Waikato Regional Council Technical Report 2016/21

Remote sensing of Waikato wetlands; a literature review

www.waikatoregion.govt.nz
ISSN 2230-4355 (Print)
ISSN 2230-4363 (Online)

Waikato REGIONAL COUNCIL
Te Kaunihera ā Rohe o Waikato

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2016

Document #: 8835308

Peer reviewed by:
Rebecca Eivers Date July 2016

Approved for release by:
Dominique Noiton Date August 2016

Doc # 8835308

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ERI report

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Citation

Allan M 2016. Remote sensing of Waikato wetlands; a literature review. Environmental Research Institute, University of Waikato, Hamilton.

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Cover photo

Sentinel 2a image of Kopuatai Peat Dome

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Remote sensing of Waikato wetlands; a literature review

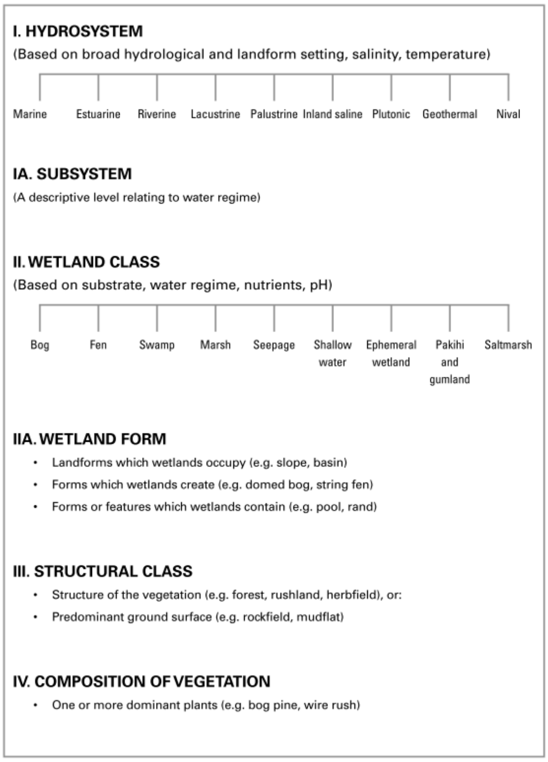
The Waikato Regional Council requested a review and summary of scientific literature on the subject of remote sensing identification of wetlands including both New Zealand and international contexts. The following review also proposes new methods for identification of wetlands, based on state-of-the-art methods identified within this report.

New Zealand wetlands extent has decreased dramatically, and it has recently been estimated that only 10% of pre-European palustrine wetlands remain, with 63% of these currently located within protected areas (Robertson, 2016). Between 1990 and 2013 the extent of current wetlands protected by Department of Conservation (DOC) administered land increased from 48% to 60% (Robertson, 2016).

Wetland types in New Zealand

Johnson & Gerbeaux, (2004) previously classified wetland types in New Zealand. At the top level the semi-hierarchical classification system is based on the hydrosystem whereby classification is based on a broad hydrological landform, salinity and temperature (Table 1). The classification then moves down to wetland classes based on substrate, water regime, chemistry, and vegetation.

Table 1. Johnson & Gerbeaux, (2004) classification system



Introduction to remote sensing

Passive remote sensing involves sensors that record electromagnetic (EM) energy reflected or emitted by the earth. The most important characteristic of EM for the purpose of remote sensing is its wavelength (λ), whereby the longer the wavelength, the lower the frequency and energy. Remote sensors record EM in the form of radiance. The radiance recorded by a remote sensor is dependent on the geometry of the light field and the earth-sun distance, combined with atmospheric effects. In oder to convert satelite radiance to surface reflectance these factors must be accounted for, which enables the interpretation of the reflectance in terms of the specific properties of the surface or medium. A generalised overview of remote sensing methodology can be seen in Fig. 1.

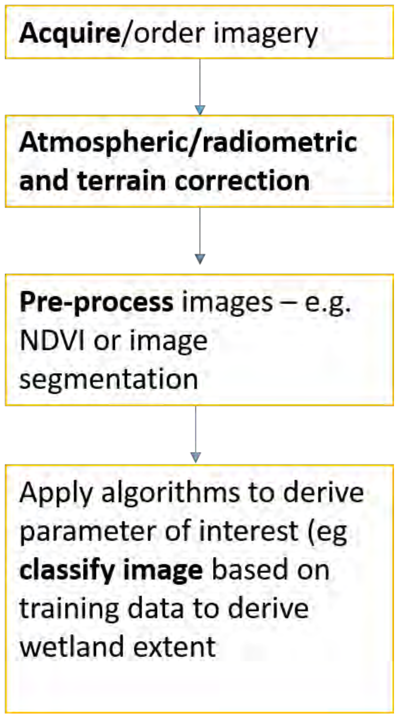


Figure 1. Overview of image processing

Classification algorithms make use of differing spectral signatures of different land cover types. For example the spectral reflectance of different wetland species and substrates vary considerably (Fig. 2). The spectral reflectance curve of green vegetation has a minimum at visible wavelengths (390 – 700 nm), resulting from absorption by plant pigments, especially in the blue and red wavelength region. Vegetation has higher reflectance in the near infrared (780 – 900 nm), due to penetration of the radiation into and through the pallisade parenchyma. The combination of low visible reflections and high near infrared reflectance is often unique for each plant species, and allows for the formulation of image classification algorithms to determine land cover.

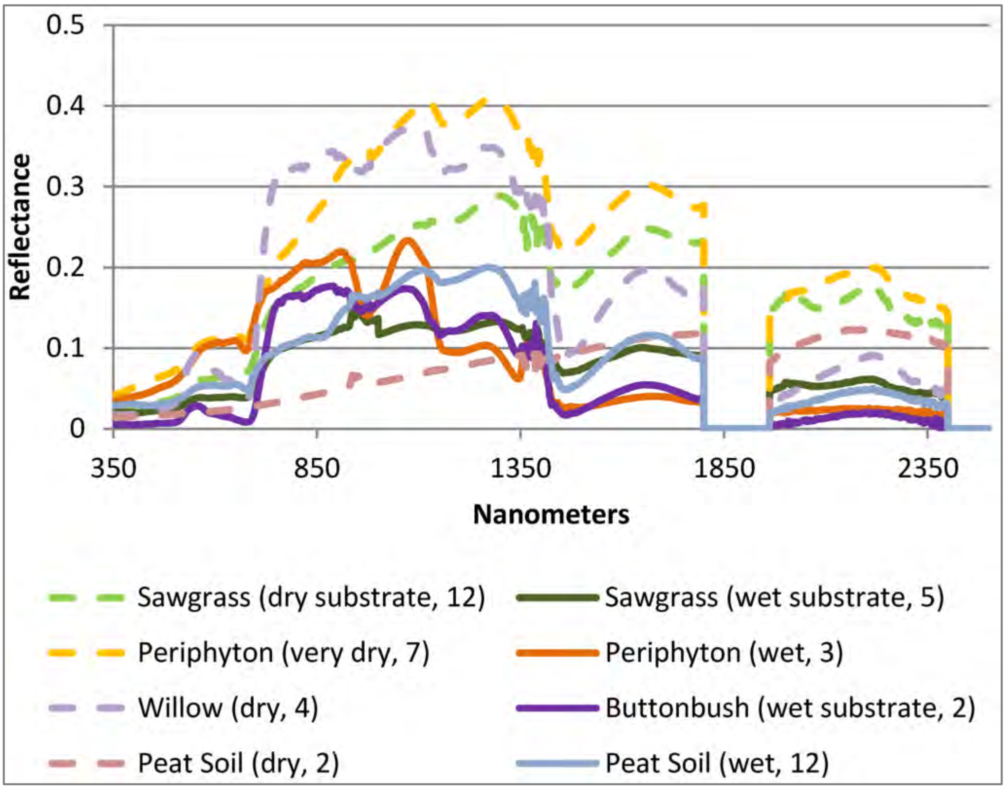


Figure 2. Spectral signatures of wetland cover captured with a field radiometer (Jones, 2015).

