CREATING A RAPID IDENTIFICATION TOOLKIT FOR RURAL PONDS

LUCY SMITH

A thesis submitted to The University of Gloucestershire in accordance with the requirements of the degree of Masters by Research in the School of Natural and Social Sciences. In collaboration with the Wildfowl and Wetlands Trust.

January 2023

Word Count: 18,558

I declare that the work in this thesis was carried out in accordance with the regulations of the University of Gloucestershire and is original except where indicated by specific reference in the text. No part of the thesis has been submitted as part of any other academic award. The thesis has not been presented to any other education institution in the United Kingdom or overseas.

Any views expressed in the thesis are those of the author and in no way represent those of the University.

Signed: [redacted] Date: 13/01/2023

DOI: 10.46289/7NH3YT56

Acknowledgements:

Dr Lucy Clarke and Dr Hannah Robson; for support and advice throughout.

Sarah Davies; for helping to collect field survey data

Abstract:

It is well known that rural ponds are a key biological resource especially in rural landscapes, providing biologically diverse hotspots and delivering ecosystem services such as flood water storage, water quality improvement and food resource. Over the last century pond numbers have decreased significantly and, although numbers appear to be increasing more recently, the lack of rural ponds is cause for concern. Due to their high contribution to regional biodiversity ponds should be included in aquatic conservation at a landscape scale. However, mapping of pond location at a country scale, i.e. the whole of Great Britain, is inconsistent and numbers can often be unreliable due to the use of estimates and scaling from small spatial areas which have been surveyed. This variability in pond mapping methods is often due to the time-consuming nature of accurately mapping ponds; this can impact the direction of conservation efforts as without the base knowledge of gaps in pond networks key conservation areas cannot be easily identified. To attempt to decrease the time and effort spent on mapping rural ponds, a rapid technique to identify ponds using remote sensing and image classification methods is explored in this research.

A 23 km^2 study site in Somerset, England was selected for this study. Manual digitising of pond location using QGIS software and in-field ecological surveys of pond condition were undertaken to provide a dataset with which to verify the remote sensing methods. Land use data was also obtained for the study area to determine if there was any relationship between land use type and the identification of ponds by remote sensing. Images acquired from six different satellite sensors were obtained; these had varying spatial resolutions, ranging from Landsat 8 with 30m resolution to World View 3 at 1.24 m. Two classification methods were performed on all six images: (1) an automated technique using the Normalised Difference Water Index (NDWI) and, (2) supervised image classification using the Semi-automated Classification Plugin (SCP). The pond location for each method was compared to the manual pond count to give a percentage of ponds correctly identified. Pond ecological condition and how this may affect identifiability of ponds when using these methods is also explored by comparing the remote sensing outputs to the in-field ecological surveys.

The highest accuracy of the NDWI outputs was 28.3% of ponds accurately identified. The supervised classifications were consistently more accurate with the highest identifying 72.4% of all ponds in the study area. A potential relationship between ecological condition of ponds and how likely they are to be identified was found; if ponds are of poor ecological condition or worse they are less likely to be classified as ponds, although this was only tested with a small sample. Examining the influence of land use, it was found that ponds in improved grassland are more likely to be identified consistently than in any other land use type.

This project provides insight into methods for mapping ponds at landscape level scale. It has found that the highest ranked method, when considering accuracy, cost and temporal resolution, is performing supervised classification on World View 3 imagery. This method can be used to identify areas of a landscape which are lacking in rural ponds or ponds of good ecological quality, as this process should be scalable to any rural landscape which is captured via remote sensing at a spatial resolution of 1.24 m or less.

Contents

List of Tables:

List of Figures:

1: INTRODUCTION

Current national numbers of ponds in the United Kingdom (UK) have been estimated at 400,000 (Haines-Young *et al.*, 2000). In the UK pond numbers have declined throughout the 20^{th} century, most rapidly after the Second World War (Boothby, 1999). This is thought to be due to the acceleration in food production leading to the need for larger areas of agriculturally viable land (Rackham, 1986). The 1947 Agricultural Act was a large part of this increased drive to attain self-sufficiency in food production (Robinson and Sutherland, 2002). In England thousands of hectares (ha) have been altered for agricultural use; crop and fallow land has increased from 3,406 ha in 1900 to 4,201 ha in 2010 (DEFRA, 2010). Anthropogenically created ponds made for a variety of functions such as a supply of freshwater for livestock, field drainage or as a by-product from marl extraction (Gledhill and James, 2012) are commonly no longer needed for their original purpose. This along with the desire for increased crop yields has resulted in a large number of ponds to go unmanaged leading to faster terrestrialisation to areas of scrub (Sayer *et al.*, 2012; Goodrich *et al.*, 2015). As the UK has seen an increase in area cover of agricultural land it can be assumed that this change in land use has influenced the increased decline in ponds over the last century. However, since the turn of the 20^{th} century net decline of ponds has slowed (Jeffries, 2010). There have been estimates indicating positive net trends in pond numbers with the 2007 Countryside Report estimating an increase of 1.4% per annum between 1998 and 2007 (Williams *et al.*, 2007). However, the number of ponds is still significantly lower than the previous century, with estimates of pond loss between 1850 to 2000 ranging up to 90% (summarised by Wood, Greenwood and Agnew, 2003).

Ponds are key habitats for British wildlife, supporting around two thirds of all wetland plants and animals found in in the UK, many of which are constrained to ponds or rely on them at key points of the life cycle (Williams *et al.*, 1997). These species which ponds support in turn can support larger species such as farmland birds (Lewis-Phillips *et al.*, 2020). Ponds are therefore species rich habitats which are important in homogenous farmland landscapes as they add local habitat spots, reducing isolation, providing refuge and increasing ecosystem services (Tscharntke *et al.*, 2005). In addition to supporting UK wildlife, ponds also support humans; ponds can retain drainage water and may have a part to play in flood prevention as many have an inflow but no direct outflow (Williams et al., 2007) and therefore act as a water store during high flow events. Indeed, the primary function of some man-made ponds is for flood alleviation (Oertli, Régis, Ae, Hull, Miracle, B Oertli, *et al.*, 2009; Hill *et al.*, 2016). Furthermore ponds can provide carbon storage (Downing *et al.*, 2008) and are used both recreationally and aesthetically (Boothby, Hull and Jefferys, 1995). These key services that ponds provide clearly show their value and that concern about their widespread decline is valid.

1.1 Pond loss and mapping

Despite the recent increase in numbers, ponds across Great Britain (GB) have declined significantly over the past century with some reporting that the amount of ponds in GB were recently at an all-time low (Biggs *et al.*, 2005). Many reasons underlie these declines in freshwater ponds, including climate change, agricultural pollution leading to degradation of ponds, and changes of function that have meant many have been infilled (Céréghino et al., 2007; Jeffries, 2005; Oertli et al., 2005; Williams et al., 2007). It is not only the number of ponds that needs to be considered, the distance between ponds is an important variable for many species; it has been found that species abundance of plants (Bosiacka and Pieńkowski, 2012), amphibians (Jeliazkov *et al.*, 2013), invertebrates (Delettre and Morvan, 2000) and even waterbirds (Sebastián-González, Sánchez-Zapata and Botella, 2009) are dependent upon distance between waterbodies. Therefore pond maps at a catchment level will allow for quick analysis of pond location in relation to other ponds. It could also help when ensuring that within a pondscape there is variation of different stages of succession, a significant influencer of biodiversity in a pond network is the heterogeneity of pond characteristics (Sayer *et al.*, 2013). A key way to ensure this is through managing ponds in the network at varying times rather than all at once. If mapping of ponds is done at a landscape level it will provide evidence for the best locations of pond management quickly for practitioners and can ensure that management is spread over the network to create a mosaic of pond types.

Due to the loss of such an important habitat the conservation of these features is becoming more pressing. Understanding the cover and ecological condition of current day ponds is key to implementation of conservation efforts. The most accurate estimates of pond numbers are at a local (reserve, city, county) level because researchers are able to survey these smaller areas more intensely. However, the restoration and creation of pond networks across the rural landscape is hindered by insufficient mapping of their locations and a lack of data concerning their condition. Knowledge of ponds on a wider scale is just as important as at a local level. Ponds can act as stepping stones through the landscape for species so should not be looked at in isolation but as part of a broader landscape (Oertli, *et al.*, 2009). In addition to this, threats to ponds operate over wide spatial and temporal scales (Jeffries, 2005), therefore knowledge of pond numbers over a wider spatial scale will allow for clearer correlations to be drawn and larger patterns to be observed. Quantifying and mapping of features at a landscape level is crucial in in nature conservation, especially when periodically mapped as this furthers the understanding of the response of the ecosystem features to change (Ayanu, Nauss and Wegmann, 2012). Mapping a larger area would encompass of a higher diversity of pond types allowing for the identification of different pond types (Fehlinger *et al.*, 2022) giving a more robust dataset. Therefore a standardised way of locating and quantifying ponds would result in a better understanding of these key habitats at landscape levels.

1.2 Aim and objectives

The overall aim of this research project is to construct and evaluate a system for the rapid identification of rural ponds. Rural ponds are key features of the landscape in which they sit, especially in homogenous agricultural landscapes providing many services to UK wildlife making them ecologically important The lack of data on pond location reduces the accuracy of national estimates and is a hindrance to the landscape-level conservation efforts of ponds. Knowing locations and conditions of ponds is key to conservation activities as to conserve we must first know what is there, and indeed the condition these rich resources are in.

To achieve this aim four objectives will be met:

(1) To identify the current approaches and resources that could be used to locate and assess ponds/small waterbodies;

(2) To determine the location, density, decline and ecological condition of ponds in the study area;

(3) To compare the accuracy of remote sensing classification methods for pond detection for different spatial resolutions of satellite imagery; and,

(4) To evaluate the factors which reduce the identifiability of ponds during classification of remote sensing imagery.

2: LITERATURE REVIEW

2.1 Rural ponds and their importance

Most commonly ponds are defined by their size. A definition coined in the 1990s that is now widely accepted will form the basis of the one used in this research: a body of water with a surface area between 1 m^2 and 20,000 m^2 (i.e. 2 ha) in area, including both manmade and natural water bodies (Pond Action, 1995; Boothby, 1999; Biggs et al., 2005). There have since been other pond based studies which use larger surface area sizes such as 5 ha (Novikmec *et al.*, 2016; Chopyk *et al.*, 2018; Richardson *et al.*, 2022), even as large as 100 ha (Choffel *et al.*, 2016). However the definition which has a maximum of 2 ha in area is now most commonly used (Richardson *et al.*, 2022) including in many important documents such as the countryside survey (Williams *et al.*, 2010). Using a size definition for ponds makes a clear distinction between lakes and ponds due to small lakes sharing many ecological characteristics meaning that the transition zone between the two habitat types can often be blurred (Søndergaard, Jeppesen, and Jensen, 2005). In GB 97% of standing water bodies are less than 2 ha in area (Bailey-Watts *et al.*, 2000), this suggests that ponds (according to the definition used in this project) make up a large majority of the water bodies in the UK; making them key components of wider landscapes despite their small size.

As a habitat ponds are of major importance to British wildlife, at regional levels they are found to support more macrophytes and macroinvertebrate species than other fresh waterbodies (Williams *et al.*, 2003; Davies *et al.*, 2008). Also often outperforming lakes and rivers in numbers of nationally scarce and IUCN listed species (Wright *et al.*, 1996), further evidencing their significance in the landscape. Additionally ponds play an important part in supporting biodiversity in environments which are less favourable for most species such as urban, fragmented and intensively agricultural areas (Hill *et al.*, 2017; Fehlinger *et al.*, 2022). This high contribution to regional biodiversity is largely due to their high β diversity (compositional differentiation among sites) (Oertli *et al.*, 2002; Williams *et al.*, 2003). This diversity is related to their high variety in characteristics, chance effects associated with their isolated nature and second order effects (De Meester *et al.*, 2005). Farmland ponds have been found to support diverse plant-pollinator networks, increasing network complexity especially when ponds are managed to maintain open-canopy conditions (Walton *et al.,* 2021). Ponds are also thought to have an important link to terrestrial food webs by providing dietary subsidies; aquatic insect taxa emerge from ponds which may be integrated into terrestrial food webs surrounding ponds (Fehlinger *et al.*, 2022). These aquatic to terrestrial linkages via emergent insects from lakes and streams have already been found to provide key fuel to terrestrial predators (Gratton, Donaldson and Zanden, 2008; Gratton and Vander Zanden, 2009; Sullivan and Manning, 2019). Ponds, especially in farmland landscapes, are clearly important at regional and landscape levels.

Ponds also provide services for humans, playing a part in flood prevention due to their ability to hold excess drainage water. During the 2007 Countryside Pond Survey a third of the ponds which were directly linked to the stream network (63% of all ponds surveyed) had no direct outflow, increasing their potential to retain and hold drainage water (Williams *et al.*, 2007). Flood prevention can be a man-made pond's primary function, for example offline ponds are sometimes created purely for the interception and storage of water. These retention ponds are often implemented in farmland due to excess runoff flooding downstream. It has also been found that shallow inland wetlands such as ponds can improve water quality significantly due to holding water long enough for phosphates within soil particles to settle (Zedler and Kercher, 2005). Wetland habitats such as ponds can have a positive impact in mitigating the levels of nitrates and phosphates in agricultural runoff due to their ability to remove sediments, nutrients, and other contaminants from water which lead to their application in wastewater treatment (Kadlec and Wallace, 2008).

Carbon burial in ponds is another service they provide. Taylor *et al.* (2019) derived organic carbon burial rates for nine mature ponds (18-20 years old) and three new ponds (3 years old). Organic carbon percentages were calculated from sediment core samples from each pond then converted into an adjusted (by removing rates of first three years after creation) organic carbon burial rate. The average burial rate was 142 ± 19 g OC m^{-2} yr^{-1} (Taylor *et al.*, 2019). This rate is similar to those reported for other terrestrial and aquatic habitats, for example mangroves have an estimated burial rate of 174 g C m^{-2} yr^{-1} (Alongi, 2012).

Additionally, an area of increasing study is the association between water and improvement in health and wellbeing. The World Health Organisation recognises that mental health condition improvement is a global priority as it is among the main contributors to disabilities worldwide (World Health Organization, 2019). There are links between interacting with 'blue space' (water sources such as lakes, rivers and ponds) and improvement in mental health due to the relaxation, improved social interaction, enhanced physical activity and relief from stress (Hart, 2019). After reviewing literature, mostly comprising of experimental studies and cross-sectional studies, on the topic Zedler and Kercher (2005) concluded that blue space has multiple positive influences on human health and wellbeing including emotional, restorative and recreational benefits. A study piloting a six-week nature-based health intervention at the Slimbridge Wildfowl and Wetland Trust wetland centre, UK in 2019 investigated the benefits a range of nature-based activities near water by 16 participants (Maund *et al.*, 2019). Through questionnaires, focus groups and interviews it was demonstrated that after the intervention there was an improvement in mental wellbeing, anxiety, stress and emotional wellbeing in the participants (Maund *et al.*, 2019). Although more qualitative and multi-faceted, interdisciplinary studies are needed in this research area it is clear that blue spaces including ponds are of great benefit to humans. This evidence shows that rural ponds are important features as all these ecosystem services provided by ponds are crucial in rural landscapes.

2.2 The importance of pond identification

Identification of pond location across broad areas could aid landscape conservation in many ways. Documentation of pond locations could influence identification of biodiversity priority areas, as selection of these areas should include all biodiversity features, including environmental ones (Margules, Pressey and Williams, 2002; Bonn and Gaston, 2005). Pond numbers therefore should be included in such datasets, meaning accurate pond identification is vital. Unfortunately, it was found that selection criterion for protected areas, including information about habitats which are important as refuge/migration routes and food sources (such as ponds), were used less frequently than species only criterion (i.e. species richness/ rarity/ endemism) (Eken, Bennun and Boyd, 2004). However, this was in 2004 and between then and 2018 there were 141 papers focused on ponds published, increasing the evidence for pond value and numbers so these findings may now be outdated (Bolpagni *et al.*, 2019). These papers are adding to the knowledge base on ponds and therefore are slowly reversing the failure of their inclusion in policy. For example, temporary and freshwater ponds are now included in classification of freshwater habitats by the Intergovernmental Science Policy Platform on Biodiversity and Ecosystem Services (IPBES, 2018). There are also now mechanisms for maintaining and protecting ponds in the UK from the Environmental Land Management Schemes (ELMS). Within ELMS is the new Local Nature Recovery scheme (which will be rolled out by 2024), this scheme includes payments for the maintenance, restoration and creation of ponds (DEFRA, 2021). Such schemes can help to ensure the protection of pond networks within the landscape. Ecological features such as ponds should be included in baseline evidence used to influence conservation guidelines, especially at a landscape level.

Accurate baseline data of pond location also needs to be established to provide a reference frame against which to judge efficacy of conservation activities (Bull *et al.*, 2014), as well as to provide baseline data of pond location and numbers to allow for future loses and gains to be recorded with more accuracy. This is important because ponds are a great biological resource

(Williams *et al.*, 2003; De Meester *et al.*, 2005) and therefore the loss of such valuable resources will affect regional biodiversity. Monitoring of environmental resources, such as ponds, can lead to determining patterns in response to wider effects such as climate change and land usage which have been shown to impact small water bodies (Boothby, Hull and Jefferys, 1995; Curado, Hartel and Arntzen, 2011). A better understanding of pond ecosystems will reduce knowledge gaps and benefit wildlife and society by increasing effectiveness of research-led conservation and management of pondscapes (Hill *et al.*, 2021). Therefore ponds should be included when constructing plans which aim to conserve aquatic biodiversity at a landscape scale, but these plans must be based on knowledge of factors such pond density and community structure (Céréghino *et al.*, 2007) and other dynamics which could influence this.

2.3 Methods used to calculate pond numbers

Calculations of national estimates often use different approaches than local estimates to identify pond locations and numbers. Due to the smaller size of local estimates more labour- intensive methods can be used which, therefore, often increase the accuracy of local estimates in comparison to national. Accurate in-field surveys can be employed to cover the whole area when a study area is small, this would likely not be done at a large scale as in-field surveys are time intensive. This is because these typically include a surveyor walking across multiple fields recording if a pond is present or not, and carrying out ecological surveys on those ponds which are present in their area.

A common method of local pond identification is to use Geographic Information Systems (GIS) to identify ponds on maps such as Ordnance Survey (OS) maps or satellite imagery of the area under investigation. Thornhill *et al.*, (2017) used ArcGIS software to manually identify ponds on 1:25,000 scale historic maps from the EDINA Digimap Service covering 268 km^2 of the Birmingham area. The use of these maps at this scale gave an estimation of the number of historic ponds in the area but it would likely have under-estimated much smaller isolated and temporary pond as this mapping scale enabled landscape features which had a surface area of 16 m^2 to be identified. Although some smaller features may have been mapped this identification size limit reduces the accuracy of pond identification overall as smaller ponds will have been missed. Smith *et al.*, (in Press) mapped historical and present day ponds at a catchment scale (14,867 km^2) to obtain the number of ponds lost since ca. 1900 to 2019 in the Severn Vale region of the UK. This was again done using OS maps in QGIS software to manually identify all ponds on both sets of maps. A smaller minimum pond size than that of Thornhill *et al*., (2017) was used, with ponds at a minimum of $1m^2$ identified which ensured the successful location of all ponds present on the two maps. Alderton (2017) also used OS map tiles (at a scale of 1:10,560) to locate ponds but went one step further by ground truthing this data by walking over these areas and marking ponds found on the OS maps. Ten 1 km^2 grids were chosen in an area with landowners known to the authors, which was considered to be representative of the wider Norfolk area in terms of land use and had a broad range of pond types. This representability is admirable but only ten one kilometre areas were surveyed on the ground, covering 0.19% of their total area surveyed using GIS. From these ground surveys they found 14 ponds which were not mapped on the OS map, mainly in woodland dominated grids. Therefore, suggesting that studies of pond numbers mapped using OS maps may underestimate the number of ponds, although ground truthing could be used to help determine this underestimation to allow adjusting of such numbers potentially increasing their accuracy.

Another way pond numbers are estimated is to use already existing databases created by surveying bodies. Clauzel, Bannwarth and Foltete (2015) used multiple land cover databases such as the agricultural census to identify forests, grasslands, croplands, built-up areas, transportation infrastructures, rivers, wetlands, and ponds. These data were used to locate already existing habitats (ponds and wetlands) and areas which could be restored to increase suitable habitat area. This method has benefits in that the data has already been collected, decreasing the time and effort required. However it may not be as accurate as if it was collected from other sources as some features may be missed or only collected once therefore meaning some features that change over time, such as temporal ponds, being missed from the data set.

Estimates for areas larger than a county are often extrapolated from smaller surveys, for example the Countryside Survey Ponds Report (Williams *et al.*, 2007) used in-field pond counts in 591 one kilometre squares across GB, these squares were also surveyed in previous iterations of this report. These data were then extrapolated to form a national estimate by assigning each kilometre square to a land class, with the mean number of ponds per square for each land class calculated and then multiplied by the area covered in GB by each respective land class. Estimates of ponds per land class added together then gave a national estimate. This method is based largely on in-field counts rather than relying on counts using maps which may have missed smaller or over vegetated ponds, giving these initial counts high accuracy. However, this involved a large amount of time and effort, a common downside of in-field surveys. The survey involved 64 surveyors over a total of ten weeks taken to review all squares (Maskell *et al.*, 2008). These squares only represent roughly 0.2% of the area of GB, raising doubts on how representative the sample is of the British countryside. Clearly although this method is accurate due to minimising the risk of missing overgrown ponds hard to see from images or smaller ponds easily missed on maps it often restricts projects to smaller scales due to time and budget constraints. In addition, the end result is still an estimation based on a small portion of the total area of GB and therefore a small fraction of the number of ponds nationally.

Haines-Young *et al.* (2000) estimated that standing waters cover an estimated 190,000 ha of land; this was estimated from the data gathered by the Countryside Survey 2000, which used similar method of surveying a random sample of one kilometre squares across GB to the Countryside Survey Ponds Report of 2007. In total 568 squares were surveyed for land use types, vegetation and water (Barr *et al.*, 2003). Although this area of 190,000 ha also includes lakes, ponds will make up a larger proportion of this as it has been estimated that ponds outnumber larger waterbodies 100 to 1 (Oertli *et al.*, 2005), calling into question the robustness of the estimate by Williams *et al.* (2007). Similarly Biggs *et al.* (2005) estimated national numbers of ponds in different years by adjusting multiple estimates of historic pond numbers for England, Wales and Scotland and compared these to current day estimates to derive data that estimated the loss of ponds right across GB. For example, to generate an estimate for the number of ponds nationally in 2000 the estimate from the Countryside Survey Pond Report published the same year was taken, a correction was made to this number by multiplying by the estimated proportion of water bodies up to 2 ha in area. This correction was due to the Countryside Survey Pond Report not including a breakdown of water-body sizes in their report, therefore giving Biggs *et al.* (2005) an estimate which fit the size parameters used to define a pond in the study. Such estimations which are based on multiple other estimations can give a good indication of the overall national picture but when the original estimations are flawed in accuracy (as discussed above) these national numbers cannot be considered to be highly accurate.

Studies have also suggested that pond numbers are not standard across a country, and that localised estimates range broadly from county to county. In the UK the predominantly urban county of Birmingham had a low pond density of 1.3 ponds per km^2 (Thornhill *et al.*, 2017), whereas more rural Cheshire had a pond density of 3.25 km^{-2} (Boothby and Hull, 1997), and heavily rural Norfolk had a high pond density of 4.2 km^{-2} (Alderton, 2017). Suggesting that at a localised landscape the levels of historic ponds and pond loss are likely to be more idiosyncratic (Wood, Greenwood and Agnew, 2003). This proposes that national pond estimates calculated in a way that assumes pond numbers are similar throughout counties should not be taken as the most accurate basis to derive national losses from.

It is clear that there is no standard way of identifying ponds in a landscape, therefore for this research alternative methods for identification will be explored from other disciplines. Ponds should be targeted as part of landscape level conservation especially in aquatic biodiversity (see

Section 2.2), however to achieve this successfully plans must be based on robust evidence (Céréghino *et al.*, 2007), which is difficult when trying to merge data from non-standardised processes. Therefore, in order to create this background knowledge the data collection and output must be standardised.

2.4 Remote sensing

Remote sensing is a method to identify features in a landscape, and refers to deriving information about the Earth's land and water surfaces and its features, using images attained from an overhead perspective (usually from a distance) using electromagnetic radiation (Campbell and Wynne, 2011). Information is obtained from sensors, typically satellites or aircrafts (Kairu, 1982). These sensors can be split into passive and active (Figure 2.1). Active sensors use their own source of energy to emit radiation (e.g. radar gun) in the direction of the target and measure the amount reflected back, whereas passive sensors record radiation that is reflected from an external energy source (e.g. the sun) (Navalgund, Jayaraman and Roy, 2007).

