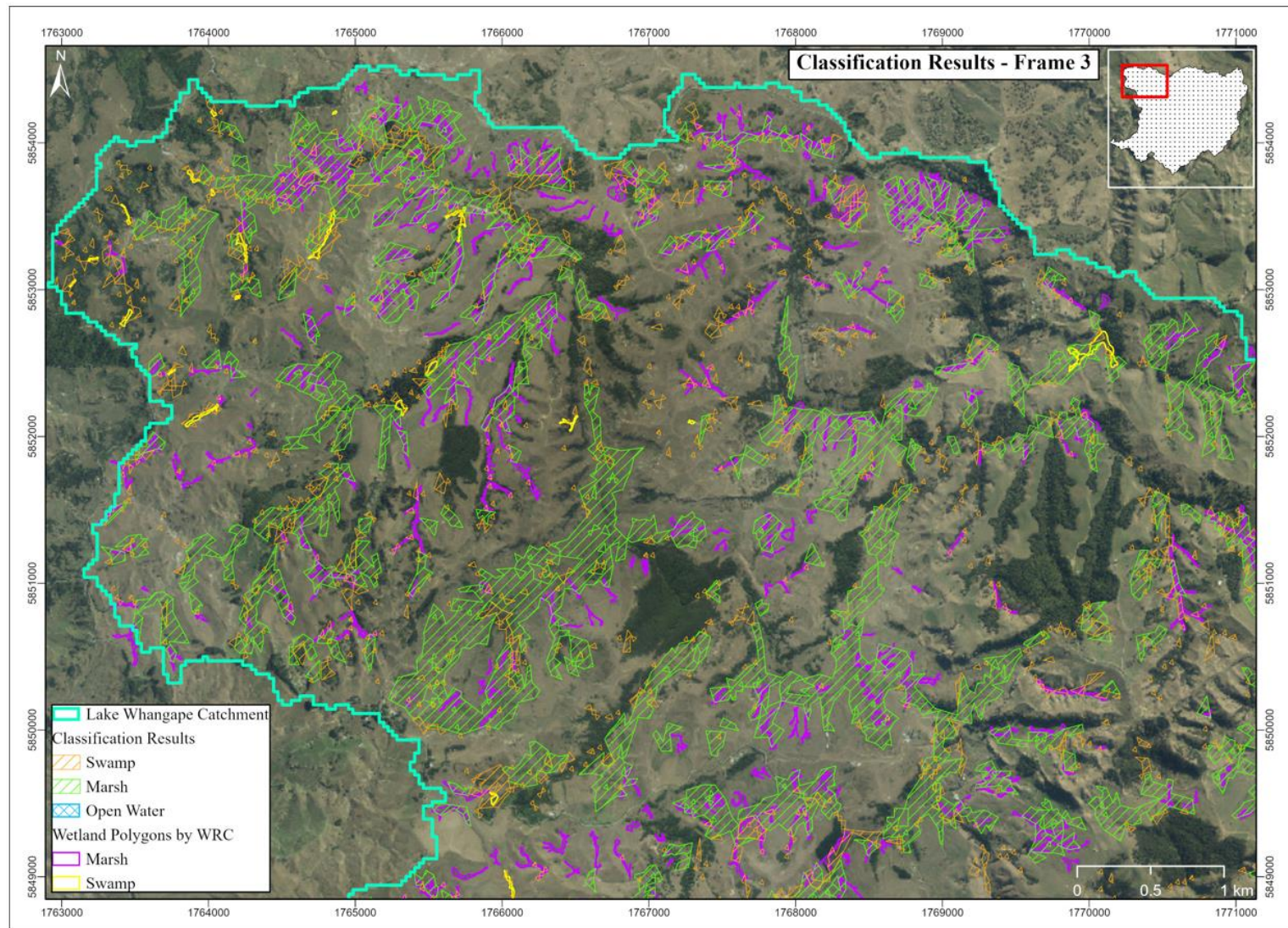


Figure 38. Frame 3.

