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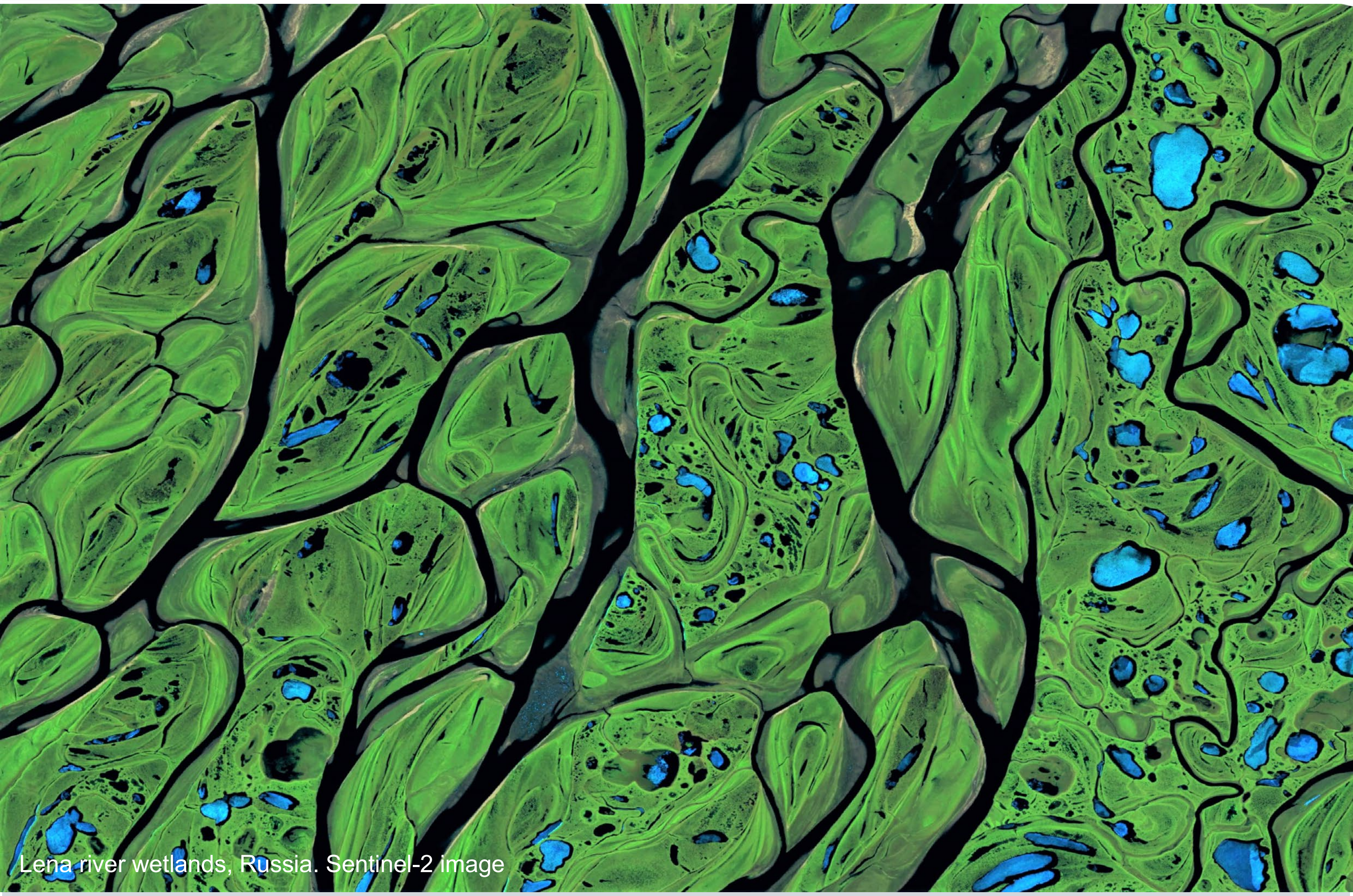
NINA Rapport 2014

Literature review of wetland remote sensing and mapping

Zander Venter, Megan Nowell, Vegar Bakkestuen, Audun Ruud, Marion Kruse, Astrid Brekke Skrindo, Magni Olsen Kyrkjeeide and Frode Thomassen Singsaas


Lena river wetlands, Russia. Sentinel-2 image

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KONTAKTOPPLYSNINGER

NINA hovedkontor
Postboks 5685 Torgarden
7485 Trondheim
Tlf: 73 80 14 00

NINA Oslo
Sognsveien 68
0855 Oslo
Tlf: 73 80 14 00

NINA Tromsø
Postboks 6606 Langnes
9296 Tromsø
Tlf: 77 75 04 00

NINA Lillehammer
Vormstuguvegen 40
2624 Lillehammer
Tlf: 73 80 14 00

NINA Bergen
Thormøhlens gate 55
5006 Bergen
Tlf: 73 80 14 00

www.nina.no

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Det er et nasjonalt mål at alle økosystemer skal ha god tilstand (nasjonalt mål 1 for naturmangfold) (Norges miljømål - Miljøstatus for Norge (miljodirektoratet.no)). Dette gjelder også for våtmark. Videre har Stortinget vedtatt mål om å restaurere 15% av økosystemer som har forringet tilstand, til god økologisk tilstand innen 2025 (Sak - stortinget.no, Meld. St. 14, 2015-2016). For å kunne nå nasjonale miljømål samt å prioritere riktig ved restaurering eller andre tiltak, er det er det nødvendig med kunnskap om status og utvikling av økosystemenes utbredelse og tilstand. Kartlegging, overvåking og forskning er nødvendig for å gi et godt og solid kunnskapsgrunnlag for forvaltningsbeslutninger og politiske prioriteringer.

Kartlegging og overvåking av natur er kostbart, og det er nødvendig å utarbeide effektive metoder som gir tilstrekkelig god kunnskap. Bruk av fjernmålte data gir en mer kostnadseffektiv kunnskapsinnhenting og det muliggjør innhenting av arealdekkende data med jevne mellomrom (altså overvåkingsdata). Dette gir tilgang til store og verdifulle datasett for status og utvikling, gitt at de gir tilstrekkelig informasjon om det som skal overvåkes, og gitt at det er bygget opp en datainfrastruktur og gode kartløsninger for sluttbruker. Bruk av fjernmålte data vil kunne gi norsk naturforvaltningen tilgang til et bedre kunnskapsgrunnlag for forvaltning av våtmark. Det gjelder kanskje aller mest for naturtyper som myr og annen våtmark som er stadig under press for forringelse og som i tillegg har vært lite prioritert kartlagt for eksempel i fjellområdene.

I denne rapporten presenterer vi en systematisk litteraturgjennomgang av vitenskapelig litteratur kombinert med innhenting av informasjon fra relevante fagmiljøer for kartlegging, overvåking og tilstandsvurdering av våtmark fra fjernanalyse. I prosjektet er det gjort en rekke vurderinger som grunnlag for forslag til løsninger og prioriteringer. Forslagene svarer på spørsmålene i spesifikasjonslisten som direktoratet har satt opp for oppdraget, og er gjennomført i samsvar med de presiseringer, avgrensninger og definisjoner som ble gjort i samråd med oppdragsgiver.

I tillegg til litteraturgjennomgangen innhentet vi informasjon fra et utvalg av nasjonale og internasjonale eksperter der vi kartla erfaringer med fjernmåling av våtmark. I tråd med hva Miljødirektoratet ønsket, ble dette gjort for å komplettere funn i litteraturgjennomgangen.

Vi utførte et systematisk litteratursøk ved å bruke prinsipper for beste praksis skissert i Moher et al. (2009). Vi brukte Web of Science og SCOPUS-databaser for søk i alle relevante engelskspråklige artikler, review-artikler, bok- og konferansekapitler. Søkeordene ble spesifisert i følgende tre kategorier: 'remote sensing' (A), 'wetland' (B) og 'mapping methods' (C), og de ble atskilt ved bruk av de boolske operatorene AND og ELLER. Artikler publisert etter 2015 ble inkludert i studiet. Dette for å begrense datastørrelsen slik at vi fikk tid til å behandle dataene gitt den korte prosjektperioden. Studier etter 2015 ble også valgt fordi vi la til grunn at de har brukt de nyeste kartteknikkene og dataene for fjernmåling, og de dermed er de mest relevante for fremtidig bruk av fjernmåling i kartlegging og overvåking av våtmark i Norge.

Litteratursøket resulterte i 3235 treff (2059 fra Web of Science, og 2611 fra Scopus med 1435 duplikater). Vi gjennomgikk titlene for disse publikasjonene og sorterte dem ved bruk av eksklusjonskriterier. Etter dette satt vi igjen med de studiene som omhandlet kartlegging av våtmark i innlandet etter 2015 ved bruk av fjernmåling. Tittelscreeningen resulterte i 508 relevante publikasjoner. Vi leste alle disse sammendragene ('abstract') og vurderte de etter relevans, noe som resulterte i vi stod igjen med 137 publikasjoner for videre bearbeiding. Videre bearbeiding innebar å lese hele teksten og registrere relevante variabler som kreves for å identifisere de vanligste metodene for fjernmåling (f.eks. sensortype, romlig oppløsning, bakkesannheter) av myr som er relevant for Norge. Til slutt la vi til ytterligere 73 publikasjoner fra Mahdianpari et al. (2020a) sin metaanalyse av fjernmåling av våtmark i Nord-Amerika. Dataene herfra ble tilpasset våre analyser ved blant annet å samle inn tilleggsinformasjon slik at de var i samsvar med de dataene vi hadde hentet ut. Totalt bestod vårt litteratursett deretter av data fra 210 studier.

Vår litteraturundersøkelse viste at de fleste studiene som benyttet fjernmåling til å kartlegge våtmark, ble gjennomført i Canada (61), USA (41) og Kina (38). Det var få studier fra Skandinavia, med kun to i Sverige og to studier i Finland. Det er ikke publisert studier i den akademiske internasjonale litteraturen knyttet til norsk våtmark eller myr og kartlegging av disse fra fjernmåling. I disse tallene har vi ikke inkluder nasjonale rapporter og annet grå litteratur. Disse er diskutert separat i eget delkapittel.

Våre undersøkelser viser at de fleste studier klassifiserer våtmarker basert på sonering. Soneringen kan bestå i ulike habitater (f.eks. kyst, elvemunning, innlandet), klimasone (f.eks. boreal, alpin) eller arealbruk (f.eks. våtmark vs. jordbruk vs. by). Færre studier definerte våtmarker basert på dominerende arter, struktur, funksjonelle grupper eller temporær dynamikk. Våtmarker ble som oftest forhåndsdefinert og kartlagt i motsetning til andre arealklasser. Dette antyder at det er nødvendig også å definere "ikke-våtmark" når man kan definere "våtmark".

Antall klasser varierte noe, men svært få studier hadde mer enn 10 klasser i sitt endelige klassifiseringskart. Medianen var 7 klasser. De fleste studier baserte seg på data fra bakkesannheter samlet inn i felt (44 studier), mens 32 studier baserte seg på visuell tolkning av høyoppløselige flyfoto og 28 baserte seg på en kombinasjon av feltdata og bildetolkning. Resultatene viste at 12 studier var avhengige av andre referansedatasett (datasett som ligner på AR5 og N50 i Norge) som bakkesannheter. Kun studiene med referansedataene viste en signifikant sammenheng mellom nøyaktighet i kartproduktet og antall bakkesannheter. Antall sannhetsdatapunkter var lavest for in situ-data (samlet i felt) (median 270 datapunkter), og høyest for referansedatasett (median 1570 datapunkter).

Nær halvparten av studiene brukte satellittdata fra mer enn et tidspunkt. Særlig Landsat ble brukt i langtidsserier for endringsanalyser. Selv om de fjernmålte dataene ble tatt opp på ulike tidspunkter, ble de gjerne satt sammen til å skaffe et produkt og ikke en endringsanalyse.

Flertallet av studier kartla våtmark/myr på landskapsnivå (<10km2) eller lokalt (> 10km2 & <50000km2), med svært få kartlegging i nasjonale eller kontinentale områder. De som kartla våtmarker i nasjonal skala, inkluderer 5 multitemporale studier i Canada ved bruk av optiske data, to studier i Kina basert på MODIS multitemporal data samt to 'single date' studier i USA med PALSAR. De fleste av studiene (73) baserte seg på Landsat-satellitter for å kartlegge våtmarker, etterfulgt av RADARSAT og Copernicus Sentinel-satellittene. Disse satellittdataene har åpen tilgang. Landsat-bilder har også vært tilgjengelige siden 1970-tallet, noe som gjør det gunstig for historiske studier. Av de dyre sensorene (de som koster > $ 30 / km^2) er flybåren LiDAR, UAV og flyfotografering mest brukt.