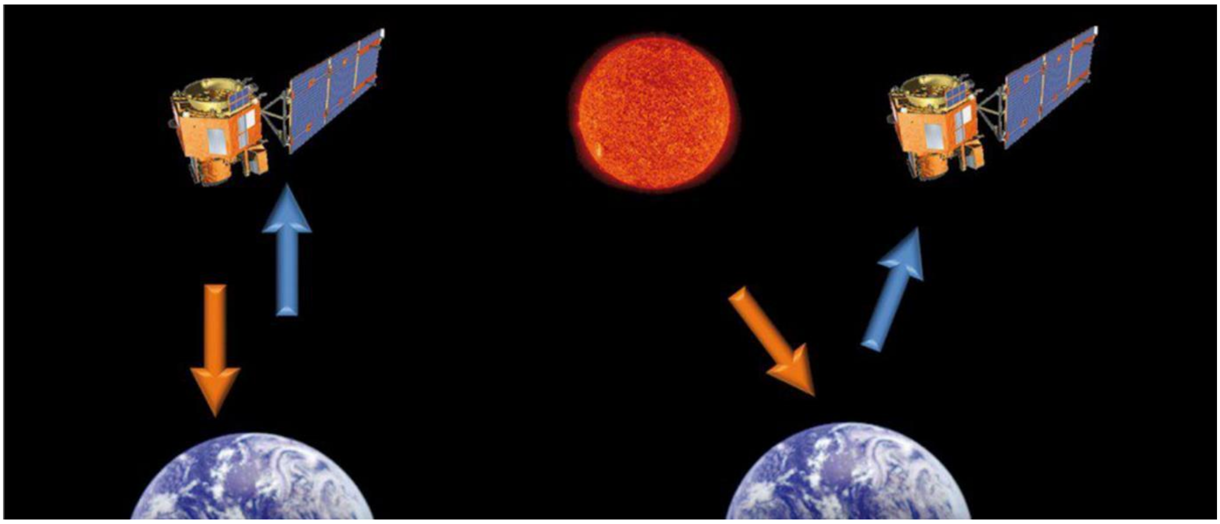

Figure 2.1 – Diagram showing the difference between active (left) and passive (right) remote sensors. Credit: Earth Imaging Journal (EIJ)

Common remotely sensed data includes, aerial photographs taken from aircrafts, satellite images, and infrared images (Kairu, 1982). A newer application of remote sensing is collecting data using Uncrewed Aerial Vehicles (UAV), commonly known as a drone. These allow the operator to collect remotely sensed imagery from an area of their choosing and the UAV can be equipped with many sensor technologies ranging from basic video cameras and thermal infrared video sensors to more complex multispectral and hyperspectral sensors (Pajares, 2020) allowing for a wide range of applications. As the technology advances UAVs have increasing potential for ecological data collection, including identification of crop types and distribution of vegetative species (Buters *et al.*, 2019), mapping sensitive marine habitats (Ventura *et al.*, 2018), surveying marine fauna (Hodgson, Peel and Kelly, 2017) and changes in vegetation dynamics (Anderson and Gaston, 2013). Imagery collected from a UAV can be up to centimetre spatial resolution allowing the user to use a spatial resolution that is appropriate for the project (Anderson and Gaston, 2013). The timing and extent of surveys are user controlled (Duffy *et al.*, 2020) which means the researcher can control the area of study and variables associated with this. However UAVs can be challenging to operate, they run on batteries, which last differing lengths of time depending on size; large sized UAVs can stay in the air for up to 2 days but these are restricted in use as they have to have full aviation clearance and are expensive, the more accessible mini UAVs normally operate for a maximum of 2 hours (Nowak, Dzіób and Bogawski, 2019), both are affected by temperature with decreasing run times as temperature drops. These differing run times can impact the ability to cover large areas in one run. Different sensor types can be attached to UAVs allowing for different applications, but sensor type usage is restricted by weight limitations of the drone (Duffy *et al.*, 2020). A common limitation of the use of UAVs is the cost of purchase and operation of them including training and certification costs, however these costs are commonly affordable for larger organisations such as universities and can be more economic long term than purchasing low resolution satellite images (Nowak, Dziób and Bogawski, 2019). Clearly use of UAVs should be considered when using remote imagery sensing to identify environmental features.

Remote sensing has many applications including identifying land use, mapping vegetation, tracking natural disasters, and can even be used to identify pollutants (Kairu, 1982; Cracknell, 2007; Ayanu, Nauss and Wegmann, 2012). This study is focused on satellite remote sensing and the remainder of the section will be based around these.

2.4.1 Resolution and sensor capabilities

When selecting satellite images there is the option of panchromatic or multispectral imagery. Panchromatic imagery combines information from the visible bands of the electromagnetic spectrum (blue green and red) into a single band, therefore the resulting image does not contain any wavelength-specific information (Lillesand *et al.,* 2015). Whereas multispectral sensors capture multiple bands each containing information from different portions of the electromagnetic spectrum; these sensors usually have between 3-10 different spectral band measurements in each pixel of the image they produce (Heywood *et al.*, 2011). Multispectral remote sensing enables analysts to differentiate objects that are hard to tell apart in the visible band, this is because a material's physical characteristics determine which types of electromagnetic waves will pass through it and which will be reflected (Zhu *et al.*, 2018). For example, green vegetation has a high reflectance in the near infrared (NIR) regions, whereas water has a low absorbance in the visible light region so these two features can be easily distinguished from each other in multispectral images. Because smaller amounts of light energy is available for multispectral bands compared to panchromatic the panchromatic sensors detect more brightness, meaning they can sample smaller areas than multispectral counterparts (Lillesand *et al.,* 2015). This translates to smaller pixels in panchromatic images, for example, Landsat single band has a resolution of 15m whereas its multispectral bands have a resolution of 30m (NASA, 2022).

An important consideration in remote sensing is the resolution of the data being acquired, both the spatial and temporal resolution should be considered. Spatial resolution is the minimum area of ground observed, known as pixels, and determines the level of detail captured by the remotely sensed image (Ayanu, Nauss and Wegmann, 2012). There are now many satellite imagery options with a variety of spatial resolution options. Launched in 1972, Landsat is a joint mission between the United States Geological Survey and the National Aeronautics and Space Administration (NASA) which provides satellite images for free. The most recent iterations of Landsat (Landsat 8 in operation since 2013 and Landsat 9 launched in 2019) have a multispectral spatial resolution of 30 m and a panchromatic resolution of 15 m (NASA, 2022). Free satellite imagery is also provided by the European Space Agency as part of their Sentinel satellite programme launched in 2014; Sentinel-2 has a spatial resolution of 20 m (ESA, 2022). To obtain a higher spatial resolution of satellite imagery there is normally a cost associated; for example, Rapid Eye satellite images have a spatial resolution of 5 m and Pléiades 1A/1B, originally designed for military purposes, offers a spatial resolution of 0.5 m, but both can only be obtained for a price (for further details see: Apollo Mapping, 2022).

Temporal resolution can affect satellite choice, this is the time it takes for a satellite to complete an orbit and revisit the same observation area (Heywood *et al.*, 2011). The more frequent an area is revisiting by a satellite the higher the temporal resolution. There are two types of satellite orbit: (1) polar orbiting satellites travel at a low orbit elevation approximately 160 to 2,000 km above Earth) and are inclined nearly 90 degrees to the equatorial plane and travel from pole to pole as Earth rotates to follow several orbital tracks around the planet; (2) satellites in geostationary orbits are in high-Earth orbit (above 35,500 km above Earth and take 24 hours to orbit the earth so the satellite appears to remain in the same part of the sky, therefore captures images of the same area of the Earth's surface (Lillesand *et al.*, 2015). This means that a satellite in polar orbit could take days to capture an image of the same site, whereas a satellite in geostationary orbit can capture the area at a higher temporal frequency, albeit at a much lower spatial resolution due to the increased orbital altitude. Due to the parameters of the orbit of a satellite (perigee, apogee and tilt) different satellites have differing temporal resolutions (Ose, Corpetti and Demagistri, 2016). Therefore, for temporal studies researchers may be restricted in satellite imagery options due to their temporal resolution not being applicable to their study time frames.

These differences in sensors gives researchers a range of options to choose from, allowing remote sensing to be applied to many study subjects, however consideration of the resolution and wavelength requirements for a project will determine which satellite sensor is appropriate.

2.4.2 Considerations in using remotely sensed data

An advantage of using remote sensing methods is that data can be collected from areas which would be inaccessible to ground surveyors, for example in dense mangroves (Lee and Yeh, 2008), in impenetrable forests (Reusing, 2000) and locating avalanche deposits (Bühler *et al.*, 2009). Data collection in these areas would otherwise be very time consuming, with higher effort and costs without the use of remote sensing. Chebud *et al.* (2012) used satellite imagery to monitor water quality in the Kissimmee River basin in South Florida to overcome high costs and site inaccessibility. They found that by using Landsat images water quality parameters could be estimated with good accuracy, concluding that this method is a cost-effective technique. In addition, data collection from satellite imagery is non-invasive so allows for monitoring of areas with less disturbance to fauna in the area. The Weddell seal has been effectively monitored using satellite imagery, along with their habitat choices in the Ross Sea, Antarctica (LaRue, *et al.*, 2019). This has helped answer questions about habitat affinity of a species which can be hard to monitor due to their use of a large area of fast ice in Antarctica.

Satellite imagery can also provide a historic record which allows retrospective change to be evaluated, allowing the construction of historical data sets for areas which were not periodically mapped. For example data from IRS 1C and CORONA images were used to analyse land-use distribution in Istanbul from 1963 to 2000 (Duran, Musaoglu and SEKER, 2006). This is a useful application in areas which were not accurately mapped over the time frame, and can help analyse and understand large temporal changes. Although remotely sensed data can often provide a valuable historic record of areas, this is not a continuous record and there can often be gaps meaning historic data may not be available for the exact location at the exact time the study requires. For example, when the historical global coverage of Landsat operations was explored, variations in coverage year to year were found, with the largest disparities found in images from Landsat 4 and 5 which predominantly covered the western hemisphere (Goward *et al.*, 20013). This results to some areas not having been mapped every year since Landsat satellite operations began.

Problems such as missing data from a specific sensor can be overcome by using data from multiple remote sensing sources, however there can be issues with this. Data obtained from different remote sensors when analysed can have different results due to variability of Earth observation input data, data resolution, classification methodologies and the period of data collection (van Beijma *et al.*, 2018). van Benjima (2018) used three different open source remote sensing datasets to estimate regional land usage changes and associated greenhouse gas emissions variability between the estimates from the different datasets were found. Therefore, when choosing remote sensing data the sensor it is derived from these variables should be considered.

Analysis of remote sensing images from passive sensors can be limited by weather conditions, as these are dependent on solar illumination (Rahman, 2013). This means that variables such as cloud cover over the area can have impacts on the images captured, therefore limiting the amount of the image that can be accurately analysed. Clouds are a major obstacle to remote sensing of areas especially in humid tropical regions that experience prolonged periods of rain (Sano *et al.*, 2007; Eberhardt *et al.*, 2016) but also globally (Whitcraft *et al.*, 2015; Wulder *et al.*, 2015). These studies are mostly based on examining the impact of cloud cover on vegetation monitoring, but the limitation of cloud cover can impact the monitoring of any features on the Earth’s surface as they can result in the ground information being weakened or even lost due to the blocking of the radiation (Richter *et al.*, 2011; Li *et al.*, 2012). Methods for removal of clouds in imagery have been explored and applied in some studies, such as Shen *et al.*, (2014) who found an effective method for the removal of thin cloud cover for large remote sensing scenes and Li *et al.*, (2019) who developed a correction method for thicker clouds that was found to be effective at recovering the original information covered by clouds and their accompanying shadows. Even though there are these methods which can reduce the effects of cloud cover the only way to get the least interference from this is to use an image with the least amount of cloud cover possible. Active sensors however are not affected by this as they use their own energy to illuminate the Earth's surface allowing data to be collected at any time of day and most weather conditions (Plank, 2014). But these active sensors usually capture data over targeted areas at request so coverage is patchy and obtaining the data can be higher cost than that captured by passive sensors (Rahman, 2013). Therefore when choosing remote sensing imagery cloud cover and the ability to reduce its effects should be taken into consideration.

Cost is a key consideration to using satellite imagery; those with a high resolution can often be out of reach for researchers with financial constraints (see section 2.4.1). However, the cost should be compared to those associated with direct observations through site visits when the study area is large in size (Edwards *et al.*, 2013) and/or widely geographically dispersed, also reducing effort needed to carry out the study, this therefore means that there is greatly reduced manpower (Sun and Yan, 2013). Costs do also decrease with resolution, and many low resolution imagery are now free to download, for example Landsat collections (dating back to 1972; 30 m spatial resolution) and Sentinel (launched 2015; 10-60 m spatial resolution), and some freely available satellite data from restricted time periods such as OrbView-3 (2003-2007; 1-4m spatial resolution) and IKONOS-2 (1999-2015; 1-4 m spatial resolution). These are valuable resources but with decreased resolution the associated analysis from this is limited, and the level of detail obscured due to spatial resolution reduces the level of detail captured in the image (Ayanu, Nauss and Wegmann, 2012) which can limit the study feature of a remote sensor in context of the size of the potential study feature. This is an important aspect to consider when looking at small features, such as ponds.

A different constraint to using remote sensing imagery is the processing power needed to open and analyse data. Higher spatial resolutions or larger study areas result in increased data size and increase in computer power to analyse these datasets. This can be a hindrance to some, and can limit the scope of research. There are solutions to this issue however, for example Google

Earth Engine (GEE) is a cloud-based remote sensing platform which provides high-performance resources for processing geospatial datasets (Gorelick, 2017). This has successfully been used in many studies, for multiple different uses; an analysis of published literature found 300 papers were published which used GEE in their research between 2011 and 2017 (Kumar and Mutanga, 2018). The use of GEE for various remote sensing applications has significantly increased since 2017 highlighting popularity by remote sensing researchers, including those in developing countries where processing power may have been a major hindrance (Tamiminia *et al.*, 2020).

With more than 100 remote sensing satellites having been launched since 1957, and with spatial, spectral and temporal resolutions having improved greatly over the years (Zhu *et al.*, 2018) there are now many applications of remote sensing imagery. However, when choosing remote sensing data there are multiple points to consider; such as the temporal resolution of sensors, processing power, cost and impacts of weather conditions on quality of images.

2.4.3 Image classification

Classification is the process of assigning pixels to classes, it is possible to assemble groups of similar pixels into classes associated with categories which the user is interested in (Campbell and Wynne, 2011) and is commonly used on remote sensing data. Image classification can be separated into two categories:

1) Supervised classification – this requires an analyst to identify training sets which represent each class in the classification scheme, together these sets define a particular profile for each of the classes. Analytical processes are then used to compare each pixel in the image to each of these training sets and assign each pixel to the class which best matches it (Khorram et al., 2021);

2) Unsupervised classification – this does not need input from an analyst, the majority of the work is done by an algorithm which determines which pixels are related and groups them into clusters, the user must input the number of desired classes and assign each cluster to the classes once the algorithm has finished (Duda and Canty, 2002).

The two classification types aim to produce the same results but involve differing levels of user input into the process. Unsupervised classification is still a valid and successful technique for classifying remotely sensed imagery, Verpoorter *et al*. (2014) found unsupervised classification of images from Landsat 7 (30 m spatial resolution) to be a successful method for the identification of waterbodies and their size distribution. However, it was noted that it was a challenge to map water bodies below 0.5 ha, water bodies smaller than this size fall into the parameters set in this research project therefore suggesting that unsupervised classification will not be suitable for identifying rural ponds. Therefore, even though unsupervised classification involves less effort initial analyst input, this can often result in less accurate classifications. Hasmadi, Pakhriazad and Shahrin (2009) compared supervised and unsupervised classification methods for land cover from SPOT-5 satellite images (10 m spatial resolution) of the Ayer Hitam Forest Reserve in Selangor, Malaysia. Accuracy assessments found that the supervised technique had a higher overall classification accuracy of 90.28% compared with the unsupervised score of 80.56%. The unsupervised technique expanded water bodies therefore overestimating the cover of these in the study area; thus making it unsuitable for pond surveys that require accurate classification of water bodies. Similarly, when comparing land cover classification from supervised and unsupervised algorithms in an area of Arkansas in USA, Enderle and Weih (2005) found that supervised classification based on 146 training areas using the maximum likelihood classification algorithm had an overall accuracy of 74.85%, whereas the unsupervised classification achieved only 40.94%.

Kafy and Ferdous (2018) used classification to examine changes of pond abundance in a defined area in Bangladesh over three different years using supervised classification. This method worked well and allowed for analysis of pond infilling in the area and demonstrated the successful use of supervised classification to identify small water bodies, however no accuracy assessment was performed to verify the quality of the findings. A key limitation of supervised classification is the availability of ground truth data to train or validate the classification algorithm (Aroma and Raimond, 2018); it is important for the analyst to have enough familiarity with the environment to create appropriate training sets, as well as to confirm that the output classifications represent the land cover on the ground. In addition to this it has been found that image classification can be a potential error source; spatiotemporal variability of biophysical measures cannot be fully reflected within the classes thus affecting accuracy of land use classification (Ayanu, Nauss and Wegmann, 2012). In this research project supervised classification has been used to identify ponds (see Section 3.5) in conjunction with in-field surveys to ground truth data.

2.4.4 Ratio imaging

In multispectral images dividing one spectral band by another produces an image that provides relative band intensities (Lillesand *et al.*, 2015), known as ratio images or band ratios. The choice of band used is what makes them appropriate for a specific purpose (see Table 2.1). One of the most commonly used is the Normalised Difference Vegetation Index (NDVI), often for exploration of drought effects (Choubin *et al.*, 2019), crop cover and yield (Marti *et al.*, 2007), urban expansion (Viana *et al.*, 2019) and degradation of vegetative habitats (Saravanan *et al.*, 2019). NDVI is calculated using the bands of satellite imagery which are most commonly associated with reflectance (NIR) and absorption (red) of vegetation (Table 2.1). Other similar indices have been created for water identification, chiefly the Normalised Difference Water Index ($NDWI_1$) first proposed by Gao (1996). This index is calculated using the near NIR, and short-wave infrared shown in Table 2.1, this is most commonly used now for evaluating and monitoring water content in vegetation. McFeeters (1996) also proposed a Normalised Difference Water Index ($NDWI_2$) which uses NIR and green wavelengths to calculate water content in waterbodies (see Table 2.1). This second water index has been successfully used to delineate water features from satellite imagery by many since its introduction. Subedi and Dev Acharya (2021) effectively used $NDWI_2$ to extract small waterbodies from Landsat 7 and Landsat 8 images of the Terai region of Nepal from two time frames. NDWI was applied to images from 2002 and 2021 with the results extracted allowing for assessment of changes in small water bodies in this area. However some issues with this method were found; small artificially constructed waterbodies were often not identified by this index. But most which were greater than 0.44 ha in size were correctly identified, suggesting that this method can be used for water body extraction and perhaps with imagery that has a higher resolution this method would identify ponds of a smaller size as the Landsat imagery used has a resolution of only 30 m.

Table 2.1: Spectral indices from the scientific literature used for water body detection. Adapted from (Soti *et al.*, 2009).

Index	**Abbreviations**	**Band ratios[a]**	**Reference**
Normalised Difference Vegetative Index	NDVI	(NIR-R)/(NIR+R)	(Tucker, 1980)
Normalised Difference Water Index	$NDWI_1$	(NIR-MIR)/(NIR+MIR)	(Gao, 1996)
Normalised Difference Water Index	$NDWI_2$	(G-NIR)/(G+NIR)	(McFeeters, 1996)
Modified Normalised Difference Water Index	MNDWI	(G-MIR)/(G-MIR)	(Clandillon, Fraipont and Yesou, 1995)

[a]NIR: Near Infrared; R: Red; G: Green; MIR: Middle Infrared

A study by Özelkan (2020) assessed the difference in spatial resolution when applying NDWI to satellite imagery. Landsat 8 multispectral (30 m spatial resolution) and panchromatic images (15 m spatial resolution) of Atikhisar Dam Lake in western Turkey providing imagery of 30m and 15m spatial resolution to allow for comparison. It was found that $NDWI_2$ models with the 15m resolution produced better results of lake surface area than those of 30m. Urban surface water bodies were extracted using NDWI from Sentinel 2A images of Beijing and Yantai, China to compare NDWI results between inland and coastal cities (Yang *et al.*, 2017). Once this was done object-level Modified NDWI (MNDWI) mapping was applied to the outputs. MNDWI replaces the NIR band (10m resolution) with the short-wave infrared band (20 m resolution) to overcome the issue of separating built-up areas and water (Table 2.1). Yang *et al.,* (2017) found that in Beijing the MNDWI mapping increased the *Kappa* coefficient by nearly 0.3 compared with the conventional NDWI method. However in the coastal Yantai area the NDWI obtained higher accuracy than the MNDWI outputs, suggesting that in less urban areas use of NDWI for water body extraction is sufficient. This suggests that with other satellite imagery of finer resolutions small waterbodies such as ponds could successfully, and accurately, be extracted at a large scale using NDWI.

2.4.5 Using remote sensing to identify ponds

Remote sensing has been widely and successfully used in assessment of rivers and lakes, but is a largely unused tool in pond research (Hill *et al.,* 2021). Pond loss in the Comilla District, Bangladesh was investigated by identifying all extant ponds (ponds which are still present and water filled) using panchromatic Landsat 8 satellite images at 15 m spatial resolution from three years to understand the change. The researchers identified water bodies less than 5 ha in area and broad land uses (Kafy and Ferdous, 2018). It was found that pond numbers decreased by 14.12% from 2013 to 2017, mostly due to urbanization and increased agricultural production, demonstrating that remotely sensed images can be a useful tool to allow for remote surveying of ponds. Revollo Sarmiento *et al.* (2016) used digital image processing on images extracted from Google Earth based on Landsat panchromatic imagery at 15 m spatial resolution, to identify geographical features in tidal flats. These features then were classified into ponds or tidal creeks using a model based on datasets and supervised classification of features with 90% accuracy. However, when comparing this technique with direct observation, Taylor *et al.* (2011) found limitations around obstruction of view, out of date imagery, and poor resolution of the images leading to some features not being accurately recorded.

Public projects also use remote sensing to inform multiple studies, 'FrackFinderPA' project by SkyTruth, which asks volunteers to identify fracking ponds on areal imagery taken of potential drilling sites (SkyTruth, 2014). Even though this project is not specifically looking for natural or manmade rural ponds it allows for successful identification of water bodies remotely using remote sensing imagery. This data has now been used in a study which has assessed the change in these fracking ponds over time with the assistance of Landsat imagery (Platt, Manthos and Amos, 2018). Automated, unsupervised classification based on a ruleset of NDVI scores was applied to images where a fracking pond had been identified, this allowed for identification of the creation and removal of these impoundments. These data were analysed for trend analysis of the duration a fracking pond is in place and the size changes over time. This highlights the value of identification of a water body via remote sensing and the applications of this location data.

$NDWI_2$ (McFeeters, 1996) has been used as an automated classification process in identifying ponds; Soti *et al.*, (2009) explored the use of NDWI to locate and monitor ponds in an area of Northern Senegal using Quickbird (2.44 m resolution), Landsat 7 (30 m resolution) and MODIS (250 m resolution) images. It was found that with remote sensing images at higher spatial resolutions smaller ponds were identified by the $NDWI_2$ classification. The smallest pond in the study identified was 70m^2 by the Quickbird imagery, but the medium spatial resolution imagery of the Landsat 7 also presented as a promising way of monitoring water bodies in arid areas, especially given the higher temporal resolution offered by this sensor. Highlighting that temporal resolution is as important a consideration as spatial resolution when selecting satellite imagery. However, when using $NDWI_2$ and MNDWI (see Table 2.1 for calculations) to delineate the size and persistence of ponds on Himalayan debris-covered glaciers. Watson *et al.*, (2018) found that imagery with higher spectral resolution was better suited. Rapid Eye, Sentinel 2 and Landsat 8 (5 m, 20 m and 30 m spatial resolution respectively) imagery were used to compare the outputs of applying $NDWI_2$ and MNDWI. It was found that $NDWI_2$ values calculated using Sentinel 2 imagery showed the greatest spectral difference between water and the surrounding debris cover, and that using NDWI calculated with NIR and green bands displayed the strongest relationship with pixel water content for all imagery with the highest value identified in Rapid Eye imagery. This suggests that using $NDWI_2$ and higher spatial resolution imagery is a reliable and accurate method for identifying ponds and their water content.

2.5 Summary

Identification of ponds has been successful by using various methods these include in-situ surveys (Williams et al., 2007), manually identifying small waterbodies using GIS and maps (Thornhill, 2017; Alderton, 2017). Similarly, many of these methods have been used to assess the conditions of such features. Methods which use in-situ surveys and manual identification are labour intensive, have trouble with inaccessible areas and are less likely to assess temporal evolution of a feature, whereas remote sensing approaches overcome these limitations (Hadjimitsis and Clayton, 2009). Ponds have successfully been identified and monitored using remote sensing imagery and classification techniques (Revollo et al., 2016; Kafy and Ferdous, 2018; Platt, Manthos and Amos, 2018). In this study multiple remote sensing imagery has been classified using an automated and a supervised method to allow for comparison (outlined in Section 3.5) to find an appropriate process for accurately identifying rural ponds. These images are varied in spatial resolution as it has been found and outlined here that this can be a factor which influences the success of remote sensing classification methods (Section 2.4.3).