Wetland identification using remote sensing, image classification and GIS data

Historically aerial photography has been extensively used to map wetland vegetation, however for monitoring on a regional scale the time-consuming nature of this manual visual interpretation based wetland delineation can be prohibitive. The use of Earth observation satellites provides a more reliable and standardised source of environmental data. Remote sensing has a long history of successful applications within the field of wetland delineation, using a multitude of satellite platforms and sensors. Historically Earth observation data made use of visible and near infrared bands for classifications, such as those found in the Landsat series of satellites (Fig. 3). Landsat ETM+ data has reasonably high spatial resolution (30 m) and has been proven to be a suitable platform for wetland mapping due to the presence of bands at visible, NIR and middle infrared (IR) wavelengths (Frohn et al., 2011). However many other satellite platform sensors have been used for the remote sensing of wetlands including Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER, Pantaleoni et al., 2009), and Systeme Probatoire d'Observation de la Terre (SPOT; Jensen et al., 1993). The recent launch of Sentinel 2 provides multispectral imagery at 10 m resolution, and possesses a significant advantage over Landsat with increased spectral resolution (more bands) in the near infrared (Fig. 3). However only one near infrared band exists at 10 m resolution, with others at 20 m resolution.

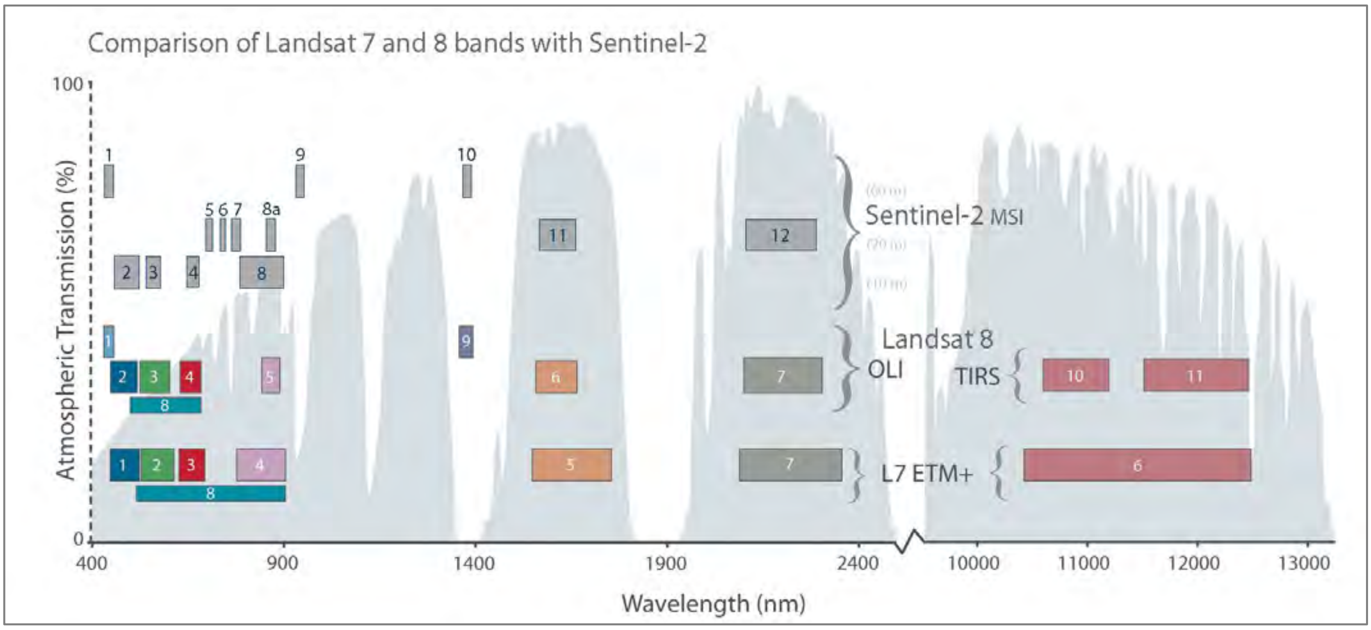


Figure 3. Atmospheric transmission versus wavelength for Landsat seven and eight and Sentinel to MSI. Source: landsat.gsfc.nasa.gov/

A multitude of different algorithms have been used to classify wetlands from remote sensing data. The most common image classification technique for the identification of wetlands is pixel based supervised or unsupervised classification using the maximum likelihood classifier (MLC) (Frohn et al., 2011). Generally, pixel based image classification involves grouping pixels into classes based on their spectral characteristics, or its feature vector, which determines the features of the cluster. During classification, the MLC algorithm considers the cluster centre, size and shape.

The most common criticism of the use of broadband remote sensors for wetland delineation is the inability discriminate wetland vegetation species (e.g. McCarthy et al., 2005). This has been attributed to the broad spectral bands (low spectral resolution) with respect to often small and detailed changes in canopy reflectance with vegetation species. In addition the low spatial resolution restricts the mapping of vegetation types below canopies (Adam et al., 2010). Furthermore, the spectral signature from wetlands can contain an averaged combination of reflectance from vegetation, soil, water and atmospheric vapour, and can have spectral overlap with terrestrial and aquatic signatures (Adam et al., 2010; Ozesmi and Bauer, 2002). This limits the ability of multispectral satellite imagery to discriminate between wetland species, and discriminate terrestrial and wetland based herbaceous/woody vegetation.

Recent advances in hyper spectral imaging offers enhanced potential to map wetlands or wetland species composition and biomass (Zomer et al., 2009). Hyper spectral data captured from airborne based images has the potential to gain both high spectral resolution and high spatial resolution information. However airborne based remote sensing techniques are costly which often limits them to applications over small areas or at a low temporal resolution. In the future, newly developed hyper spectral satellites such as the Hyperspectral Infrared Imager (HyspIRI, no predicted launch date set) will sense visible (revisit time of 19 days) and shortwave infrared radiation at 10 nm contiguous bands, with multispectral bands in the mid and thermal infrared (revisit time of five days for thermal infrared) (Turpie et al., 2015). However this satellite will contain 60 m resolution pixels, thus limiting the remote sensing of small wetlands.