Når det gjelder typen klassifiseringsmodell, brukte 125 studier pikselbasert bildeklassifisering og 71 brukte objektbasert. Pikselbaserte klassifiseringsstudier produserte kart med en medianoppløsning på 16m, mens objektbaserte kart ga en median på 10m oppløsningskart. Til tross for dette, var det svært liten forskjell i kartnøyaktighet mellom de to metodene. Resultatene indikerer at antall prediktorvariabler (dvs. bildebånd eller båndindekser) i klassifiseringsmodeller økte kartnøyaktigheten for objektbasert klassifisering, men hadde ingen effekt for pikselbasert klassifisering. Imidlertid var det en trend at den objektbaserte klassifiseringen ble forsøkt brukt på vanskeligere problemstillinger som for eksempel å skille nært beslektede klasser, noe som vi tolker dithen at objektbaserte metoder skal løse problemene de pikselbaserte metodene ikke har klart hittil. Dette kan forklare at det er liten forskjell mellom nøyaktigheten på metodene selv om de objektbaserte metodene ser ut til å gjøre det generelt litt bedre enn de pikselbaserte. Dette gjenspeiles også i de studiene som sammenligner metodene på like vilkår.

De vanligste metodene for maskinlæring som ble brukt til å generere kart over våtmark/myr, var beslutningstrær (f.eks. Random Forest,), etterfulgt av støttevektormaskiner (Support vector machine). Toppmoderne (state-of-art) nevrale nettverksmodeller ble brukt i 13 av studiene, men den anvendte typen maskinlæringsmodell hadde ingen merkbar effekt på kartnøyaktigheten. Ingen av studiene hadde dog tatt i bruk TensorFlow.

Svært få av publikasjonene (19) kartla økologisk tilstand eller påvirkningsfaktorer. Av de som gjorde det, var de mest kvantifiserte tilstandsfaktorene artssammensetning og oversvømmelsesområde. Den eneste påvirkningsfaktoren som ble kvantifisert i studiene, var endring av arealbruk (f.eks. våtmarkskonvertering til jordbruk).

Basert på litteraturgjennomgangen, ekspertbasert spørreskjema og personlig erfaringer som forskere i NINA, gir vi følgende anbefalinger for kartlegging og overvåking av våtmark i Norge basert på fjernanalyse. Det er viktig å merke seg at disse anbefalingene kan endres betydelig avhengig av de nøyaktige spesifikasjonene for kartleggingsprosjektet (f.eks. budsjett, nøyaktighetskrav osv.).

- Våtmarkstypologien som brukes, bør være en forening av NiN-systemet og internasjonale standardsystemer som det kanadiske Cowardian systemet. Beslutninger om typologi bør tas i samarbeid mellom botanikere og fjernmålerutøvere. Botanikere vil kunne sikre klassifiseringens teoretiske integritet, og utøvere av fjernmåling vil gi råd om hva som er og ikke er mulig å se og skille på satellittbilder. Basert på våtmarksklassene som brukes i litteraturen, ser det ut som om det er mulig å skille mellom blant annet jordvannsmyr, nedbørsmyr og sump. Det kan derfor være urealistisk å prøve å kartlegge mer detaljerte hierarkier som definert i NiN.

- Fusjon ‘fusion’ av optiske data og radardata vil ikke bare gi komplementære data om spektrale, strukturelle, strukturelle og dielektriske egenskaper (indikasjoner på fuktighet), men vil også kompensere for det frekvente skydekket i Norge.

- Bruke Sentinel-1 og Sentinel-2 som har åpen kildekode og har inntil 10m romlig oppløsning. Ettersom begge har polarbaserte baner, er repetisjonstiden mye mindre for land nær polarområdene. Selv om disse satellittene ikke er tilgjengelig langt bak i tid (lansert i 2014 og 2015), har de en lang fremtid framover, noe som gjør dem nyttige for overvåking av våtmarker.

- Sentinel-1-data bør anskaffes i dobbel polarisasjonsmodus (HH / HV) med både høy og lav innfallsvinkel, der det er mulig.

• Høyoppløselige satellittbilder med 2-4 m piksler er foreløpig ikke funnet brukt i regionale eller nasjonale kartmodeller for våtmark. Dersom disse vil bli tilgjengelig til lavere kostnad i framtiden bør de vurderes som egnete datakilder.

• De nasjonale LiDAR- og ortofotodatasettene i Norge har foreløpig ikke nådd full dekning og utelukker også noen høyalpine områder som kan inneholde våtmarker. Videre oppdateres ikke LiDAR- og ortofotodataene årlig, men regelmessig, og tillater derfor ikke årlig operativ overvåking. Derfor bør disse datasettene med høy oppløsning brukes til å rengjøre, kvalitetskontrollere og muligens bidra med ytterligere bakkesannhetsdata. I tilfelle Miljødirektoratet ønsker et enkelt 'baseline' våtmarkskart over Norge som ikke oppdateres regelmessig, kan det vurdere å bruke LiDAR og ortofotoer i klassifiseringsmodellen.

• Data for fjernmåling bør ideelt sett behandles i en skybasert plattform på grunn av nasjonal skala som gir store datamengder, spesielt når man fusjonerer sammen mulititemporal og multisensor-tilnærminger som krever bearbeidelse av en atskillig mengde data. Å bruke Google Earth Engine (GEE) som behandlingsplattform er fordelaktig fordi det allerede er vert for Sentinel-data og tilgangskopier av Kartverket LiDAR-datas om er lastet opp og er klare for behandling. GEE kan brukes til å generere et pilotnasjonalt våtmarkskart, men operativ overvåking i fremtiden vil kreve evaluering av det kommersielle GEE-programmet som en bærekraftig løsning.

• Bakkesannheter for våtmarker i Norge eksisterer i form av NiN, ANO, AR5 og N50, men definisjonene og datakvaliteten til våtmark varierer betydelig. Derfor må man bruke betydelig tid på å harmonisere disse datasettene og kvalitetskontrollere dem ved hjelp av ortofotoer med høy oppløsning (Norge i bilder, norgeibilder.no) og satellittbilder. Hvis tilstrekkelig budsjett er tilgjengelig, bør feltarbeid vurderes for å samle gode treningsdata og for å tilpasse og verifisere nøyaktigheten av NiN, AR5, ANO eller N50.

• Spektrale indekser, slik som NDVI, NDWI og NDMI, anbefales for å skille mellom våtmarkstyper og for å vurdere tilstanden til våtmarker.

• Vi anbefaler å teste flere metoder før man går i gang med å lage et nasjonalt kart, gjerne teknikker som ikke krever enormt mye regnekapasitet og ofte brukes i andre studier. Spesielt anbefaler vi å teste både Random Forest beslutningstrær og dyplæring (Fully Convolutional Neural Networks – FCNN). Dette er to av de mest brukte modellene som i dag brukes og siteres i litteraturen, og gir dermed mest sannsynlig de beste resultatene. Vær oppmerksom på at modellopplæring og tuning vanligvis er ganske tidkrevende når dette skal gjøres optimalt.

Mangelen på studier i Skandinavia gjør at det finnes lite erfaring med slik kartlegging i Norge. Dette gjelder også studier på observasjon av økologisk tilstand fra fjernmåling. Det trengs mer forskning på dette temaet i Norge.

Zander Venter, Norsk institutt for naturforskning (NINA), zander.venter@nina.no
Megan Nowell, Norsk institutt for naturforskning (NINA), megan.nowell@nina.no
Vegar Bakkestuen, Norsk institutt for naturforskning (NINA), vegar.bakkestuen@nina.no
Audun Ruud, Norsk institutt for naturforskning (NINA), audun.ruud@nina.no
Marion Kruse, Norsk institutt for naturforskning (NINA), marion.kruse@nina.no

Astrid Brekke Skrindo, Norsk institutt for naturforskning (NINA), astrid.skrindo@nina.no
Magni Kyrkjeeide, Norsk institutt for naturforskning (NINA), magni.kyrkjeeide@nina.no
Frode Thomasen Singsaas, Norsk institutt for naturforskning (NINA), frode.singsaas@nina.no

Abstract

Venter, Z.S., Nowell, M.S., Bakkestuen, V., Ruud, A., Kruse, M., Skrindo, A.B., Kyrkjeeide, M.O. & Singsaas, F.T. 2021. Literature review of wetland remote sensing and mapping. NINA Report 2014. Norwegian Institute for Nature Research.

Mapping and monitoring of nature is expensive but it is necessary to develop knowledge sufficient for data-driven decision making and managing of nature. The use of remote sensing provides more cost-effective knowledge acquisition and enables the provision of area-wide, spatially-explicit data at regular intervals. This provides access to large and valuable data sets, provided that they are accurate accounts of the reality on the ground and that uncertainty is quantified, and that a good data infrastructure and a map solution has been developed for the end user. In this report, we present a systematic literature review, combined with data from questionnaire surveys from practitioners, on the mapping, monitoring and condition assessment of wetlands using remote sensing.

We used Web of Science and Scopus databases to search all relevant English language articles, reviews, book chapters and conference chapters. Relevance was defined by keywords specified in three categories including ‘remote sensing’ (A), ‘wetland’ (B) and ‘mapping methods’ (C), separated by AND and OR boolean operators. Articles published after 2015 were included to limit the data size so that we had enough time to process the data given the short project period. Studies after 2015 are also likely to adopt the latest mapping techniques and data for remote sensing, and are therefore most relevant for future wetland mapping applications in Norway. In addition to the literature review, we obtained information from a number of national and international experts from whom we mapped experiences with remote sensing of wetlands. In line with what the Norwegian Environment Agency wanted, this was done to supplement findings in the literature review.

The literature search returned 3235 entries (2059 from Web of Science, and 2611 from Scopus with 1435 duplicates). We then screened the publication titles for relevance using exclusion criteria. The title screening resulted in 508 relevant entries which were further screened with abstract and full-text reading resulting in 137 entries left for further processing. Further processing involved reading the entire text and registering variables relevant to wetland remote sensing (e.g. spatial resolution, sensor type) that are of interest to the Norwegian Environment Agency. Finally, we added another 73 publications from Mahdianpari et al. (2020a) meta-analysis of remote sensing of wetlands in North America. These additional data were adapted to our analysis by, among other things, collecting additional information so that they were in accordance with our extracted data. Thus, in total our literature set consisted of data from 210 studies.

Our literature review showed that most studies using remote sensing to map wetlands were in Canada (61), USA (41) and China (38). Overall, few studies were available for Scandinavia, with only two in Sweden and two in Finland. No studies were published in the academic international literature on Norwegian wetlands or bogs and mapping of these from remote sensing.

Our results revealed that most studies classified wetlands based on a zonal typology defined by the spatial context of the wetland (e.g. coastal vs inland). Fewer studies defined wetlands based on their dominant species (e.g. grass vs sedge), structure (e.g. basin vs swale), functional group, or temporal dynamics. Wetlands were most often defined and mapped in contrast to other land

cover classes. This suggests that it is equally important to define “non-wetland” when one is mapping “wetland” so as not to produce false-positive wetland predictions.

Studies classified land cover into a median of 7 classes. Very few studies had more than 10 classes in their final classification map. In terms of the wetland typology used, the wetland sub-classes were dominated by names from the Canadian wetland typology including fen (“jordvannsmyr” på norsk), marsh, swamp (“sump”), and bog (“nedbørsmyr”).

The majority of studies mapped wetlands at landscape (< $10km^2$) or provincial (>$10km^2$ & < $50000km^2$) extents, with very few mapping at national or continental extents. Most studies (73) relied on Landsat satellites to map wetlands, followed by RADARSAT, and the Copernicus Sentinel satellites. The most common map resolution was >10m, which included satellites such as Landsat, Sentinel-1, PALSAR and RADARSAT. The map accuracy was not significantly related to the spatial resolution of the map. There was large variation in map accuracies at both high and low spatial resolutions, suggesting that other study-specific factors are more important determinants of accuracy.

Regarding the type of classification model, 125 studies used pixel-based image classification and 71 used object-based. Pixel-based classification studies produced maps with a median resolution of 16m while object-based maps gave a median of 10m resolution maps. Despite this, there was very little difference in map accuracy between the two methods. The results indicate that the number of predictor variables (i.e. image bands or band indices) in classification models increased the map accuracy for object-based classification, but had no effect for pixel-based classification. This may explain why there is little difference between the accuracy of the methods even though the object-based methods seem to generally perform a little better than the pixel-based ones. This is also reflected in the studies that compare the methods on equal terms.

The most common machine learning framework used to generate wetland maps was decision trees (e.g. Random Forest), followed by support vector machines (SWM). State-of-the-art neural network models were used in 13 of the studies. The type of machine learning model adopted had no discernible effect on map accuracy.

Very few of the publications (19) map ecological status or influencing factors. Of those that did, the most quantified condition factors were species composition and flood area. The only influencing factor quantified in the studies was the change in land use (e.g. wetland conversion to agriculture). The lack of studies in Scandinavia means that there is little experience with such mapping in Norway, although a thorough search of the grey literature may change this conclusion. This also applies to studies on observation of ecological condition from remote sensing. More research needs to be done on these scientific issues.