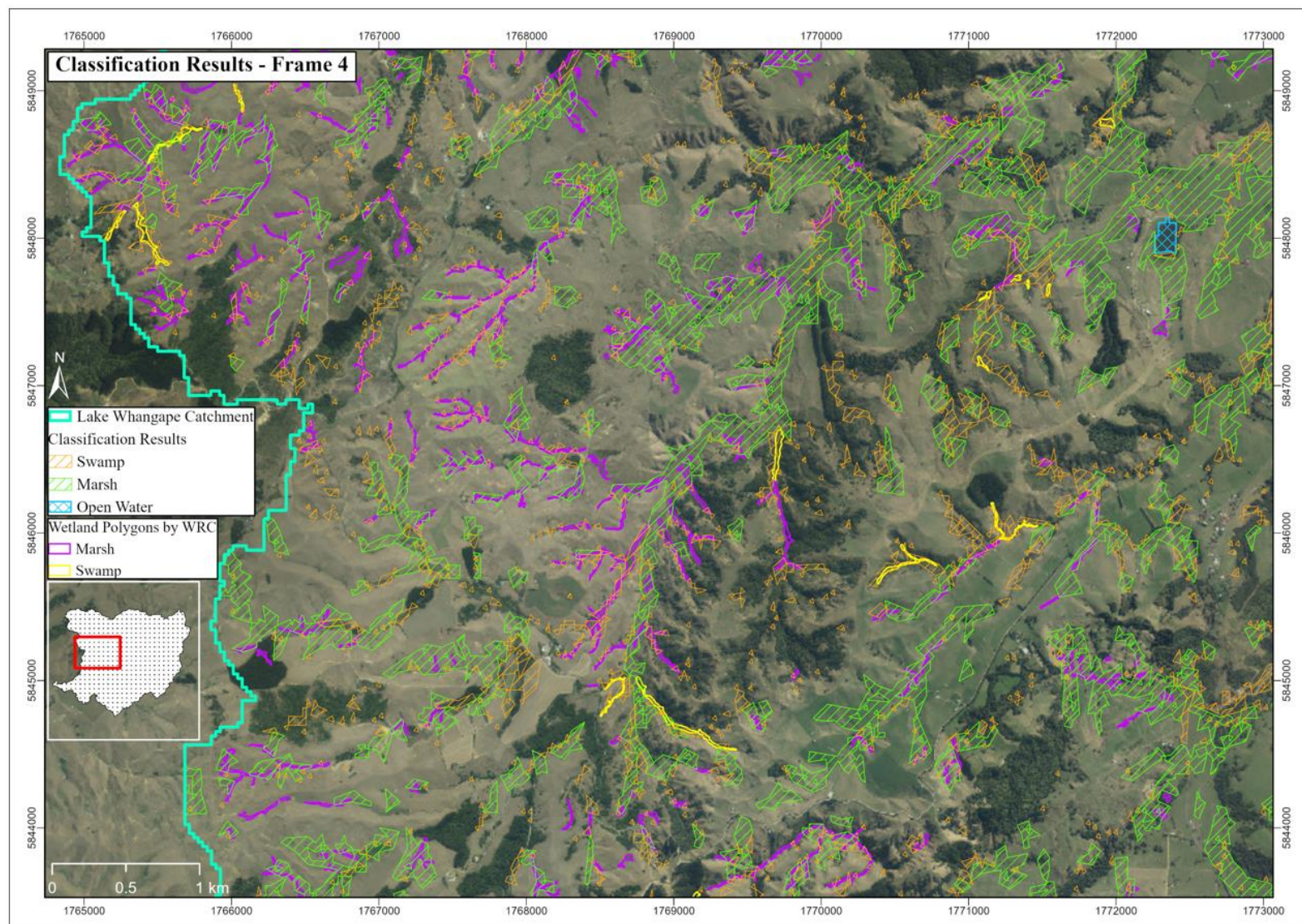


Figure 39. Frame 4.