In order to address the shortcomings of traditional classification using visible and NIR data, studies are incorporating thermal infrared, synthetic aperture radar and lidar, individually or in combination, with visible and NIR data (e.g., Pham et al., 2016). Along with these data sources, classification algorithms have been developed to address shortcomings of traditional pixel based classification. The application of more complicated algorithms such as spectral angle mapping (SAM), Support Vector Machine (SVM), neural network (NN) and rule-based classifiers has increased the accuracy of wetland monitoring. A recent meta-analysis reviewing pixel based supervised classification of land cover using remote sensing found that the inclusion of texture based information and classification routines resulted in the greatest improvement of accuracy with an average increase of 12.1% (Khatami et al., 2016). The study also found that the most accurate classification algorithm was SVM, followed by NN methods. The inclusion of ancillary data (e.g., DEM, LIDAR, GIS soil/ geologic databases), multi-angle and time series imagery also offered significant accuracy improvements. The study found that manipulation of spectral imagery creating indices such as the Normalised Difference Vegetation Index (NDVI) and feature extraction (e.g. principal component analysis) offered only small improvements in accuracy.

Due to the limitations of optical based remote sensing, in recent years more effort has been applied in the use of active remote sensors such as synthetic aperture radar (SAR). Radar data capture has a great advantage over optical infrared data capture in that microwaves can penetrate cloud cover. In addition, radar waves interact with land surface revealing information on three-dimensional structure (Furtado et al., 2016), including canopy structure.

Lidar is a survey technology that measures distance using laser 3-D scanning which, when applied over large areas, is usually aircraft based. While lidar data is useful in creating high-resolution topography data, it has also been investigated for vegetation classification. Topographical data and watershed morphology is useful for the identification of potential wetland areas. For example, flow direction can be calculated directly from DEM data, which can then be used to calculate a Topographic Wetness Index (TWI), which has the potential to identify locations with sufficient wetness to allow the formation of wetlands. Rampi et al., (2014) investigated the application of TWI for identification of wetlands in Minnesota using various flow direction algorithms and achieved an accuracy of 92%. The authors concluded that the spatial resolution and accuracy of the DEM is critical for accurate representation of wetlands.

For the remote sensing of wetlands, image segmentation and object oriented classification has shown significant improvements of accuracy over traditional classifying techniques (Frohn et al., 2011). Segmentation involves the subdivision of a pixel based image into regions based on scale, shape-colour, smoothness-compactness and texture. Once completed image objects can be further segmented or classified based on characteristics of the individual object. Traditional pixel based classification techniques can be applied at an image object scale to classify objects into classes (e.g., landcover classes). Once classification is complete polygon boundaries of like classes can be dissolved, creating a classified image. Image segmentation and object oriented processing of Landsat 7 imagery has been previously used to map wetlands and has been shown to outperform maximum likelihood classification (MLC) with an accuracy of 91% as opposed to the accuracy of 78% for MLC (Frohn et al., 2011). In addition, using primitive objects as mapping units instead of pixels allows local spatial context, moderation of the effect of local pixel variation on classification uncertainty (Dronova et al., 2015), as well as the rude "salt and pepper" effect common to pixel based classification (Dronova et al., 2012). Another advantage of object based image classification is the potential to combine spatial data from multiple sources. For example, a combination of RADARSAT-1 and Landsat ETM imagery has previously been used to identify wetlands and map into distinct wetland classes, using an object oriented methodology (Grenier et al., 2007). The identification of wetland versus non-wetland sites resulted in 80% accuracy, and accuracy of wetland class differentiation (bog, fen, swamp, marsh, and shallow water) ranged from 67 to 76% for the two test sites.

The National Wetlands Inventory (NWI) of Minnesota has been updated in 2013 using a method that integrates air photo interpretation, image segmentation, and object oriented image analysis. Historically, forested and emergent wetlands in Minnesota have been under assessed (Scarbrough et al., 2013) due to limitations in classification methodology or subjective interpretation classification. In order to address these limitations the NWI was updated to incorporate air photo interpretation, image segmentation, and object oriented image analysis. Briefly, the method used 50 cm resolution aerial photography, PULSAR L-band radar data (freely available from https://www.asf.alaska.edu/sar-data/palsar/), hydric soils GIS layer, TWI, and Topographic Position Index (TPI) (mapping depressions) derived from LIDAR 3 m DEM's. This data was then subjected to image segmentation algorithms and classification. For the final step, image objects were manually selected (in combination with reference imagery) to create the final NWI database.

Wetland identification in in New Zealand using GIS and remote sensing

Current knowledge of wetland extent in New Zealand was investigated through the Freshwater Ecosystems of New Zealand (FWENZ) initiative (Leathwick et al., 2010). The FWENZ wetlands GIS database was derived from Landsat images captured from 1999 – 2003 (Ausseil et al., 2008; Ausseil et al., 2011). These images were atmospherically corrected, terrain illuminated and pan-sharpened (Shepherd and Dymond, 2003). Standardised images were then classified based on spectral rules and a decision tree analysis. Land cover classifications including: water, bare ground, indigenous forest, herbaceous vegetation, cloud, seawater, narrow- leaved scrub, planted conifer forest, unspecified woody vegetation, urban bare ground, rock, tussock grassland, snow, and subalpine scrub, lacustrine, estuarine, riverine, and marine wetlands were derived directly from the land cover classification. Estuarine and marine water were classified using visual interpretation. Riverine water was determined using a 75 m buffer zone from the LINZ river network. Remaining water pixels were classified as lacustrine (lentic). Palustrine and estuarine vegetation mapping using spectral rules was not applicable due to the similarity of their spectral signals to other vegetation types.

In order to overcome the difficulties in classifying palustrine and estuarine vegetation due to their spectral similarities, predefined wetland locations were used to seed region growing algorithms. Region growing algorithms examine neighbouring pixels of seed locations and ads like pixels to the region. These predefined wetland locations were derived from regional council GIS databases. Vector data (point, polygon) of wetland extent and location was compiled from field surveys, and photo-interpretation. The vector data was then used to seed the region growing algorithm which identified spectrally similar pixels allowing wetland extent to be mapped. A spectral threshold for pixel selection was manually defined for each wetland location point.

The current FWENZ wetland database used fuzzy export rules to apply seven wetland classes: bog, fen, swamp, marsh, pakihi ⁄gumland, seepage and inland saline. The fuzzy classification uses a soil attributes GIS layer and a 15 m DEM. This method was validated in the Otago region, and found 60% agreement, with the major source of error due to misclassification of marshes as swamps. It was found that swamps had undergone the greatest reduction in extent compared to historical extent estimations, with only 6% remaining (Ausseil et al., 2011).

The current FWENZ historical extent (pre-human) layer was estimated using soil information from the Fundamental Soils Layer (FSL) and a digital elevation model. This included the selection of polygons where wetlands could potentially occur from the Land use capability CORRelation (LCORR). National New Zealand Soils Classification (NZSC) soil types were selected where a 95% or greater wetland coverage occurred, drainage class < 3. Polygons were refined using a sloped threshold derived from the DEM, with sloped thresholds greater than the maximum 95% of current wetlands (Ausseil et al., 2008).