Finally, we provide recommendations for generating a national-scale wetland map for Norway both in terms of a static base map and an operational workflow to provide such maps at regular intervals in the future.

Zander Venter, Norsk institutt for naturforskning (NINA), zander.venter@nina.no
Megan Nowell, Norsk institutt for naturforskning (NINA), megan.nowell@nina.no
Vegar Bakkestuen, Norsk institutt for naturforskning (NINA), vegar.bakkestuen@nina.no
Audun Ruud, Norsk institutt for naturforskning (NINA), audun.ruud@nina.no
Marion Kruse, Norsk institutt for naturforskning (NINA), marion.kruse@nina.no
Astrid Brekke Skrindo, Norsk institutt for naturforskning (NINA), astrid.skrindo@nina.no
Magni Olsen Kyrkjeeide, Norsk institutt for naturforskning (NINA), magni.kyrkjeeide@nina.no
Frode Thomasen Singsaas, Norsk institutt for naturforskning (NINA), frode.singsaas@nina.no

Contents

Foreword

This report has been commissioned by the Norwegian Environment Agency. The assignment has lasted mainly in the period March - May 2021.

This report contains a literature study with the intention of elucidating the status of the use of remote sensing to map, monitor and evaluate condition of wetlands and associated areas.

The purpose has also been to propose the best possible approach for a satellite-based mapping and monitoring of bogs, mires and other wetlands in Norway.

We would like to thank all the contributors who answered our questionary. We would also like to thank Masoud Mahdianpari for accessing his literature database and for important discussions.

We have received constructive input along the way from Tomas Holmern, Ellen Arneberg, Agnès Moquet-Stenback, Vibeke Husby, Jakob Sandven, Ingvild Byskov, Åse Alexandra Borg Pedersen, Gunnar Kjærstad, Ragnvald Larsen and Ingunn Margrethe Limstrand, all at the Norwegian Environment Agency (Miljødirektoratet). We thank Stefan Blumentrath who provided valuable comments that improved the quality of the report.

Tomas Holmern has been an inspiring contact person throughout the project period.

Hamar, 30.06.2021

Vegar Bakkestuen

1 Introduction

Wetlands are ecosystems that are permanently or periodically saturated or inundated with water and cover habitats in the transition between terrestrial and freshwater or marine ecosystems. These ecosystems support plants and other organisms that are adapted to a life in wet conditions and are often highly productive. Thus, they offer a wide range of ecosystem services including, for example, water purification, flood control and carbon sequestration. Wetlands hold the highest density of carbon in the soil of all terrestrial ecosystem types (Villa & Bernal 2017). That makes them efficient and cost-effective nature-based solutions to climate change as they sequester atmospheric carbon and are therefore important in the long-term storage of carbon. Despite this, wetlands are constantly under pressure from human activity (Lyngstad et al. 2018, Nybø, S. & Evju, M. (eds) 2017). Land use change of wetlands often leads to biodiversity loss and as well as net carbon loss, because change in hydrology shifts the carbon cycling and turns the ecosystems from sinks to sources of carbon.

Wetland habitats are found throughout Norway, from the coast to the alpine zone, and from south to north. A varied topography and large span of climate zones has given rise to a broad variation of habitats in Norway. The habitats include mires and peatlands, swamp forests, floodplains, marshes and springs. The variation of peatland types in Norway are high and unique even in a global context (Moen et al. 2017). The habitat classification system Nature in Norway 2.2.0 (NiN, Halvorsen et al. 2020), includes 13 main habitat types in the ecosystem wetland. These are fen (V1), bog (V3), peatland forest (V2), swamp forest (V8), snowbed (V6), spring (V4 and V5), arctic permafrost wetland (V7), and semi-natural fen (V9) and wet meadow (V10), peat extraction sites (V11), drained peatland (V12), and new wetlands (V13). Peatlands are the most common wetland type in Norway (accounting for approx. 90% of wetland cover; Bryn et al. 2018). Peatlands are peat-forming ecosystems, and are usually defined as having a peat layer of 30 cm or deeper (Moen et al. 2011). Habitats that are actively accumulating peat through its vegetation and waterlogged conditions is called a mire, but the type of water supply feeding the system defines the type. The two main habitats are bogs and fens. Bogs get water from precipitation, while fens also gain water from the surroundings (see examples in **figure 1** below). Norwegian wetlands have been classified in different ways throughout the last decades. Magnussen et al. (2018) summarizes different classification systems and used eight different types when addressed the ecosystem services for wetlands in Norway.




Figure 1. *Examples of different bogs and fens in Norway. Upper left: Atlantic raised bog and hummocks (V3) in a mixture of nutrient poor coastal heath (T34-C2) at Finnøy municipality, Møre og Romsdal, Upper right. Fen (V1) in Rendalen municipality, Innlandet. Lower left: Bog with cloudberry (V3), at Torgerstuen in Rendalen municipality, Innlandet. Lower right. Atlantic raised bog (V3) at Gule-Stavmyrane nature reserve in Fræna municipality, Møre og Romsdal.*

Wetlands support a wide range of unique, often specialized species, including amphibians, bryophytes, vascular plants, and birds. Altogether 14 wetland habitat types including sump forests are Red Listed in Norway (Lyngstad et al. 2018), nine mire types, four sump forest types and one spring type. Land use change of wetlands often leads to net carbon loss, because change in hydrology shifts the carbon cycling and turns the ecosystems from sinks to sources of carbon. Direct human interventions are the biggest threat to wetland habitats, especially in lowland areas in southern Norway. Drainage for agriculture and forestry is the main threat to peatlands (e.g. Lyngstad et al. 2018), but infrastructure, housing, river modifications, and renewable energy developments are also among the threats to wetlands habitats. Harvesting peat is not yet forbidden.

About 10% of the mainland of Norway is covered by wetlands (Bryn et al. 2018). Peatlands are the wetland type with highest coverage in Norway (ca. 9% land cover; Bryn et al. 2018). Despite these estimates, the actually aerial coverage of wetlands over Norway remains uncertain because, depending on the data source used (e.g. AR5 vs N50 vs AR18X18) one will end up with different percentage estimates. This is partly because previous mapping efforts are based on manual in-situ mapping procedures which require substantial financial investment and adopt different definitions of wetland habitats. Furthermore, employing fieldworkers to digitize habitat types introduces a sampler bias which makes the resulting map vulnerable to spatial and temporal inconsistencies (Erikstad et al. 2011). Mapping instructions and methods can also change over time and therefore make it difficult to discern whether changes in wetland cover are real or merely an artifact of changes in mapping methodology. Wetlands are mapped as a broad group and it is not possible to distinguish between most wetland types in existing national maps. Apart from mostly single-timepoint aerial coverage estimates, there is even less active monitoring and surveillance of wetland condition or changes through time. For example, the Norwegian Nature Index contains very few indicators specific to wetlands (Pedersen et al. 2018). Active monitoring and annual or biennial mapping of wetlands will become important given the revised management plan for restoration of wetlands in 2021 (Norwegian Environmental Agency 2021).

It is often challenging to make clear criteria for classification of habitat types, and wetland types are no exception. Hence, particular geographical distribution and accurate location and mapping of different types of wetlands are still deficient. This in turn has created challenges in creating unambiguous area statistics that can be helpful in the management of these systems, in for example assessment of state, condition, changes and area accounts such as carbon storage and prioritization for restoration. The environmental administration has accordingly significant mapping and monitoring needs, in particular of the status and changes of the habitat types found in Norway. This is necessary in order to be able to provide a good basis for targeted management and policy-making.

Wetlands have not been monitored in a systematic way in Norway, although some types have been included in, for example, the terrestrial monitoring ‘TOV’ (Framstad et al. 2020), the wilderness mapping ‘utmarkskartleggingen’, (AE18x18) and in the Land Forest Assessment (LST) (Viken 2018). The area-representative nature monitoring (ANO) (Tingstad et al. 2019) will enter its third year in 2021 with full botanical registrations where all types of wetlands can occur in the monitored areas. With the development that is taking place in remote sensing and with the increased access to satellite data, and also aerial photography, LiDAR, drone data, etc., the possibilities will be better than ever to be able to map wetlands with remote sensing methods. However, there are some important prerequisites that must be in place in order to make the most of the available data and tools.

Despite the opportunities that lie in remotely measured products, they also have a number of challenges associated with them when it comes to making the products management relevant. The management is particularly dependent on nature type map products being accurate with regard to the correct classification of areas. This requires for instance access to ground truths of sufficient number and spatial distribution and accuracy, knowledge to make the right selection of sensors and platforms and knowledge for choosing the optimal statistical classifier and for selecting the right spatial scale for the classification.

An important prerequisite for doing remote sensing on wetlands is access to good ground truths data (Loew et al. 2018). This includes also ground truth data on assessments of status, condition and changes in wetland areas over time. Another prerequisite is to have a set of division rules that can be applied for separation of wetland and other land cover types from each other by means of remote sensed data. In the vegetation ecology, it is common to use indicator species to distinguish between for example nutrient-poor and nutrient-rich (e.g. low vs high Nitrogen content) bog types. The species used by field biologists could be typical and specific, but also small and often tiny. Thus, these species might not be dominant at all in the area cover and will therefore be very difficult to capture by remote sensing. A remote sensing approach to mapping and monitoring must therefore take into account these challenges and other challenges related to cost-effectiveness, level of detail, accuracy requirements and more. These are important prerequisites for whether remote sensing can contribute to a better knowledge base for a more comprehensive management of wetlands and, for example, evaluation of restoration. At the same time, it is important to note that identifying methodological requirements (e.g. required accuracy level) is very dependent on the specific purpose of the mapping exercise (Lennert et al., 2019).

In contrast to Norway, countries such as Canada have supplemented in-situ wetland inventories and mapping with remote sensing data and machine learning classification workflows. Remote sensing workflows typically follow the steps outlined in **figure 2**. Perhaps the most important thing to note is that they are heavily dependent on ground-truth data for calibrating and validating the resulting wetland maps. Therefore, remote sensing should never be viewed as a substitute for in-situ mapping and fieldwork, but rather as an important supplement for scaling and operationalizing monitoring. In this context, remote sensing offers some significant advantages over in-situ and manual mapping: 1) it is spatially explicit and consistent over both space and time – in that sense it is objective; 2) it is scalable because one can extrapolate over time and space using machine learning models: 3) it is cost-effective because the cost of remote sensing data is generally a fraction of the cost of employing field worker; 4) it is continually updateable and often available in near real-time thereby allowing for ongoing monitoring and surveillance.

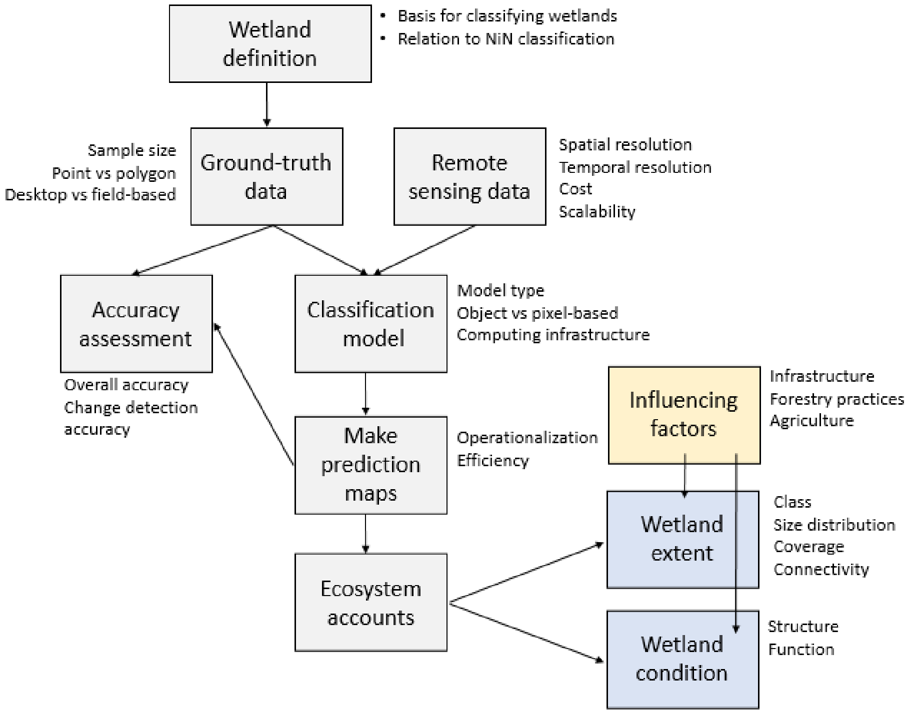

Figure 2. *Conceptual framework outlining the typical workflow in remote sensing and mapping of wetland ecosystems.*

In the process of mapping land cover classes like wetland there are some terms that are commonly used. We have explained some of these in **table 1**.