3: METHODS

3.1 Study area

This project is set in a 23km^2 area of the Somerset levels, which is located in the South-West of England (Figure 3.1) near to the coastal town of Weston-super-Mare. This size was chosen, as 25km^2 is often the minimum required purchase area for satellite imagery. This area is rural agricultural in nature; primarily improved grassland (88.7%), whereas suburban areas make up only 7.6% of this study area (Figure 3.2). This is a pond-rich area with only four small urban areas, which provides a suitable landscape to determine the most appropriate remote sensing imagery and classification methods for identifying rural ponds.

In this study, due to the need for training sets using strict parameters, a working definition for ponds must be set. In addition to setting size limits for pond identification of 1 to 20,000 m^2 which ensured that all ponds of smaller size were identified and lakes were excluded (see Section 2.1). Only ponds that are present year-round will be included in the training sets to allow for easier identification and facilitates ground truthing visits. Any ponds identified by remote sensing approaches which do not fall within these constraints are classified as inaccurate.

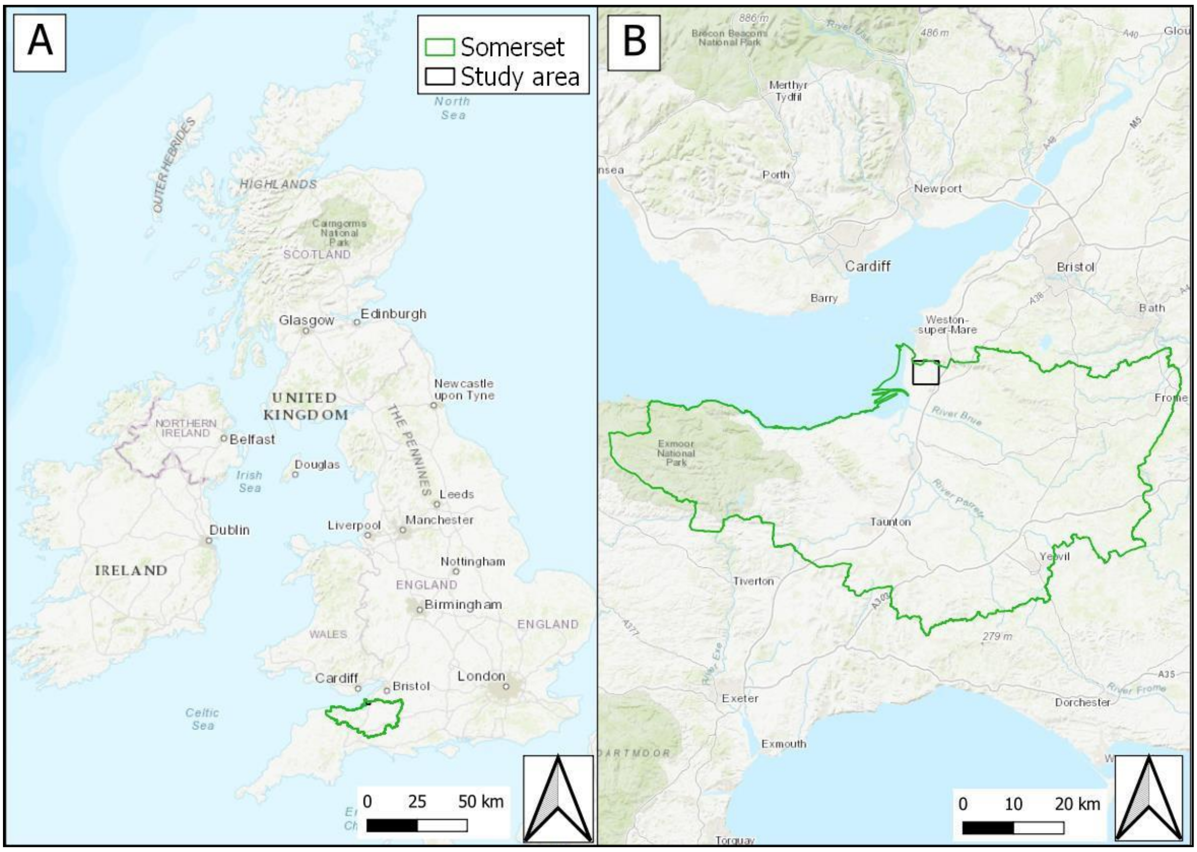

Figure 3.1 – Study area in relation to (A) Great Britain and, (B) the county of Somerset.

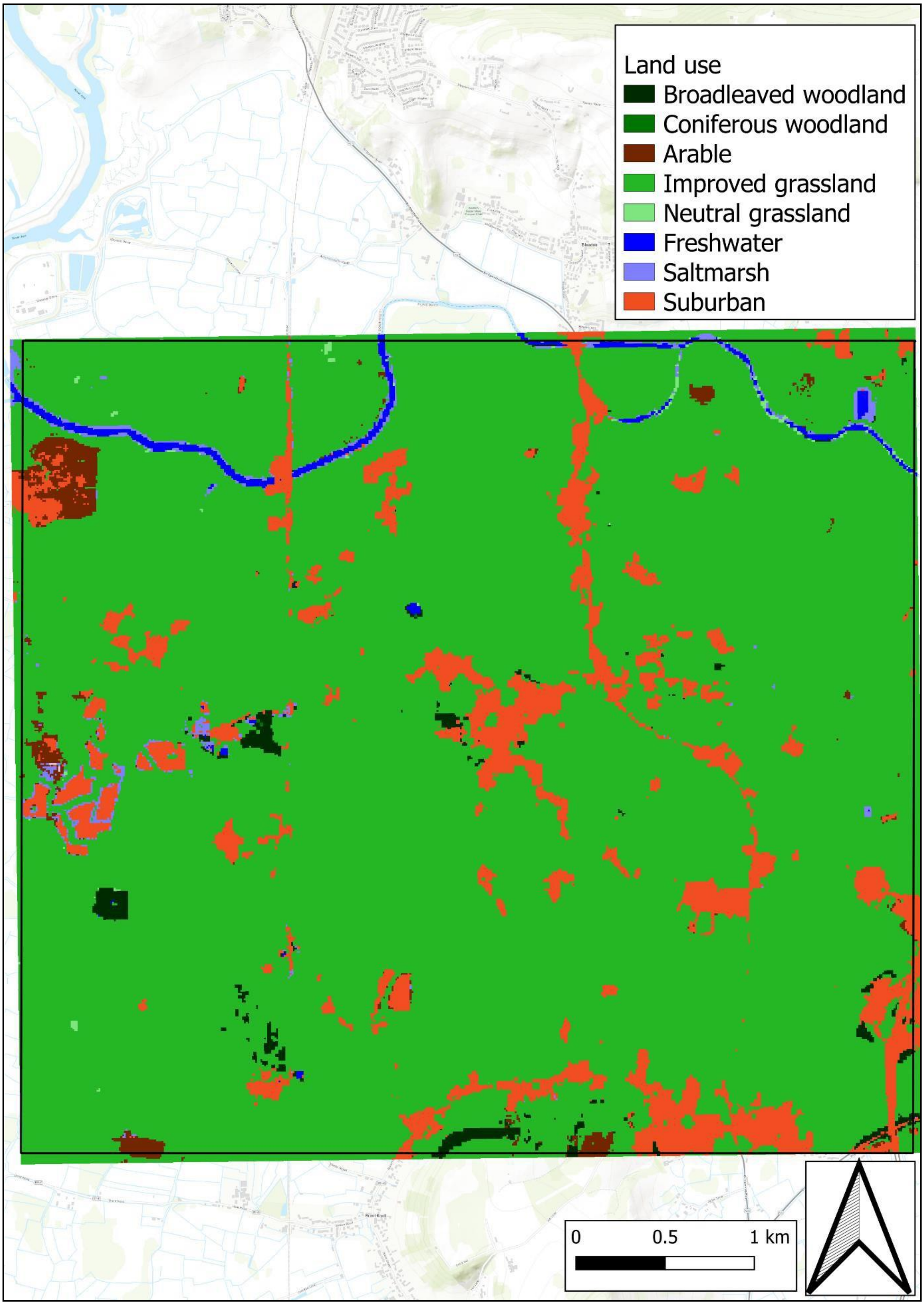

Figure 3.2 – Land use across the 23 km^2 study area; improved grassland (88.8%), Suburban (7.6%), freshwater (1.2%), arable (0.9%), saltmarsh (0.7%), Broadleaved woodland (0.7%), neutral grassland (0.1%), coniferous woodland (0.004%).

3.2 Manual pond identification

Using QGIS software version 3.10.10, OS Zoomstack 1:10,000 waterbodies shapefile layer (OS Zoomstack, 2021) and Google satellite basemaps ponds that fit within the specified size limits were manually identified and mapped as polygon shapefiles. Both of these layers were needed as the OS Zoomstack layer did not consistently include small ponds present on the Google satellite basemap layer. In addition to the contemporary maps (from 2021) OS 1:10,560 County Series historic maps from 1853 and 1946 (EDINA Digimap Service, http://edina.ac.uk/digimap) were used to identify the location of historic ponds in these two time frames. For all pond layers the polygons were also converted into point data to allow for easier data analysis. These historical maps were chosen as they include pre- and post-war periods. This is important because pond loss has been associated with the increasing demand for crops and changes to intensive farming practise in the UK that occurred after the Second World War (Rackham 1986). Once a water body was identified in QGIS the surface area was calculated using the field calculator to determine whether it fit the specification for a pond.

The 2021 pond location data was used when assessing accuracy of classification outputs. All contemporary ponds are also categorised by surrounding land use type, this was done using 2021 land cover data from the UK Centre for Ecology and Hydrology (Morton *et al.,* 2021) which is classified at a 10 m scale.

For an overall representation of distances between all ponds the nearest neighbour analysis tool was used to obtain the distance to the nearest pond from all ponds in the same point layer (i.e. ponds present in 1853, 1946 and 2021). Pond density in 1853, 1946 and 2021 was calculated by dividing the total number of ponds present by the catchment area, generating ponds km^{-2} and permitting a calculation of change in pond density. Contemporary pond density was also calculated with respect to land use category. Using the Count Points in the Polygon Analysis tool the number of ponds present in 2021 were counted for each current land use type, this count was then divided by the area (km^2) covered by the relevant land use type.

3.3 In-field pond surveys

To increase the understanding of pond quality in the study area in-field surveys of 15 of the ponds in the study area was undertaken (Figures 3.3 and 3.4). These surveys also allow for comparison of time and effort spent on each method used in this research.

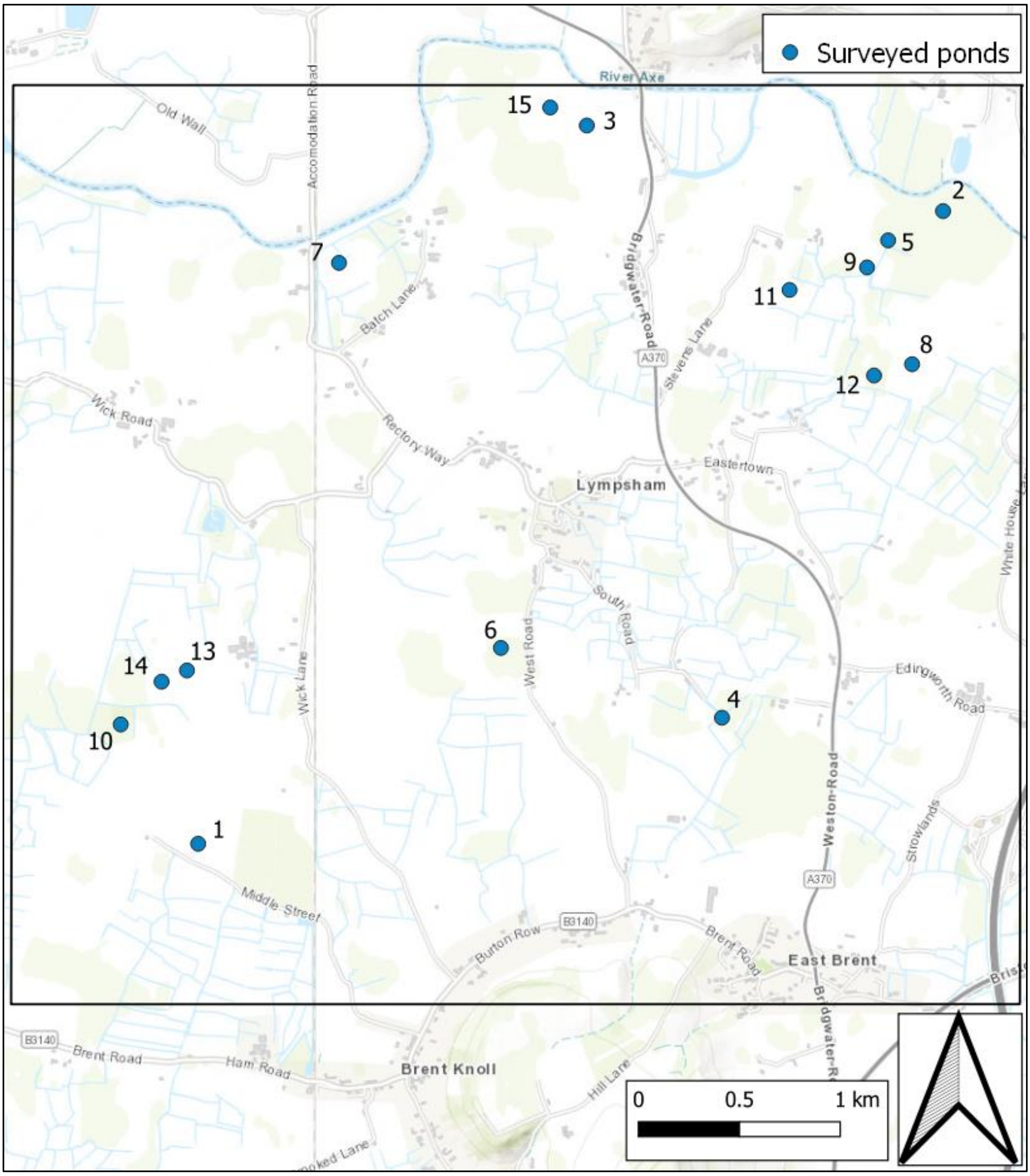

Figure 3.3: Location of the ponds which were surveyed for ecological condition, labelled 1-15.

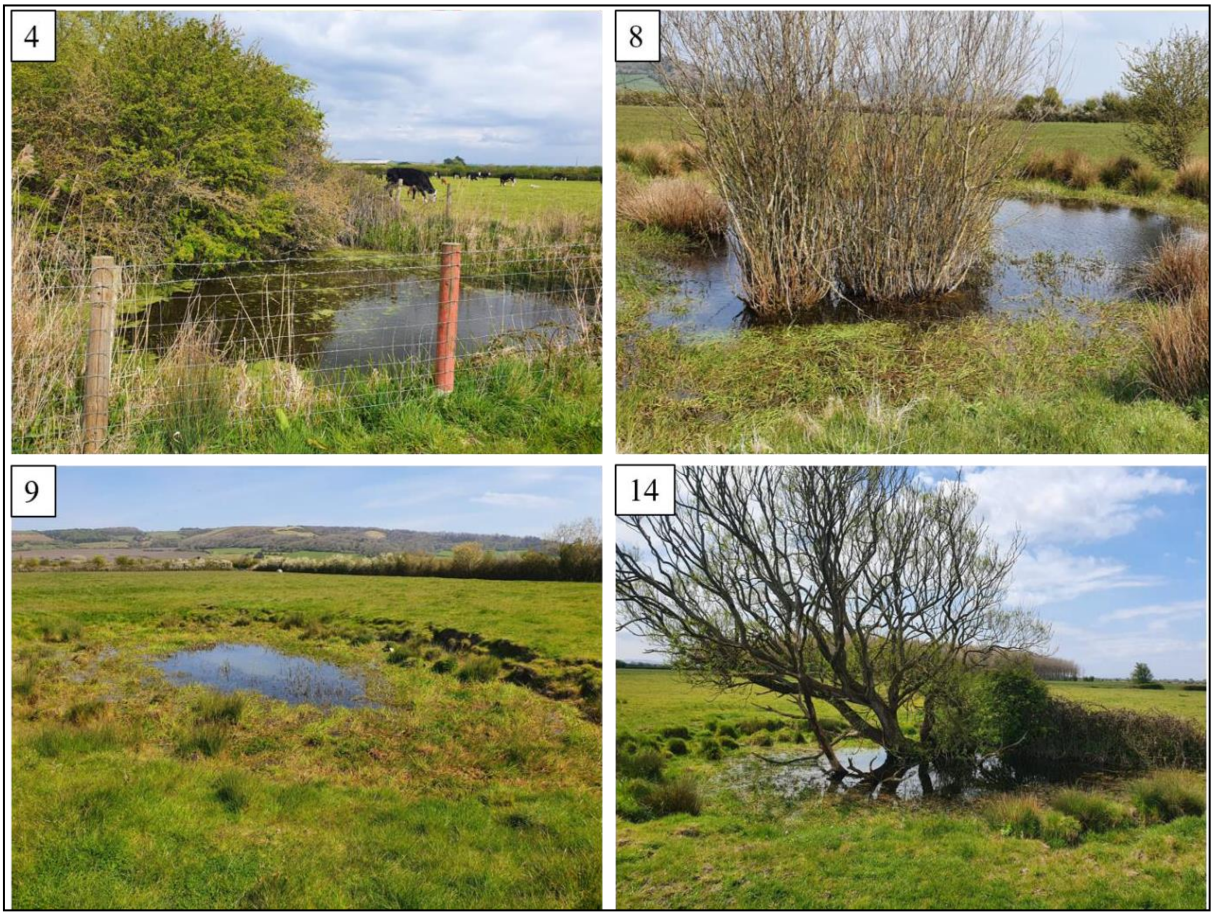

Figure 3.4: Photographs of four ponds which were surveyed in-field, labelled with ID number used, showing variation in characteristics of the ponds surveyed.

The in-field pond surveys followed a method adapted from The Freshwater Habitats Trust (Freshwater Habitats Trust, 2015). Some data collected has been omitted (see Table 3.1) due to typically not being important factors in ecological condition or, although important in effecting pond condition, a variable is challenging to quantify as having a negative or positive effect on ecological condition of a pond therefore making it hard to rank quantifiably. The variables were all turned into metrics, with 1 being the least desirable, and summed to give an overall value for the ecological condition of the pond. With a total score of 51 a ranking system was created. Ponds with values of 0-11 fall into ‘poor’, 12-21 equates to ‘below average’, 22-31 is categorised as ‘average’, values of 32-41 equate to ‘good’ and ponds which are ‘excellent’ have values of 42-51.

Table 3.1: Variables collected in in-field pond surveys and, if used to calculate pond condition, their ranking ranges.

Variable name	Description	Measured by	Used in study	Ranking range
Area	Area of pond perimeter	m^2	No	-
Disturbance by dogs	Estimation of effect dogs have on the pond	Major/minor/none	Yes	0-3
Emergent aquatic vegetation cover	Cover of emergent vegetation of the whole pond	Percentage	Yes	0-8
Extent of modified bank	How artificial/reinforced banks of ponds are	Percentage	No	-
Fish presence	Estimation of presence of fish species	Major/minor/possibl e/absent	Yes	0-4
Grazing	Evidence of grazing by livestock	Yes/No	Yes	0-1
Great Crested Newt	Location score for Great Crested Newt suitability	Optimal, marginal, unsuitable	No	-
Habitat quality for amphibians	Quality of habitat available for amphibian species	None/poor/moderate /good	Yes	1-4
Inflow/outflow	If any inflows or outflows are present	Yes/No	No	-
Invasive species	Record of any invasive species present	List of invasive species	No	-
Modified hydrology	If there is a structure on the outflow or evidence of abstraction, includes ditches.	List of modifications	No	-
Number of ponds	The number of ponds within a 1 km radius	Number	No	-
Overhanging trees and shrub	How much of the pond is directly overhung by trees and shrubs	Percentage	Yes	0-5
Pollution	Evidence of pollution includes chemical and litter	Yes/No	Yes	0-1
Pond base	The geology which underlines the pond	Geology types	No	-
Pond dries	How often the pond fully dries	Never/rarely/someti mes/annually	Yes	1-4
Pond management	Known management of pond in the last 12 months	Yes/No	Yes	0-1

Surface aquatic vegetation cover	Amount of the pond's surface water is covered by aquatic vegetation	Percentage	Yes	0-8
Surrounding land use	Estimates of the make-up of the 100m surrounding land use	Percentages	No	-
Turbidity	Water clarity of sample taken from pond	Scale of clear – turbid	Yes	1-4
Waterfowl impact	Estimation of effect waterfowl have on the pond	Major/minor/none	Yes	0-3
Water left in the pond	Amount of water left in the pond relative to maximum water level, and drawdown.	Percentage, cm	No	-
Water chemistry	pH, conductivity, nitrate and phosphate levels in pond water estimated using fresh water watch kits	µS cm-1, ppm	No	-
Water quality for amphibians	Suitability of water quality for amphibian species	None/poor/moderate /good	Yes	1-4

Ideally to gain a full understanding of the biological condition of a pond a more intensive survey of the macroinvertebrates present would also be undertaken. When assessing invertebrate and amphibian metrics' relationship to pond degradation it was found that macroinvertebrate family richness, general richness of Coleoptera, and Ephemeroptera, Plecoptera and Trichoptera family richness were strong indicators of pond ecological condition (Menetrey, Oertli and Lachavanne, 2011). Oertli et al., (2005) produced a standardised method for sampling and assessing biodiversity in ponds (PLOCH), the taxonomic groups used to assess indicators were selected as they fulfilled criteria set out by New (1995). These groups include aquatic plants, aquatic Coleoptera, Odonta, aquatic Gastropoda and Amphibia, it was found that the ratio of measured richness to predicted richness of each group provided an allocation of quality status to each pond (Oertli et al., 2005). Macroinvertebrates and amphibians are good indicators of pond condition, however aquatic plants have also been found to be important (Mahaney, Wardrop and Brooks, 2004; Oertli et al., 2005; Sass et al., 2010; Han and Cui, 2016). The Environment Agency (2002) argues that even though using a combination of macrophytes and macroinvertebrates in assessments of the quality of still waters is preferable, partial assessment can be made using just macrophytes. Therefore, the use of these in this method for assessing biological condition of ponds is sound for this research.

Undertaking these in-field surveys will also allow comparison to the remote sensing classification of ponds in terms of time and effort. Even though field surveys may take more time and effort from the surveyor there is a question of accuracy; does the extra time and effort required for in-field surveys make up for this in the increased accuracy of their results? Therefore, comparing the field surveys results, time allocated to them, and number of surveyors required, to the remote sensing classification will answer this question and therefore allow others to decide which method is best for their research question.

3.4 Satellite imagery

In order to assess the application of remote sensing for pond identification effectively comparison of different imagery of varying spatial resolutions was needed. Images from six satellites were used in this study: Landsat 8, Sentinel 2, Spot 6, World View 2, World View 3, Rapid Eye (specifications for each of these can be found in Table 3.1).

Table 3.2: Details of the satellites data has been acquired from for use in this study.

Satellite sensor	Date captured	Spatial resolution (m)	Temporal resolution (days)	Panchromatic (P) or Multispectral (M)	Number of bands	Cost for study area (USD)	Minimum area purchased (km^2)	Acquired from
Landsat 8	11/04/2019	30	16	M	8	0	0	USGS Earth explorer
Sentinel 2	20/10/2019	20	10	M	6	0	0	USGS Earth explorer
Spot 6	07/11/2016	6	26	M	5	85.80	100	Apollo Mapping
Rapid Eye	13/03/2017	5	5.5	P	3	128.16	375	Apollo Mapping
World View 2	30/11/2016	1.8	1.1	M	8	401.50	25	Apollo Mapping
World view 3	1/04/2019	1.24	1	M	8	478.5	25	Apollo Mapping

For this study, all datasets used were images captured in the months between November and April. In these months (November-April) vegetation cover should also be less dense which will enable ponds to be more clearly defined within the landscape and ponds located under tree cover should be easier to be located in the classification. A range of capture dates were used here as it was not possible to acquire the same date or even year for all of them due to issues of availability and cloud cover, which would naturally be higher in these months. Cloud cover was a particular issue with the World View imagery, which resulted in very few images being available and none with the images covering the full study area. Differences in the temporal resolution of the sensors also made it challenging to obtain images from the same capture date.

Remote sensing images are acquired from multiple sources and the cost for purchasing these varied depending on the spatial resolution, this is shown in Table 3.1, and will be considered as part of the assessment into applicability of using the different remote sensing satellites.

3.5 Remote sensing analysis

Pre-processing steps were undertaken on all images, this included reducing extent of cloud cover, creating a layer stack to create a single image file combining the different bands, re-projecting the images into British National Grid (EPSG:27700) and clipping the images to represent the study area. QGIS software version 3.10.10 was used for image processing, classification, and analysis of the remote sensing imagery.