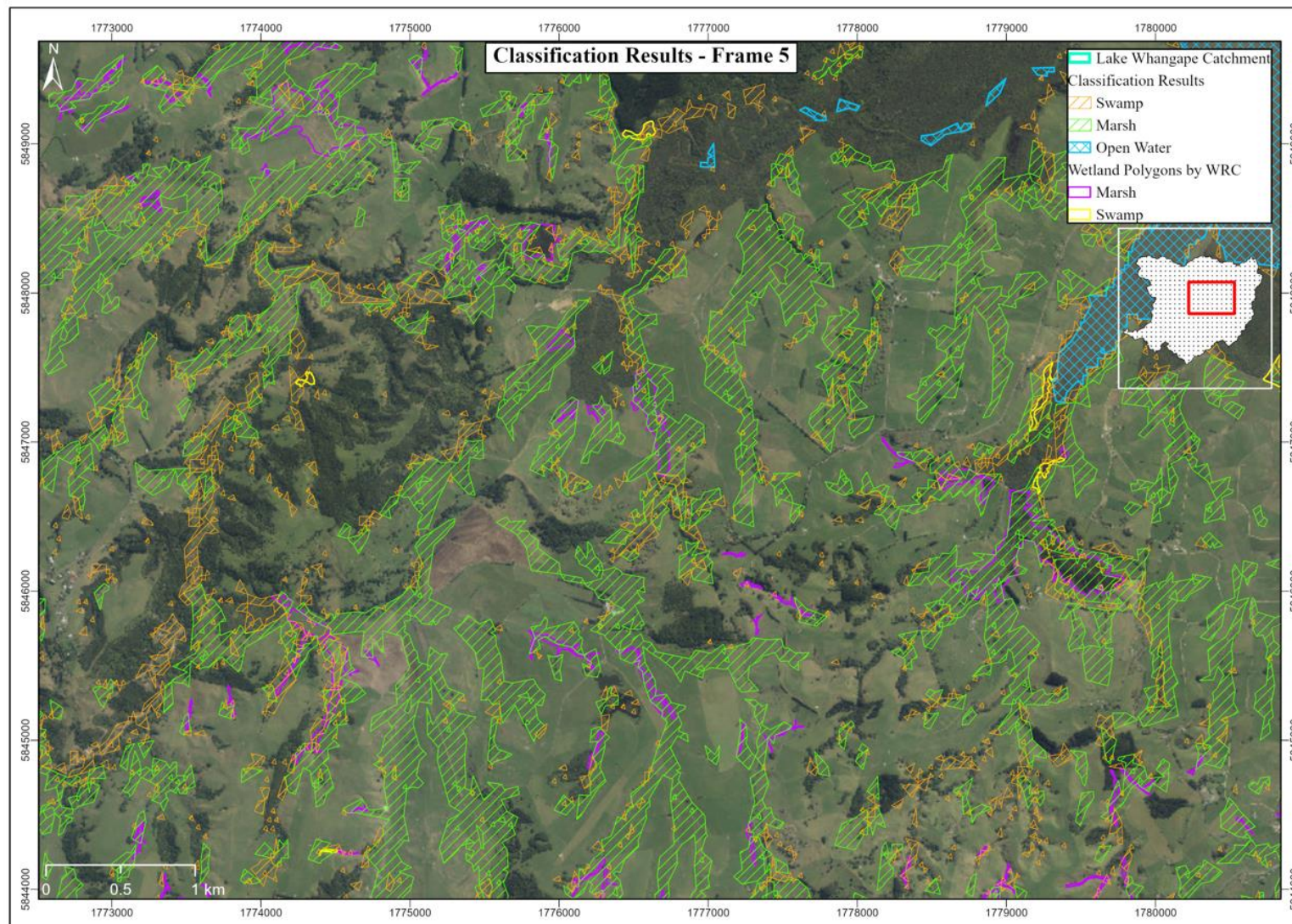


Figure 40. Frame 5.