Table 1. *Explanation of some commonly used terms in the report*

Terms	**Explanation**
Ground truth	Refers to information collected on location, could be vectors like points or polygons, or pixels. The aim is to train or validate classification models
Classifier	The method used to assigning a pixel, or groups of pixels, of remote sensing image to a land cover class
Training data	Is the ground truth you train your classifier on.
Validation data	Is the ground truth you use to assess the uncertainties in your results
Reference data	Training or validation data extracted from existing maps
Segmentation	Process of partitioning an image into multiple segments (sets of pixels, also known as image objects)
Image labeling	Process of label objects in a segmented image
Random Forest (RF)	A classifier which constructs a multitude of decision trees at training. For classification tasks, the output of the random forest is the class selected by most trees.
Convoluted Neural Networks (CNN)	A classifier that is a type of deep learning network, most commonly applied to analyze visual imagery.
TensorFlow	Free and open-source software library for machine learning and deep learning

1.1 Aims and objectives

The purpose of this study is to assess the advantages and disadvantages of the various methodological approaches and provide recommendations for which remote sensing methods can quickly and objectively develop national coverage maps and area estimates. In this report we synthesize the national and international literature on wetland remote sensing and mapping. We use both a systematic literature review and targeted online questionnaire with relevant experts to summarize the state-of-the-art knowledge and methodology in the wetland mapping field.

Below are specific issues that were raised by the Norwegian Environmental Agency and were the targets for the literature review. These included the assessment of advantages and disadvantages of the following aspects of remote sensing methodology (also outlined in **figure 1**):

- The basis for classifying wetlands including the wetland typology and its relation to the NiN classification system.

- The type and amount of ground truth data needed to inform satellite-based classification models.
- The type, spatial and temporal resolution, purchase cost, and scalability of different remote sensing platforms (both airborne and satellite).
- The statistical methodology used to classify remote sensing imagery into wetland and non-wetland classes including the raster processing method (object- vs pixel-based analysis). Details about the number of explanatory variables and type of machine learning model are also of interest.
- Methods for assessing the accuracy of the resulting wetland map and also the effect of the above methodological options on resulting accuracies.

As a part of the project the Norwegian Environmental Agency also asked for advices about scalability of the methods in terms of operational mapping of wetlands in Norway. Finally, they were also interested in the application of remote sensing to quantifying the ecological condition of wetlands and their influencing factors.

2 Materials and methods

This project has carried out a systematic literature review of scientific literature on remote sensing of habitat types in wetlands. We have done this in combination with obtaining information from relevant remote sensing professionals through an online survey. Both the literature review and online questionnaire with relevant professionals were designed to meet the aims and objectives outlined above.

2.1 Literature search

We performed a systematic literature search using best-practice principles outlined in Moher et al. (2009). Firstly, we searched Web of Science and SCOPUS databases for all relevant English language articles, review articles, book chapters and conference papers. Relevance was defined by search terms specified in three categories including remote sensing (A), wetlands (B), and mapping methods (C) (**table 2**), separated by AND and OR boolean operators. Only records published after 2015 were included in order to limit the data size so that we had enough time to process the data given the project budget. Studies post-2015 are also likely to use the latest mapping techniques and remote sensing data and are therefore most relevant to future wetland mapping applications in Norway.

Table 2. *Search query design used in systematic literature search.*

	------------ AND -----------		
	A	B	C
------------ OR ------------	remote sens*	Wetland*	classif*
	satellite image*	Mire*	discriminat*
	aerial photo*	Bog	monitor*
	UAV	fen	object-based
	"Unmanned Aerial Vehicle"	marsh	pixel-based
	Radar	swamp*	object-oriented
	optical	peatland*	invento*
	SAR	flooded vegetation	
	Synthetic Aperture Radar	salt marsh*	
	multispectral	land*cover	
	hyperspectral		
	LiDAR		
	"Light Detection And Ranging"		
	DEM		
	"Digital Elevation Model"		
	Sentinel		

The literature search returned 3235 records (2059 from Web of Science, and 2611 from Scopus with 1435 duplicates). We then screened the publication titles for relevance using exclusion criteria defined in **table 3**. If there was not enough information in the title to decide on exclusion, we left the publication for the next processing phase which included full-text assessment. The title screening resulted in 508 relevant records. The abstracts and full-texts of these were processed for relevance resulting in 137 records left for data extraction. The data extraction involved reading the full text and recording relevant variables required to answer the questions specified in the contract with the Norwegian Environment Agency. Finally, we added an additional 73 publications from Mahdianpari et al. (2020a) meta-analysis of wetland remote sensing in North America. The authors agreed to share their database with us which contained information for each study that largely overlapped with our project specifications. The data were processed and additional information was collected so that it was commensurate with our extracted data. Finally, our literature dataset consisted of data from 210 studies. We also completed qualitative analysis of selected, national studies.

Table 3. *Exclusion criteria used in the literature screening before final data extraction. The justifications included: not relevant to the scope of mapping wetlands specifically (A), not relevant to Norwegian wetland ecosystems (B), pragmatic decision to allow for data processing within project budget allowance (C).*

Exclusion criterion	**Justification**
Exclude studies already present in the Mahdianpari et al. (2020a) meta-analysis of wetland remote sensing.	**C**
Exclude general land cover mapping studies that do not have a focus on wetlands in the title or abstract. May be included if wetland is mentioned as a sub-class in the classification.	**A**
Exclude studies that map single plant species in wetlands or vegetation cover, or plant metrics alone. E.g. Phragmites, aquatic vegetation, mangrove biomass, NDVI.	**A, C**
Exclude modelling studies that model ecosystem services from wetlands. E.g. Carbon, methane, emission, water regulation.	**A, C**
Exclude studies that map influencing factors alone.	**C**
Exclude hydrological modelling studies – wetlands are modelled from terrain data instead of remote sensing data.	**A**
Exclude studies mapping wetland water extent alone (i.e. inundation)	**A**
Exclude studies mapping flood events (i.e. short water flooding in areas with vegetation not necessarily adapted to water)	**A**
Exclude studies of agricultural “wetlands” – e.g. rice paddies.	**B**
Exclude studies mapping soil moisture alone.	**A**
Exclude studies mapping open water bodies (e.g. rivers, dams, lakes)	**A**
Exclude poster presentations.	**C**
Exclude studies on mangrove forests.	**B**
Exclude coastal wetlands.	**C**

2.2 Additional provision of information from experts

In order to gather information from both the academic and non-academic communities and other parties who have mapped wetlands with remote sensing, an online questionnaire was created and circulated to respondents identified by the research team and the Norwegian Environment Agency. The aim of the questionnaire was to obtain information about wetland mapping that is not necessarily published in peer-reviewed journals like time and costs for map production and other purposes and uses of the map. The request for information was sent as an online questionnaire to 42 potential respondents in eight countries including Sweden, Denmark, Finland, Switzerland and Canada. The questions covered 7 main topics, namely:

1. Information about the respondent
2. Scale of the map
3. Ground-truth data
4. Cost
5. Data infrastructure
6. Purpose of map
7. Lessons learnt

The online questionnaire was open for replies from 19.05.2021 to 26.05.2021.
20 respondents answered the online questionnaire. Ten answered all questions of the questionnaire while the other ten answered questions selectively.

3 Results

3.1 Literature review results

The initial search for published studies meeting our criteria identified a total of 3235 results. Web of Science returned 2059 publications and Scopus returned 2611. Of these, 1435 were duplicates. The titles of these results were filtered manually according to the exclusion criteria (**table 3**), with 508 chosen for abstract or full-text reading. Of these, 137 were included in the final literature database. Furthermore, we included 73 papers from a meta-analysis done by Mahdianpari et al. (2020a), which resulted in 210 studies included in this literature review. The presentation of the literature results follows the general structure of a typical remote sensing workflow introduced in the introduction in **figure 1**.

The literature survey showed that the majority of studies that utilised remote sensing to map wetlands were in Canada (61), USA (41) and China (38) (**figure 3**). Few studies were available for Scandinavia, with two in Sweden and two in Finland. No studies had been published in the academic literature on Norwegian wetlands.

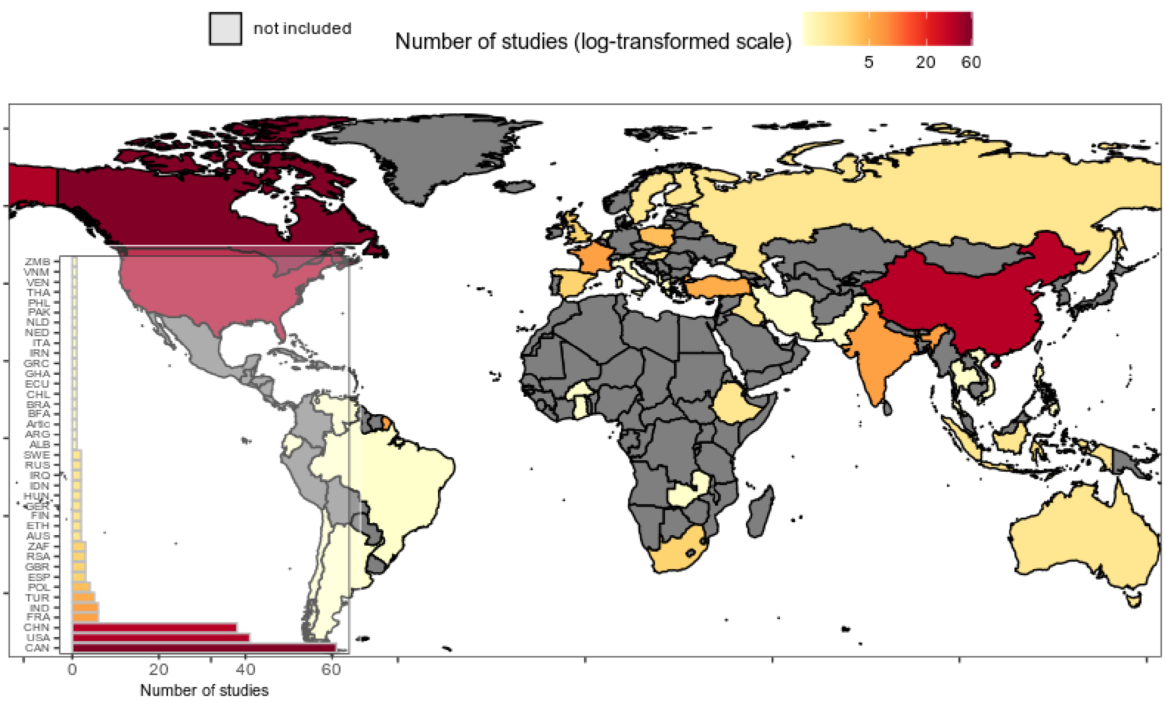

Figure 3. *Distribution of studies included in the systematic literature review. Areas in grey were not represented in the literature. The colour scale is log-transformed, however the inset graph shows the study numbers per country without a log-transformed scale.*

3.2 Wetland definitions and classifications

Our results revealed that most studies classified wetlands based on a zonal typology (**figure 4A**). We define zonal typologies as those that differentiate wetlands based on their spatial context and surrounding habitat (e.g. coastal, estuarine, inland), climate zone (e.g. boreal, alpine), or land-use (e.g. wetland vs agriculture vs urban). Fewer studies defined wetlands based on their dominant species (e.g. grass vs sedge), structure (e.g. basin vs swale), functional group, or temporal dynamics (**figure 4A**). Wetlands were most often defined and mapped in contrast to other land cover classes (**figure 5A**). This suggests that it is necessary to define "non-wetland" and "wetland" simultaneously. Defining "non-wetland" is particularly relevant when collecting ground truth data because the classification model needs to be trained on all the possible non-wetland cases to prevent misclassification.

Studies classified land cover (including wetland and wetland subclasses) into a median of 7 land cover classes (**figure 4B**). Very few studies had more than 10 classes in their final classification map. In terms of the wetland typology used, the wetland sub-classes were dominated by names from the Canadian wetland typology including fen ("jordvannsmyr" på norsk), marsh, swamp ("sump"), and bog ("nedbørsmyr") (**figure 5B**; see Mahdianpari et al., 2020a).