3.5.1 Automated identification of NDWI

For each remote sensing image the $NDWI_2$ was calculated to give a raster layer which contained only water bodies. $NDWI_2$ was chosen as $NDWI_1$ is more often used for monitoring water content in vegetation (see Section 2.4.4), whereas $NDWI_2$ has been used successfully in identifying and monitoring waterbodies (Özelkan, 2020; Subedi and Dev Acharya, 2021). From this point onwards $NDWI_2$ will be referred to as NDWI as this was the selected method. This was done using the raster calculator in QGIS, applying the NDWI formula shown in Figure 3.5. NDWI is commonly used to detect and monitor water bodies, a formula is used to calculate moisture content using the green and NIR spectral bands. The visible green wavelengths maximise the typical reflectance of water surfaces, while the NIR maximises high reflectance of terrestrial vegetation and soil. The result of the equation gives values between - 1 and +1, positive values indicate water and negative values indicate soil/terrestrial vegetation (McFeeters, 1996). For this research a value of larger than 0.2 was used to distinguish water features, as often built up features and damp vegetation will have values between 0 and 0.2. Therefore calculation values of >0.2 were extracted using the raster calculator to produce a final raster with only water features identified.

$$NDWI = \frac{(Green - NIR)}{(Green + NIR)}$$

Figure 3.5: Normalised Difference Water Index (NDWI) formula, which uses green and near-infrared (NIR) spectral bands of images to identify water. (McFeeters, 1996)

The raster layer was then vectorised using the Polygonise function and in the vector field calculator a new column was created for area, which was then sorted by size to quickly show the largest and smallest area of feature that has been identified as a body of water. Anything over 2 ha in area was then removed as this exceeded the definition of what constituted a pond (Section 3.2). This area column will also enable the minimum and maximum pond size each classification has identified correctly to be found. These analyses were performed for each image, except Rapid Eye as it only has three bands, not including NIR, the NDWI calculation could not be done for this image.

3.5.2 Supervised pond identification

An open source semi-automatic classification plugin (SCP) for QGIS has been developed by Congedo (2021) to facilitate land cover monitoring of large areas which can be used in remote sensing analysis. The tools and interface in this plugin assists in the pre-processing, processing and post processing stages of land cover classification (Congedo, 2021). The image processing technique uses supervised classification methods to classify the land cover by training an algorithm with samples of the spectral signature of the image via the creation of training inputs in the form of polygons.

The identification of appropriate training sets is an important stage in supervised classification, as the quality of training data can influence the performance of classification algorithms (Foody, McCulloch and Yates, 1995). Using the training input tool in the SCP a new training set is created by digitising (i.e. tracing around) representative regions of interest. Multiple regions of interest are selected to build up training sets for each class, with each region of interest being set a micro-class (i.e. unique identifier for each) and class name (i.e. the land cover type for the training set). The training sets created will be evaluated prior to the supervised classification being performed to ensure that they represent unique land covers.

In total three classes were created; water, vegetation, and built-up. Within these three classes 27 micro classes were created which included; pond, river, ditch, field, trees, building, solar panel, road, and railway. All, excluding railway, had multiple training signatures. Once the supervised classification was performed using the SCP plug-in, the output raster are vectorised and categorised by the training classes allowing for rapid assessment of the number of ponds identified by the classification. For the World View imagery the number of features was so high that the vectorisation process could not happen due to the amount of processing power needed for vectorization of the outputs. Therefore to identify the ponds identified from the supervised classification outputs the raster data of these were overlaid with the polygon shapefile of the outline of all ponds present in the study area, each polygon was checked for areas identified as water by the classification. If the polygon had more than 20% of the area identified as water this was classified as identified by the output. This was recorded in the attribute table of the pond layer.

3.5.3 Accuracy assessment and verification

It is widely agreed that land use data gathered from remotely sensed dataset classification needs to be fairly and robustly assessed for accuracy and reliability of results, as statistical presentation of the accuracy and reliability of categorical maps produced from using a remote sensing approach is critical (Lyons et al., 2018). To assess the accuracy of both the automated (Section 3.5.1) and supervised classification (Section 3.5.2) outputs reference data from the manual mapping outlined in section 3.2 has been used. Each output is compared against this each pond that has coverage identified as pond by the classification output is recorded as identified and a percentage of ponds correctly identified was calculated. Some outputs identified a pond at multiple points within its boundary due to some pixels in this boundary not being identified as water in such cases this identification will only be recorded as a single pond correctly identified. For the World View 2 imagery the ponds which the output is being compared against will differ slightly as the image does not completely fill the study area, therefore the total number of ponds for comparison is slightly lower. The polygon outline of each pond surveyed in field was lain over each satellite sensor output to extract the percentage of ponds correctly identified. Additionally the ground data collected from in-field surveys (Section 3.3) was used in accuracy assessment of condition. This was used to assess whether the condition of ponds is important in identification using remote sensing methods.

3.6 Ranking system

This project aims to produce a toolkit allowing other researchers and landowners to easily decide which remote sensing approach is best for their project/question. It has been acknowledged that remote sensing is a valuable tool but there are many options which must be carefully considered when deciding which remote sensing system to use (Althausen, 2001). Therefore, to allow for users to decide which remote sensing approach is fit for purpose when identifying ponds a ranking system is to be devised. The remote sensing approach was ranked according to their accuracy values for each classification (Section 3.5) as this resulted in eleven outputs (as Rapid Eye could not be classified by NDWI) these are ranked 1-11. This provided a system showing which approaches produced the most accurate results. Other factors which affect the accessibility and usability for regular monitoring will be considered and ranked for each imagery. Price per km^2 was ranked for each image at a scale of 1 to 5 as there are five different price points for the six images, and ranking of temporal resolution (on a scale of 1-6 due to the six different resolutions of the imagery) has also been applied. All rankings outlined here were then totaled to give an overall rank for each imagery in conjunction with the classification method.

4. RESULTS

4.1 Manual mapping of pond location

A total of 250 ponds were mapped in the study area using the historical maps from 1853 (Figure 4.1A), this number increased to 265 in 1946 (Figure 4.1B). Of these 265 ponds, 79 were retained and 23 new ponds were created, resulting in a total of 105 ponds present in the study area in 2021 (Figure 4.1C). These numbers provide evidence for a net loss of 58% ponds since 1853 (Figure 4.2). Historic ponds (i.e. those that existed previously but were no longer present in 2021) were most commonly associated with improved grassland based on 2021 land use type, this was a total of 83% of all ponds lost in this study area. Suburban land use type was the next most commonly associated with pond loss with 15% of lost ponds in this land use type. Improved grassland was also the land use which most ponds were retained (83%) and created (42%). These land use types mirror the proportions of overall land use in the study area.

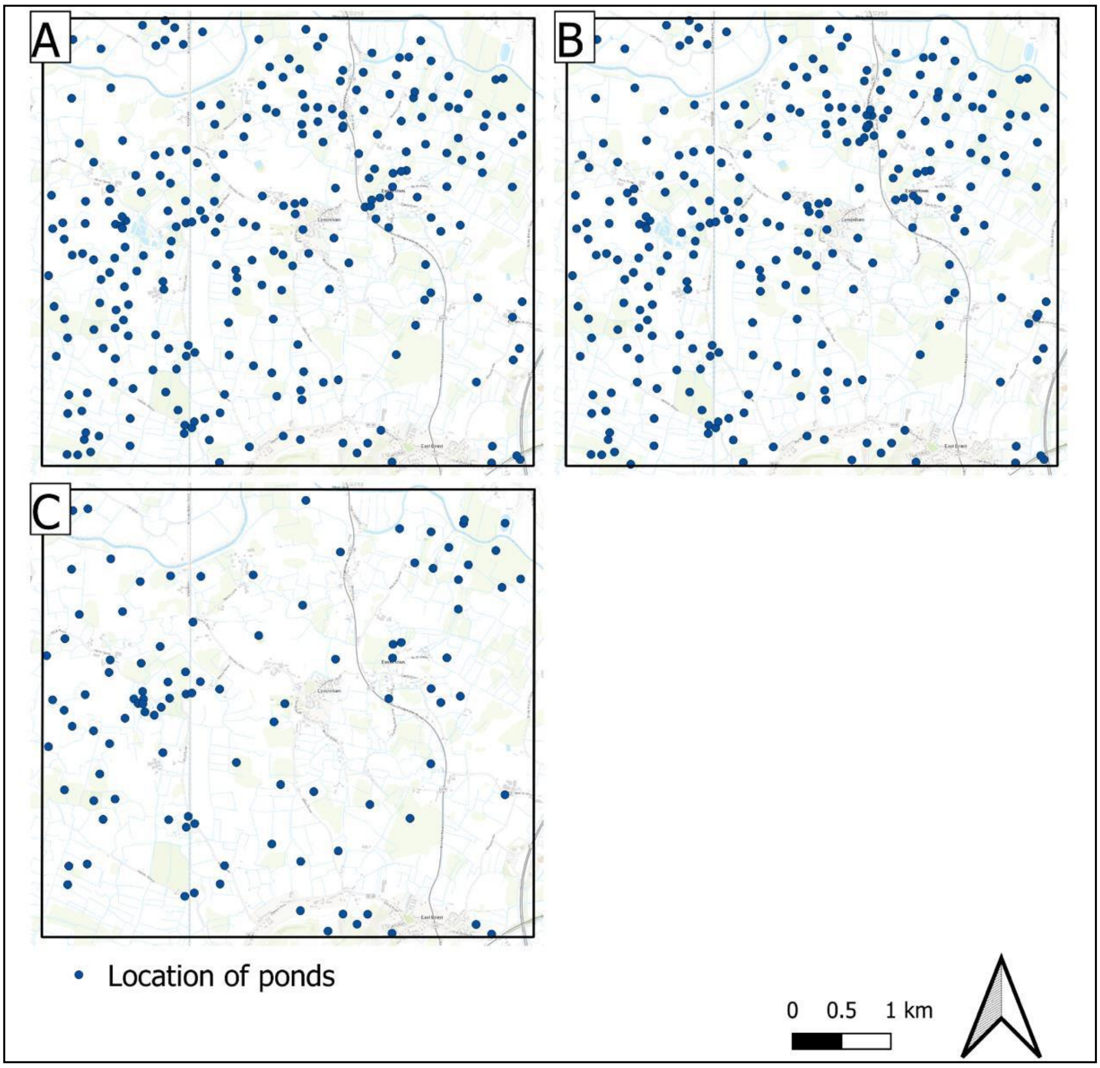

Figure 4.1: Total number of ponds mapped in the study area present in (A) 1853, (B) 1946 and (C) 2021.

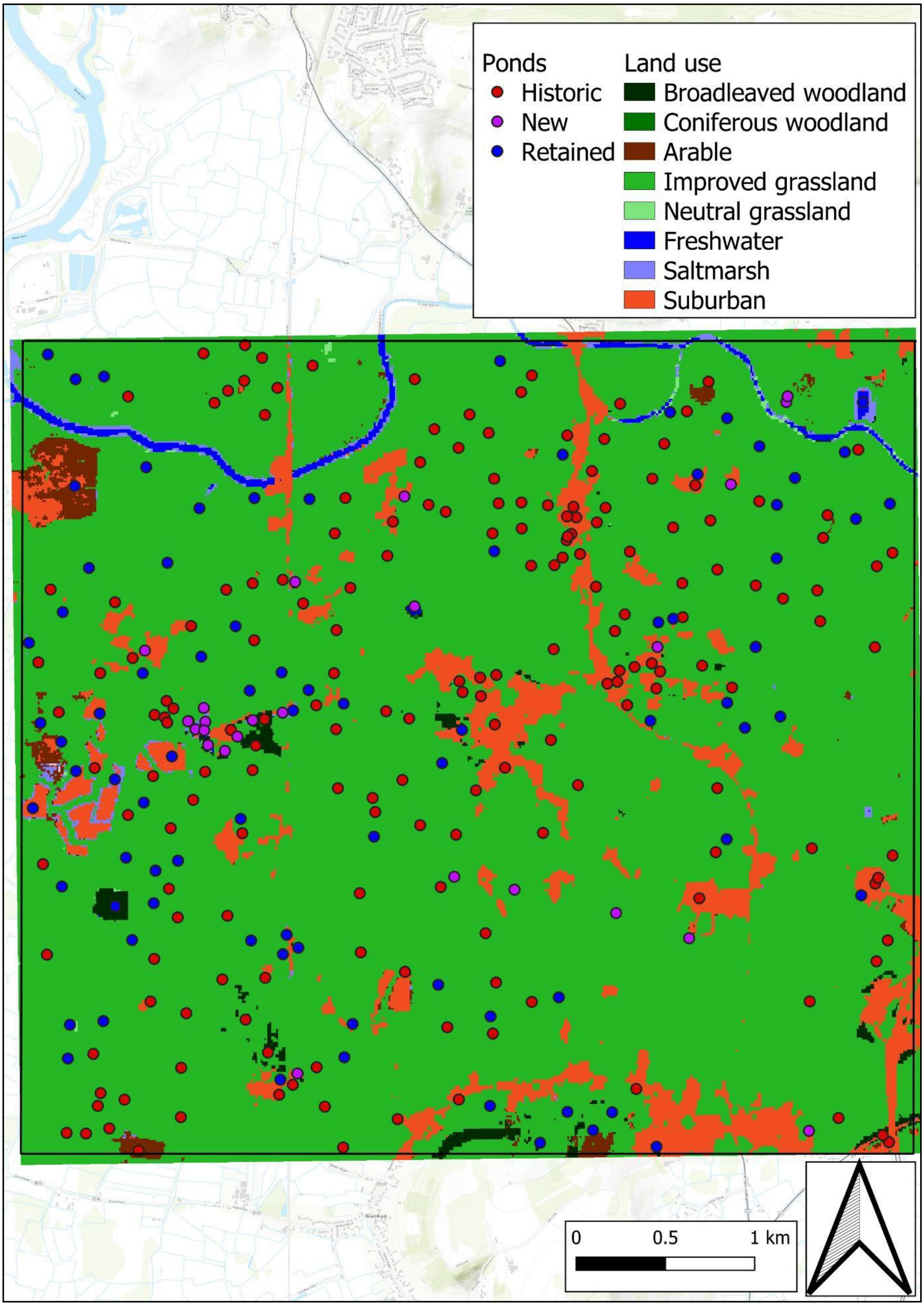

Figure 4.2: Total number of ponds mapped in the study area of historic (no longer on 2021 layers), retained (present on all layers), and new (only on 2021 layers) on top of 2021 land use.

Pond density increased from 10.9 km^{-2} in 1853 to 11.52 km^{-2} in 1946 then decreased to 4.6 km^{-2} in 2021 (Figure 4.3). Average distance between ponds also increased between 1853 to 2021 from 174.4 m to 259.1 m, however there was a slight reduction from 1853 to 1946 (170.4 m). The average surface area for ponds in 1853 was 183 m^2, this decreased slightly to 181 m^2 in 1946 by 2021 the average area had increased to 729 m^2. The minimum surface area for all three time frames was 1.1 m^2. The maximum pond size was 2,732 m^2 in 1853 and 1946 increasing to a maximum surface area of 13,946 m^2 in 2021.

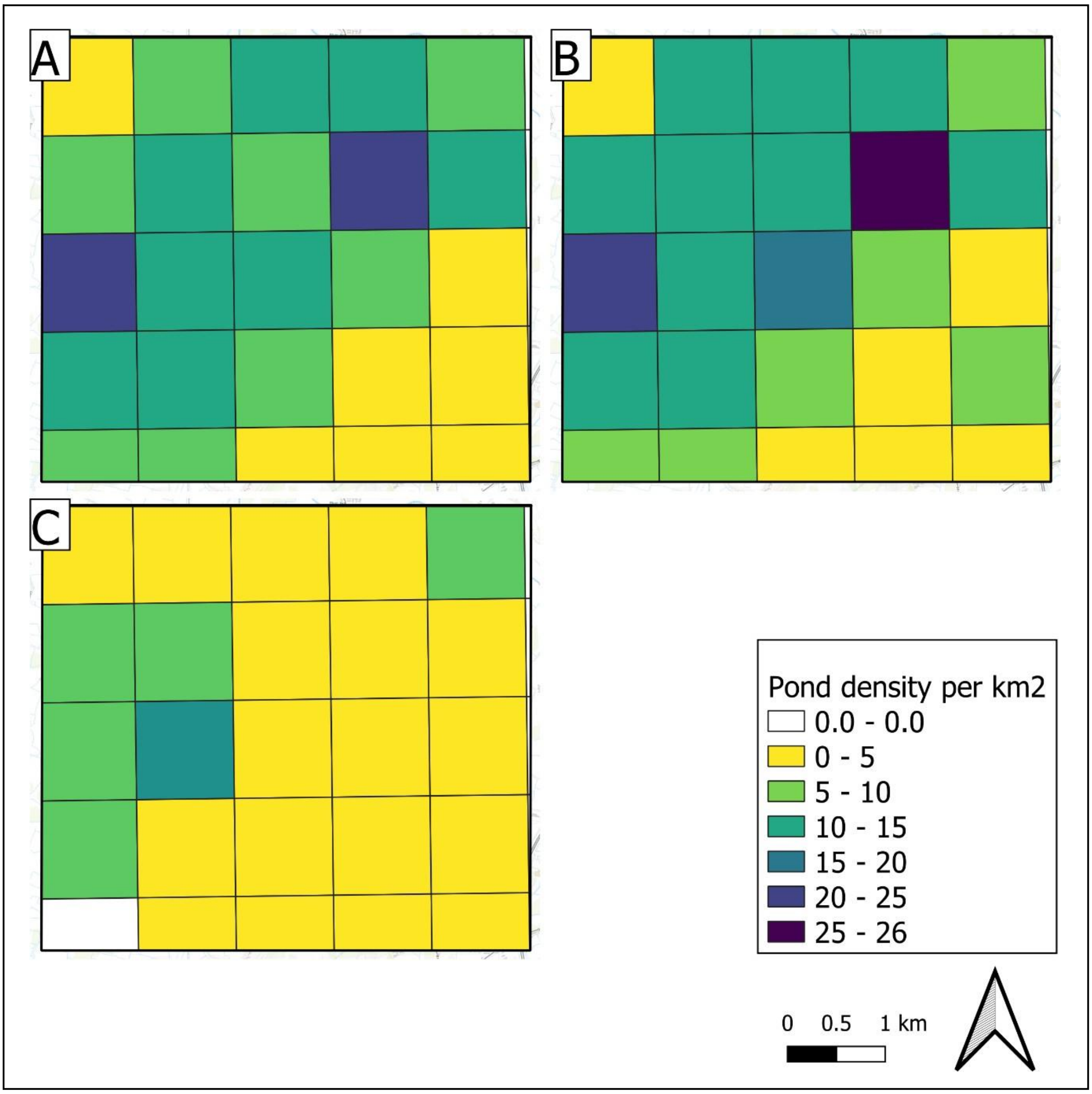

Figure 4.3: Pond density by count in (A) 1853, (B) 1946 and (C) 2021.

In 2021 the highest density of ponds was associated with land classified as improved grassland at 3.4 ponds per km^2 - a total of 73 ponds in this land use type (figure 4.2). In this part of the Somerset levels this improved grassland will most likely be pasture for cattle as this is the most common agricultural practice in this area. Suburban was the second highest land use surrounding ponds with 3 ponds km^{-2} (14 ponds).

4.2 Pond condition

The 15 ponds used for the in-field surveys have been categorised into five categories of condition; poor, below average, average, good and excellent. Most ponds were of good condition with results between 32 and 41 (Table 4.1). No ponds were classified as poor and only one was found to be excellent (Figure 4.4). No relationship between pond condition and land use could be identified as all but one pond were in areas classed as improved grassland.

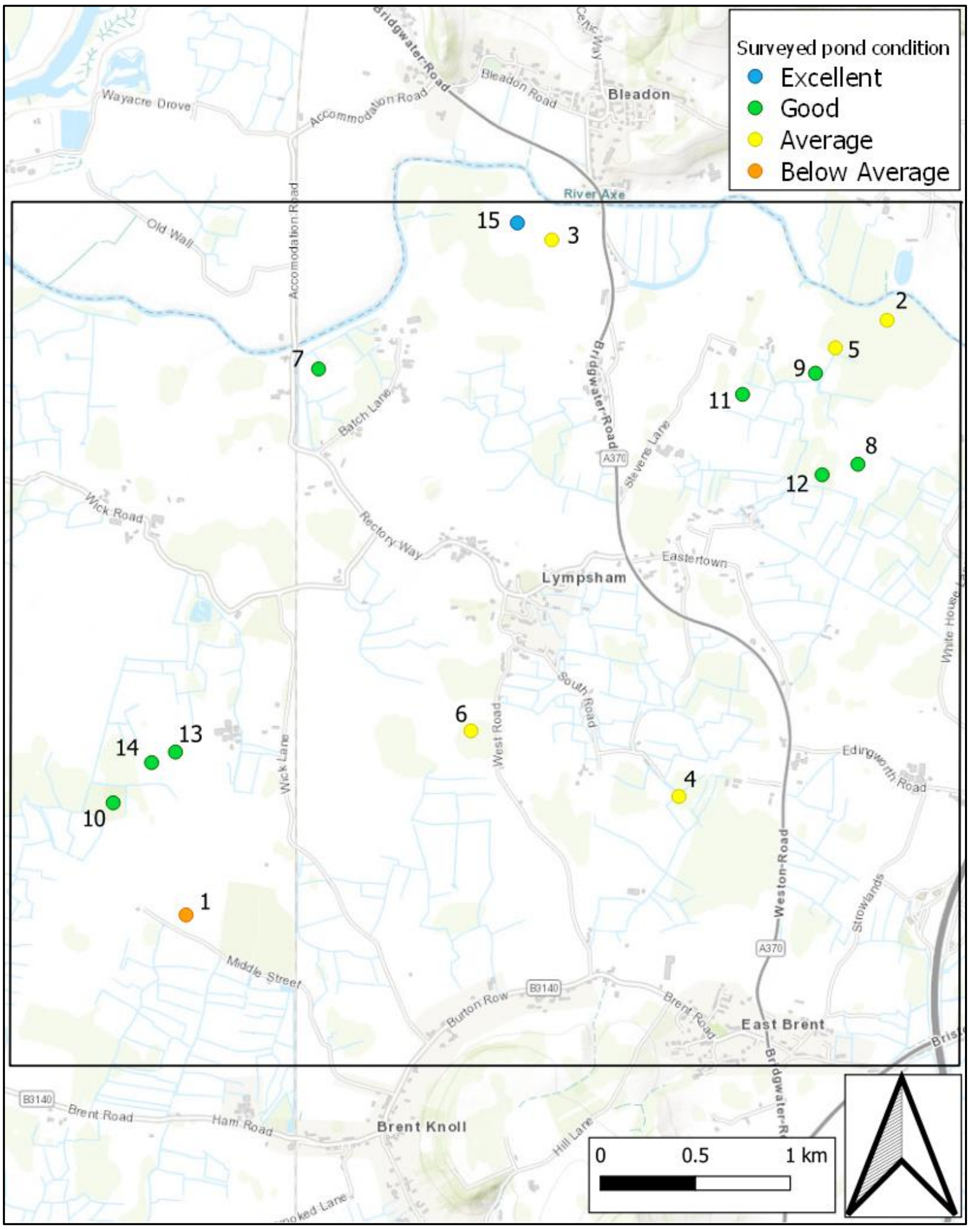

Figure 4.4: In-field ecological condition of ponds in the study area.

Table 4.1: Results of the pond net surveys used in the classification of pond condition. The condition has been colour coded as follows: Poor = red, Below average = orange, Average = yellow, Good = green, Excellent = blue

Pond ID	Pond Dries	Dog disturbance	% emergent macrophytes	Fish presence	Grazing	% surface macrophytes	Overhanging trees and shrubs	Pollutants	Pond management	Turbidity	Water quality for amphibians	Waterfowl presence	Total	Condition
1	4	3	0	4	0	0	0	1	0	2	0	3	**17**	**Below average**
2	2	3	0	4	0	0	4	1	0	2	7	2	**25**	**Average**
3	2	3	1	3	1	1	3	1	1	3	6	2	**27**	**Average**
4	2	3	2	3	1	1	4	1	1	3	5	2	**28**	**Average**
5	2	3	1	3	0	5	2	1	0	3	7	2	**29**	**Average**
6	1	3	7	3	0	7	1	1	0	1	5	2	**30**	**Average**
7	3	3	6	3	0	5	0	0	0	3	7	2	**33**	**Good**
8	2	3	4	3	1	5	1	1	0	4	8	2	**34**	**Good**
9	3	3	6	4	0	7	0	1	0	3	6	2	**35**	**Good**
10	2	3	4	3	1	7	2	1	0	3	8	2	**36**	**Good**
11	4	3	7	4	0	7	0	1	0	3	7	2	**38**	**Good**
12	2	3	6	3	1	8	0	1	0	4	8	2	**38**	**Good**
13	3	3	7	4	0	7	2	1	0	3	8	2	**40**	**Good**
14	3	3	5	4	0	6	4	1	0	4	8	2	**40**	**Good**
15	2	3	7	3	1	8	5	1	1	3	7	2	**43**	**Excellent**

4.3 Automated classification: NDWI

Figure 4.5 shows the outputs of the NDWI classification and figure 4.6 shows the location of ponds correctly identified through the NDWI analysis and those that were missed. Accuracy of pond identification by NDWI classification can be seen in Table 4.2, which shows that the classification of World View 2 produced the highest accuracy (28.7%) with all others being below 20% accuracy and Landsat 8 under 1% accuracy.