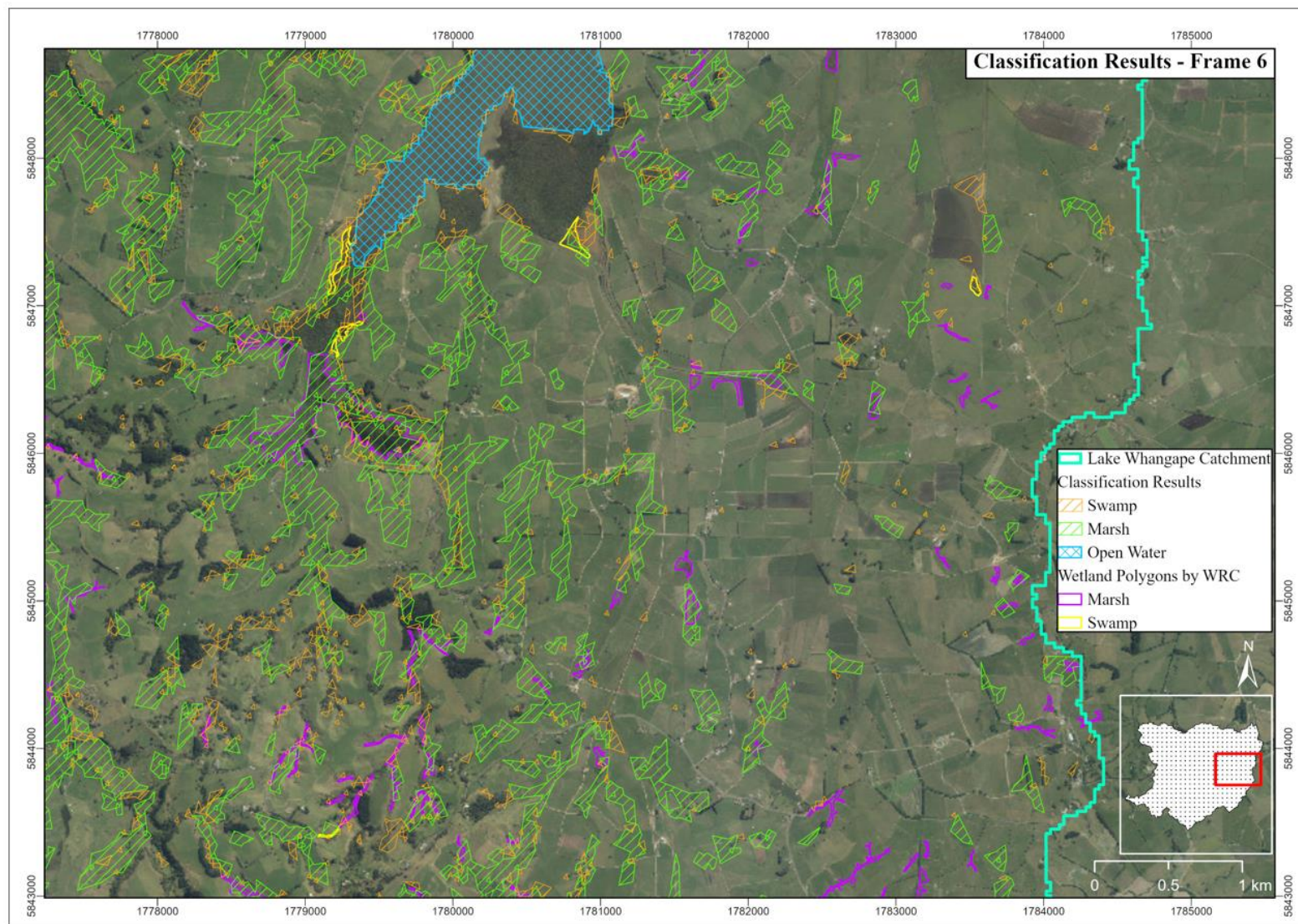


Figure 41. Frame 6.

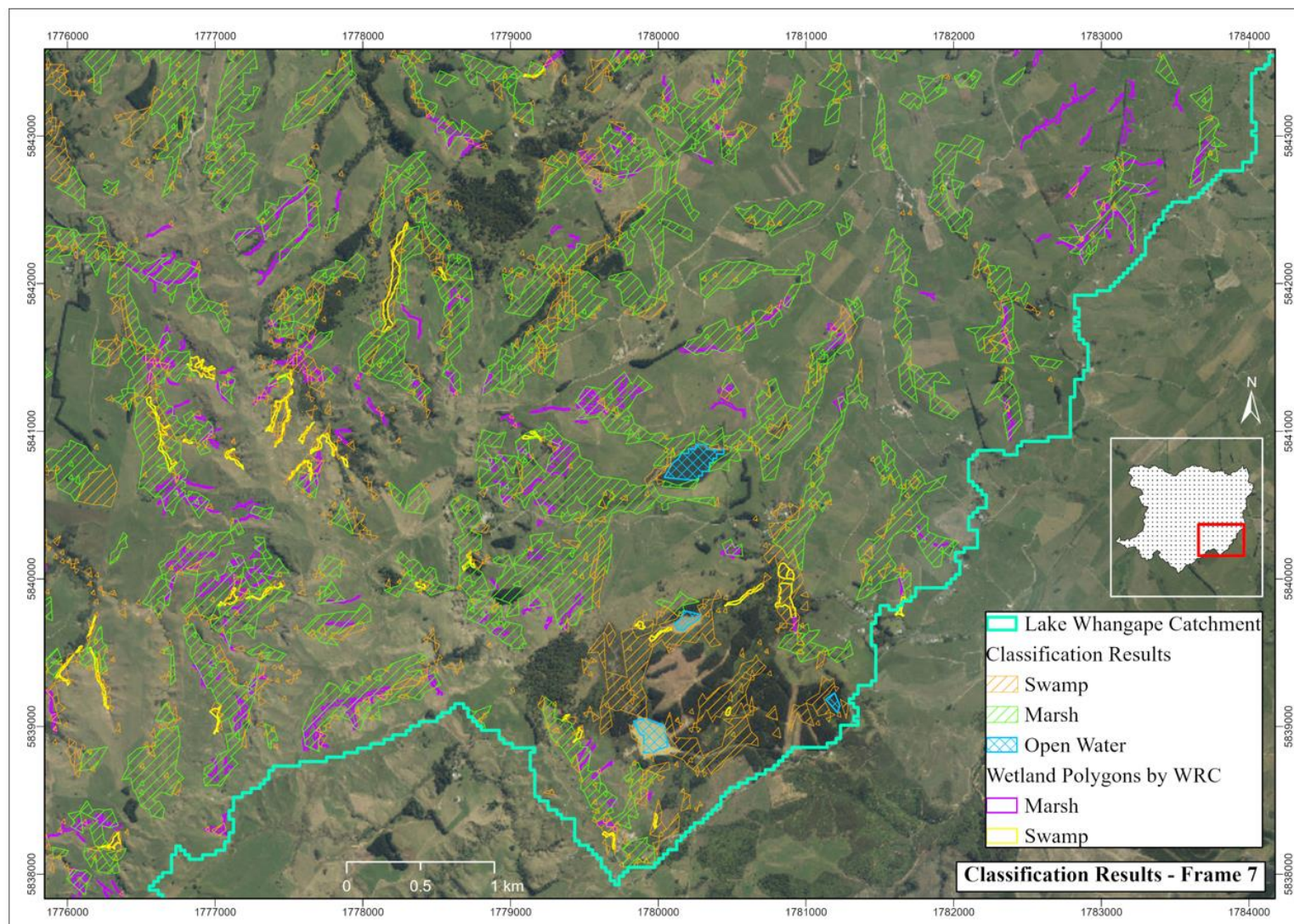


Figure 42. Frame 7.