Regional councils such as the Waikato Regional Council have compiled their own wetlands databases, including the Waikato Wetlands Probability Layer (WWPL). The creation of these datasets was prompted by a need for more detailed and extended wetlands coverage than what is currently included by FWENZ and other sources. The method was based on the Wetlands-At-Risk Protection Tool (WARPT) developed by the Centre for Watershed Protection under cooperative agreement from the U.S. EPA, Office of Wetlands, Oceans and Watersheds. WARPT uses a GIS-based analysis to map “potential wetlands”. The WWPL was created by combining six wetland datasets into one layer, whereby a numerical score of 1 or 1.5 was applied to each layer that indicated the potential presence of a wetland. A score of 1.5 was applied to BIOVEG 2012, as a higher confidence was observed for wetlands based on this layer then and other layers. BIOVEG 2012 was created by the Waikato regional Council by manually digitising aerial photos into terrestrial vegetation types, sand dunes and wetlands. The manually digitised nature of this dataset results in a higher accuracy than that derived from other sources such FWENZ. Other layers include Landcare Research Wetlands layer, Drainage, FENZ wetland, LINZ topo wetland, and LCDB4.

The findings of aforementioned studies of wetland identification in New Zealand are in line with international literature. In particular, the difficulty of classifying palustrine and estuarine vegetation using image classification or spectral rules. Therefore misclassification techniques used ancillary vector data and region growing algorithms to identify wetlands. This method has been proven to accurately determine wetland boundaries and locations, and is potentially the most accurate method applicable. However the discovery of small unmapped wetlands may be limited using this method. This becomes apparent when comparing the WWPL to FWENZ delineated wetlands, as there are many small wetlands identified in WWPL that are not present within FWENZ.

Case study: Sentinel-2 10 m resolution bands

Introduction

The Waikato Regional Council requested some example products and images for remote sensing of wetlands in the region. After reviewing the relevant literature it was decided that traditional supervised classification techniques would be compared to object oriented classification. The aim was to provide example imagery and a preliminary investigation into classification techniques, therefore the results were not validated.

Please note, the case study results presented are not rigorous scientific results, but demonstration products, designed to indicate types of data output and the potential of remote sensing of wetlands in the Waikato region. The case study also suggests methods that could be investigated further.

The European space agency has recently launched Sentinel-2A (launch date 23 June, 2015), the first of a constellation of two satellites designed for land monitoring. The mission provides global coverage of land surface every 10 days, via the multispectral imager, offering resolutions of optical imagery ranging from 10 to 60 m. Data will be made publicly available at no charge in addition to image processing software which can apply othorectification and atmospheric correction.

Method

A Sentinel-2a image captured on 30 Dec 2015 (NZST) was downloaded using a python script and the Sentinel API from: https://scihub.copernicus.eu/dhus/#/home
Image processing used SNAP 2.02 installed on a Linux (Ubuntu 64 bit) machine with 16 gb memory and quad core intel processor. Images were orthorectified and atmospherically corrected using Sentinel 2 Level 2A Atmospheric Correction Processor (Sen2Cor) version 2.0. After correction, images were subset to the interest areas using SNAP, and exported to geotiff. Object oriented classification was completed using a demonstration version of eCognition.

The eCognition image processing first creates a true colour image for visualisation and area of interest selection, and creates NDVI (Normalised Difference Vegetation Index), NDSI (Normalized Soil Index), NDWI (Normalized Water Index), which are used in image segmentation and classification. The image then undergoes image segmentation. The user identifies land cover classes of interest and selects multiple training image segments (6 – 8).

The demonstration did not allow the exportation of results or saving projects, therefore any results are presented as screen captured images. Supervised classification procedures using SAM were applied in ENVI/IDL.

Results

The atmospherically corrected surface reflection produced using Sen2Cor produced high contrast detailed imagery at 10 m resolution (Fig 4a). An initial image segmentation was classified using SVM, based on training object classes (Fig 4b-4c, 5b-5c). Preliminary results suggest both bog and swamp are readily differentiated from other vegetation classes during the classification. There appears to be misclassification of tree dominated wetland classes, potentially due to the same species being present in these areas as other areas of non-wetland woody vegetation such as Manuka and/or Kanuka. This misclassification may be addressed using more ancillary data within classification, in addition to further rule based classifications.

The atmospherically corrected surface reflection was also classified using SAM near the Kopuatai Peat Dome (Fig. 6a-b). A supervised SAM based classification was trained using wetland sites within the scene. Many wetlands within the scene were correctly classified with SAM, however there appears to be more misclassification of forested areas as wetland, and also some pastoral areas as wetland. Small streams and drains were also often misclassified as wetlands. This method will also benefit with more contextual GIS information such as Lidar and DEM data, however initial results are promising.

In conclusion from the results of initial classification, the most challenging wetland areas to classify will be forested/emergent wetlands, due to the spectral similarity to native forest and other tree-based land covers. The use of the image segmentation based classification appears to have a clear advantage over traditional pixel based classification. However misclassification still occurs, and ancillary geospatial information will be required to improve classification accuracy (see following proposed method).

Figure 4a. A true colour composite of Sentinel bands two, three and four, showing lakes and wetlands in the North Waikato.