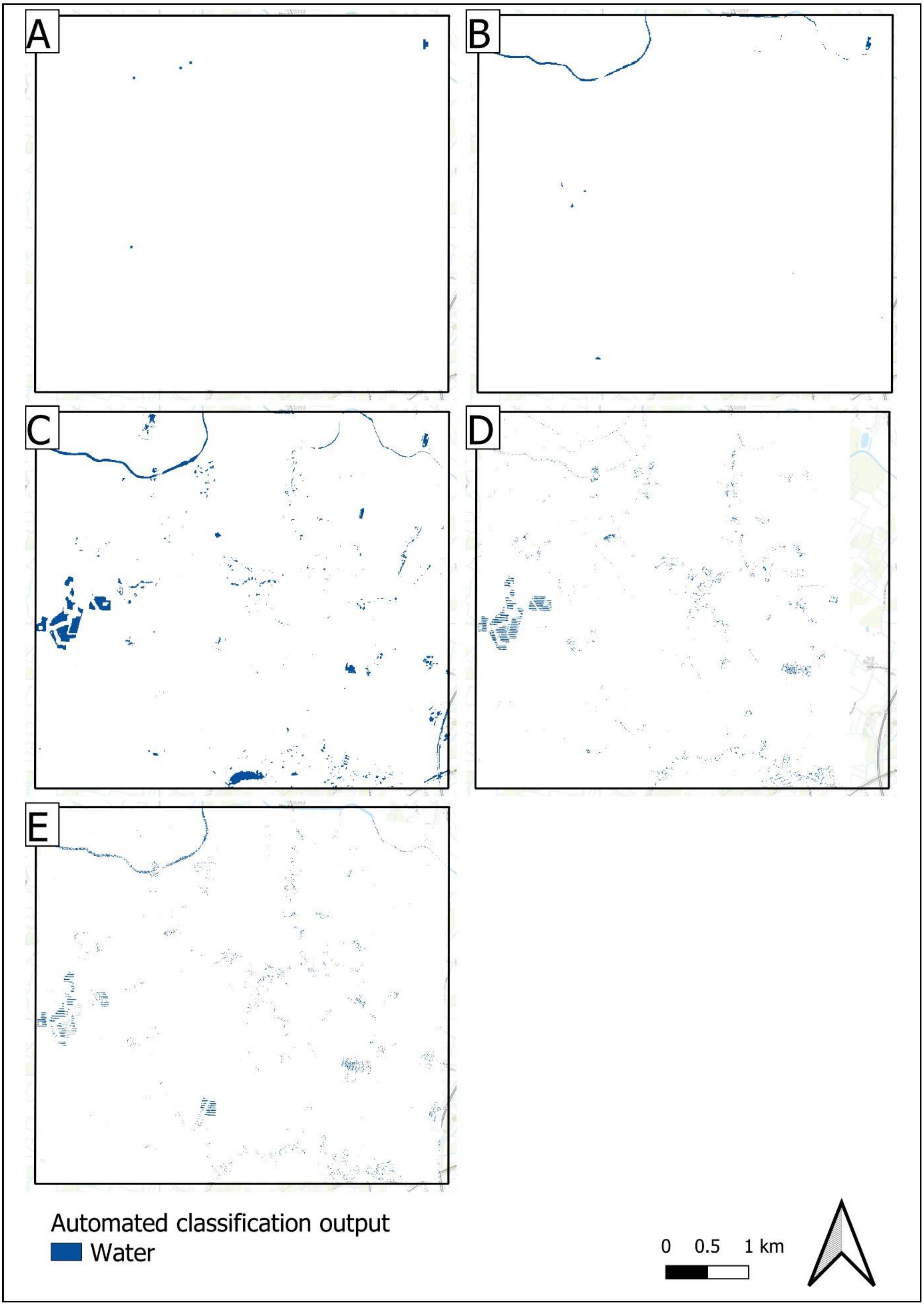

Figure 4.5: Outputs of the NDWI classification for (A) Landsat 8, (B) Sentinel 2, (C) Spot 6, (D) World View 2 and, (E) World View 3.

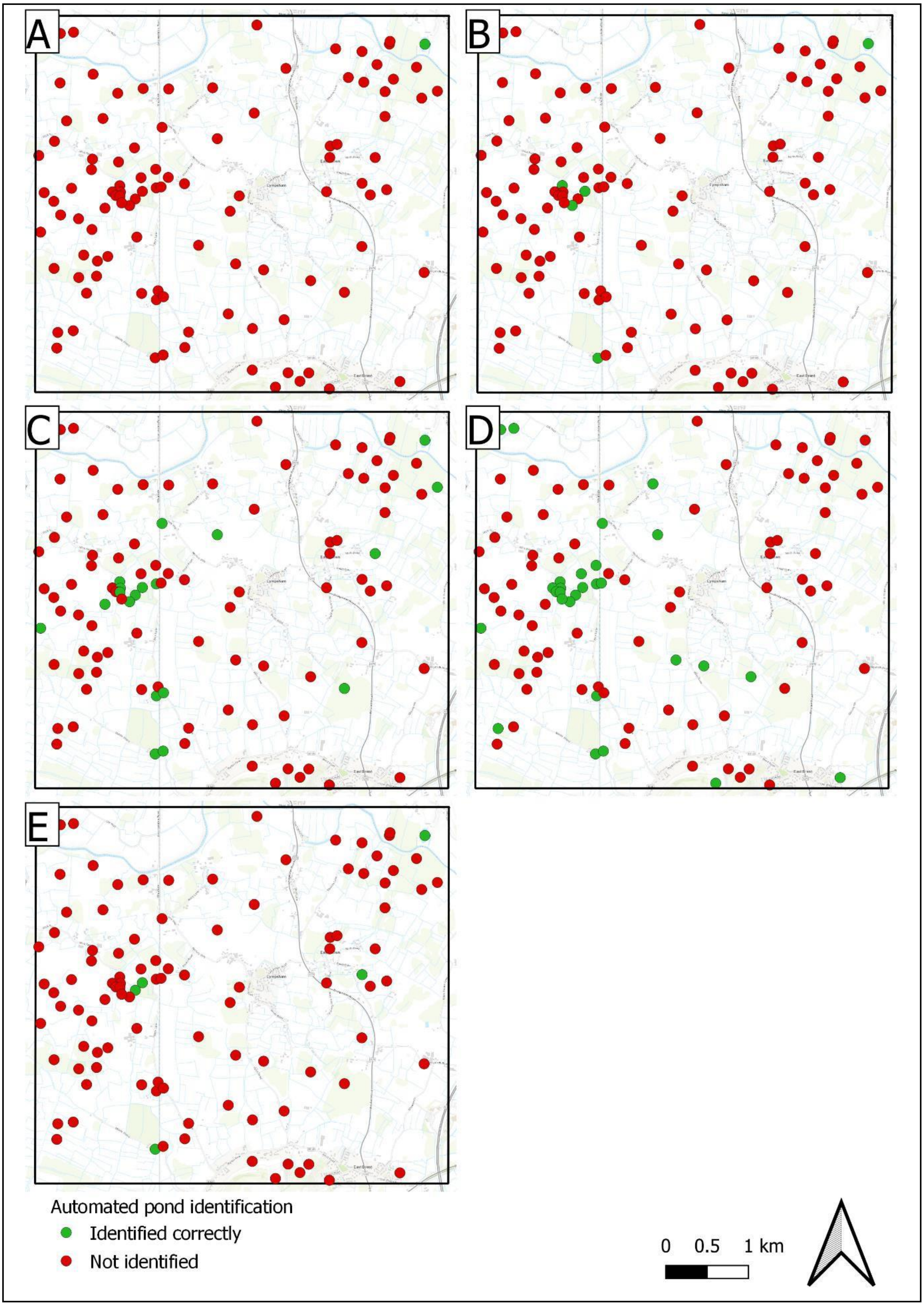

Figure 4.6: Location of ponds correctly identified from the NDWI outputs against all the ponds in the study area for (A) Landsat 8, (B) Sentinel 2, (C) Spot 6, (D) World View 2 and, (E) World View 3.

Table 4.2: Pond identification accuracy by each NDWI classification output. Accuracy assessment was compared against the 105 ponds identified in the manual pond count, with the exception of World View 2 which due to a reduced spatial coverage was compared against the 99 ponds in this area.

Imagery	Ponds Identified	Accuracy (%)
Landsat 8	1	0.95
Sentinel-2	5	4.76
Spot 6	19	18.10
World View 2	28	28.28
World View 3	5	4.76

The smallest pond identified by the NDWI classification has a surface area of 10 m^2, this was identified in the World View 2 imagery. The largest pond identified NDWI classifications was 4,837 m^2, this was identified in all but Spot 6 imagery.

Most ponds identified are in areas of improved grassland; of all the ponds identified by NDWI classification 18 of these are in improved grassland accounting for 54.4% of the ponds identified by NDWI outputs combined (Figure 4.7). Suburban land use had the next highest number of ponds identified, with 17 ponds in this land use type from the combined outputs of NDWI classification (19.3% of all ponds correctly identified in combined outputs of the NDWI classification).

4.4 Supervised classification

Figure 4.8 shows the output of the supervised classification for each satellite sensor, and figure 4.9 shows the associated ponds that were correctly identified through this method. The accuracy of pond identification increases with spatial resolution of the sensors; with the lowest spatial resolutions sensor (i.e. Landsat 8 and Sentinel 2) having under 25% accuracy. Supervised classification of the World View 3 imagery produced the highest pond identification accuracy with 72.4% of all ponds in the area identified (Table 4.3).

The largest pond identified in SCP classification 4,837 m^2, this was identified in Spot 6 and World View 2 imagery. The smallest pond identified in SCP classification outputs was 62 m^2 this was identified by both World View 2 and 3.

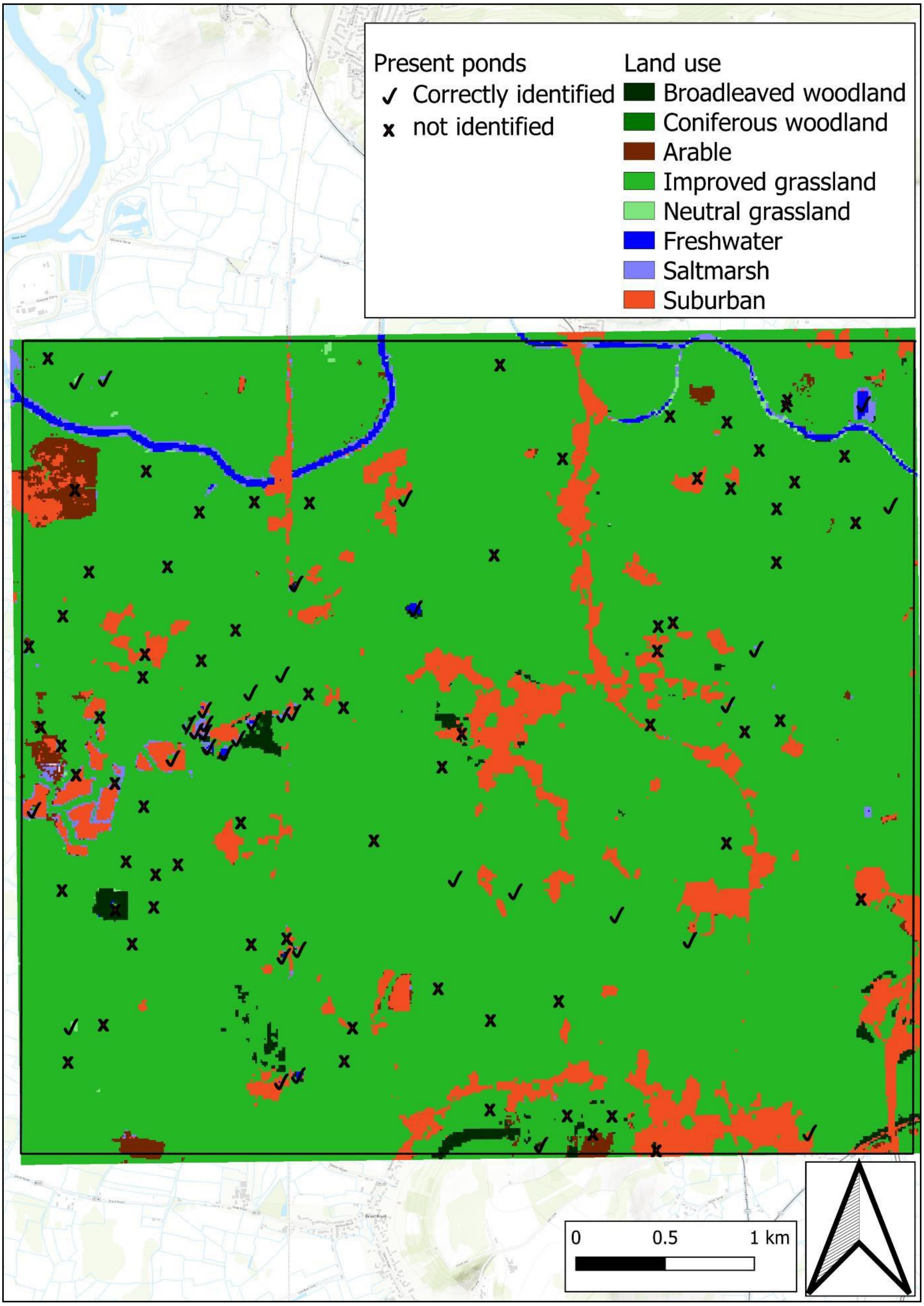

Figure 4.7: Ponds correctly identified by all NDWI outputs with the land use of the study area. Number of ponds correctly identified for each land use type; improved grassland = 16, suburban = 11, saltmarsh = 4, woodland = 2.

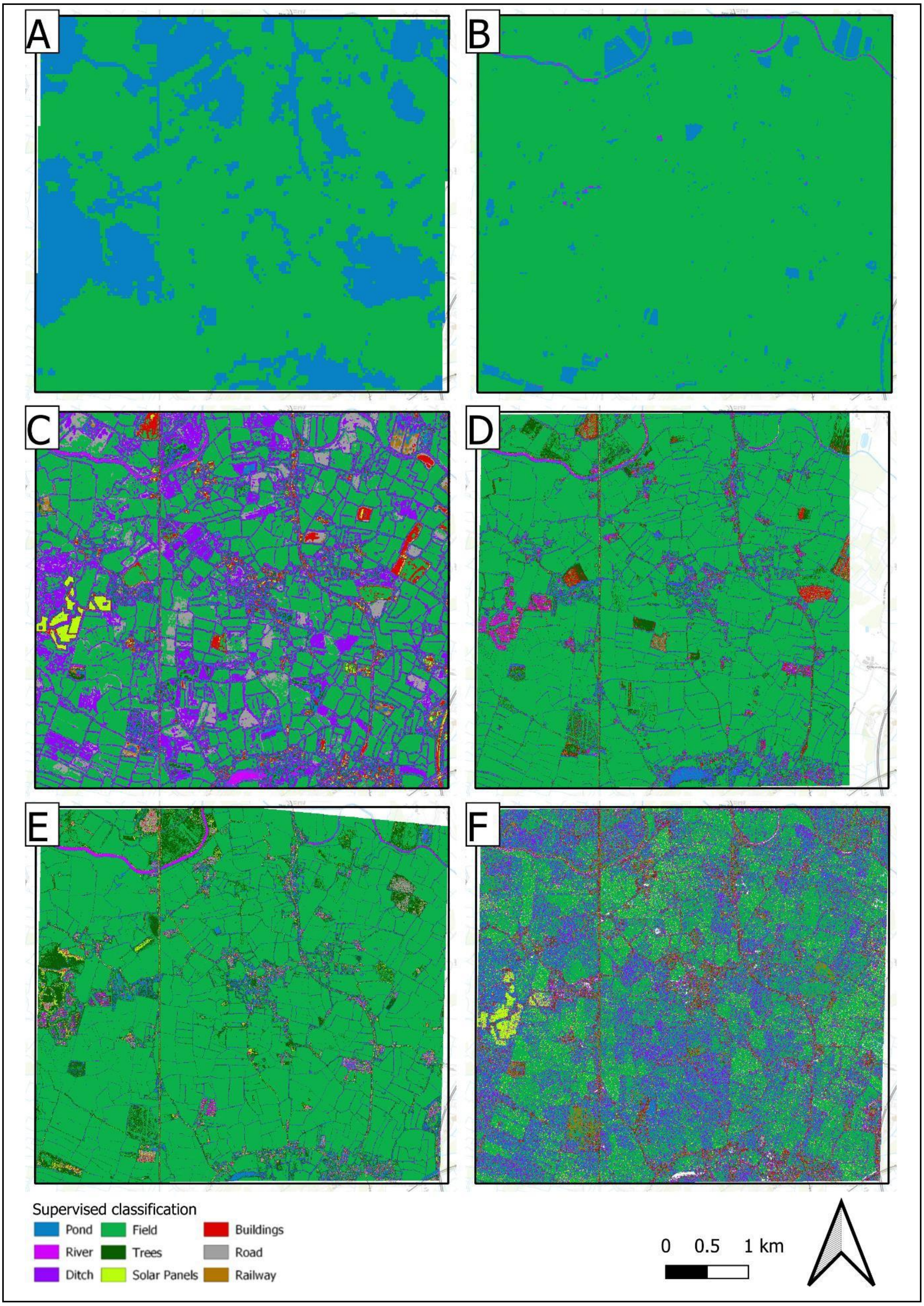

Figure 4.8: Outputs from the supervised classification for (A) Landsat 8, (B) Sentinel 2, (C) Spot 6, (D) World View 2, (E) World View 3 and (F) Rapid Eye.

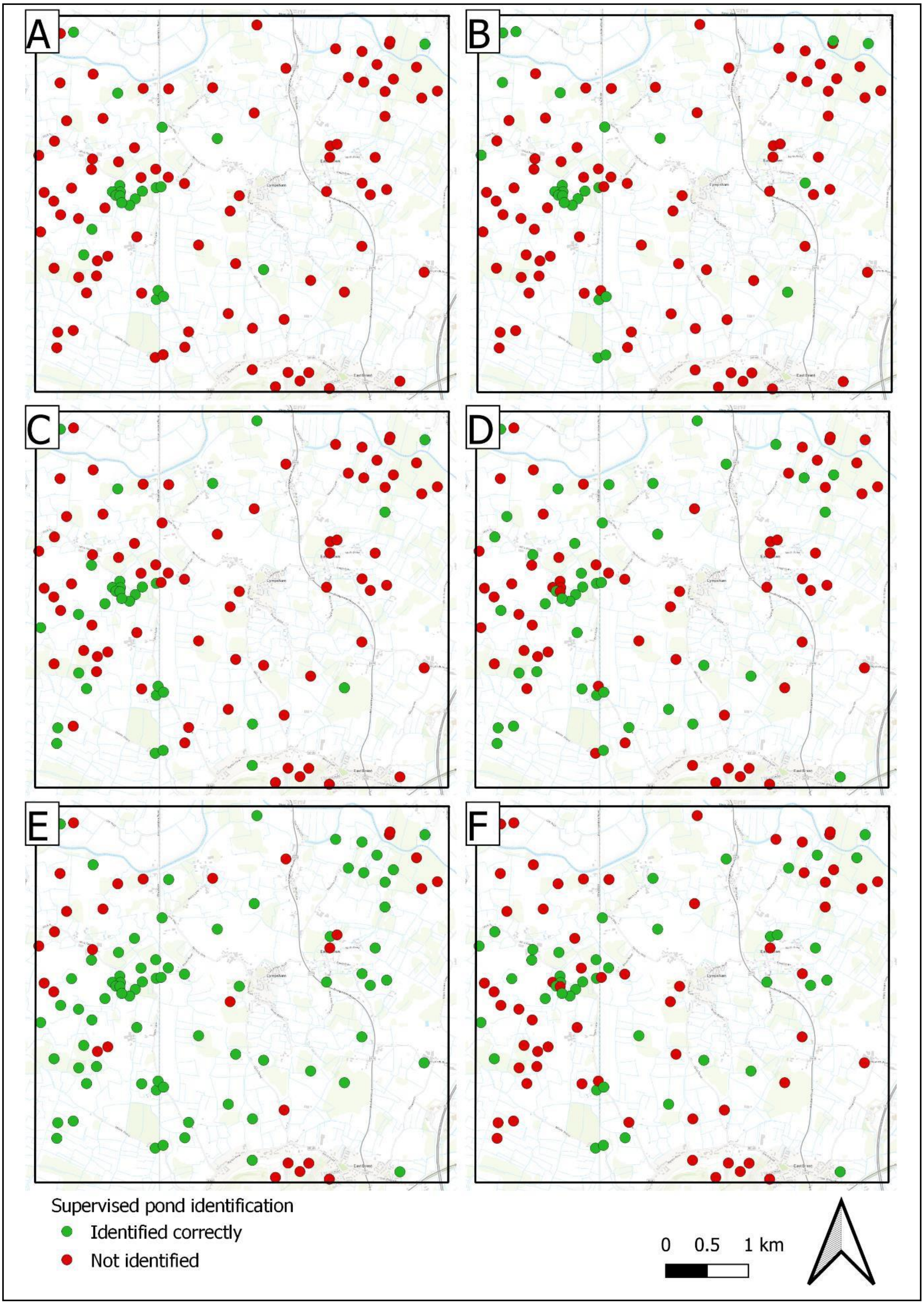

Figure 4.9: Accurate pond identification (green) and ponds unidentified from the supervised classification outputs by (A) Landsat 8, (B) Sentinel 2, (C) Spot 6, (D) World View 2, (E) World View 3 and (F) Rapid Eye.

Table 4.3: Number and percentage of correctly identified ponds from the supervised classification outputs for each image. Accuracy assessment was compared against the 105 ponds identified in the manual pond count, with the exception of World View 2 which due to a reduced spatial coverage was compared against the 99 ponds in this area.

Imagery	**Ponds Identified**	**Accuracy (%)**
Landsat 8	22	20.95
Sentinel 2	25	23.81
Spot 6	32	30.48
Rapid Eye	44	41.90
World View 2	43	43.43
World View 3	73	69.52

Of the ponds correctly identified by all the supervised classification outputs 62 are in land use type of improved grassland, this is 70.5% of all the ponds found by all semi-automated classification outputs combined (Figure 4.10). The next most commonly associated land use with identified ponds was suburban areas within which 19.3% of the ponds were identified.

4.5 Remote sensing and pond condition

Using the field pond survey data the extent to which pond condition influenced the accuracy of remote sensing identification was assessed. The results are shown in Table 4.4 and on Figure 4.11. None of the surveyed ponds were identified in any outputs from the NDWI classification. The outputs from supervised classification of Landsat 8 and Sentinel 2 also did not include any of the surveyed ponds. Spot 6 identified 2 surveyed ponds one pond ranked good and one excellent. World View 2 correctly identified four ponds; one average, two good and one excellent. World View 3 resulted in five identifications comprised of one average, three good and one excellent. Rapid Eye had the fewest correct identifications of one pond ranked average (Table 4.4).

Table 4.4: Number of surveyed ponds identified by classification outputs for each satellite.

Satellite imagery	**NDWI**	**Supervised classification**			
		Total	**Average**	**Good**	**Excellent**
Landsat 8	0	0	0	0	0
Sentinel-2	0	0	0	0	0
Spot 6	0	2	0	1	1
Rapid Eye	0	1	1	0	0
World View 2	0	4	1	2	1
World View 3	0	5	1	3	1

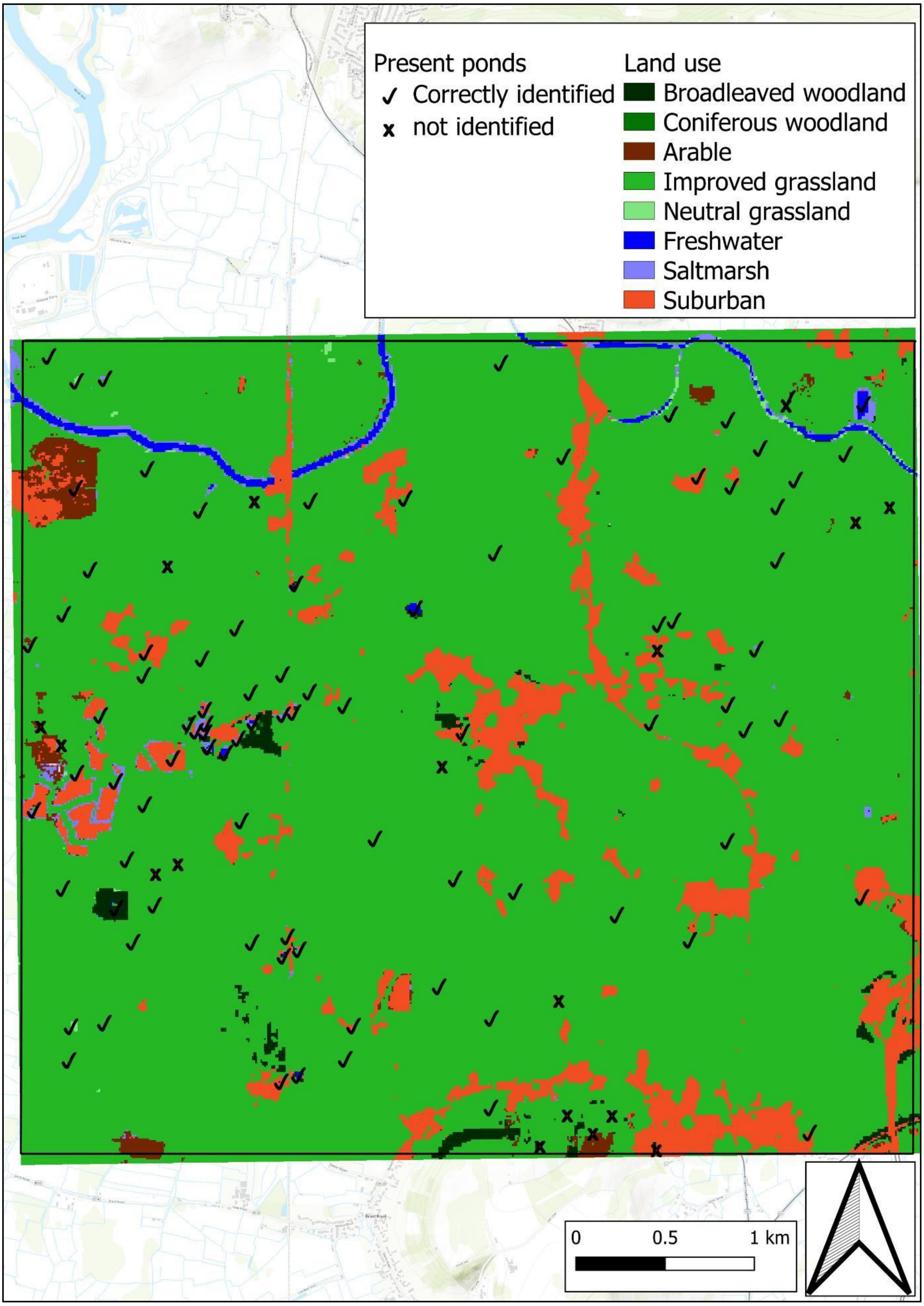

Figure 4.10: All ponds identified by supervised classification onto land use of the study area. Number of ponds correctly identified per land use type; improved grassland = 62, suburban = 17, woodland = 5, saltmarsh = 4.