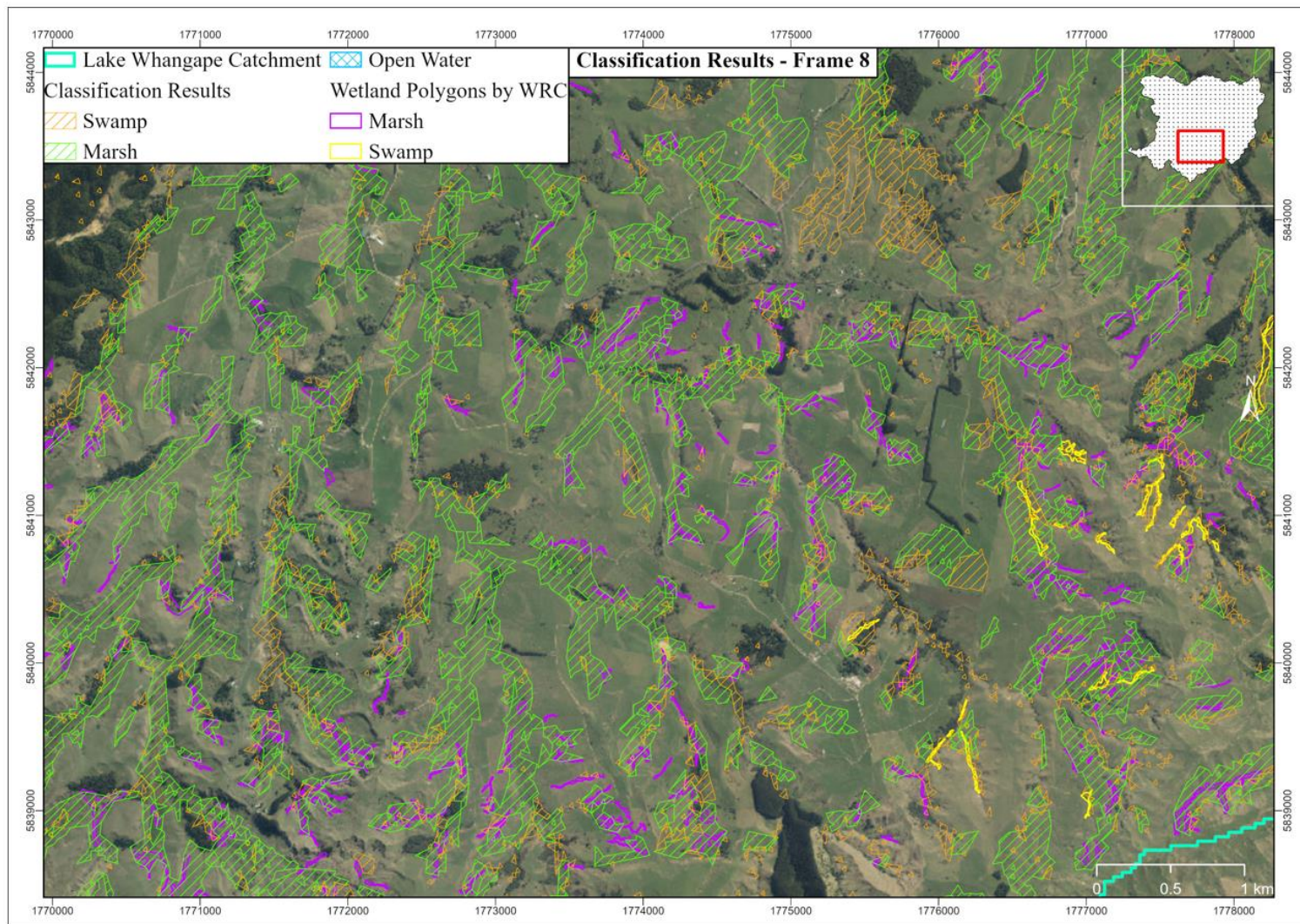


Figure 43. Frame 8.