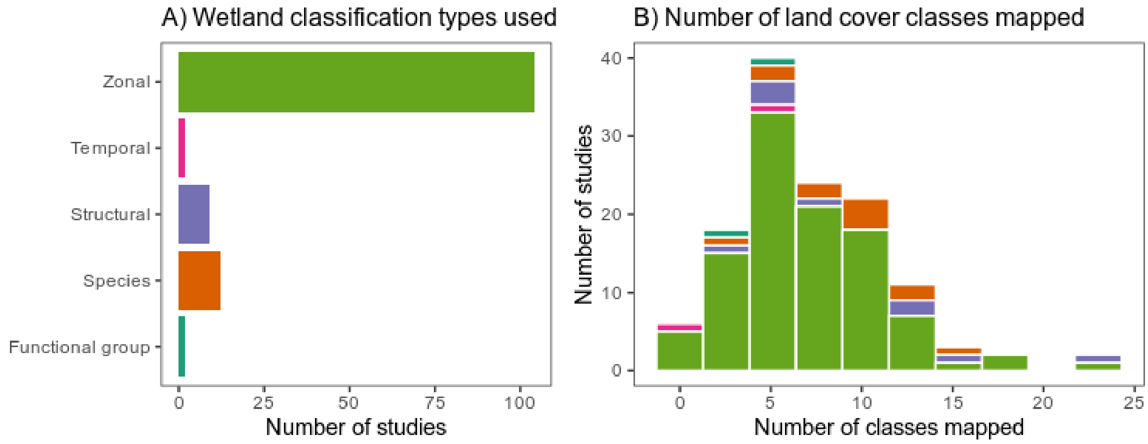

Figure 4. *Wetland classification types used in studies (A) and the number of land cover classes mapped (B).*

Figure 5. *Word clouds for the map classification typologies used in the studies (A). The size of the word indicates the frequency of use across studies. Panel B shows the wetland sub-classes included in the studies reviewed.*

3.2.1 Ground truth data

Ground truth data is used to train the classifiers and validate the accuracy of models in remote sensing studies. Most studies relied on ground truth data collected in the field (44 studies; **figure. 6A**), while 32 relied on visual interpretation of very high-resolution aerial imagery, and 28 relied on a combination of field data and image interpretation. The results showed that 12 studies relied on other reference datasets as ground truth. These included national land-use maps, wetland inventories, or other vector-based spatial data. The amount of ground truth data points collected was lowest for in-situ data (median 270 data points), and highest for reference datasets (median 1570 data points) (**figure 6B**). However, the amount of ground truth data was unrelated to the resulting map classification accuracy (**figure 6C**) for all data types except for reference data (lines are almost flat with exception of the solid purple reference data relationship line in Fig. 5C), where accuracy increased with increasing ground truth sample size. The size of ground truth datasets generally increased with the spatial scale of the study (**figure 6D**) with national-scale studies having a median of 16000 points (minimum of 300 and maximum of 132 000 points). This is probably also the reason why the amount of ground truth is little correlated to accuracy, as with increasing extent one usually get more overall variation.

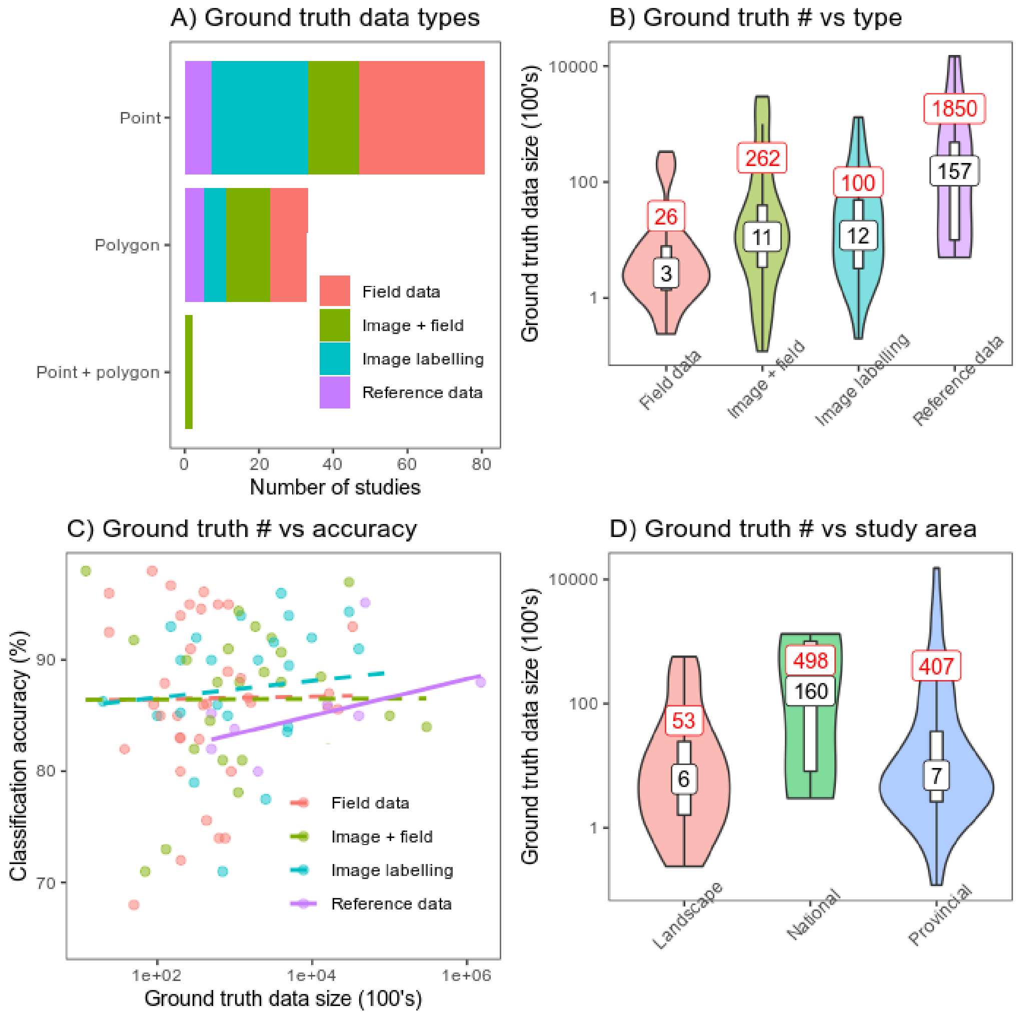

Figure 6. *The geometry and type of ground truth data included in studies are plotted in A. Ground truth data are either collected at point locations or for homogenous polygons, and can be measured in-situ (i.e. field data) or ex-situ (i.e. image interpretation or reference datasets). The number of ground truth points (quantified as labelled image pixels) are plotted in B. The relationship between ground truth data size (log-transformed axis) and map classification overall accuracy is shown in C, with solid lines showing significant linear relationships. The number of ground truth points vs study area is plotted in D. The red and black numbers in B and D represent data means and medians, respectively.*

On average, 2603 field-data points were used to train models, however this ground truth collection method was only used in landscape and provincial scale studies. Image labelling saw an average of around 5000 points used at landscape and provincial scales, and 66406 points used in national-scale classification. Combining image labelling and field-data allowed for considerably more training data to be collected, with an average of 26243 points used. National-scale studies using both image labelling and field-data used nearly 39000 points on average. On average, 2603 field-data points were used to train models, however this method was only used in landscape and provincial scale studies. Image labelling saw an average of around 5000 points used at landscape and provincial scales, and 66406 points used in national-scale classification. Combining image labelling and field-data allowed for considerably more training data to be collected, with an average of 26243 points used. National-scale studies using both image labelling and field-data used nearly 39000 points on average. The relationship between the spatial extent of the study area and the source of training data did not show any large differences (**table 4**).

Table 4. *Relationship between training data source and spatial extent of the study area*

Training data source	National	Provincial	Landscape	Total
Field data	/	88	85	86
Image labelling	83	88	87	87
Image labelling + field	83	88	85	87
Reference data	80	86	84	85

3.2.2 Remote sensing: temporal scope

We limited our review to post-2015 and obtained an even spread of studies between 2015 and 2020, with 4 studies from 2021 (**figure 7A**). It should be noted that studies using historical data were also included when the data included more recently acquired imagery.

The number of studies that mapped wetlands for a single point in time (109) was very similar to the number of studies that mapped wetlands over more than one year (100; **figure 7B**). Some studies mapped wetlands over more than three decades (using historical aerial photos or Landsat satellite archive imagery), however most studies mapped a few years centred around 2015 (**figure 7C**). The oldest data used was aerial images data from 1952 and Landsat imagery from 1970.

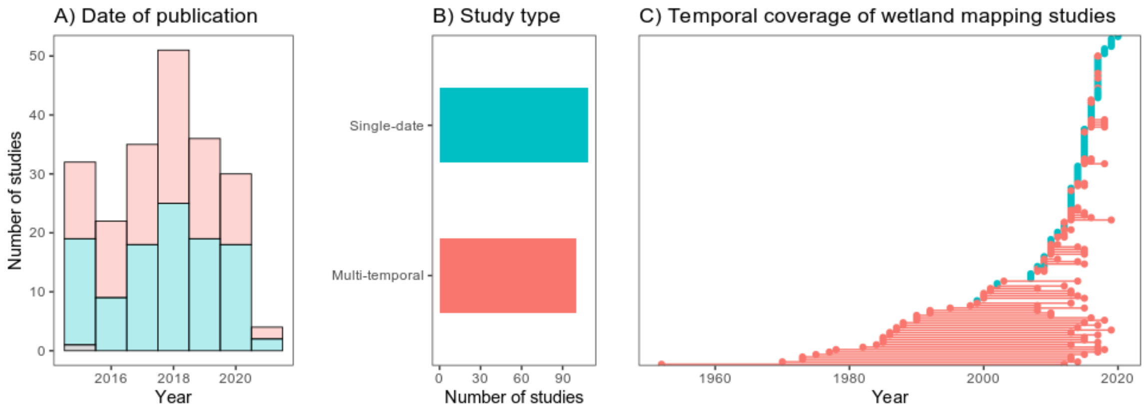

Figure 7. *The temporal distribution of publication dates for studies included in our literature review since 2015 is shown in A. Studies either mapped wetlands for a single date, or for multiple time points (B). The temporal coverage of mapping studies and their durations are plotted in C. Points represent start and end points of wetland mapping. Colours are red for multi-temporal studies and greenish for single data studies.*

3.2.3 Remote sensing: spatial scope and sensors

The majority of studies mapped wetlands at landscape (< 10km2) or provincial (> 10km2 & < 50000 km2) extents, with very few mapping at national or continental extents (**figure 8A**). Those that mapped wetlands at a national scale included 5 multi-temporal studies in Canada using optical data, 2 studies in China based on MODIS multi-temporal data and 2 single date studies in the USA using PALSAR. There were also multi-temporal national scale studies in Albania and India that both used combined optical and radar data.

Most studies (73) relied on Landsat satellites to map wetlands, followed by RADARSAT, and the Copernicus Sentinel satellites (**figure 8C**). The aforementioned satellite data are open-access, which clearly promotes their adoption in wetland mapping. Landsat imagery is also available since the 1970s, making it favourable for historical studies. Of the expensive sensors, (costs >$30/km2), which happened to be mostly airborne sensors, LiDAR, UAV and aerial photography were most commonly used (**figure 8C**).

The most common map resolution was >10m, which included satellites such as Landsat, Sentinel-1, PALSAR and RADARSAT (**figure 8C**). Of the 12 studies that were mapped at national or continental scale, 4 used either Sentinel-1 or Sentinel-2 imagery at 10m resolution, 2 used 30m Landsat imagery, one combined IRS and MODIS imagery at 37m resolution, 2 used 50m PALSAR data and 2 used 250m MODIS imagery (**figure 8A).** None of the 12 studies that mapped at the national scale used VHR imagery (very high resolution data).

Very high resolution satellite imagery was only used at the provincial and mostly at the landscape scale (**figure 8A**).The map accuracy was not significantly related to the spatial resolution of the map (**figure 8B**). There was large variation in map accuracies at both high and low spatial resolutions, suggesting that other factors are more important determinants of accuracy. Indeed, comparing accuracy across such a heterogenous range of studies is challenging because we cannot control for confounding factors between studies.