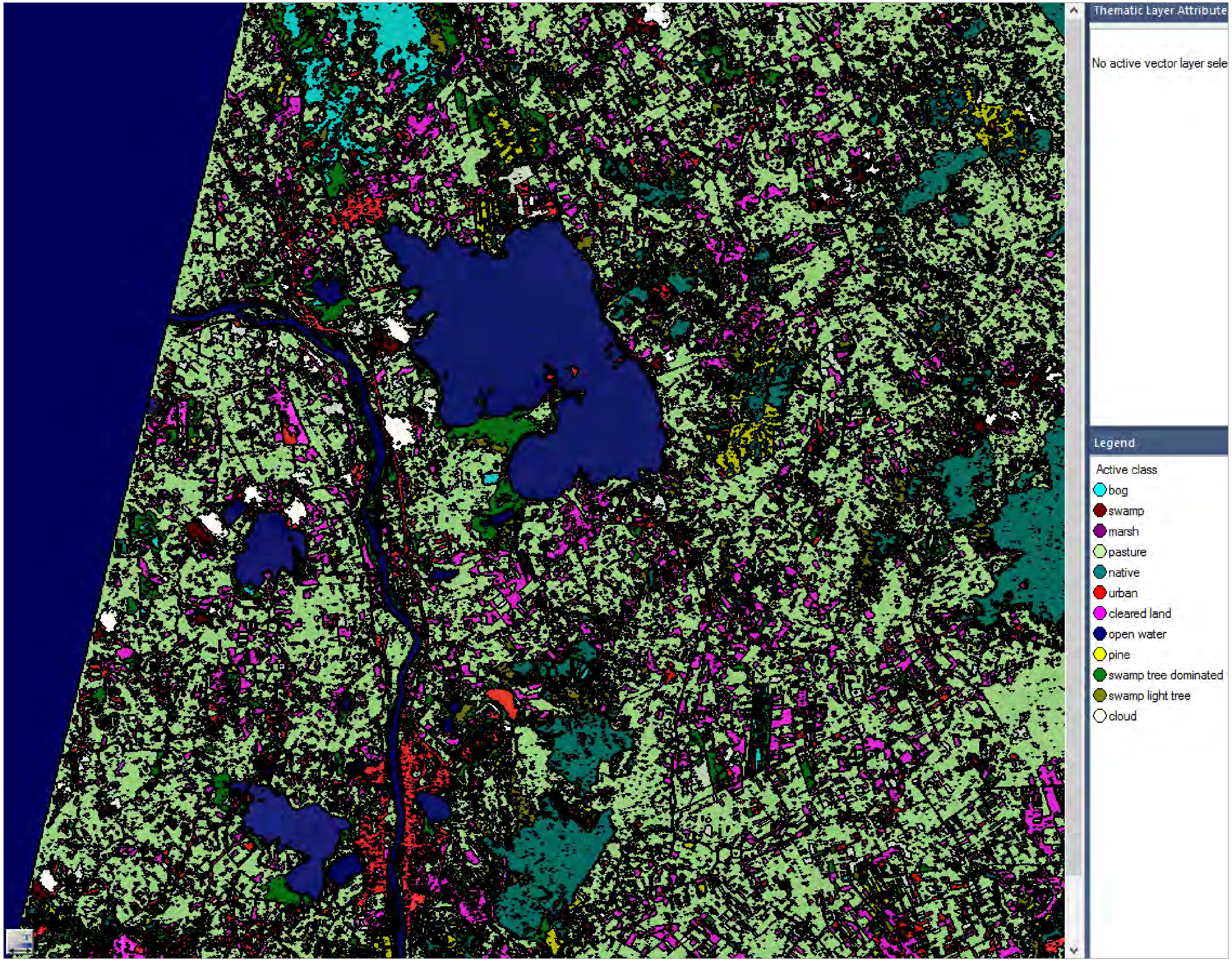


Figure 4b. The results of object oriented classification of the North Waikato, overlaid with polygon boundaries.

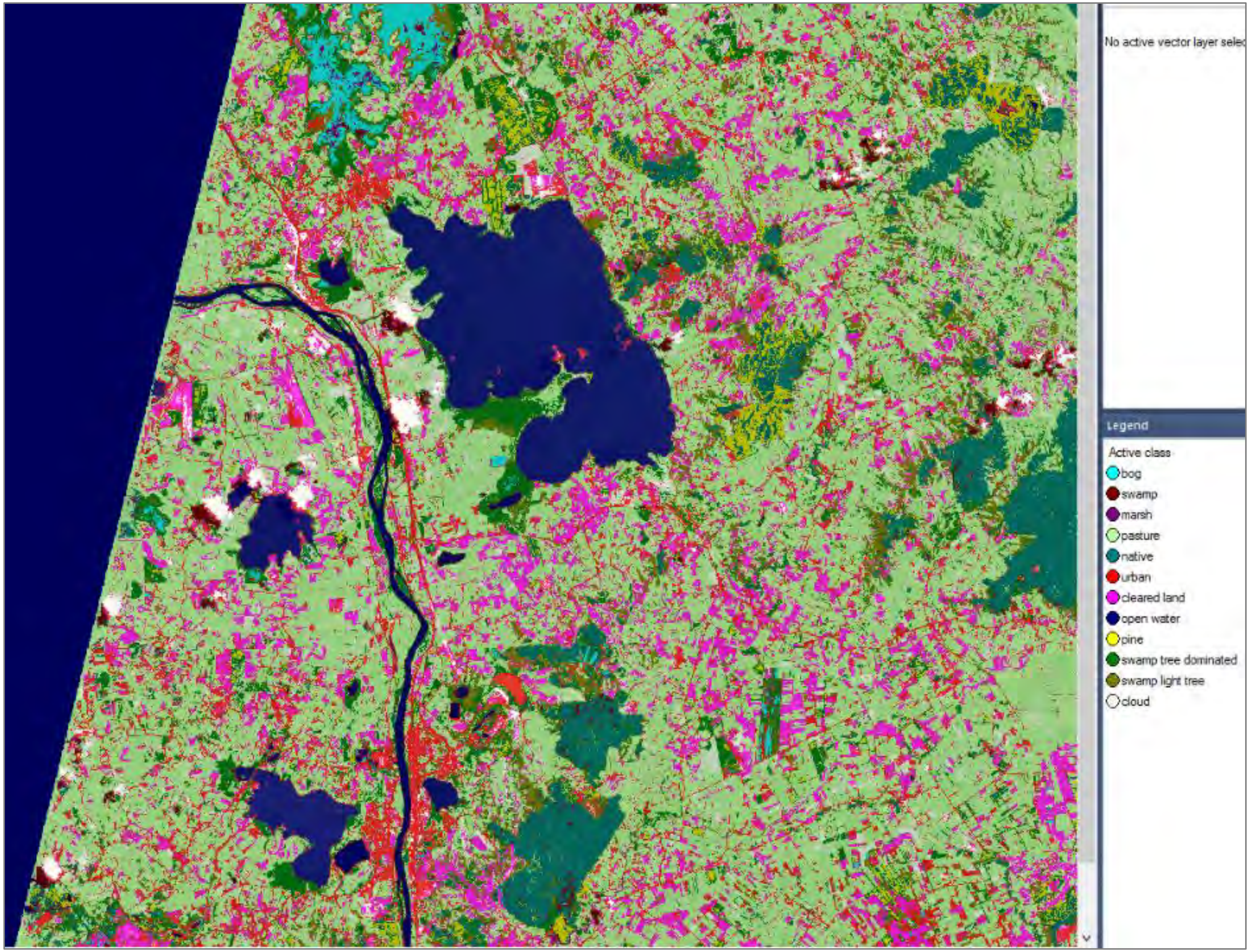


Figure 4c. The results of object oriented classification of the North Waikato, without polygons

Figure 5a. A true colour composite of Sentinel bands two, three and four, showing lakes and wetlands in the Huntly area.