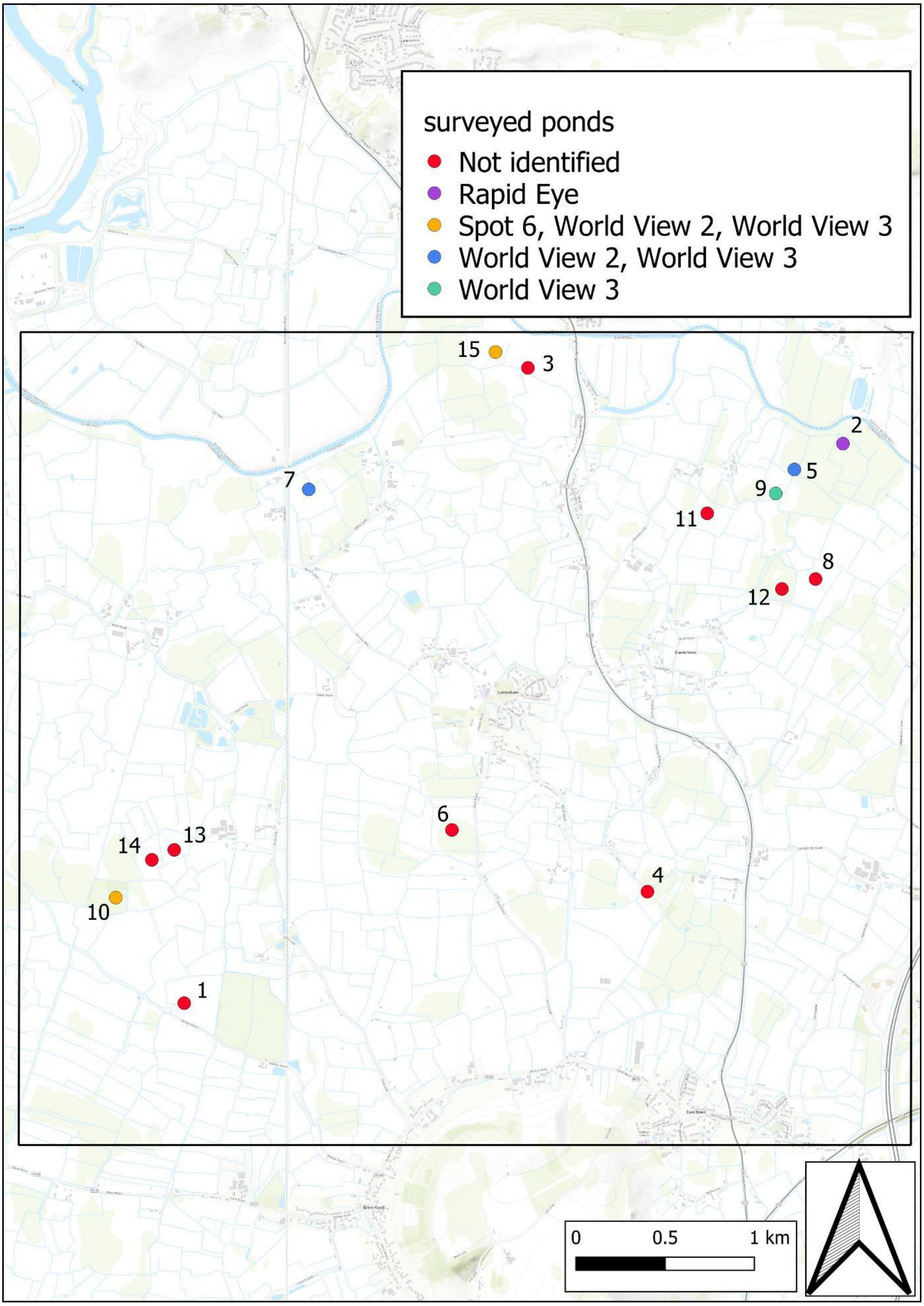

Figure 4.11: Surveyed ponds which were correctly identified by SCP classification of Spot 6, World View 2 and 3, and Rapid Eye.

4.6 Ranking system

The accuracy of each remote sensing method gives a clear ranking for the most accurate satellite sensor and classification technique for identifying ponds in the landscape; World View 3 using supervised classification. When cost and temporal resolution grading is applied to this accuracy ranking this has effected the standing of which imagery and classification methods are best, however World View 3 and supervised classification is the top method despite its high cost (Table 4.5).

Table 4.5: Ranking for each imagery and classification method.

Imagery	Classification	Accuracy	Accuracy rank	Cost (USD)	Cost rank	Temporal resolution (days)	Resolution rank	Sum	Overall rank
WV3	Supervised	69.52	11	478.50	1	1	6	18	**1**
WV2	Supervised	43.43	10	401.50	2	1.1	5	17	**2**
Rapid Eye	Supervised	41.90	9	128.16	3	5.5	4	16	**3**
WV2	NDWI	28.28	7	401.50	2	1.1	5	14	**4**
Sentinel-2	Supervised	23.81	6	0.00	5	10	3	14	**4**
Spot 6	Supervised	30.48	8	85.80	4	26	1	13	**5**
Landsat 8	Supervised	20.95	5	0.0	5	16	2	12	**6**
WV3	NDWI	4.76	3	478.50	1	1	6	10	**7**
Sentinel-2	NDWI	4.76	2	0.00	5	10	3	10	**8**
Rapid Eye	NDWI	0	0	128.16	3	1	6	9	**9**
Spot 6	NDWI	18.10	4	85.80	4	26	1	9	**9**
Landsat 8	NDWI	0.95	1	0.00	5	16	2	8	**10**

5. DISCUSSION

5.1 Distribution and condition of ponds in the study area

The study area has overall seen a 58% loss of ponds over the past 170 years; in 1853 250 ponds were present in this landscape, after an increase to 265 in 1946 the number of ponds more than halved to 105 ponds in the present day. Biggs *et al*. (2005) estimated national pond loss in the UK to be 18.4% over a 50-year period (1948-2000). Losses found in this study are far greater than this with a 59% decrease of ponds from 1946 to 2021. The time period examined here does cover an additional 21 years which would give more time for pond losses however it is generally agreed that since the turn of the 20th century overall pond numbers are no longer decreasing and positive net trends have been reported (Jeffries, 2010; Williams *et al.*, 2007). This suggests that the losses in this area are significantly higher than national losses. There have been similar estimates found elsewhere though. Alderton (2017) examined pond loss in Norfolk from 1955 to 2014, and reported a 47% pond loss, Smith *et al.,* (In Press) found a 57.7% loss in the Severn Vale catchment (1900-2019). This indicates that regional areas of the UK are experiencing higher declines over the last century than national estimates calculate, suggesting that pond decline should be looked at on a regional scale rather than national due to spatial disparities.

Ponds which were lost in the landscape were most commonly associated with improved grassland land use, 83% of all ponds classes as historic were found to be on this 2021 land use type (Figure 4.2). This land use type was also associated most with ponds retained throughout the time span and ponds which were created. This is most likely due to improved grassland being the most widespread land use in the study area in 2021 so where most ponds would be. In 2021 the highest density of ponds was associated with land classified as improved grassland at 3.4 ponds per km^2.

Pond density values are important to ensure standardised estimates of pond losses. This study has evidenced an overall decrease in pond density, from 10.9 ponds per km^2 in 1853 to 4.6 km^{-2} in 2021. The current day density is higher than the national estimates of 1.8, 2.5 and 2.2 ponds km^{-2} for England Scotland and Wales respectively (Williams et al., 2010). Which could suggest that this area is of potential importance in pond density, however similar densities have been found elsewhere; Cheshire had a pond density at 3.25 km^{-2} (Boothby and Hull, 1997), and Norfolk 4.2 ponds km^{-2} (Alderton, 2017). This could be due in part to the prevailing land use of the area, Cheshire, Norfolk and the Somerset levels where this current study is located, are all mostly rural in nature. In this study it was found that highest densities of ponds were related to an agricultural land use type (improved grassland) which often covers a high percentage of rural areas. Whereas, the more urban county of Birmingham was found to have a pond density of 1.3 k m^{-2} (Thornhill *et al.*, 2017), which is much closer to the national estimate for England. This again shows that regional pond landscapes tend not to be consistent and the land uses of the area will have impacts on pond densities, therefore national densities should not assume the pondscape is similar in nature throughout an area as large as a country.

Pond losses in this study area have also influenced a change in the distance between ponds. In this study on average ponds are now 84.7 m further apart. Increased distance between ponds has found to have negative effects on the species which rely on ponds, such as invertebrates (Delettre and Morvan, 2000), amphibians (Jeliazkov et al., 2013), and plant species (Bosiacka and Pieńkowski, 2012). Isolation between ponds has also been found to effect relationships between species; Shulman and Chase (2007) found that when distances between ponds increased predator:prey ratios were affected. The predator richness within isolated ponds decreased more rapidly than prey richness, thought to be due to their lower population tendencies or being more limited in dispersal than prey. Overall the isolation of ponds led to alterations in the trophic ratios in the ponds (Shulman and Chase, 2007). Therefore, it is not only pond loss that can be detrimental to the wider landscape but also the increasing distance between ponds cutting off vital ecological corridors and pathways.

The historic maps clearly show that there was an increase in pond numbers between 1853 and 1946 followed by a large decrease in the years up to 2021 (Figure 4.1). The pond recovery up to 1946 is most likely due to the increase in food production after the Second World War which led to the expansion of agricultural land (Rackham, 1986). The 1947 Agricultural Act came into effect just after the last historical map used here was produced, this Act drove accelerated food production in the UK. Therefore after the 1946 ponds were mapped the land use would have changed to be more agriculturally dominated which has been linked to a decrease in pond numbers (Smith *et al*, 2022; Sayer *et al.*, 2012; Goodrich *et al.*, 2015).

From the in-field surveys it appears that the pond ecological condition in this area is of a good level. Of the 15 ponds surveyed none were classified as being in poor condition, and only one as being below average (Table 4.1). This is unusual compared to other studies and monitoring programmes. The Countryside Pond Survey (Williams 2007) found that 80% of ponds were of poor or very poor quality. Although there is little up-to-date data on pond condition other than small studies (for example, Alderton *et al.*, 2017; Rosset *et al.*, 2012; Reyne *et al.*, 2020), it is known that as pond isolation increases abiotic features of ponds (i.e. water quality) tend to degrade (Williams *et al.*, 2010). As this study found that distance between ponds increased between 1893 and 2021, it would be thought that the condition of ponds would therefore have decreased but the in-field surveys proved this was not the case. These results may be influenced by the small sample size for the field data collection, with just under 15% of the ponds in the study area surveyed for condition. It is also more likely for landowner permission to be granted to access ‘good’ ponds over ponds of poor condition. Therefore leading to a bias in the sampling of the ponds in this area.

5.2 Accuracy of identifying pond locations

This study demonstrates that pond identification can be achieved by classification of remotely sensed imagery however spatial resolution and the method selected was an important consideration in the accuracy. It was found that this identification is only successful when imagery with a spatial resolution of 1.24 m is used in conjunction with supervised classification using the SCP in QGIS; 69.52% of ponds correctly identified from World View 3 imagery. With imagery of lower resolutions (30 m – 1.8 m) accurate identification of ponds performed considerably less well.

When images were classified to identify ponds using supervised classification it is clear that the higher the spatial resolution the better accuracy of the outputs. However, with automated NDWI classification, it appears that highest spatial resolution is not always best. When exploring the results from the automatic classification of the same images (excepting the Rapid Eye image) it was found that NDWI does correctly identify water bodies, some of which are ponds, in the satellite imagery with a spatial resolution higher than 20 m. The highest accuracy for pond identification for NDWI (28.28%) was from the outputs of the World View 2 (1.8 m spatial resolution) followed by Spot 6 (6 m spatial resolution) with 18.10% accuracy. World View 3 with a spatial resolution of 1.24 m only identified 5 out of 105 ponds, giving an accuracy of 4.76%, the same as the results from Sentinel 2 imagery which has a spatial resolution of 16 times that of World View 3 at 20 m. The raster layer of the NDWI output from World View 3 (Figure 4.5) suggests that when using automated classification the highest spatial resolutions may be too fine and pick up too much water content in other areas. Small discrete parcels of water on the land (such as wet vegetation and buildings) were being consistently identified leading to over identification of ponds. This over-analysis means that the user has to put in more effort and post processing to identify where exactly the ponds are. This conflicts with the findings of Soti *et al.*, (2009) who found that NDWI classification of imagery with higher spatial resolutions also produced higher accuracy in pond identification. In their study Quickbird imagery (2.44 m spatial resolution) identified the most ponds and smaller surface areas of water than other images with lower spatial resolutions. Similarly, Watson *et al.*, (2018) found that when comparing satellite imagery in their ability to correctly differentiate ponds from glacial debris NDWI application to Rapid Eye imagery provided the best separation in comparison to Sentinel 2 and Landsat imagery. Rapid Eye has a spatial resolution of 6m which is less than that of the World View 2 which in this study had the highest accuracy. Rapid Eye imagery could not be used in the NDWI classification, as the imagery provided did not have the correct bands to calculate NDWI. This would have been interesting to compare with Spot 6 (spatial resolution of 6m) results. It also had the most consistent relationship between NDWI values and known pixel water content in the ponds (Watson *et al.*, 2018), proposing that imagery with similar spatial resolutions can not only be used to identify ponds but also estimate the water content of said ponds. Although studies may find that higher resolution is better the methods outlined in the present study did use imagery with resolutions lower than the most accurate used in these methods by others. This suggests that although there is an improvement in water body identification accuracy with spatial resolution increase, this is only true to a certain point. Once spatial resolution is smaller than 1.8 m (World View 3) the accuracy deteriorates.

In this study the over-analysis of high resolution NDWI outputs reduces the effectiveness of the process; automated classification should be rapid method that can be quickly performed by the operator but the post-processing required by the over-analysis meant that more effort and time is needed than for supervised classification. However, when using lower spatial resolutions the NDWI automated process was significantly quicker and was accurate in identifying large water bodies, demonstrating its potential use in identification and assessment of large water bodies at a landscape scale. This has been successfully used by others to assess lakes using Landsat 8 imagery (Özelkan, 2020). Though this accuracy of identifying larger water body features was not found for the Landsat 8 imagery in this study, the river running through the study area was not identified by the NDWI classification (Figure 4.5). This river covers a total of 150,782 m^2 of the study area, which is much larger than any other body of water in this area. Landsat 8 was the only imagery which did not identify this river, all the others classified this feature as water. Suggesting that for water body identification of any size, imagery with spatial resolutions of a minimum of 20 m is required for accurate identification.

5.3 Factors influencing correct pond identification

There was a strong relationship between land use type and pond identification. The majority of ponds identified by both automated and supervised classifications were within open improved grassland, 54.4% and 70.5% respectively. This is most likely due to the differentiation between water and grassland. When Mishra *et al.,* (2016) conducted a separation analysis, the land use pairs of open vegetation and water and, of agricultural land and water both resulted in the highest differentiation values possible. Therefore this relationship between improved grassland and pond identification is expected. This association was stronger in the supervised classification 70.5% of the ponds identified across all supervised classifications were within improved grassland land usage, compared to 54.4% ponds identified across all NDWI outputs. A rural pond tends to be surrounded by land which is not deemed as urban. In the UK these land uses would typically be open grassland, crops or woodland as shown by this data ponds are more likely to be identified if in these rural land uses when classifying remotely sensed images using supervised classification. This suggests that for rural pond identification supervised classification is an appropriate method to use.

A clear issue with both classification methods was the misidentification of buildings as water. This was more common in the NDWI classification and in the supervised classification of the lower spatial resolution images. This is a problem that has been identified previously in the literature; Yang *et al.* (2017) explored the use of NDWI to identify ponds in urban and coastal areas of China and found that pond identification was higher in the less urban coastal areas due to the interference of buildings. This issue is based on limitation to adaption in a complicated background (Ding *et al.,* 2016); in regions where there are multiple features which have similar reflectance to water the ability of the NDWI to only identify water can diminish. From the outputs here this also seems to be an issue with solar panels. These misidentifications resulted in an increased time spent post processing the images to separate if what was identified was a pond or not. This again limits its use in pond identification as ponds will only be accurately and efficiently mapped in more rural areas with similar land uses to that of the study area in this project.

A potential link between the likelihood that a pond is identified and its ecological condition was identified; with those field ponds identified as having excellent or good condition consistently identified (Table 4.5). The one pond which was ranked as 'below average' was consistently not identified by classification of any imagery. This points to a relationship between the ecological condition of a pond and identification via remote sensing classification, although due to the small number of ponds surveyed in-field this relationship is speculative.

This could mean that if using a similar classification process to map ponds at a large scale there may be a bias of identification towards ponds which have good ecological condition. For example, water which has high turbidity will be less likely to be picked up in remote sensing classification, especially when using NDWI as turbid water has maximum reflectance in the mid-infrared band rather than the infrared band used in the index (Sun *et al.,* 2012). This led others such as Sun *et al.*, (2012) to use an integrated method to consider diversity of waterbodies.

There could also be a link between the amount of vegetation covering the surface and the likelihood of identification in classification. The more vegetation the less open surface water available for the classification to identify. This relationship was not found in this study, but this could have been due to dates the images were captured. The time of year which remote sensing imagery is captured has been found to impact accuracy of identification of features, largely due to seasonal variation in vegetation (Bradter *et al.*, 2020; Senf *et al.*, 2015). None of the images were captured on the same date, these dates span almost seven months which would mean that the seasonal differences in vegetation patterns could cause interference in this relationship. Although this relationship was not found in the ecological condition data set in this study, this has been found to cause problems in classification by others. It has been found that when using other indices such as NDVI there is confusion between vegetation within and outside of ponds (Lacaux *et al.*, 2007). This suggests that vegetation covering pond surfaces may be commonly identified as non-aquatic vegetation by other land use classification systems, therefore missing the pond in the output.

Within this study only 15 ponds out of the 105 present ponds in the study area were surveyed in the field, this is only 14.3% of the ponds within this landscape. Therefore this is not the best representation of ponds in the area. But if these relationships between pond condition and identifiability are present, it may potentially result in an under estimation of ponds and produce gaps in the network especially in larger areas, which could be important for practitioners as these maps showing 'good' ponds will also show gaps in these pond networks, easily identifying areas which will either have ponds of poor condition or lacking in ponds. This will allow practitioners to focus conservation efforts in these areas of the landscape. This will reduce time spent identifying areas in need of pond restoration or creation, potentially resulting in restoration processes beginning faster. This gap identification could also help ensure that more ponds are not created in areas which are already filled with 'good' ponds and instead focused on the areas which are lacking in ecologically good ponds. Restoration of poor quality ponds is particularly important, management of overgrown ponds has been shown to increase aquatic biodiversity (Sayer *et al.*, 2012). But that a mosaic of ponds with different levels of management favours increased landscape level biodiversity (Sayer *et al.*, 2013). It is now generally recognised that the catchment scale is the appropriate spatial scale of restoration intervention (Bolpagni *et al.*, 2019), therefore mapping techniques such as the ones explored here in this study are necessary for informing catchment scale restoration projects.

There is also a potential relationship between size of ponds and accuracy of identification. The smallest pond identified by either classification method is 10 m^2, this was identified within the World View 2 imagery by NDWI classification. The size of ponds identified by all NDWI classifications was between 10 – 4,837 m^2, and between 62 – 4,837 m^2 from the supervised classification. All ponds larger than 230 m^2 were correctly identified in at least one imagery data set by supervised classification. Subedi and Dev Acharya (2021) however had a minimum pond size of 4,400 m^2 when using NDWI to identify ponds in Nepal, however they did only use Landsat 7 and 8 imagery which has a spatial resolution of 30 m whereas the smallest ponds identified by classification in this study were identified in World View 2 and 3 images which have spatial resolutions of 1.8 and 1.24 m respectively. Soti *et al.* (2009) did find that when applying NDWI to imagery from Quickbird satellite which has a spatial resolution of 2.44 m the smallest pond identified was 70 m^2. This suggests that there is a relationship between size of ponds and identifiability, and that higher spatial resolution of remote sensing imagery is needed to identify smaller ponds within a landscape. Although the NDWI was not highly accurate for ponds it did identify the larger waterbodies in the study area such as the river and canal that runs through the area. Others have also found NDWI to be an accurate tool to identify large waterbodies such as lakes, even with low resolution imagery such as Landsat 8 (Du *et al.*, 2014; Özelkan, 2020) and Sentinel 2 (Yang *et al.*, 2017).

It could be argued that the definition of a pond used here has resulted in a reduction of accuracy by the methods compared in this study due to the 2 ha size constraint. This size constraint excludes larger bodies of water from the outputs of the classification techniques. Although recent research advises that a larger surface area of up to 5 ha in surface area should be used and to take depth into consideration (Richardson *et al.*, 2022), the results from this study would have not differed significantly. The size definition used here is one that has also been widely used for many years (Pond Action, 1995; Boothby, 1999; Jeremy Biggs *et al.*, 2005) and before new research had been published this definition is the one most studies would apply. In the study area there are 105 ponds which fit into the definition of 1 m^2 – 2 ha in area and no standing water bodies which were too large to be classed as ponds. In addition it is known that in GB standing water bodies smaller than 2 ha in area are the most numerous (Bailey-Watts *et al.*, 2000), this study area demonstrates that. Therefore it can be argued that these size of pond are critical to include when landscape level ecology is discussed, and understanding if these types of waterbodies can be mapped more rapidly is arguably just as important as mapping the larger water bodies. Therefore the definition used in this study based solely on size of 1 m^2 to 2 ha in area is suitable for the aims of the project and the area in which remote sensing is being tested.

5.4 Efficiency considerations

Although the NDWI was quick and efficient to perform, the analysis of the output was not; it was quicker than manual mapping for the lower resolution images but these provided low accuracy results. The high resolution images such as the World View series decreased the efficiency of the process due to the number of features identified as water by the classification it took a long time to separate which features identified as water were actually ponds. For example the NDWI classification of the Spot 6 imagery identified 737 features as water, out of these 26 were pond features but as some of these ponds had been identified as multiple smaller ponds it actually only correctly identified a total of 19 ponds. The World View 2 and 3 supervised outputs identified even more features of which only 28 and five, respectively, were ponds; considerably increasing the time taken for this post-processing and reducing the overall efficiency of the technique. However, this was partially down to the issue of vectorisation which could not be applied to the supervised classification outputs from World View 2 and World View 3. Often the data generated by remote sensing can exceed the capacity of GIS systems to handle such data (Lillesand *et al.,* 2005), this became an issue during the attempt to vectorise the World View series imagery. The classification of these images produced a large number of features identified, requiring higher processing power to convert to vectors than was accessible. Due to the lack of vectorisation the output raster of the supervised classification had to be manually checked to obtain if the features identified were ponds.

For the size of the study area in this project the time and effort spent on identifying ponds manually compared to using supervised classification of remote imagery was comparable, however over a larger area the use of classification would most likely reduce the time spent on pond identification. Both of these methods of pond identification still take considerably less time and effort than in-field surveys. It took only a few hours per sensor to do each of the individual manual and remote sensing classification pond mapping to identify a max of 105 ponds, whereas the field surveying of 15 ponds took a number of days. This shows that digital mapping of ponds is a more time effective in pond identification across a large landscape.

5.5 Ranking system

From the accuracy results and addition of factors which may affect users choosing the imagery, such as cost and temporal resolution, a ranking system was constructed (Table 4.5). This showed that the supervised classification of the World View 3 imagery was the best choice, closely followed by the World View 2 imagery. Cost is a key consideration (see Section 2.4.2) but even with the weighting for the high cost of the World View imagery both images were ranked in first and second place. This is due to their high accuracy and fast temporal resolution. A high temporal resolution ensures that the chances to get an image of a specific place on a specific date is higher, this is important when monitoring over longer timescales.