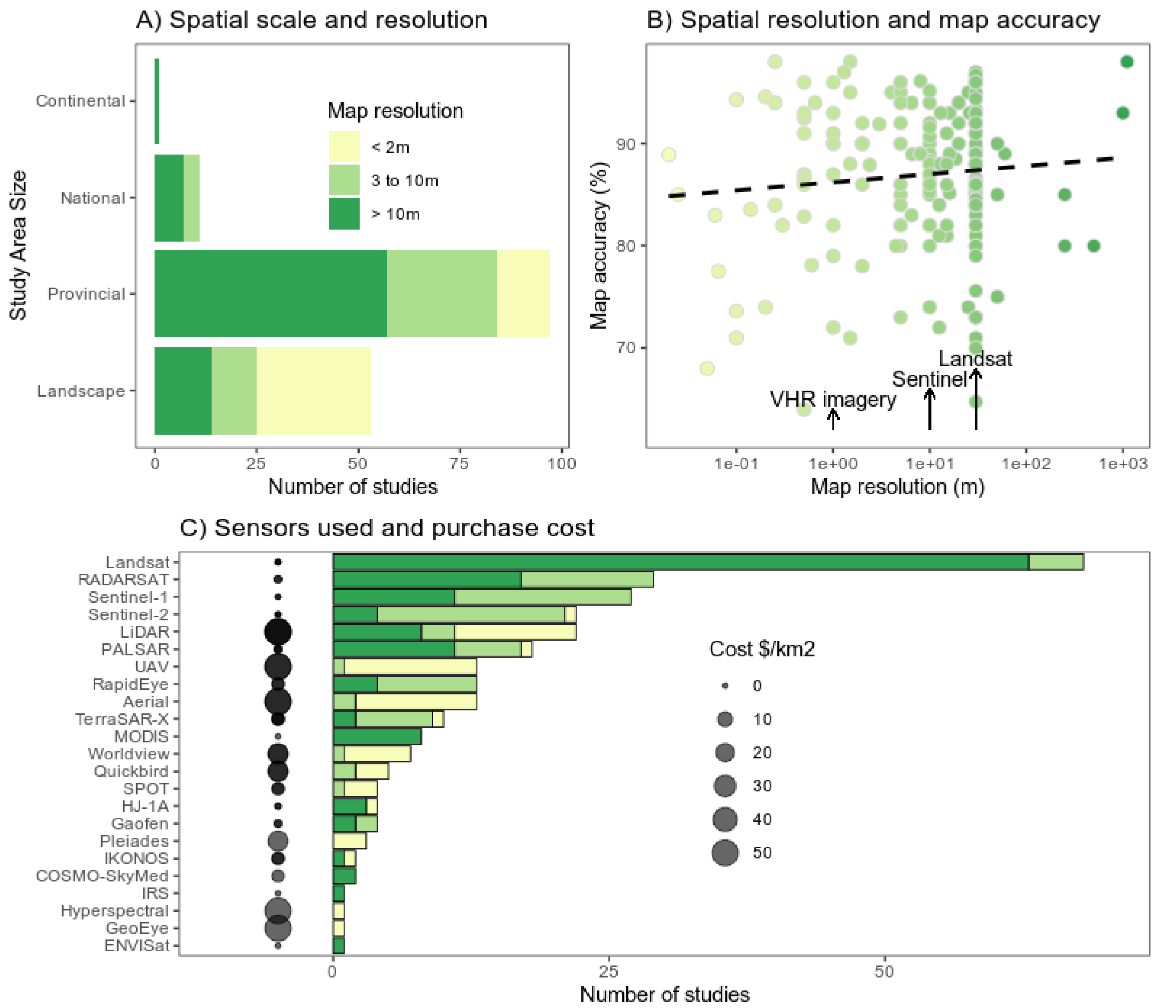

Figure 8. *The spatial extent and mapping resolution of studies is shown in A. The relationship between map resolution (log-transformed axis) and classification overall accuracy is shown in B with a linear regression line plotted. The distribution of studies across remote sensing platforms is plotted in C with an estimated acquisition cost per square kilometre of imagery*. *Estimated based on ESA (https://business.esa.int/newcomers-earth-observation-guide) and may vary substantially due to shifts in market value.*

3.2.4 Classification models: structure and performance

In terms of the type of classification model used,125 studies used pixel-based image classification and 71 used object-based. Pixel-based classification studies produced maps at a median resolution of 16m whereas object-based maps produced a median of 10m resolution maps (**figure 9A**). Despite this, there was very little difference in map accuracy (**figure 9B**) between the two methods. The results indicate that the number of predictor variables (I.e. image bands or band indices) in classification models increased the map accuracy for object-based classification but had no effect for pixel-based classification (**figure 9C**).

The most common machine learning framework used to generate wetland maps was decision trees (e.g. Random Forest, **figure 10A**), followed by support vector machines. State-of-the-art neural network models were used in 13 of the studies. The type of machine learning model adopted had no discernible effect on map accuracy (**figure 10B**).

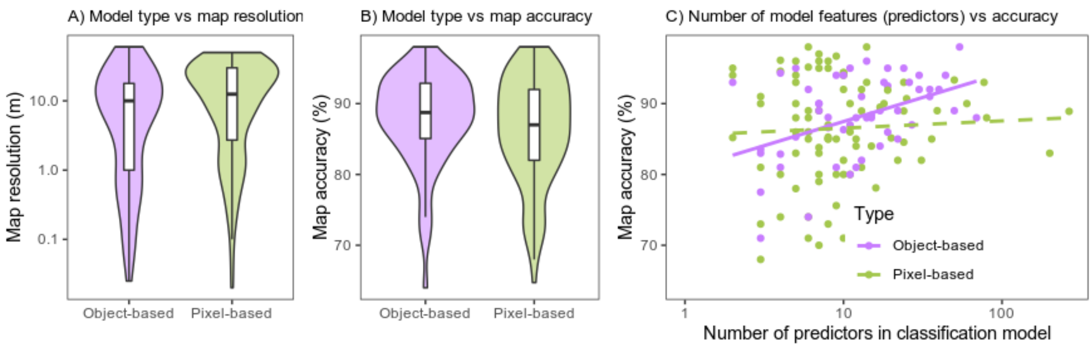

Figure 9. *Difference in map resolution (A) and map accuracy (B) between pixel- and object-based classification models. Violine plots show the data distributions and inset boxplots show the median (horizontal line) and interquartile (box) values. Relationship between the number of predictor variables and classification model overall accuracy is plotted in C. Linear regression lines are fitted (significant lines are solid, whereas non-significant lines are dashed).*

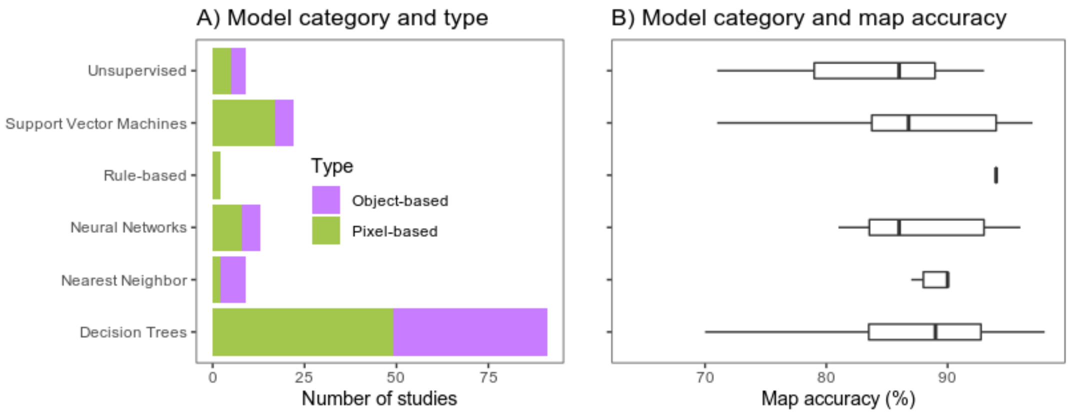

Figure 10. *The distribution of studies across machine learning model category and type is shown in A. The resulting classification overall accuracy per model category is shown in B. Median and interquartile values are shown with centre line and boxes, respectively.*

Our literature review revealed that 25% of the wetland studies used both optical and radar data, most for provincial scale studies (**table 5**). The studies that combined optical and radar sensores achieved the highest average accuracy at 89 %.

Table 5. *Data type, number of studies and average accuracy obtained in the wetland classification results.*

Data type	*Number of studies*	*Average accuracy (%)*
LiDAR	4	87
Optical	106	86
Optical + LiDAR	8	85
Optical + Radar	52	89
Optical + Radar + LiDAR	1	NA
Radar	38	87
Total	210	

3.2.5 Influencing factors and ecological condition

Very few of the publications (19) mapped ecological condition or influencing factors, other than the extent of wetland coverage (**figure 11**). Of those that did, the most commonly quantified condition factors were species composition and inundation area. However, only species or composition of species that cover larger areas are assumed to classified high certainty from remote sensed data. The only influencing factor quantified in the studies was land use change (e.g. wetland conversion to agriculture).

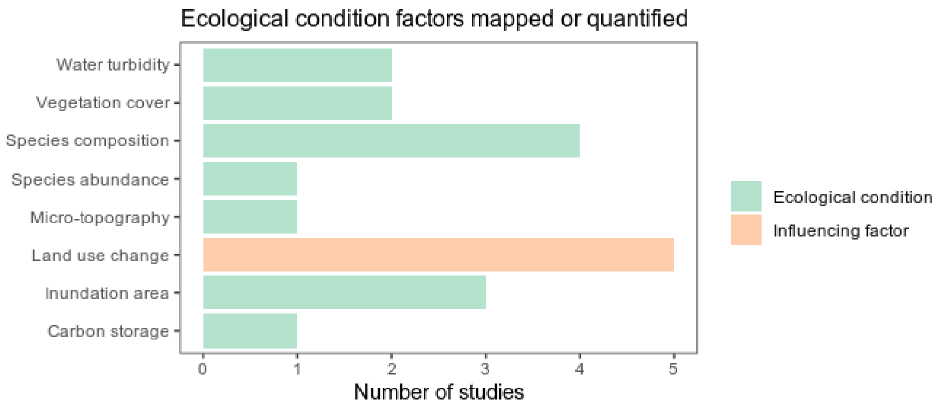

Figure 11. *Number of studies that quantified ecological condition or influencing factors using remote sensing.*

4 Responses to survey

We received 20 responses to our questionnaire of which 14 described themselves as researchers/scholars, two were government employee and four were consultants in the private sector. Among the 20 respondents, 8 have been directly involved with wetland mapping projects using remote sensing. 5 have not been specifically involved, but have experience with landcover mapping of other types.

However, not all of the respondents were mapping wetland ecosystems primarily. They were among others mapping aquatic environments or sea ice. Therefore, not all questions were answered by all respondents and the results from the questionnaire give limited additional information.

11 answers were provided to the question *on the collection of ground-truth data*. Four did in situ field sampling. One did interpretation of areal imagery and 6 did pursue this through other existing datasets such as published map data. Others collected ground-thruth data through elevation, peat depth, and single tree measurements. Others again referred to field and high-resolution satellites. Several emphasized a combined use of in-situ (forestry), interpretation of aerial imagery (NiN), other sources (FKB, area resource map), but the methods chosen depended on the project specific requirements. Sometimes field information and other ground information were provided by the purchaser of the study so the choice of in-situ data was neither made deliberately by the respondent. All the 11 answering to this question, confirmed that the map is once-off product for developing a “basemap”.

Nine responded to the question concerning the spatial scale of the wetland mapping projects. Of these, four had a focus on landscape and single wetland, two had a focus on State/province/county while nine had a national approach.

Concerning the question “*As opposed to processing remote sensing data and making the map, what percentage of the project budget did you dedicate to collecting ground-truth data?”* we received 10 responses that varied between 0, 10, 15 towards 50 %. One respondent emphasized that the time associated with contacting the authorities that hold the data, was very time consuming.

We got nine answers on the question ”*How long did it take you to produce your wetland map from project conception to the delivery of the final map?”.* One person responded that this depends on the request as well as on the spatial resolution. Such projects may take weeks to months depending on the requirements. Another emphasized that the mapping of wetland was only a small part of the larger project or only a part of a overall project mapping habitat types. One responded that such projects may even take months depending on the requirements.

On the question: “*Can you estimate the total costs to produce your wetland map? If possible, can you divide your estimate into operational costs, and data purchase costs*.” We received nine answers that were rather different with respect to the degree of specificity. One estimated a manpower cost of 180,0000 INR (Indian rupees) which equals 207,409 NOK. Another indicated 20 Euros/hectare with a 20 cm resolution 3D map of species composition. One respondent indicated 300,000 CHF (Swiss francs) which equals 2,778,941 NOK, while a Norwegian respondent indicated 400.000 NOK.

Among the eleven respondents answering the question" *what type of data infrastructure was used to produce the map?"*, eight answered that they used local computers. One did use a cloud solution. This answer was further specified with respect to the type of software that were used to produce the map:

- eCognition Developer / Server
- R, Pix4D, ArcGIS Desktop, ArcGIS online,
- Google Earth Engine

We further asked in our questionnaire "*How is your wetland map being used?"*. Among the nine answers we received, four stated that the wetland maps were only used for research purpose. Three of the answers did refer to public service. Of other uses, references were made to impact quantification and on land cover types that had been replaced by aquaculture ponds and thus where biodiversity is at threat. One referred to research and management. Another wrote that it was used by customer who requested the map for their own, undisclosed purposes. One referred to an official national map.

Then we asked: *What best describes the purpose of the wetland map.* Among the ten answers, three referred to testing remote sensing techniques. None referred to mapping wetland types, one referred to monitoring wetland conditions and three referred to landcover mapping that included wetland as a class option. Among other purposes, the following were mentioned: Impact quantification of pond creation, long term monitoring of vegetation changes at 20 cm resolution, but several emphasized that the purpose varies depending on the request.