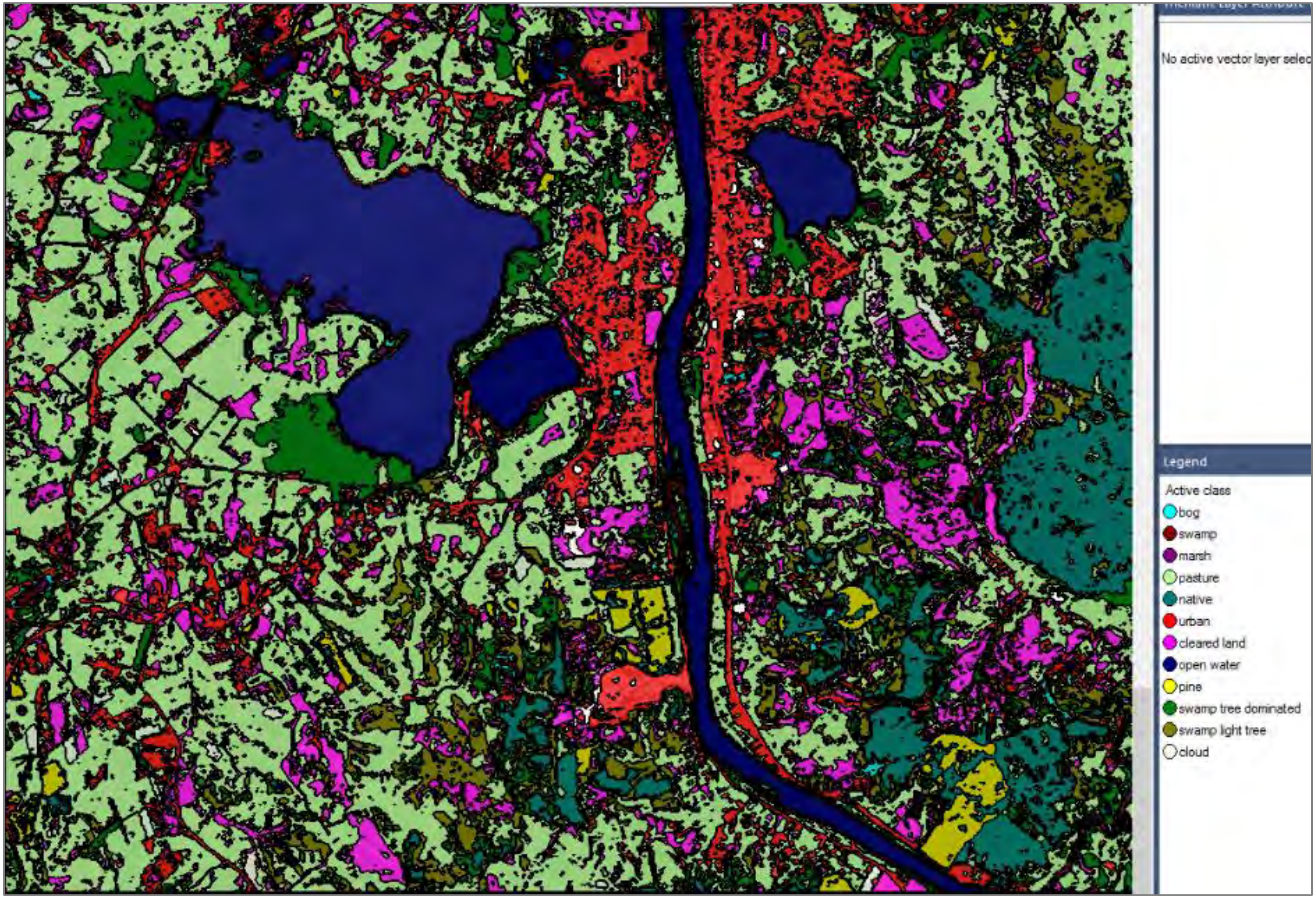


Figure 5b. The results of object oriented classification of the Huntly area, overlaid with polygon boundaries

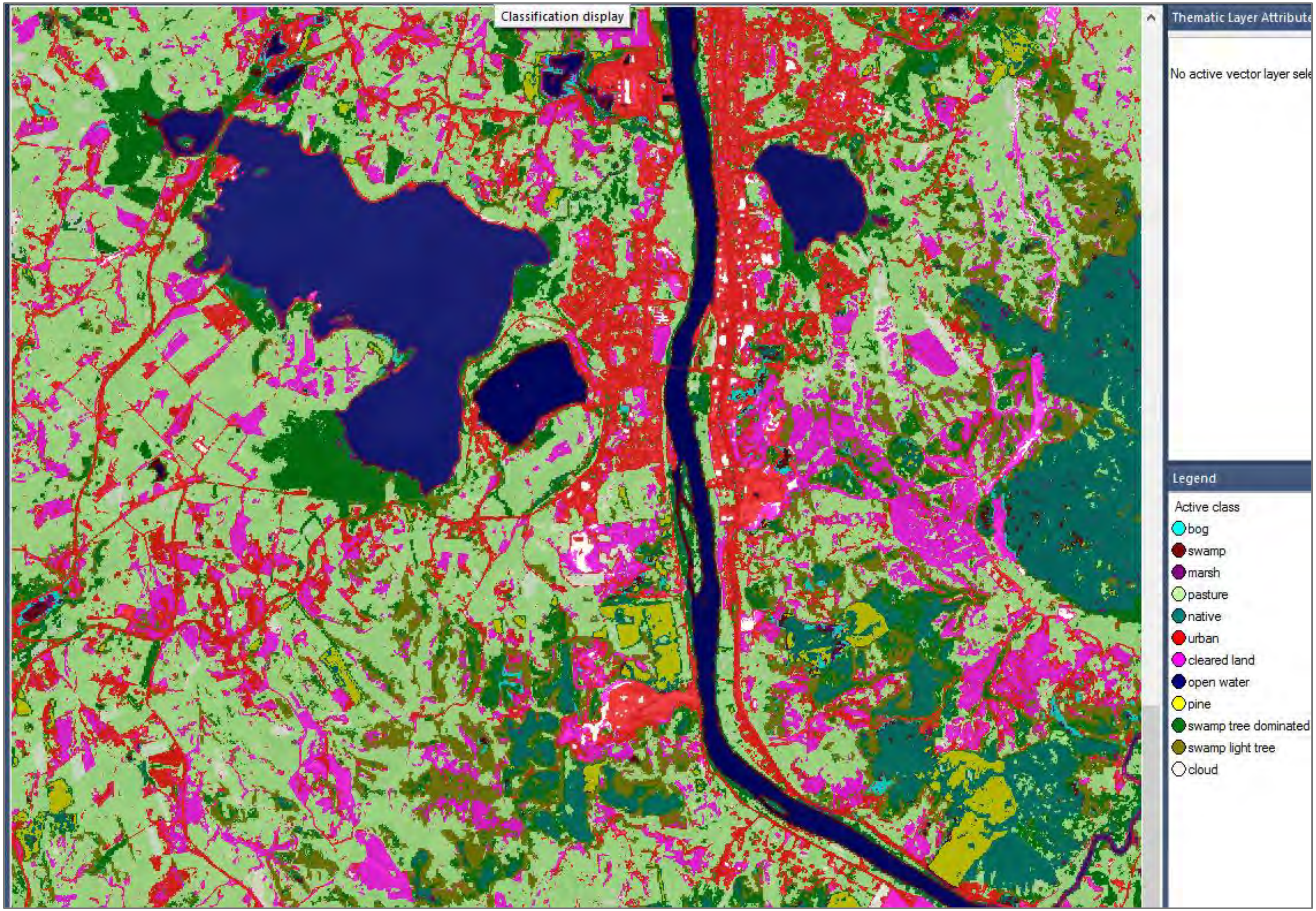


Figure 5c. The results of object oriented classification of the Huntly area, without polygon boundaries.