Although it has been found here and by others (Watson *et al.*, 2018; Soti *et al.*, 2009) that imagery with higher spatial resolutions result in higher feature identification accuracy there are limitations of using these images. One issue with needing a higher resolution is that the cost of the resources will be greater. Often images with high spatial resolution are not freely available and so have to be purchased at a price per km^2 and often have a minimum purchase area. The imagery which had the most successful classification in this study was World View 3, this was the most expensive imagery to purchase at 21.75 USD per km^2 with a minimum purchase of 25 km^2. The ability to purchase this imagery for large areas will be constrained by budget and the study area, meaning that some projects will not be able to use the best imagery to achieve their objectives. However this cost should be considered in regards to the alternative costs for other methods available. For example if the best alternative method is in-field surveys the cost of hiring surveyors this could be just as expensive as remote sensing imagery. This also reduced the availability to practitioners and landowners who want to map the ponds on their land or in areas where conservation interventions are to be achieved. This therefore has been considered in the ranking of satellite imagery.

This system did allow for the best method to be identified, however it could be improved upon. If the same method of comparing supervised classification outputs of different spatial resolution imagery is conducted over a larger area, it would provide more data and give a more robust analysis of comparison of accuracy between high resolution imagery. This study has shown that satellite imagery with spatial resolutions below 5 m are not suitable for identification of rural ponds, therefore these imagery need not be tested over a larger area, allowing for less time spent on the post-processing stage as there would be fewer outputs to go through; thus enabling a larger area to be studied in a similar time frame. However, a larger area for testing would bring in more factors that could potentially reduce the ability for direct comparison. As found in this study, land use can affect the identification of ponds, this would likely be more pronounced in larger areas due to a greater number of land use types, and could potentially affect the accuracy of classification. However the larger area will produce more data which would allow for statistical analysis which could not be done in this study to further strengthen the ranking system.

6. CONCLUSION

6.1 Objectives

This project aimed to find a rapid method for identifying ponds using remotely sensed imagery by comparing automated NDWI and semi-automated supervised classification methods performed on satellite images of different spatial resolutions. This research also originally had four main objectives:

1. To identify the current approaches and resources that could be used to locate and assess ponds/small waterbodies.

The literature review presented in this study provides an overview of a large range of approaches used by others to locate and assess water bodies. Positives and negatives of remote sensing are also discussed to give a full description of remote sensing techniques. From this review it was determined that $NDWI_2$ and supervised classification were the most appropriate methods to trial. It also highlighted that accuracy assessment is important to fully evaluate remote sensing outputs to fully understand which method is superior in identifying waterbodies.

2. To determine the location, density, decline and ecological condition of ponds in the study area.

This objective was met via the use of non-remote sensing methods. Manual mapping using GIS was applied to the study area and found that although there was a temporary increase in pond numbers between 1853 and 1946, there has been a significant reduction in the number of ponds in the study area from 1946 to 2021. This has negatively impacted the density of ponds, as well as increasing the distance between ponds over this time frame. Ecological condition was assessed by carrying out in-field surveys, creating a condition classification system from the data collected. This showed that the ponds surveyed were mostly of good ecological condition. Implementing these methods provided data for verification of the remote sensing classification methods.

3. To compare the accuracy of remote sensing classification methods for pond detection for different spatial resolutions of satellite imagery.

Using the manual mapping data each pond identified by both the automated NDWI and semi-automated supervised classification of six satellite sensors of different spatial resolution was verified. This resulted in accuracy percentages for each method which allowed for the best methods to be quickly identified and subsequently a ranking order to be constructed. It was found that higher spatial resolutions had higher accuracy percentages, and that automated classification and supervised classification with lower resolutions are not highly accurate in identifying ponds. The best accuracies came from supervised classification of World View 3 imagery (72.4%) and the worst was NDWI classification of Landsat 8 imagery (0.95%).

4. To evaluate the factors which reduce the identifiability of ponds during classification of remote sensing imagery.

Factors such as land usage and pond ecological condition were explored to find any relationships between these variables and the identifiablility of ponds. It was found that in areas of improved grassland ponds are more frequently identified by both automated and supervised classification. There is also a potential link between ecological condition of ponds and identifiability, however this link needs to be examined further with a larger dataset. Temporal resolution and cost are also important in deciding on an appropriate remote sensor, these were therefore included in the ranking system to evaluate the most suitable satellite sensor and remote sensing procedure. Supervised classification of World View 3 imagery came out as the top ranking method and sensor.

Within this study area it was found that the net decline of ponds since 1853 was 58%. This has led to decreasing pond density and increasing pond isolation. To allow for more frequent and rapid mapping of an area like this one remote sensing images were compared and have been found to be applicable to the identification of ponds. The accuracy of pond identification is dependent of the spatial resolution of the images, and it was found that the best method was supervised classification of World View 3 imagery. The method proposed here can be used by practitioners to identify pond networks which are composed of ponds of ‘good’ ecological conditions allowing the rapid identification of areas which either lack ponds or only have ponds which are poor in ecological condition. This can therefore be used as a rapid way to identify areas which pond conservation efforts should be concentrated within.

6.2 Future work

To expand on the relationships found here between pond identification and pond characteristics the methods employed could be repeated over a wider range of pond conditions and land use types. In this study a relationship between land use and pond loss could not be fully established due to the lack of variability in the 2021 land use, but a larger area with more land use heterogeneity would allow for such a relationship to be confirmed. Additionally, in this study no ponds were classified as poor and only one was found to be excellent (Figure 4.4), whereas in a larger area there will be higher pond variability to ascertain which factors influence the likelihood of pond identification. This knowledge could then be used to further refine methods of pond identification via remote sensing to ensure that all ponds of different sizes and in different land uses are identified. A larger area would allow for statistical testing to find a significant relationship between pond identification and land use; if the habitat differences in ponds identified are significantly different from the expected proportions of habitat occurrence in the landscape. Repeating the methodology used here, including the manual mapping and in-field surveys whilst recording the time taken on each method used would also provide a quantification for the efficiency of each method. This would further strengthen the ranking system and ensure future users have an understanding of time allocation for these methods.

Methods similar to the ones explored here have been used to assess the ecological condition of larger waterbodies such as lakes and rivers (Chebud *et al.,* 2012), which indicates that this could be done for ponds too if terrestrial vegetation cover such as tree overhang does not obscure ponds in the imagery. To reduce the amount of vegetation cover obscuring the water the imagery chosen should have been captured in later autumn and winter so that leaf cover is lower. All images used in this study were captured during late autumn, winter and early spring for this purpose of reducing influence of vegetation. However, this exclusive use of images in this seasonal time frame could pose a problem as often parameters of ecological quality of a pond are impacted by the seasons. Seasonal variation in precipitation, surface run off and water temperature can strongly influence aspects that influence the ecological quality of a pond (Dar, Pandit and Ganai, 2014; Kalengo *et al.*, 2021). Therefore expanding the research to include multiple points during a year could give a better indication of the potential of remote sensing in pond classification. However, accessibility of cloud free images is a major constraint for this in temperate regions for the UK, i.e. for this study only two cloud-free World View 3 images were available over the entire year for the area under investigation. A ranking system similar to the one produced here but with the added factor of accuracy on different land uses would be helpful in the future. This study has shown that spatial resolutions and classification methods perform best in different land use types. Pond identification techniques could be compared to find the best for land use types most often mapped for ponds such as urban, sub-urban and agricultural areas. This would then allow practitioners and land owners to choose the best methods for the area they are studying. This would also be most helpful when aiming to classify an area which incorporated multiple major land uses as the operator could split the area by major land use types and classify each area by a different method according to the ranking. If this were to work at catchment level then it could be assumed that this would work at a national level to give the most accurate data as variation in identification over different land uses would be taken into consideration rather than applying one method to the whole area which would potentially have biases in certain land use types.

REFERENCE LIST

Alderton, E. (2017) “Ghost ponds”: Resurrecting lost ponds and species to assist aquatic biodiversity conservation, Doctoral thesis. UCL (University College London).

Anderson, K. and Gaston, K. J. (2013) Lightweight unmanned aerial vehicles will revolutionize spatial ecology, Frontiers in Ecology and the Environment, 11(3), pp. 138–146. doi: 10.1890/120150.

Apollo mapping (2022) PLÉIADES 1 SATELLITE. Available at: https://apollomapping.com/pleiades-1-satellite-imagery (Accessed: 28 July 2022)

Aroma, R. J. and Raimond, K. (2018) A novel two-tier paradigm for labelling water bodies in supervised satellite image classification, Proceedings of IEEE International Conference on Signal Processing and Communication, ICSPC 2017, pp. 384–388. doi: 10.1109/CSPC.2017.8305875.

Ayanu, Y. Z., Nauss, T. and Wegmann, M. (2012) Quantifying and Mapping Ecosystem Services Supplies and Demands: A Review of Remote Sensing Applications, Environmental science and technology, 46, pp. 8529–8541. doi: 10.1021/es300157u.

Bailey-Watts, T., Lyle, A., Battarbee, R., Harriman, R. and Biggs, J. (2000) Lakes and Ponds, in Acreman, M. (Ed.) *The hydrology of the UK: A study of change*, 1st edn. pp. 180–202.

Barr, C. J., Bunce, R G H., Clarke, R.T., Firbank, L G., Gillespie, M K., Howard, D C., Petit, S., Smart, S M., Stuart, R C. and Watkins, J.W. (2003) Methodology of Countryside Survey 2000 Module 1 : Survey of Broad Habitats and Landscape Features (Final Report).

van Beijma, S., Chatterton, J., Page, S., Rawlings, C., Tiffin, R. and King, H.(2018) The challenges of using satellite data sets to assess historical land use change and associated greenhouse gas emissions: a case study of three Indonesian provinces, Carbon Management, 9(4), pp. 399–413.

Biggs, J., Williams, P., Whitfield, M., Nicolet, P. and Weatherby, A. (2005) 15 Years of pond assessment in Britain: Results and lessons learned from the work of Pond Conservation, Aquatic Conservation: Marine and Freshwater Ecosystems, 15(6), pp. 693–714. doi: 10.1002/aqc.745.

Biggs, J., von Fumetti, S. and Kelly-Quinn, M. (2017) The importance of small waterbodies for biodiversity and ecosystem services: implications for policy makers, Hydrobiologia. Springer International Publishing, pp. 3–39. doi: 10.1007/s10750-016-3007-0.

Bolpagni, R., Poikane, S., Laini, A., Bagella, S., Bartoli, M. and Cantonati, M. (2019) Ecological and conservation value of small standing-water ecosystems: A systematic review of current knowledge and future challenges, Water (Switzerland), 11(3). doi: 10.3390/w11030402.

Bonn, A. and Gaston, K. J. (2005) Capturing biodiversity: Selecting priority areas for conservation using different criteria, Biodiversity and Conservation, 14(5), pp. 1083–1100. doi: 10.1007/s10531-004-8410-6.

Boothby, J. (1999) Framing a strategy for pond landscape conservation: aims, objectives and issues, Landscape Research, 24(1). doi: 10.1080/01426399908706551.

Boothby, J. and Hull, A. P. (1997) A census of ponds in Cheshire, North West England, Aquatic Conservation: Marine and Freshwater Ecosystems, 7(1), pp. 75–79. doi: 10.1002/(SICI)1099-0755(199703)7:1<75::AID-AQC215>3.0.CO;2-7.

Boothby, J., Hull, A. P. and Jefferys, D. A. (1995) Sustaining a Threatened Landscape: Farmland Ponds in Cheshire, Journal of Environmental Planning and Management, 38(4), pp. 561–568. doi: 10.1080/09640569512823.

Bosiacka, B. and Pieńkowski, P. (2012) Do biogeographic parameters matter? Plant species richness and distribution of macrophytes in relation to area and isolation of ponds in NW Polish agricultural landscape, Hydrobiologia, 689, pp. 79–90. doi: 10.1007/s10750-011-0850-x.

Bradter, U., O'Connell, J., Kunin, W.E., Boffey, C.W., Ellis, R.J. and Benton, T.G., 2020. Classifying grass-dominated habitats from remotely sensed data: The influence of spectral resolution, acquisition time and the vegetation classification system on accuracy and thematic resolution. Science of the Total Environment, 711, p.134584. doi: 10.1016/j.scitotenv.2019.134584Bühler, Y., Hüni, A., Christen, M., Meister, R. and Kellenberger, T. (2009) Automated detection and mapping of avalanche deposits using airborne optical remote sensing data, Cold Regions Science and Technology, 57(2), pp. 99–106.

Bull, J. W., Gordon, A., Law, E. A., Suttle, K. B. and Milner-Gulland, E. J. (2014) Importance of baseline specification in evaluating conservation interventions and achieving no net loss of biodiversity, Conservation Biology, 28(3), pp. 799–809. doi: 10.1111/cobi.12243.

Buters, T. M., Gordon, A., Law, E. A., Suttle, K. B. and Milner-Gulland, E. J. (2019) Methodological ambiguity and inconsistency constrain unmanned aerial vehicles as a silver bullet for monitoring ecological restoration, Remote Sensing, 11(10), pp. 1–16. doi: 10.3390/rs11101180.

Campbell, J. B. and Wynne, R. H. (2011) Introduction to Remote Sensing. 5th edn. New York: The Guilford Press.

Céréghino, R., Biggs, J., Oertli, B. and Declerck, S. (2007) The ecology of European ponds: defining the characteristics of a neglected freshwater habitat, Hydrobiologia, 597, pp. 1–6. doi: 10.1007/s10750-007-9225-8.

Chebud, Y., Naja, G. M., Rivero, R. G. and Melesse, A. M. (2012) Water quality monitoring using remote sensing and an artificial neural network, Water, Air, and Soil Pollution, 223(8), pp. 4875–4887. doi: 10.1007/s11270-012-1243-0.

Choffel, Q. Touchart, L., Bartout, P. and Al Domany, M. (2016) Temporal and spatial variations in heat content of a French pond, Geographica Technica, 11(2), pp. 39–50. doi: 10.21163/GT.

Chopyk, J., Allard, S., Nasko, D. J., Bui, A., Mongodin, E. F. and Sapkota, A. R. (2018) Agricultural freshwater pond supports diverse and dynamic bacterial and viral populations, Frontiers in Microbiology, 9, pp. 1–14. doi: 10.3389/fmicb.2018.00792.

Choubin, B., Soleimani, F., Pirnia, A., Sajedi-Hosseini, F., Alilou, H., Rahmati, O., Melesse, A. M., Singh, Vijay. P. and Shahabi, H. (2019) Effects of drought on vegetative cover changes: Investigating spatiotemporal patterns, Extreme Hydrology and Climate Variability, pp. 213–222.

Clandillon, S., Fraipont, P. and Yesou, H. (1995) Assessment of the future SPOT 4 MIR for wetland monitoring and soil moisture analysis: simulation over the Ried Center Alsace (France), Remote Sensing for Agriculture, Forestry, and Natural Resources, 2585, pp. 102-111.

Clauzel, C., Bannwarth, C. and Foltete, J. C. (2015) Integrating regional-scale connectivity in habitat restoration: An application for amphibian conservation in eastern France, Journal for Nature Conservation, 23, pp. 98–107. doi: 10.1016/j.jnc.2014.07.001.

Comber, A., Fisher, P., Brunsdon, C. and Khmag, A. (2010) Spatial analysis of remote sensing image classification accuracy Alexis, Remote Sensing of Environment, 127, pp. 237–246.

Congalton, R. G. (1991) A review of assessing the accuracy of classifications of remotely sensed data, Remote Sensing of Environment, 37(1), pp. 35–46. doi: 10.1016/0034-4257(91)90048-B.

Congedo, L. (2021) Semi-Automatic Classification Plugin: A Python tool for the download and processing of remote sensing images in QGIS, Journal of Open Source Software, 6(64), p. 3172. doi: 10.21105/joss.03172.

Cracknell, A. P. (2007) Introduction to Remote Sensing. 2nd edn. Boca Raton: CRC Press.

Curado, N., Hartel, T. and Arntzen, J. W. (2011) Amphibian pond loss as a function of landscape change-A case study over three decades in an agricultural area of northern France, Biological Conservation, 144, pp. 1610–1618. doi: 10.1016/j.biocon.2011.02.011.

Dar, N. A., Pandit, A. K. and Ganai, B. A. (2014) Factors affecting the distribution patterns of aquatic macrophytes, Limnological Review, 14(2), pp. 75–81. doi: 10.2478/limre-2014-0008.

Davies, B., Biggs, J., Williams, P. J., Lee, J. T. and Thompson, S. (2008) Comparative biodiversity of aquatic habitats in the European agricultural landscape, Agriculture, Ecosystems & Environment, 125, pp. 1–8. doi: 10.1016/j.agee.2007.10.006.

DEFRA (2021) Environmental Land Management schemes: overview. Available at: https://www.gov.uk/government/publications/environmental-land-management-schemes-overview/environmental-land-management-scheme-overview (Accessed 21 December 2022)

Delettre, Y. R. and Morvan, N. (2000) Dispersal of adult aquatic Chironomidae (Diptera) in agricultural landscapes, Freshwater Biology, 44(3), pp. 399–411. doi: 10.1046/j.1365-2427.2000.00578.x.

Ding, Z., Qi, N., Dong, F., Jinhui, L., Wei, Y. and Shenggui, Y. (2-16) Application of multispectral remote sensing technology in surface water body extraction, International Conference on Audio, Language and Image Processing (ICALIP), pp. 141-144, doi: 10.1109/ICALIP.2016.7846565.

Downing, J. A., Cole, J. J., Middelburg, J. J., Striegl, R. G., Duarte, C. M., Kortelainen, P.,

Prairie, Y. T. and Laube, K. A. (2008) Sediment organic carbon burial in agriculturally eutrophic impoundments over the last century, Global Biogeochemical Cycles, 22(1), p. n/an/a. doi: 10.1029/2006GB002854.

Du, Z., Li, W., Xhou, D., Tian, L., Ling, F. and Wang, H. (2014) Analysis of Landsat-8 OLI imagery for land surface water mapping, Remote sensing letters, 5(7), pp. 672–681. doi: 10.1080/2150704X.2014.960606.

Duda, T. and Canty, M. (2002) Unsupervised classification of satellite imagery: Choosing a good algorithm, International Journal of Remote Sensing, 23(11), pp. 2193–2212. doi: 10.1080/01431160110078467.

Duffy, J., Anderson, K., Shapiro, A., Avino, F. S., Debell, L. and Glover, P. (2020) Drone technologies for conservation, WWF Conservation Technology Series. Available at: www.paneemadesign.com (Accessed: 15 December 2020).

Duran, Z., Musaoglu, N. and SEKER, D. (2006) Evaluating urban land use change in historical peninsula, Istanbul, by using GIS and remote sensing, Fresenius Environmental Bulletin, 15(8), pp. 806–810.

Earth Imaging Journal (2013) Exploring the benefits of active vs. passive spaceborne systems. Available at: https://eijournal.com/print/articles/exploring-the-benefits-of-active-vs-passive-spaceborne-systems (Accessed: 18 July 2022).

Eberhardt, I. D. R., Schultz, B., Rizzi, R., Sanches, I. D. A., Formaggio, A. R., Atzberger, C., Mello, M. P., Immitzer, M., Trabaquini, K., Foschiera, W. and Luiz, A. J. B. (2016) Cloud cover assessment for operational crop monitoring systems in tropical areas, Remote Sensing, 8(3), pp. 1–14. doi: 10.3390/rs8030219.

EDINA (2021) Digimap Service. Available at: http://edina.ac.uk/digimap (Accessed 8 September 2021).

Edwards, N., Hooper, P., Trapp, G. S.A., Bull, F., Boruff, B. and Giles-Corti, B. (2013) Development of a Public Open Space Desktop Auditing Tool (POSDAT): A remote sensing approach, Applied Geography, 38(1), pp. 22–30. doi: 10.1016/j.apgeog.2012.11.010.

Eken, G., Bennun, L. and Boyd, C. (2004) Protected areas design and systems planning: key requirements for successful planning, site selection and establishment of protected areas, in *Biodiversity Issues for Consideration in the Planning, Establishment and Management of Protected Area Sites and Networks*. Montreal SCBD, pp. 37–44.

Enderle, D. I. and Weih Jr, R. C. (2005) Integrating Supervised and Unsupervised Classification Methods to Develop a More Accurate Land Cover Classification, Journal of the Arkansas Academy of Science. 59(10), pp. 65-73.

Environment Agency and Pond Action (2002) A guide to monitoring the ecological quality of ponds and canals using PSYM. Peterborough, UK.

ESA, (2022) Sentinel 2 User Guide. Available at: https://sentinels.copernicus.eu/web/sentinel/home (Accessed 13 July 2022)

Fehlinger, L., Misteli, B., Morant, D., Juvigny-khenafou, N., Cunillera-montcusí, D., Chaguaceda, F., Stamenković, O., Kolář, V., Halabowski, D. and Nash, L. N. (2022) The ecological role of permanent ponds in Europe : a review of dietary linkages to terrestrial ecosystems via emerging insects, Inland Waters, pp. 1–47. doi:

10.1080/20442041.2022.2111180.

Foody, G. M., McCulloch, M. B. and Yates, W. B. (1995) Classification of remotely sensed data by an artificial neural network: issues related to training data characteristics, Photogrammetric Engineering & Remote Sensing, 61(4), pp. 391–401.

Freshwater Habitats Trust (2015) Pond Habitat Survey Method Booklet. Freshwater Habitats Trust. Oxford, UK. Available at: www.freshwaterhabitats.org.uk/projects/waternet (Accessed: 15 April 2021).

Gao, B-C. (1996) NDWI - A Normalized Difference Water Index for Remote Sensing of Vegetation Liquid Water From Space, Remote Sensing of Environment, 58(3), pp. 257–266. doi: 10.1080/00220973.1955.11010524.

Gledhill, D, and James, P (2012) Socio-economic variables as indicators of pond conservation value in an urban landscape, Urban Ecosystems, 15(4), pp. 849-861.doi: 10.1007/s11252-012-0242-7

Goodrich, S., Goldsmith, B., Sayer, C., Alderton, E. and Kernan, M. (2015) Inventory of ponds in the Norfolk Coast AONB-recommendations for pond survey and conservation. ECRC Research Report Number 166.

Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D. and Moore, R (2017) Google Earth Engine: Planetary-scale geospatial analysis for everyone, Remote Sensing of Environment, 202, pp. 18-27. doi: 10.1016/j.rse.2017.06.031.

Goward, S., Arvidson, T., Williams, D., Faundeen, J., Irons, J. and Franks, S (2013) Historical record of Landsat global coverage. Photogrammetric Engineering & Remote Sensing, 72(10), 1155-1169. doi: 10.14358/PERS.72.10.1155.

Gratton, C., Donaldson, J. and Zanden, M. J. V. (2008) Ecosystem linkages between lakes and the surrounding terrestrial landscape in northeast Iceland, Ecosystems, 11(5), pp. 764–774. doi: 10.1007/s10021-008-9158-8.

Gratton, C. and Vander Zanden, M. J. (2009) Flux of aquatic insect productivity to land: comparison, Ecology, 90(10), pp. 2689–2699. doi: 10.1890/08-1546.1.

Haines-Young, Barr, Black, Briggs, Bunce, Clarke, Cooper, Dawson, Firbank and Fuller (2000) Assessing Habitats in the UK Countryside. Executive Summary.

Hart, J. (2019) Blue Space: How Being Near Water Benefits Health, Alternative and Complimentary Therapies, 25(4), pp. 208–210. doi: 10.1089/ACT.2019.29228.JHA.

Hasmadi, M., Pakhriazad, H. and Shahrin, M. (2009) Evaluating supervised and unsupervised techniques for land cover mapping using remote sensing data. Malaysian Journal of Society and Space, 5 (1). pp. 1-10. ISSN 2180-2491.

Heywood DI, Cornelius SJ, Carver SJ (2011) *An Introduction to Geographical Information Systems* (4^{th} Edn). Pearson Prentice Hall: London.

Hill, M. J., Biggs, J., Thornhill, I., Briers, R. A., Gledhill, D. G., White, J. C., Wood, P. J. and Hassall, C. (2016) Urban ponds as an aquatic biodiversity resource in modified landscapes, Global Change Biology, 23(3), pp. 986–999. doi: 10.1111/gcb.13401.

Hill, M. J., Hassall, C., Oertli, B., Fahrig, L., Robson, B. J., Biggs, J., Samways, M.J., Usio, N., Takamura, N., Krishnaswamy, J. and Wood, P. J. (2017) Urban ponds as an aquatic biodiversity resource in modified landscapes, Global Change Biology, 23(3), pp. 986–999. doi: 10.1111/gcb.13401.

Hill, M. J., Greaves, H. M, Sayer, C. D., Hassall, C., Milin, M., Milner, V. S., Marazzi, L., Hall, R., Harper, L. R., Thornhill, I., Walton, R., Biggs. J., Ewald, N., Law, A., Willby, N., White, J., Briers, R. A, Mathers, K. L., Jeffries, M. J. and Wood, P. J. (2021) Pond ecology and conservation: research priorities and knowledge gaps, Freshwater Ecology, 12(12), e03853

Hodgson, A., Peel, D. and Kelly, N. (2017) Unmanned aerial vehicles for surveying marine fauna: Assessing detection probability, Ecological Applications, 27(4), pp. 1253–1267. doi: 10.1002/eap.1519.