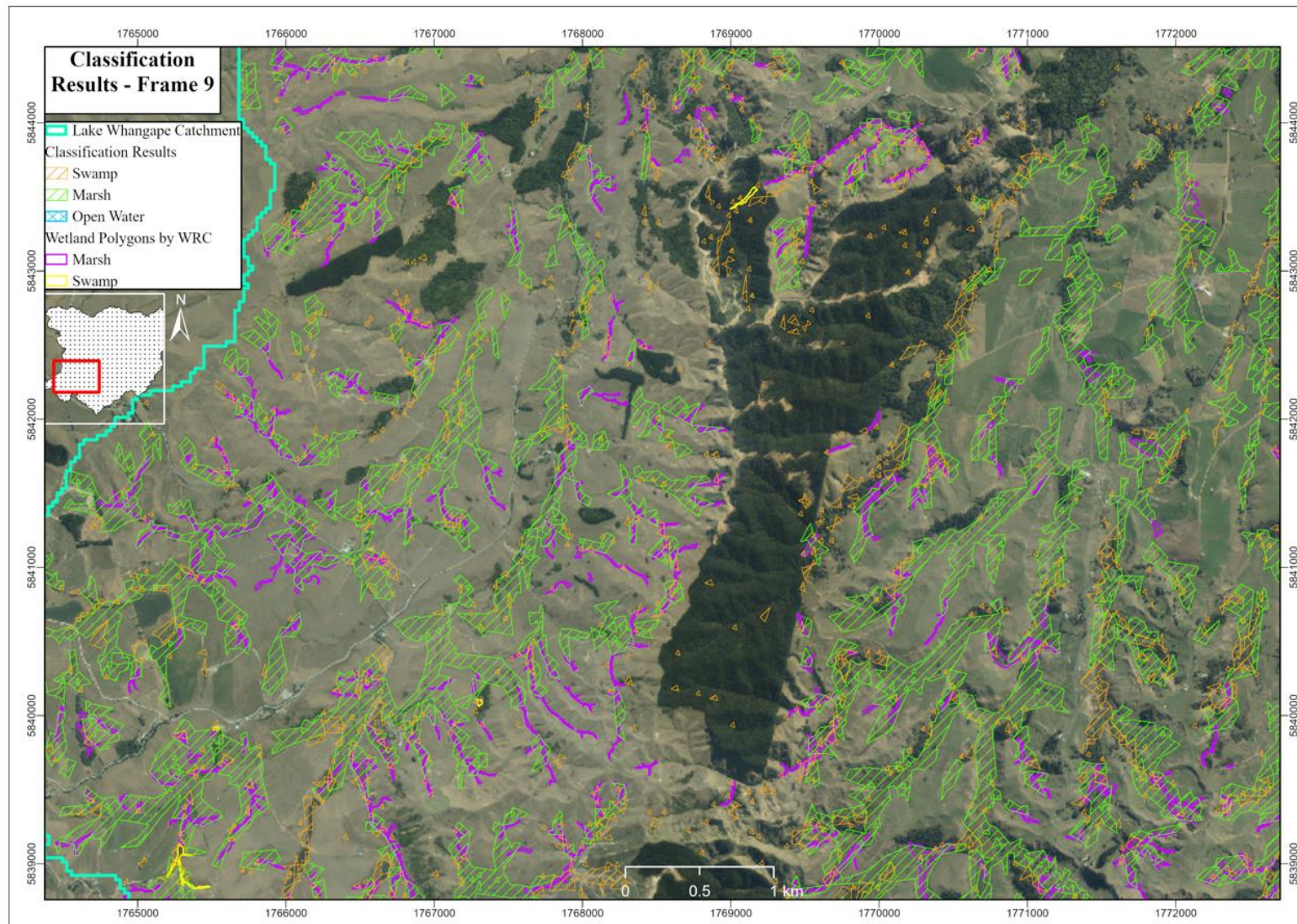


Figure 44. Frame 9.