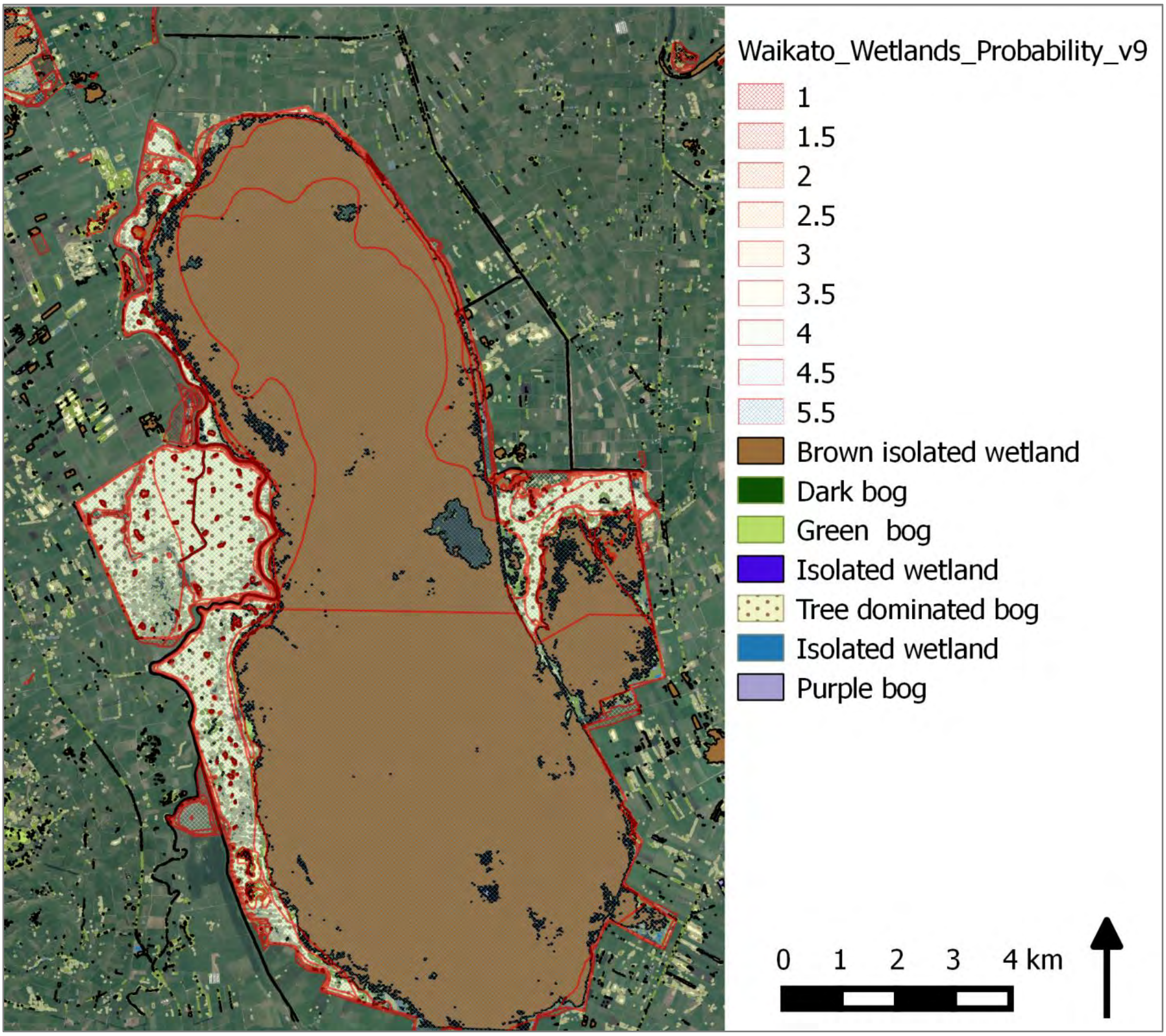


Figure 6a. Wetland classification around the Kopuatai Peat Dome using Sentinel-2a surface reflectance and supervised classification using Spectral Angle Mapping. Waikato Wetlands Probability layer is displayed with a red outline, and cross hatching colour ramp representing probability score. WRAPS aerial imagery is displayed in the background.