Hull, A. P. (1997) The pond life project: a model for conservation and sustainability., in Boothby, J. (ed.) *British Pond Landscape, Proceedings from the UK conference of the Pond Life Project*. Liverpool, pp. 101–109.

Hunter, M. L., Acuña, V., Bauer, D. M., Bell, K. P., Calhoun, A. J. K., Felipe-Lucia, M. R., Fitzsimons, J. A., González, E., Kinnison, M. and Lindenmayer, D. (2017) Conserving small natural features with large ecological roles: A synthetic overview, Biological Conservation, 211, pp. 88–95. doi: 10.1016/j.biocon.2016.12.020.

IPBES. 2018. The IPBES regional assessment report on biodiversity and ecosystem services for Europe and Central Asia. Pages 892 in M. Rounsevell, M. Fischer, A. Torre-Marin Rando, and A. Mader, Ed. Secretariat of the IntergovernmentalScience-Policy Platform on Biodiversity and Ecosystem Services, Bonn, Germany.

Jeffries, M. (2005) Small ponds and big landscapes: The challenge of invertebrate spatial and temporal dynamics for European pond conservation, Aquatic Conservation: Marine and Freshwater Ecosystems, 15(6), pp. 541–547. doi: 10.1002/aqc.753.

Jeffries, M. J. (2010) Ponds and the importance of their history: an audit of pond numbers, turnover and the relationship between the origins of ponds and their contemporary plant communities in south-east Northumberland, UK, Hydrobiologia, 689(1), pp. 11–21. doi: 10.1007/s10750-011-0678-4.

Jeliazkov, A., Chiron, F., Garnier, J. A., Besnard, A., Silvestre, M. and Jiguet, F. (2013) Level-dependence of the relationships between Amphibian biodiversity and environment in pond systems within an intensive agricultural landscape, Hydrobiologia, 723, pp. 7–23. doi: 10.1007/s10750-013-1503-z.

Kadlec, R. H. and Wallace, S. (2008) *Treatment Wetlands*. 2nd edn. Boca Raton, Florida: CRC Press.

Kafy, A. A. and Ferdous, L. (2018) Pond filling locations identification using Landsat-8 images in Comoilla district, Bangladesh. Available at: www.cuet.ac.bd (Accessed: 10 December 2020).

Kairu, E. N. (1982) An introduction to remote sensing, GeoJournal, 6(3), pp. 251–260. doi: 10.1007/BF00210657.

Kalengo, L., Ge, H., Liu, N. and Wang, Z. (2021) The Efficiency of Aquatic Macrophytes on the Nitrogen and Phosphorous Uptake from Pond Effluents in Different Seasons, Journal of Ecological Engineering, 22(8), pp. 75–85. doi: 10.12911/22998993/140308.

Khorram, S., Koch, F. H., van der Wiele, C. F. and Nelson, S. A. C. (2021) *Remote Sensing*. Springer Science & Business Media.

Kumar, L. and Mutanga, O (2018) Google Earth Engine Applications Since Inception: Usage, Trends, and Potential, Remote Sensing, 10(10), pp. 1509. doi: 10.3390/rs10101509

Lacaux, J. P., Tourre, Y. M., Vignolles, C., Ndione, J. A. and Lafaye, M. (2007) Classification of ponds from high-spatial resolution remote sensing: Application to Rift Valley Fever epidemics in Senegal, Remote Sensing of Environment, 106(1), pp. 66–74. doi: 10.1016/j.rse.2006.07.012.

LaRue, M. A., Ainley. D. G., Pennycook, J., Stamatiou, K., Salas, L., Nur, N., Stammerjon, A. and Barrington, L. (2019) Remote Sensing in Ecology and Conservation, 6(1), pp. 70-78. doi: 10.1002/rse2.124.

Lee, T-M. and Yeh, H-C. (2008) Applying remote sensing techniques to monitor shifting wetland vegetation: A case study of Danshui River estuary mangrove communities, Taiwan, Ecological Engineering, 35, pp. 487–496. doi: 10.1016/j.ecoleng.2008.01.007.

Lewis-Phillips, J., Brooks, S. J., Sayer, C. D., Patmore, I. R., Hilton, G. M. and Harrison, A. (2020) Ponds as insect chimneys: Restoring overgrown farmland ponds benefits birds through elevated productivity of emerging aquatic insects, Biological Conservation, 241. doi: 10.1016/j.biocon.2019.108253.

Li, H., Zhang, L., Shen, H. and Li, P. (2012) A variational gradient-based fusion method for visible and SWIR Imagery, Photogrammetric Engineering and Remote Sensing, 78(9), pp. 947–958. doi: 10.14358/PERS.78.9.947.

Li, X., Wang, L., Cheng, Q., Wu, P., Gan, W. and Fang, L. (2019) Cloud removal in remote sensing images using nonnegative matrix factorization and error correction, ISPRS Journal of Photogrammetry and Remote Sensing, 148, pp. 103–113. doi: 10.1016/j.isprsjprs.2018.12.013.

Lillesand, T., Kiefer RW, Chipman J (2015) *Remote sensing and image interpretation* (7th Edn). Wiley: Chichester, UK.

Lyons, M. B., Keith, D. A., Phinn, S. R., Mason, T. J. and Elith, J. (2018) A comparison of resampling methods for remote sensing classification and accuracy assessment, Remote Sensing of Environment, 208, pp. 145–153. doi: 10.1016/j.rse.2018.02.026.

Mahaney, W. M., Wardrop, D. H. and Brooks, R. P. (2004) Impacts of sedimentation and nitrogen enrichment on wetland plant community development, Plant Ecology, 175, pp. 227-243.

Margules, C. R., Pressey, R. L. and Williams, P. H. (2002) Representing biodiversity: Data and procedures for identifying priority areas for conservation, Journal of Biosciences. Indian Academy of Sciences, pp. 309–326. doi: 10.1007/BF02704962.

Marti, J., Bort, J., Slafer, G. A. and Araus, J. L. (2007) Can wheat yield be assessed by early measurements of Normalized Difference Vegetation Index?, Annals of Applied Biology, 150(2), pp. 253–257. doi: 10.1111/j.1744-7348.2007.00126.x.

Maskell, L. C., Norton, L. R., Smart, S. M., Carey, P. D., Murphy, J., Chamberlain, P. M., Wood, C. M., Bunce, R. G. H. and Barr, C. J. (2008) Countryside Survey; Field Mapping Handbook., NERC/Centre for Ecology & Hydrology, pp. 130.

Maund, P. R., Irvine, K. N., Reeves, J., Strong, E., Cromie, R., Dallimer, M. and Davies, Z. G. (2019) Wetlands for Wellbeing: Piloting a Nature-Based Health Intervention for the Management of Anxiety and Depression, International Journal of Environmental Research and Public Health, 16(22). doi: 10.3390/ijerph16224413.

McFeeters, S. K. (1996) The use of the Normalized Difference Water Index (NDWI) in the delineation of open water features, International Journal of Remote Sensing, 17(7), pp. 1425–1432.

De Meester, L., Declerck, S., Stoks, R., Louette, G., Van De Meutter, F., De Bie, T., Michels, E. and Brendonck, L. (2005) Ponds and pools as model systems in conservation biology, ecology and evolutionary biology, Aquatic Conservation: Marine and Freshwater Ecosystems, 15(6), pp. 715–725. doi: 10.1002/aqc.748.

Menetrey, N., Oertli, B. and Lachavanne, J. B. (2011) The CIEPT: A macroinvertebrate-based multimetric index for assessing the ecological quality of Swiss lowland ponds, Ecological Indicators, 11(2), pp. 590–600. doi: 10.1016/j.ecolind.2010.08.005.

Mishra, V.N., Rai, P.K., Kumar, P. and Prasad, R. (2016) Evaluation of land use/land cover classification accuracy using multi-resolution remote sensing images. Forum geografic 15(1) pp. 45-53. doi: 10.5775/fg.2016.137.i

Morton, R. D., Marston, C.G., O'Neil, A.W. and Rowland, C.S. (2021) Land Cover Map 2020 (10m classified pixels, GB), NERC EDS Environmental Information Data Centre. Available at: https://doi.org/10.5285/35c7d0e5-1121-4381-9940-75f7673c98f7 (Accessed: 10 May 2022).

Navalgund, R. R., Jayaraman, V. and Roy, P. S. (2007) Remote sensing applications: An overview, Current Science, 93(12).

New, T. R. (1995) *Introduction to invertebrate conservation biology*. New York: Oxford University Press.

Novikmec, M., Hamerlík, L., Kočický, D., Hrivnák, R., Kochjarová, J., Oťaheľová, H., Paľove-Balang, P. and Svitok, M. (2016) Ponds and their catchments: size relationships and influence of land use across multiple spatial scales, Hydrobiologia, 774(1), pp. 155–166. doi: 10.1007/s10750-015-2514-8.

Nowak, M. M., Dzióbs, K. and Bogawski, P. (2019) Unmanned Aerial Vehicles (UAVs) in environmental biology: A review, European Journal of Ecology, 4(2), pp. 56–74. doi: 10.2478/eje-2018-0012.

Oertli, B., Biggs, J., Cereghino, R., Grillas, P., Joly, P. and Lachavanne, J-B. (2002) Does size matter? The relationship between pond area and biodiversity, Biological Conservation, 104(1), pp. 59–70. doi: 10.1016/S0006-3207(01)00154-9.

Oertli, B., Biggs, J., Cereghino, R., Grillas, P., Joly, P. & Lachavanne, J.B. (2005) Conservation and Monitoring of Pond Biodiversity, Aquatic Conservation: Marine and Freshwater Ecosystems, 15, pp. 535–540. doi: 10.1002/aqc.752.

Oertli, B., Céréghino, R., Hull, A. and Miracle, R. (2009) Pond conservation: from science to practice, Hydrobiologia, 634, pp. 1–9. doi: 10.1007/s10750-009-9891-9.

Olofsson, P., Foody, G. M., Herold, M., Stehman, S. V., Woodcock, C. E. and Wulder, Mi. A. (2014) Good practices for estimating area and assessing accuracy of land change, Remote Sensing of Environment. Elsevier Inc., pp. 42–57. doi: 10.1016/j.rse.2014.02.015.

Ordnance Survey (2021) OS Zoomstack. Available at: https://osdatahub.os.uk/downloads/open/OpenZoomstack (Accessed 6 September 2021)

Ose, K., Corpetti, T. and Demagistri, L. (2016) Multispectral Satellite Image Processing, in Baghhadi, N. and Zribi, M. (eds) *Optical Remote Sensing of Land Surface: Techniques and Methods.* 1st edn. Oxford, UK: ISTE press, pp. 57–124.

Özelkan, E. (2020) Water body detection analysis using NDWI indices derived from landsat-8 OLI, Polish Journal of Environmental Studies, 29(2), pp. 1759–1769. doi: 10.15244/pjoes/110447.

Pajares, G. (2020) Overview and Current Status of Remote Sensing Applications Based on Unmanned Aerial Vehicles (UAVs), Photogrammetric Engineering & Remote Sensing, 81(4). doi: 10.14358/PERS.81.4.281.

Pettorelli, N. (2013) *The Normalised Vegetation In*dex. 1st edn. Oxford, UK: Oxford University Press, pp. 18–29.

Plank, S. (2014) Rapid damage assessment by means of multi-temporal SAR-A comprehensive review and outlook to Sentinel-1, Remote Sensing, 6(6), pp. 4870–4906. doi: 10.3390/rs6064870.

Platt, R. V., Manthos, D. and Amos, J. (2018) Estimating the Creation and Removal Date of Fracking Ponds Using Trend Analysis of Landsat Imagery, Environmental Management, 61(2), pp. 310–320. doi: 10.1007/s00267-017-0983-4.

Pond Conservation Group, 1993. *A Future for Britain's Ponds: An Agenda for Action*. Pond Conservation Group.

Rackham, O. (1986) The Countryside: History & Pseudo-History. London: Phoenix Press.

Rahman, M. T. (2013) Applications of Active Remote Sensing Technologies for Natural Disaster Damage Assessments, in Santra, A., & Mitra, S. S. (Eds.) *Remote Sensing Techniques and GIS Applications in Earth and Environmental Studies.* IGI Global.

Reusing, M. (2000) Change detection of natural high forests in Ethiopia using remote sensing and GIS techniques, International Archives of Photogrammetry and Remote Sensing, 33, pp. 1253-1258.

Revollo, S. G. N, Cipolletti, M. P., Perillo, M. M., Delrieux, C. A. and Perillo, G. M. E. (2016) Methodology for classification of geographical features with remote sensing images: Application to tidal flats, Geomorphology, 257, pp. 10–22. doi: 10.1016/j.geomorph.2015.12.020.

Reyne, M., Nolan, M., McGuiggan, H., Aubry, A., Emmerson, M., Marnell, F. and Reid, N., 2021. Artificial agri-environment scheme ponds do not replicate natural environments despite higher aquatic and terrestrial invertebrate richness and abundance. Journal of Applied Ecology, 58(2), pp.304-315. doi: 10.1111/1365-2664.13738.

Richardson, D. C., Holgerson, M. A., Farragher, M. J., Hoffman, K. K., King, K. B.S., Alfonso, M. B., Andersen, M. R., Cheruveil, K. S. and Coleman, K.A. (2022) A functional definition to distinguish ponds from lakes and wetlands, Scientific Reports, 12(1), pp. 1–13. doi: 10.1038/s41598-022-14569-0.

Richter, R., Wang, X., Bachmann, M. and Schläpfer, D. (2011) Correction of cirrus effects in Sentinel-2 type of imagery, International Journal of Remote Sensing, 32(10), pp. 2931–2941.

Robinson, R. A. and Sutherland, W. J. (2002) Post-war changes in arable farming and biodiversity in Great Britain, Journal of Applied Ecology, 39(1), pp. 157–176. doi: 10.1046/j.1365-2664.2002.00695.x.

Rosset, V., Simaika, J.P., Arthaud, F., Bornette, G., Vallod, D., Samways, M.J. and Oertli, B., 2013. Comparative assessment of scoring methods to evaluate the conservation value of pond and small lake biodiversity. Aquatic Conservation: Marine and Freshwater Ecosystems, 23(1), pp.23-36. doi: 10.1002/aqc.2287.

Sano, E. E., Ferreria, L.G., Anser, G.P. and Steinke, E.T. (2007) Spatial and temporal probabilities of obtaining cloud-free Landsat images over the Brazilian tropical savanna, International Journal of Remote Sensing, 28(12), pp. 2739–2752.

Saravanan, S., Jegankumar, R., Selvaraj, A., Jacinth Jennifer, J. and Parthasarathy, K.S.S. (2019) Utility of Landsat Data for Assessing Mangrove Degradation in Muthupet Lagoon, South India, Coastal Zone Management, pp. 471–484.

Sass, L. L., Bozek, M. A., Hauxwell, J. A., Wagner, K. and Knight, S. (2010) Response of aquatic macrophytes to human land use perturbations in the watersheds of Wisconsin lakes, U.S.A., Aquatic Botany, 93(1), pp. 1–8. doi: 10.1016/j.aquabot.2010.02.001.

Sayer, C., Andrews, K., Shilland, E., Edmonds, N., Edmonds-Brown, R., Patmore, I., Emson, D. and Axmacher, J. (2012) The role of pond management for biodiversity conservation in an agricultural landscape, Aquatic Conservation: Marine and Freshwater Ecosystems, 22(5). doi: 10.1002/aqc.2254.

Sayer, C., Shilland, E., Greaves, H., Dawson, B., Patmore, I., Emson, D., Alderton, E., Robinson, P., Andrews, K., Axmacher, J. and Wiik, E. (2013) Managing Britain's Ponds - conservation lessons from a Nolfork farm.

Sebastián-González, E., Sánchez-Zapata, J. A. and Botella, F. (2009) Agricultural ponds as alternative habitat for waterbirds: spatial and temporal patterns of abundance and management strategies, European Journal of Wildlife Research, 56(1), pp. 11–20. doi: 10.1007/s10344.

Senf, C., Leitão, P.J., Pflugmacher, D., van der Linden, S. and Hostert, P., 2015. Mapping land cover in complex Mediterranean landscapes using Landsat: Improved classification accuracies from integrating multi-seasonal and synthetic imagery. Remote Sensing of Environment, 156, pp.527-536.

Shen, H., Li, H., Qian, Y., Zhang, L. and Yuan, Q. (2014) An effective thin cloud removal procedure for visible remote sensing images, ISPRS Journal of Photogrammetry and Remote Sensing, 96, pp. 224–235. doi: 10.1016/j.isprsjprs.2014.06.011.

SkyTruth (2014) SkyTruth Releases Map of Drilling-Related Impoundments Across PA. Available at: https://skytruth.org/2014/10/pa-drilling-impoundments-2005-2013/ (Accessed: 1 March 2022).

Smith, L. P., Clarke, L. E., Weldon, L. and Robson, H. (2022) An evidence-based study mapping the decline in freshwater ponds in the Severn Vale catchment in the UK between 1900 and 2019, Hydrobiologia, 849(21) pp. 4637-4649 doi: 10.1007/s10750-022-05000-w

Søndergaard, M., Jeppesen, E. and Jensen, J. P. (2005) Pond or lake: does it make any difference?, Fundamental and Applied Limnology / Archiv für Hydrobiologie., 162(2), pp. 143–165. doi: 10.1127/0003-9136/2005/0162-0143.

Soti, V., Tran, A., Bailly, J. S., Puech, C., Seen, D. L. and Bégué, A. (2009) Assessing optical earth observation systems for mapping and monitoring temporary ponds in arid areas, International Journal of Applied Earth Observation and Geoinformation, 11(5), pp. 344–351. doi: 10.1016/j.jag.2009.05.005.

Story, M. and Congalton, R. G. (1986) Accuracy Assessment: A Users Perspective, Photogrammetric Engineering & Remote Sensing, 52, pp. 397–399.

Subedi, A. and Dev Acharya, T. (2021) Small Water Bodies Detection and Evaluation using Normalized Difference Water Index (NDWI) from Landsat Image in Western Terai, Nepal Bulletin of Nepal Hydrogeological Association, 6, pp. 89-96

Sullivan, S. M. P. and Manning, D. W. P. (2019) Aquatic–terrestrial linkages as complex systems: Insights and advances from network models, Freshwater science, 38(4). doi: https://doi.org/10.1086/706071.

Sun, T. H. and Yan, G. Q. (2013) Land classification method and analysis based on remote sensing technology, in Advanced Materials Research, pp. 4582–4586. doi: 10.4028/www.scientific.net/AMR.726-731.4582.

Taylor, B. T. Fernando, P., Bauman, A. E., Williamson, A., Craig, J. C. and Redman, S. (2011) Measuring the quality of public open space using google earth, American Journal of Preventive Medicine, 40(2), pp. 105–112. doi: 10.1016/j.amepre.2010.10.024.

Taylor, S., Gilbert, P. J., Cooke, D. A., Deary, M. E. and Jeffries, M. J. (2019) High carbon burial rates by small ponds in the landscape, Frontiers in Ecology and the Environment, 17(1), pp. 25–31. doi: 10.1002/FEE.1988.

Tamiminia, H., Salehi, B., Mahdianpari, M., Quackenbush. L., Adeli, S. and Brisco, B (2020) Google Earth Engine for geo-big data applications: A meta-analysis and systematic review, ISPRS Journal of Photogrammetry and Remote Sensing, 164, pp. 152-170. doi: 10.1016/j.isprsjprs.2020.04.001

Thornhill, I., Batty, L., Hewitt, M., Friberg, N. R. and Ledger, M. E. (2017) The application of graph theory and percolation analysis for assessing change in the spatial configuration of pond networks, Urban Ecosystems, 21, pp. 213–225. doi: 10.1007/s11252-017-0724-8.

Tscharntke, T., Klein, A. M., Kruess, A., Steffan-Dewenter, I. and Thies, C. (2005) Landscape perspectives on agricultural intensification and biodiversity - Ecosystem service management, Ecology Letters, 8(8), pp. 857–874. doi: 10.1111/j.1461-0248.2005.00782.x.

Tucker, C. J. (1980) Remote sensing of leaf water content in the near infrared, Remote Sensing of Environment, 10(1), pp. 23–32.

NASA (2022) Landsat 8 Available at: https://landsat.gsfc.nasa.gov/satellites/landsat-8/ (Accessed 12 February 2022).

Ventura, D., Bonifazi, A., Gravina, M. F., Belluscio, A. and Ardizzone, G (2018) Mapping and Classification of Ecologically Sensitive Marine Habitats Using Unmanned Aerial Vehicle (UAV) Imagery and Object-Based Image Analysis (OBIA), Remote Sensing, 10(9), p. 1331. doi: 10.3390/rs10091331.

Verpoorter, C., Kutser, T., Seekell, D. A. and Tranvik, L. J (2014) A global inventory of lakes based on high-resolution satellite imagery, Geophysical Research Letters, 41. doi: 10.1002/2014GL060641.

Viana, C. M., Oliveira, S., Oliveira, S. and Rocha, J. (2019) Land Use/Land Cover Change Detection and Urban Sprawl Analysis, Spatial Modelling in GIS and R for Earth and Environmental Sciences, pp. 621–651.

Watson, C. S., King, O., Miles, E. S. and Quincey, D. J. (2018) Optimising NDWI supraglacial pond classification on Himalayan debris-covered glaciers, Remote Sensing of Environment, 217(September 2017), pp. 414–425. doi: 10.1016/j.rse.2018.08.020.

Walton, R. E., Sayer, C. D., Bennion, H. and Axmacher, J. C. (2021) Improving the pollinator pantry: Restoration and management of open farmland ponds enhances the complexity of plant-pollinator networks, Agriculture, Ecosystems and Environment, 320, doi: 10.1016/j.agee.2021.107611

Whitcraft, A. K., Vermote, E. F., Becker-Reshef, I. Justice, C. O. (2015) Cloud cover throughout the agricultural growing season: Impacts on passive optical earth observations, Remote Sensing of Environment, 156, pp. 438–447. doi: 10.1016/j.rse.2014.10.009.

Williams, P., Biggs, J., Corfield, A., Fox, G., Walker, D. and Whitfield, M. (1997) Designing New ponds for Wildlife, British Wildlife, 8(3), pp. 137-150.

Williams, P., Whitfield, M., Biggs, J., Bray, S., Fox, G. and Nicolet, P. (2003) Comparative biodiversity of rivers, streams, ditches and ponds in an agricultural landscape in Southern England, Biological Conservation. doi: 10.1016/S0006-3207(03)00153-8.

Williams, P., Biggs, J., Crowe, A., Murphy, J., Nicolet, P., Weatherby, A. and Dunbar, M. (2007) Countryside Survey: Ponds Report from 2007, CS Technical Report No. 7/10, p. 77.

Williams, P., Biggs, J., Crowe, A., Murphy, J., Nicolet, P., Weatherby, A. and Dunbar, M. (2010) Countryside Survey: Ponds Report from 2007, CS Technical Report No. 7/10, p. 77.

Wood, P. J., Greenwood, M. T. and Agnew, M. D. (2003) Pond biodiversity and habitat loss in the UK, Area, 35(2), pp. 206–216. doi: 10.1111/1475-4762.00249.

World Health Organization (2019) Motion for your mind, World Health Organization, pp. 1–12.

Wright, J. F., Blackburn, J. H., Gunn, R. J.M., Furse, M. T., Armitage, P. D., Winder, J. M., Symes, K. L. and Moss, D. (1996) Macroinvertebrate frequency data for the RIVPACS III sites in Great Britain and their use in conservation evaluation, Aquatic Conservation: Marine and Freshwater Ecosystems, 6(3), pp. 141–167. doi: 10.1002/(SICI)1099-0755(199609)6:3<141::AID-AQC189>3.0.CO;2-Z.

Wulder, M. A., Hilker, T., White, J. C., Coops, N. C. Masek, J. G., Pflugmacher, D. and Crevier, Y. (2015) Virtual constellations for global terrestrial monitoring, Remote Sensing of Environment, 170, pp. 62–76. doi: 10.1016/j.rse.2015.09.001.

Xu, H. (2006) Modification of normalised difference water index (NDWI) to enhance open water features in remotely sensed imagery, International Journal of Remote Sensing, 27(14), pp. 3025–3033. doi: 10.1080/01431160600589179.

Yang, X., Zhao, S., Qin, X., Zhao, N. and Liang, L. (2017) Mapping of urban surface water bodies from sentinel-2 MSI imagery at 10 m resolution via NDWI-based image sharpening, Remote Sensing, 9(6), pp. 1–19. doi: 10.3390/rs9060596.

Zedler, J. B. and Kercher, S. (2005) Wetland Resources: Status, Trends, Ecosystem Services, and Restorability, Annual Review of Environment and Resources, 30, pp. 39–77. doi: 10.1146/annurev.energy.30.050504.144248.

Zhu, L., Suomalainen, J., Liu, J., Hyyppä, J., Kaartinen, H. and Haggren, H. (2018) A Review: Remote Sensing Sensors, in Rustamov, R. B., Hasanova, S. and Zeynalova, M. H. (eds.) *Multi-purposeful Application of Geopspatial Data*. 1st ed. London, pp. 19–42. doi: 10.5772/intechopen.71049.