We also asked for input on how to develop an accurate wetland map at a national scale and specifically we asked: "*what do you think are the most important "ingredients" to produce an accurate wetland map at a national extent?".* We received nine answers that were distributed in the following way:

- Six emphasized ground truth data
- One referred to the remote sensing sensor used
- Two stated that the machine learning model is the most important ingredient
- None referred to the data infrastructure

In addition, we asked for further comments and got the following answers: Accurate wetland maps can be made with the combination of high resolution satellite data and ground truth data, which are both equally important. Medium resolution satellite data can cover larger areas, but then accuracy might decrease. Good data and good software that include both machine learning and several hundred other functions, are crucial. All mentioned "ingredients" are important, it's the combination of them that matters. Another reference was made to the combination of automated and semi-automated interpretation and the use of existing data and LiDAR with good penetration properties. It was suggested one should not go for single-photos. One respondent stated that machine learning model and remote sensing sensor, data selection and preprocessing is crucial. Both ground-truth and remote sensing data are equally important. The sensor has to be able to observe the characteristics (or the proxies) while the ground-truth is necessary to calibrate and validate the models. Finally, one stated that all the above will be needed to work together to develop an accurate map. The more data, the more context and therefore more accuracy can be provided.

5 Discussion

5.1 Lessons from national-scale mapping studies

Of the handful of national scale studies, three had a classification accuracy of 85% or higher. The study by Clewley et al. (2015) produced a wetland map of Alaska (approximately 1.6 million km^2) with a classification accuracy of 85% for wetland classes. This study used PALSAR data and a random forest classifier. It was a pixel-based classification with 100 000 training points. The resulting map was produced with a spatial resolution of 50m for a single date in 2007. Clewley et al. based the wetland classes on the Cowardin classification system (Appendix A), which separates wetlands based on vegetation type and major wetland systems (i.e.- estuarine, riverine, lacustrine and palustrine). Wetland traits, such as water regime were used to augment the basic classes, resulting in 23 classes. Due to difficulty distinguishing between some of these classes, they were aggregated post-classification. The final classification consisted of 12 classes, of which 8 were wetland classes, namely: estuarine emergent, estuarine scrub-shrub, estuarine forested, riverine emergent, lacustrine emergent, palustrine moss-lichen, palustrine emergent, palustrine scrub-shrub, palustrine forested. The authors note the importance of including non-wetland classes in the training data to avoid confusion. One of the limitations of this study was that the authors used national-scale reference maps to produce training data. These had a level of error associated and were 30-40 years old, which may have resulted in inaccuracies. As random forest is relatively robust to outliers and noise in the training data, the authors compensated by using a large amount of training data (100 000 pixels). The wetland map of Alaska will continue to be updated in the future as new methods and SAR data become available, allowing them to improve the classification accuracy. In particular, the authors are exploring geographic object-based image analysis (GEOBIA) for classification.

The study by Xing et al. (2017) used MODIS imagery to map and monitor the status of 20 Ramsar sites in China between 2001 and 2013. The wetlands were all greater than 11 579 ha in size. The authors used a support vector machine (SVM) to classify 9 classes, namely: open water, permanent marshes, seasonal marshes, flood plain wetlands, rice field, forest or shrub, grass, human-made cover or bare land, and drylands. Xing et al. included 3 spectral indices in their features. These were the normalised difference water index (NDWI), the normalised difference moisture index (NDMI) and the normalise difference vegetation index (NDVI). The inclusion of NDMI was found to improve the classification accuracy. Validation data were created using image-labelling of 1624 points. The final map had a spatial resolution of 250m and overall classification accuracies of 85% for 2001 and 87% for 2013. The authors also measured the wetland landscape integrity index (capturing the range in variability associated with the structure, composition and function of wetlands) and the disturbance and degradation of wetland ecosystems index (indicator of transformation to other land cover types). A limitation of these two indices is that they do not capture the quality of the wetland. The authors suggest including other remote sensing derived indices such as biomass, the fraction of absorbed photosynthetically active radiation, evapotranspiration and vegetation height. A disadvantage of using MODIS imagery is that the spatial resolution is very coarse, meaning only large wetlands can be mapped and monitored.

Mahdianpari et al. (2019) on the other hand, achieved an 88% accuracy at 10m resolution. The authors compared Sentinel-1 (radar) and Sentinel-2 (optical) data for mapping wetlands and found that combining both achieved the highest classification accuracy. They used a random forest classifier to produce a map of wetlands for Newfoundland in Canada, an area approximately 106 000km^2. The resulting map contained 8 classes, of which 4 are specific wetland types and 2 classes describe water depth. The classes included: bog, fen, marsh, swamp, shallow water, deep water, upland and urban. The wetland classes are derived from the Canadian Wetland Classification System (CWCS, Appendix B). The authors used object-based classification with in-situ data collected via an extensive field campaign between 2015-2017. A total of 1200 wetland and non-wetland sites were visited during this period, contributing to a robust wetland training sample. In addition to four bands from the optical data (red, green, blue, near-infrared), NDVI, NDWI and MSAVI2 were included as features, along with the backscatter data from the radar. Google Earth Engine (GEE), the cloud computing platform, was used for the classification. The authors found that using the combined optical and radar data improved the classification of individual wetland classes, but bog and fen were the least discernible. A limitation of the study was that the Sentinel-2 imagery available on GEE were not atmospherically corrected at the time of the study. Another limitation was that mosaicking over a long time period was necessary due to cloud cover, which may have resulted in classification errors and the overlooking of seasonality. This is probably a challenge for Norwegian approaches as well. To reduce this, only summer imagery were included in the mosaic. In terms of upscaling their methodology to the whole of Canada, the authors state the following challenges. Cloud cover limits the availability of optical data, but this could potentially be mitigated by using both Landsat and Sentinel-2 imagery. The biggest challenge identified was that of collecting sufficient, high quality training data.

Our results show that remote sensing has seldomly been used for national scale wetland mapping. This may be attributed to a lack of infrastructure to support the scale of processing in the past. Recent cloud-based platforms like Google Earth Engine, hold much potential for large scale mapping because not only do they host libraries of imagery and data, but also allow for resource-intensive processing. Recent studies, like that of Mahdianpari et al. (2019) demonstrate how cloud-based processing can be used to map wetlands for large areas.

5.2 Technical discussion

5.2.1 Sensor type

There are three main remotely sensed data types, which are optical data (passive remote sensing such as satellite imagery or aerial photographs), Synthetic Aperture Radar (SAR, measures backscatter from pulses of light), and LiDAR (laser scanning which creates point clouds of data). The choice of sensor type is determined by the size of the area (and thereby also the time and cost) and the objective of the study.

Satellite imagery, like aerial photography, use sensors to capture reflectance. While traditional aerial photography generally only captures information on the red, green and blue wavelengths of light (and occasionally also near-infrared), satellite imagery capture a wider range of the electromagnetic spectrum, including reflectance that is not visible to the human eye. Satellite imagery are taken along set paths and rows meaning scenes are repeated at set intervals, an important consideration for monitoring studies. How often an image is taken of the same site varies depending on the satellite mission, with some as often as every 2-5 days (e.g. Sentinel-2) and others every 16 days (e.g. Landsat). There can be considerable variation in the spatial resolution of the imagery, ranging from 0,5m (Pléiades) to 250m (MODIS). Similarly, there is also much variation in the number of bands and the cost of acquisition. Sentinel-2 (10m resolution), Landsat (30m) and MODIS (250m) imagery are available free of charge and contain between 7 and 36 bands. Sentinel-2 contains 3 red-edge bands in addition to near-infrared which make it especially suited to vegetation mapping, however it should be noted that the red-edge bands are at 20m spatial resolution. Landsat contains a thermal band (100m resolution) which has been explored for studying wetland dynamics (e.g. Kaplan et al. 2019, Zhao et al. 2019). The Satellite-based Wetland Observation Service (SWOS) generates information on wetland ecosystems using the possibilities offered by freely available satellite data (https://www.swos-service.eu) (accessed 11.06.2021). They also give overview over what sensors are used for what purpose in wetland monitoring. An advantage of satellite imagery is that large areas can be covered in a single scene making it much less costly and time consuming over large areas than aerial photography (Ozesmi & Bauer 2002). The limitations of satellite imagery is that the spatial resolution can make it challenging to identify very small or narrow wetlands. It is also difficult to distinguish between types of wetlands because their spectral signatures may overlap (Ozesmi & Bauer 2002). When water levels are low, wetlands can be misclassified as upland areas. One of the most significant disadvantages of satellite imagery is cloud-cover. Presence of cloud in an image makes interferes with the reflectance of the land cover below and cloud pixels need to undergo further preprocessing to substitute them with other from different dates. The United States Nation Wetland Inventory project (began in 1975) decided to use aerial photography over satellite imagery because 1) fluctuating water levels change the reflectance of vegetation, 2) fire scars can be misclassified as open water, 3) periphyton masses in certain seasons can influence the classification, and 4) certain species (*Typha spp.)* complicated image classification because of changing growth patterns (Ozesmi & Bauer 2002). Despite these disadvantages, satellite imagery has major advantages for monitoring over time and are especially well-suited to large geographic areas. Ozesmi & Bauer (2002) suggest that in national scale maps, satellite imagery be used to identify where changes are occurring and where more detailed maps should be prioritized for updates. However, all optical approaches can suffer for wetland in forests, so for ecosystem and climate accounts it could be a problem to have those areas underrepresented.

Radar data are complementary and supplementary to optical and thermal data because they operate in the microwave portion of the electromagnetic spectrum (Henderson & Lewis 2008, Ozesmi & Bauer 2002). Synthetic Aperture Radar (SAR) is an active form of remote sensing where the backscatter from pulses of light are captured by sensors at different wavelengths. The backscatter provides information about surface roughness and the moisture content of soil and vegetation. A significant advantage of radar data is that it can penetrate cloud and is therefore not greatly influenced by weather (Brisco 2015). Like optical data, SAR also has bands that represent the length of the wavelength being captured. In wetland mapping, previous reviews of the literature (e.g. Hess et al. 1990, Kasischke et al. 1997) have found that the L-band is most suited to mapping wetlands in forested areas. This is because the longer wavelength of the L-band is able to penetrate the tree canopy and has a double-bounce effect from the water below the trees, resulting in a unique signature. The C-band is appropriate for mapping herbaceous wetlands and performs best when there is low biomass and leaf-off conditions (Henderson & Lewis 2008). Because of the challenge of differentiating between wetland types (Brisco 2015), Henderson & Lewis (2008) conclude that multiple wavelengths are needed for consistent and accurate mapping of wetlands using SAR. With regard to polarization, dual- (HH/HV) is preferable to single- (VV) with multipolarized imagery outperforming single polarization. Mahdianpari et al. 2019 mention that being near the Polar regions is an advantage because both HH/HV) and VV polarized data are available from Sentinel-1. Another consideration with SAR data is the incidence angle. Some studies suggest that steep incidence angles are better suited to mapping water bodies under vegetation (Mahdavi et al. 2017), however the literature is inconclusive and studies suggest using varying incidence angles (Henderson & Lewis 2008). Some disadvantages of using SAR data are that the processing can be more time-consuming because of the need for multiple bands and varying incidence angles, and that speckle sometimes can hinder image segmentation and classification (Henderson & Lewis 2008; Mahdavi et al. 2017). Another challenge is that training data must be much larger than that required for optical data to compensate for speckle (Mahdavi et al. 2017).

Mahdianpari et al. (2019) explain that optical and radar data can be synergistic because optical data provides information on the reflective and spectral characteristics of wetlands, while radar provides information on the structural, textural and dielectric characteristics. Several studies have demonstrated the potential of this data fusion for wetland classification, including Whyte et al. 2018, Bwangoy et al. 2010, van Beijma et al. 2014 and Mahdianpari et al. 2019.

LiDAR is similar to radar in that it is an active form of remote sensing. LiDAR measures the distance to objects on the ground using the time it takes for a sensor to detect the light pulses sent out by a laser. LiDAR has enough power to penetrate vegetation and therefore provides 3D topographic information of the Earth's surface. This data is used to predict the location and distribution of wetlands. LiDAR is mostly used as ancillary data in wetland mapping in addition to optical or radar data (Mahdavi et al. 2018). LiDAR is normally derived from an airborne laser scanner which provides high spatial resolution data, but is also amongst the most expensive data sources.

The availability of cloud-free imagery is a challenge for countries like Norway. There are methods of creating cloud-free mosaics by substituting pixels based on specific criteria, for example selecting the greenest pixel. In this regard, radar imagery is useful because it penetrates clouds. Similarly, LiDAR is not affected by clouds, however LiDAR is limited in the information it can provide on wetland classes. Many studies combine optical data with either radar or LiDAR.

5.2.2 Ground truth data

Training data is used to tell the remote sensing model what spectral, textural, structural and dielectric characteristics correspond to specific wetland classes. There are three main techniques for collecting training data, namely in-situ field data, image labelling and reference data. The term 'reference data' is here synonymously used for extracting training data from existing maps such as vegetation maps, land cover maps in different resolutions, cadastral maps etc. In Norway reference data can be collected from N5, AR5, N50 and so on. Generally speaking, collecting field data is the most expensive, time-consuming and highest quality source, and reference data is the cheapest, fastest and lowest quality. However, this is related to the purpose of which the data has been collected for. Our results showed that the most common source of training data is from field-data (36%), however it should be noted that 89 of the 210 studies did not report their source of training data. Image labelling was the next most common method with 30% of the studies where information was available, using this method. Combining field data and image labelling data was also a common method (24%). Of the national-scale studies, 3 used this combination, 3 used image labelling, 1 used reference data and 4 didn't document the source of their training data.