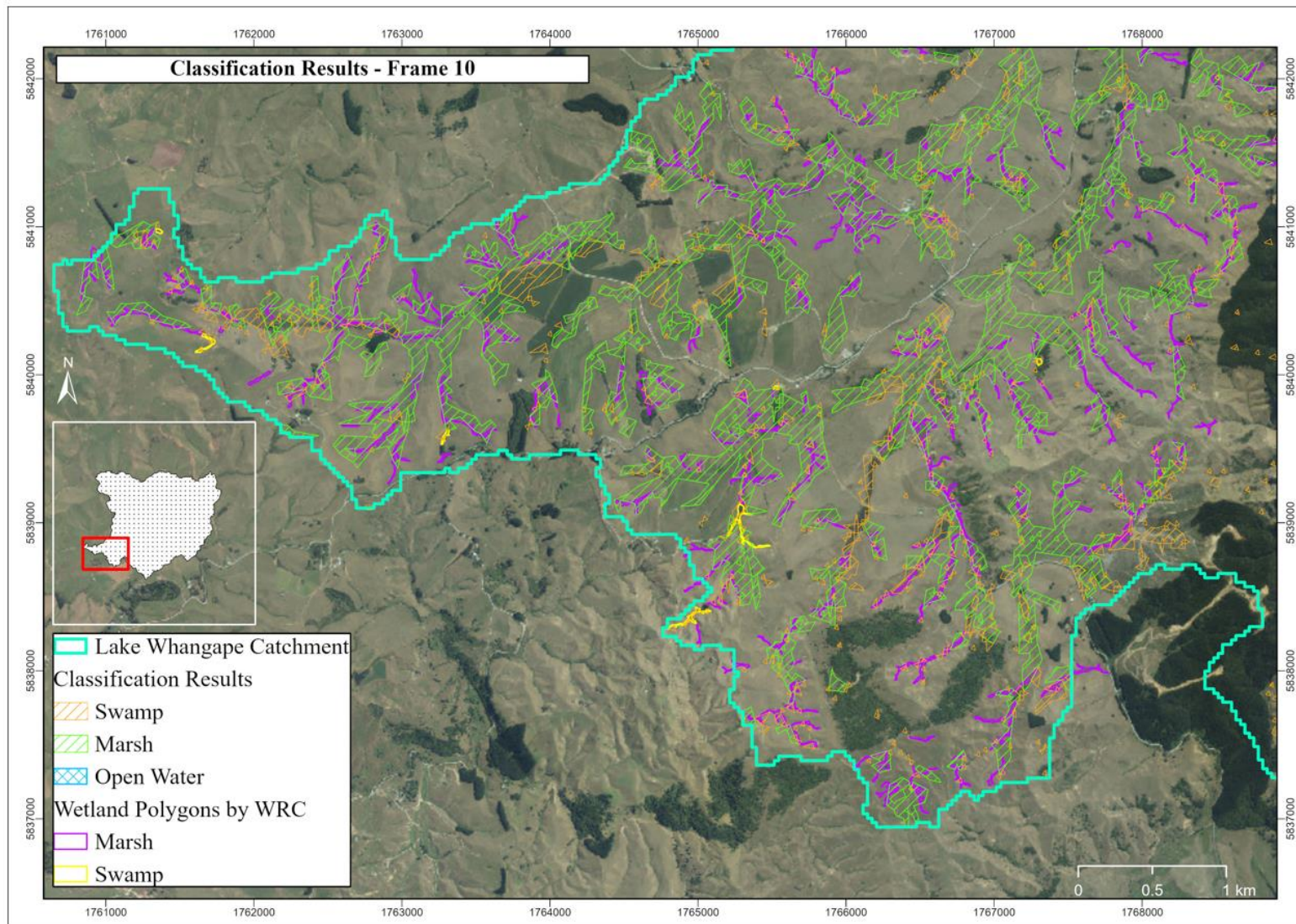


Figure 45. Frame 10.