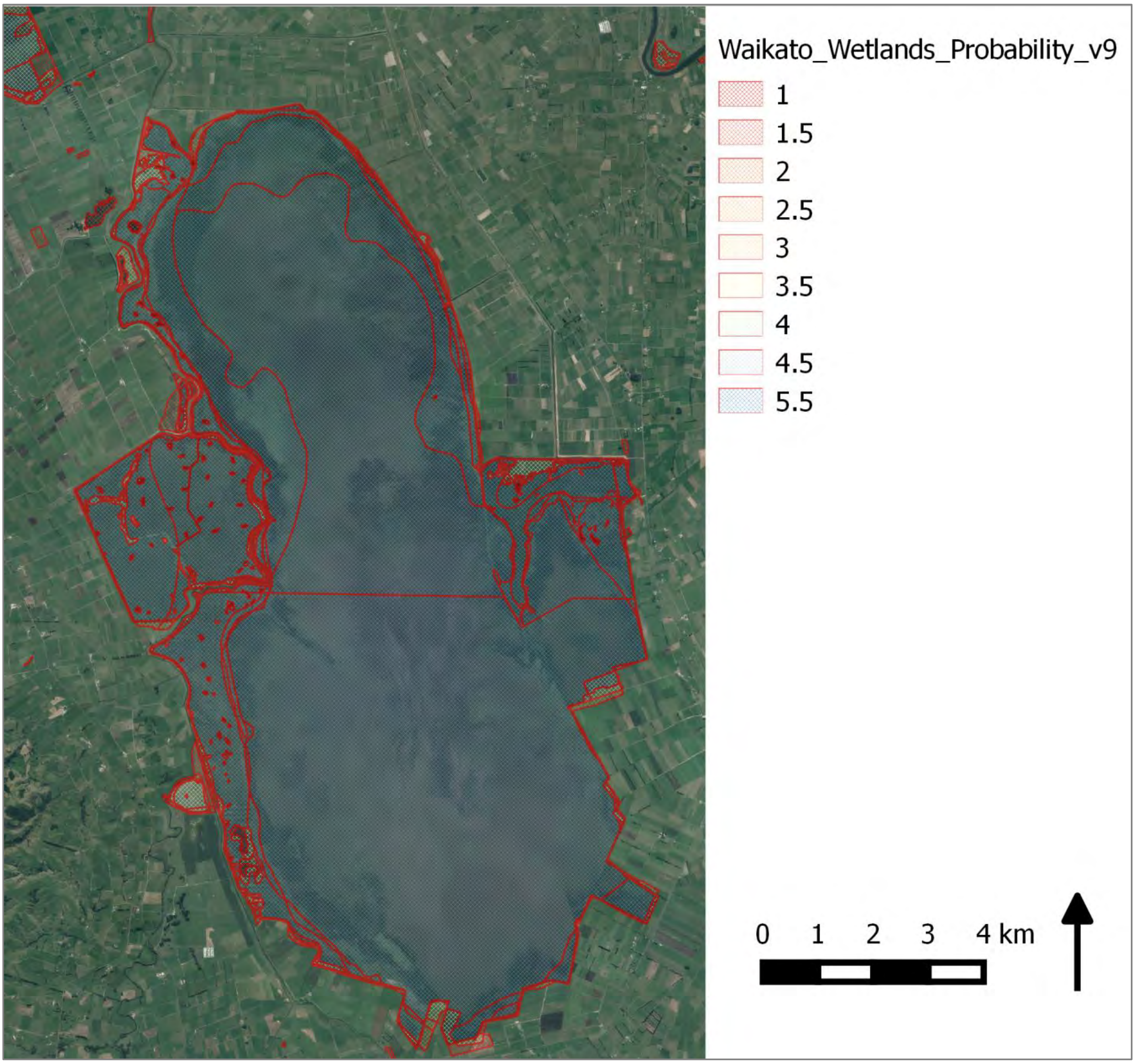


Figure 6b. WRAPS aerial photography of Kopuatai Peat Dome. Waikato Wetlands Probability layer is displayed with a red outline, and cross hatching colour ramp representing probability score.

Recommended method

Due to the complexities of the remote sensing of wetlands, simple pixel based methods are not appropriate for classification of New Zealand wetlands. A more complex method using ancillary data is required to reduce classification errors (e.g., Ausseil et al., 2008; Ausseil et al., 2011). Figure 5 presents a potential method to identify previously unclassified New Zealand wetlands using a combination of state-of-the-art methods identified in the previous literature review. This combines previously generated datasets of New Zealand wetlands and previously developed New Zealand wetland identification methods with image segmentation methods. The suggested method is comprehensive and would require considerable human resources to undertake at the regional scale, but smaller subsets of this method could be applied more readily on a case-by-case basis. For example image segmentation and classification could be developed solely using Sentinel2a satellite imagery. Depending on the accuracy of results, previously unidentified wetland polygons could be added to the current 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.

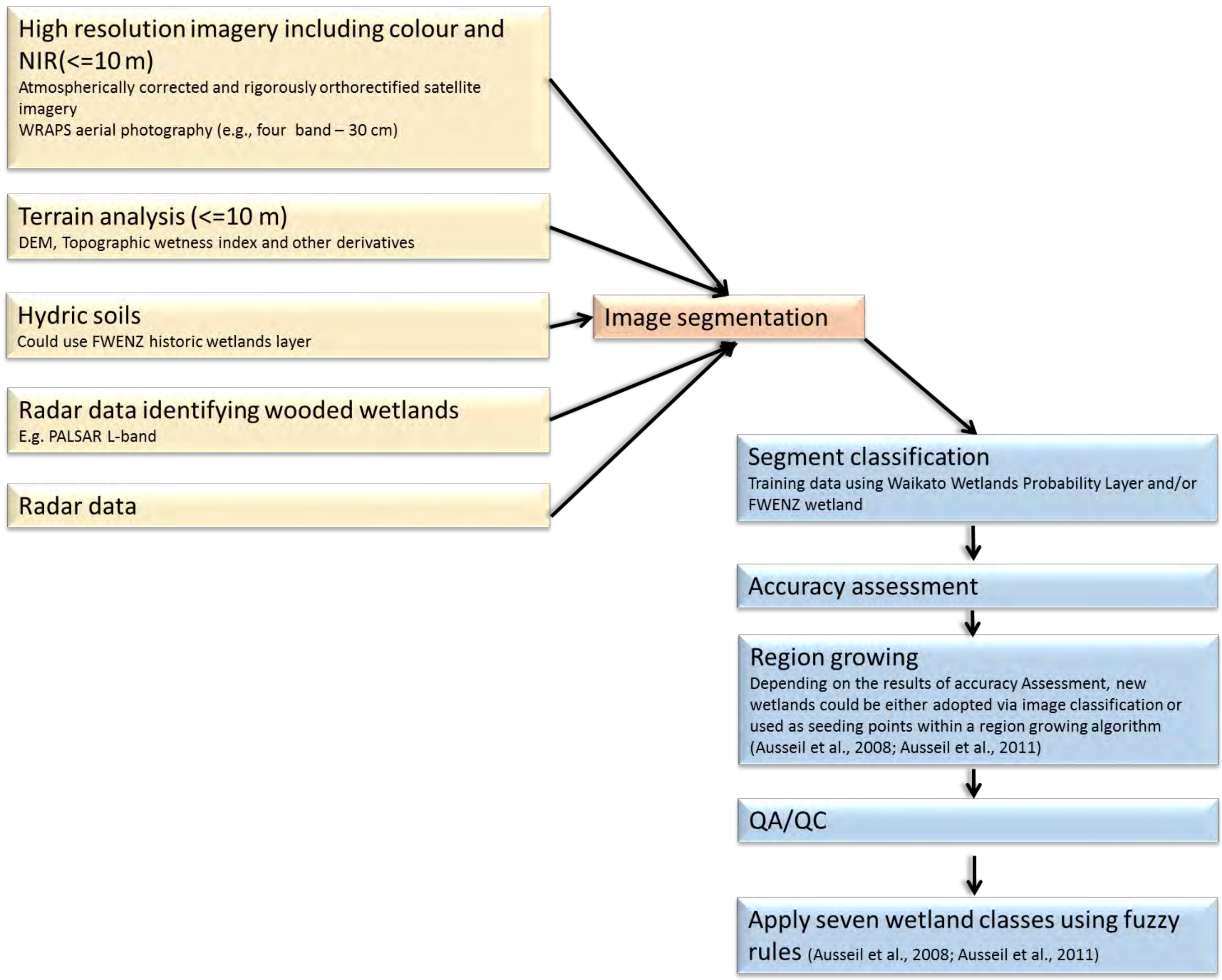


Figure 7. Outline of the proposed method for the identification of previously unclassified wetlands using GIS and remote sensing data. The method is adapted from Scarbrough et al., (2013).

Key finding/recommendations

- For the identification of small wetlands a minimum image and DEM resolution of 10 m is recommended;
- Image segmentation presents the potential to significantly increase the accuracy of remote sensing of wetlands, when compared to typical pixel based classification algorithms;
- The inclusion of ancillary data (e.g., DEM, LIDAR, GIS soil/ geologic databases, wetland location vector data), also offers significant accuracy improvements;
- Object based image classification has the potential to combine spatial data from multiple sources; and

- SAR Sentinel 1, PULSAR or lidar may be critical to enable differentiation of wooded wetlands from other forest land covers.

While the suggested method outlined in Fig. 7 would be a comprehensive method, considerable time and effort would be needed to achieve this. We recommend the initial studies focus on a combination of remotely sensed elevation data (Lidar/Radar) and pixel based spectral information. The literature review suggests that Image segmentation and classification of these two data sources would lead to significant increases in wetland classification accuracy.

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