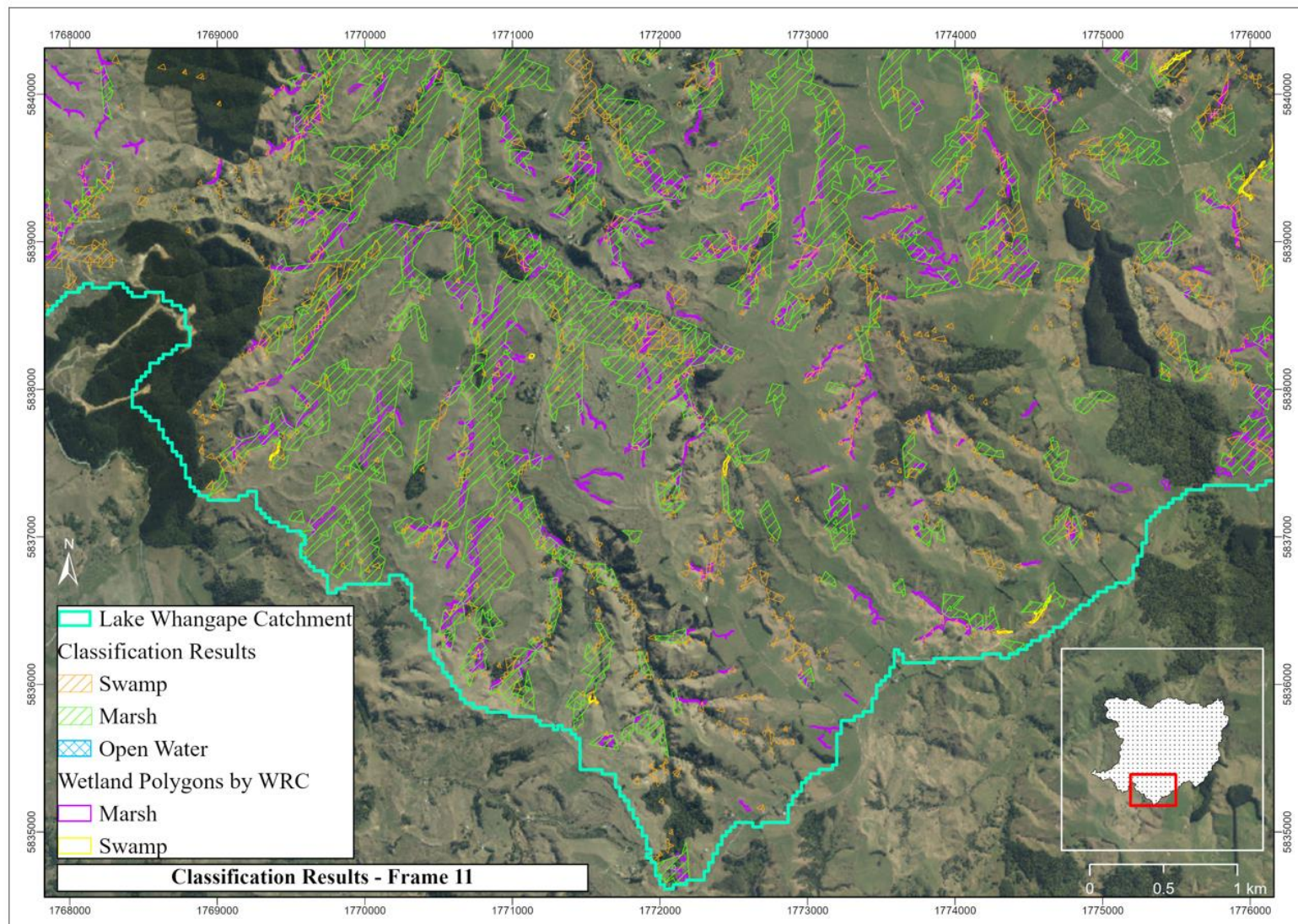


Figure 46. Frame 11.

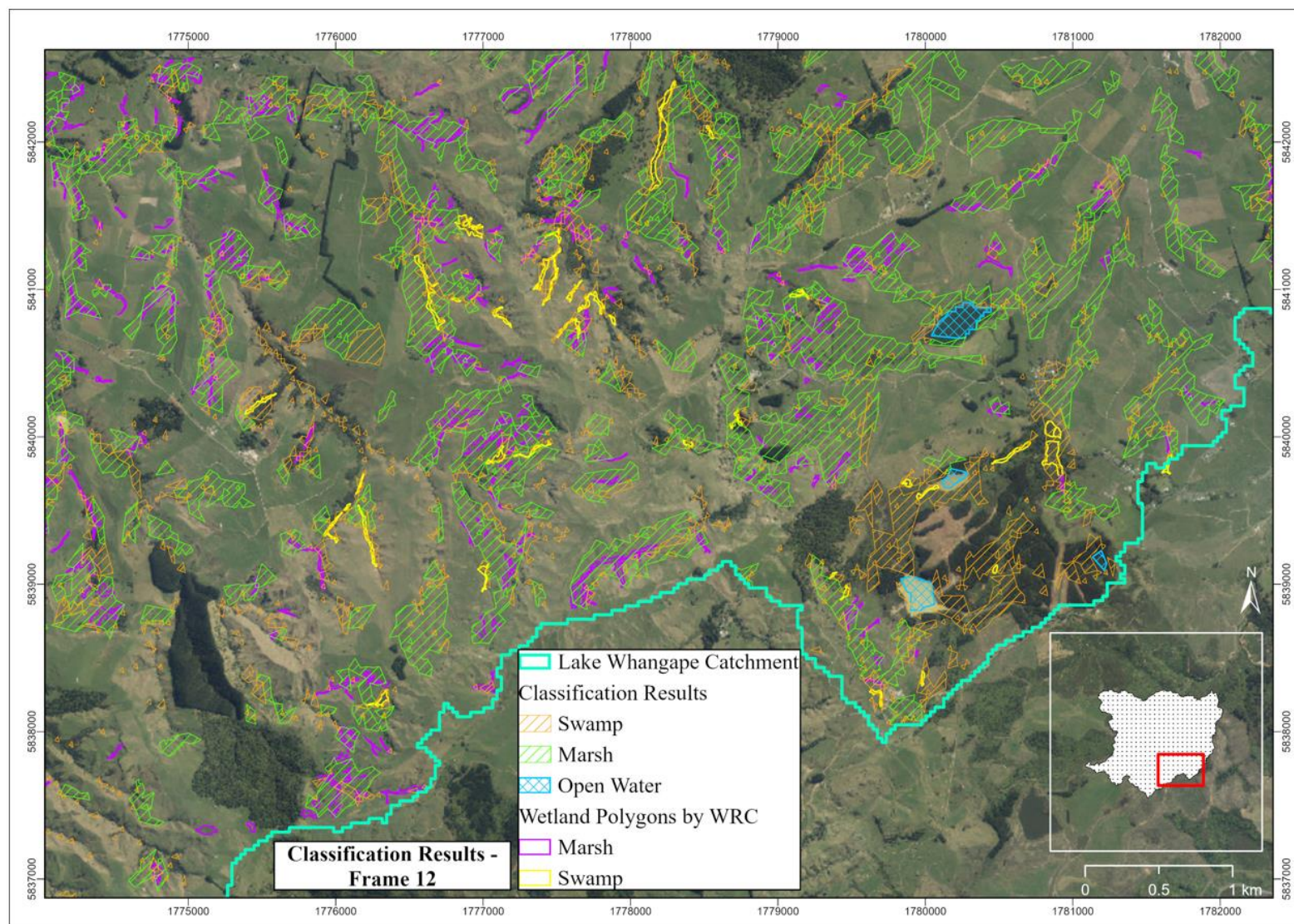


Figure 47. Frame 12.