There is broad agreement that an increasing amount of training points gives better classification results (Foody 2002, Loew et al. 2017). However, when this is not always the case, as we see in our results with the exception of reference data, this may be due to several things such as imbalanced training data. Bakkestuen & Venter (2021) mentions six dimensions of data quality that are important in collecting ground truths as training points are. These six requirements are (i) general requirements for statistical interpretation of ground truth that meet the requirements of modern sampling methodology also in terms of representative samples, (ii) meet the homogeneity requirement for ground truth, (iii) meet the area requirement for minimum size for ground truth, (iv) meets the requirement for a sufficient number, (v) has the built-in ability to capture rare area types and (vi) that ground truth is freely available machine-readable on the web. The vast majority struggle, among other things, to meet requirements (ii) homogeneity and (iii) sufficient minimum area (d'Andrimont et al. 2020). An additional challenge are timeliness of the data (temporal match with the imagery).

Accuracy of classifications is also given in slightly different ways. The two most common were either on the basis of a confusion matrix and kappa statistics. Both of these methods have their advantages and disadvantages and there are no correct answers as to which is best because the starting points for the different studies are so different in terms of number of classes and type of classes, area, distributions and so on. For further discussion of confusion matrix and kappa statistics, see the section on validation below.

There were many studies that had placed great emphasis on meeting the requirement for a representative selection of training points. Therefore our results also show that the number of training points is probably not the bottleneck for achieving higher or desired accuracy on the classification product as we did not get a significant relationship between accuracy and the number of training points, although image labelling and combined image labelling and field-data performed slightly better than reference data at national-scales. However, we must acknowledge that comparing accuracy levels across different studies with different spatial extents and wetland typologies is difficult because various confounding factors can influence single relationships.

Ideally one would perform a pilot study to test the relationship between ground truth sample size and classification accuracy. For instance, Venter and Sydenham (2021) found that classification accuracy of land cover types in Europe is not linearly related to the size of ground truth samples. In the case of LUCAS ground truth data, they found that accuracy gains plateau after approx. 10K points so that the difference in accuracy between 5K and 50K LUCAS points is only 3%. There is much theory written about ground truth, for instance see Beleites et al. (2013) and Loew et al. (2017).

There were quite a few of the studies that acquired the training data from fieldwork where the data were collected using traditional botanical analyses, such as relevés that usually serve a very different purpose. In such cases, the accuracy of the classification is unlikely to increase with more training data. The advantages of making intensive registrations in the field versus interpreting aerial photographs are also not seen to be significant in our results, which in turn may be caused by this violation of the area and homogeneity requirement. Lack of literature where the collection of ground truths was fully satisfactory makes it difficult to fully confirm our assumptions.

Reference data, such as land use maps in vector format has already been through a process where the person or persons who made this has made some guidelines for how much variation is allowed within each polygon before dividing it and how large the minimum size is. Thus, those who have access to reference data will also inherently have access to training data where the two requirements regarding size of area and homogeneity in some way have been accounted for. It can be highly probable that it what give us a significant relationship between the amount of "reference data" and classification results.

The way models are validated can also affect how good the accuracy of the author's results is. Kappa statistics and statistics from a confusion matrix are two common ways to report accuracy. A confusion matrix is often based on points or pixels and on whether these are correctly or incorrectly classified by the model (Loew et al. 2017). A known fault that occurs when using statistics from a confusion matrix is that validation points can be assigned the correct classification by pure chance. This error can be amplified if the model consists of large area-covering classes where there is a high probability that a completely random point can hit this class. The kappa statistic is used to control only those instances that may have been correctly classified by chance. This can be calculated using both the observed (total) accuracy and the random accuracy. Kappa can be calculated as: Kappa = (total accuracy – random accuracy) / (1- random accuracy). It was sometimes difficult to understand which statistics for accuracy were given in the articles, often where several methods, sensors and data sets were used in addition.

It was also often common to collect both training and validation points at the same time with the same methodology. In this way, points could be distributed randomly between training and validation.

5.2.3 Processing infrastructure

There has been a major shift in recent years to cloud-based computing platforms for geospatial and remote sensing analyses. The main paradigm shift with the free availability of large amounts of data is to move algorithms to where the data is located. Cloud-based platforms allow users to scale remote sensing workflows over larger areas because one can simply purchase more computing power and storage space without having to install any hardware or local infrastructure. While some government and private institutions are concerned about data privacy and protection with third-party cloud service providers (like Google, Microsoft or Amazon), many research institutes have decided to acknowledge these agreements and now rely on these services. A complex analysis regarding the use of “big-data” in public authorities in Norway is given by Kommunal- og moderniseringsdepartementet (2016) which also covers e.g. possibilities for establishing cloud services for the public sector in Norway. The few national-scale wetland mapping studies reported on in our review did use cloud-based platforms. The most notable platform for remote sensing workflows is Google Earth Engine (GEE). GEE has both a Python and JavaScript API and provides access to petabytes of open-access satellite data. GEE has allowed for many national to global mapping studies and has significantly advanced the state-of-the-art in remote sensing research (Tamiminia et al., 2020). The most important contribution is probably better opportunities for large extent studies even in areas with low bandwidth and limited financial resources. However, it is important to note that there are many alternative cloud platforms available that are specific to remote sensing analysis. The disadvantages of GEE is that the server-side backend is not open access or transparent and therefore the user is restricted to utilizing the functions and processing structures provided by Google. Furthermore, GEE is meant for research and development purposes and it may not be used in an operational manner for commercial purposes. However, GEE is developing a commercial programme which may allow for adoption in the governmental and private sectors. Alternative cloud platforms to GEE include Sentinel Hub, Open Data Cube (ODC), System for Earth Observation Data Access, Processing and Analysis for Land Monitoring (SEPAL), JEODPP, pipsCloud and DIAS. Each has its own advantages and disadvantages which has recently been reviewed by Gomes et al. (2020) (**table 6**). There has also been Norwegian initiatives (in particular NBS). Blumentrath et al. (2019) adresses Norwegian infrastructure in particular.

Table 6. Capacities of the platforms for big EO data management and analysis (after Gomes et al. 2020)

CAPABILITY	ODC	GEE	SEPAL	JEODPP	PIPSCLOUD	OPENEO	SH
DATA ABSTRACTION	High: Product and Dataset	High: Image, ImageCollection, Feature and FeatureCollection	Low: Direct file handling	Low: Direct file handling	Low: Direct file handling	High: Collection and Granule	High: Data Source, Instances and Layers
PROCESSING ABSTRACTION	Medium: Xarray and celery	Medium: Predefined pixel-wise functions	Low: User runs his own code	Low: User runs his own code	Low: User runs his own code	Medium: User-Defined Functions, Process graphs and Jobs	Medium: Custom scripts (Evalscripts) layers perform pixel-wise processing
PHYSICAL INFRASTRUCTURE ABSTRACTION	Medium: Only data storage infrastructure infrastructure	High: Both data storage and processing infrastructure	Medium: Only data storage infrastructure	Medium: Only data storage infrastructure	Medium: Only data storage infrastructure	High: Both data storage and processing infrastructure	High: Both data storage and processing infrastructure
OPEN GOVERNANCE	High: Defined governance process	Low: Proprietary software, closed source software	Medium: Only open source repository	Low: Proprietary software, closed source software	Low: Proprietary software, closed source software	Medium: Only open source repository	Low: Proprietary closed source software
REPRODUCIBILITY OF SCIENCE	Low: Without any ease	Medium: Data links and scripts shareable without guarantee to be reproducible	Low: Without any ease	Low: Without any ease	Low: Without any ease	Low: Without any ease	Low: Without any ease
INFRASTRUCTURE REPLICABILITY	High: Open source code, docker containers and documentation available	Low: Proprietary closed source software	Medium: Open source code with basic documentation available	Low: Proprietary closed source software	Low: Proprietary closed source software	Undefined: Dependent on the backend used	Low: Proprietary closed source software
PROCESSING SCALABILITY	Medium: A template application available (Python and Celery)	High: Code automatically executed in parallel using a MapReduce approach	Low: User runs his own code	Medium: HTCondor	Medium: A template application available (C++ and MPI)	Undefined: Dependent on the backend used	High: Closed solution
STORAGE SCALABILITY	High: Distributed File System, S3 and HTTP	High: Google storage services	High: Google storage services	High: Distributed File System	High: Distributed File System	Undefined: Dependent on the backend used	High: Closed solution
DATA ACCESS INTEROPERABILITY	High: OGC Services	Medium: Tile service	Low: Without any ease	Low: Without any ease	Low: Without any ease	High: OGC Services	High: OGC Services
EXTENSIBILITY	High: Open source and modular code	Low: Proprietary closed source software	High: Open source	Low: Proprietary closed source software	Low: Proprietary closed source software	Medium: open source software integrated with proprietary software	Low: Proprietary closed source software

5.2.4 Spectral indices and spectral-temporal metrics

In addition to the satellite bands, spectral and temporal indices have been used in wetland classification and are often referred to as artificial bands. Spectral indices are equations that are applied to two or more bands to provide additional information and are commonly used in remote sensing applications. An advantage of using spectral indices is that they stabilise noise in the data caused by differences in illumination or cloud shadows. Many different spectral indices exist. One of the most well-known for vegetation studies is NDVI (normalised difference vegetation index) which is based on differences in the red and near-infrared bands. NDVI is a good indicator of plant productivity and biomass, and is often used for vegetation classification. A limitation of NDVI is that it is sensitive to atmospheric affects like clouds, shadows and soil brightness (Xue & Su 2017). NDWI (normalised difference water index) is often used in wetland studies to measure vegetation water. NDWI is less affected by atmospheric scattering than NDVI and can be used to predict canopy water stress and plant productivity (Adam et al. 2010). NDWI can also be useful in distinguishing wetlands from uplands. MSAVI (modified soil-adjusted vegetation index) was used by Mahdianpari et al. (2019) to compensate for the limitations of NDVI in areas with a lot of exposed soil. Mahdianpari et al. (2019) found that spectral indices were far better at distinguishing wetland classes than the original bands alone. In addition to spectral indices, modern remote sensing methods frequently quantify spectral-temporal metrics which define the change in spectral response over time. For instance, when mapping wetlands for a given year, one can calculate the minimum, maximum, median and standard deviation in the NDVI signal over all the satellite images available during that year. This is particularly important for distinguishing wetland types which have a strong phenological signal.

5.2.5 Object-based or pixel-based

Image classification is done by these two techniques: pixel based and object based. The Pixel-based approaches work on each individual pixel and extract information from remotely sensed data based on spectral information only (Gupta and Bhadauria 2014). The increased variability that comes naturally with high spatial resolution imagery confuses traditional pixel based classifiers resulting in lower accuracies (Aggarwal et al. 2016). The problems faced by pixel based in high resolution imagery approaches are overcome by the Object Based image classification. Object-Based information interprets an image not only by single pixel but also in meaningful image objects and their mutual relationships (**figure 13**). Object-based information extraction not only depends upon spectrum character, but also on geometry and structure information (Aggarwal et al. 2016).

A concept scheme of pixel versus object based classification is shown in **figure 12** and an example is shown in **figure 13**.

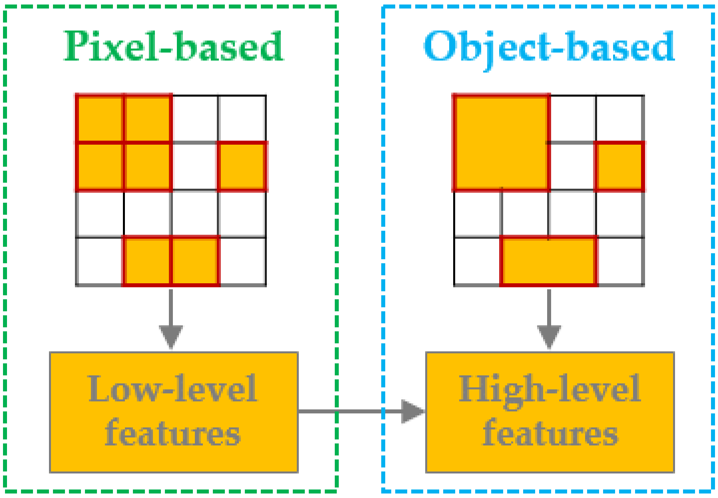

Figure 12. *Taken from Crommelinck et al. (2016). Pixel-based and object-based feature extraction approaches aim to derive low-level (only pixels) and high-level features (includes aggregation of pixels) from images. Object-based approaches may include information provided by low-level features that is used for high-level feature extraction*

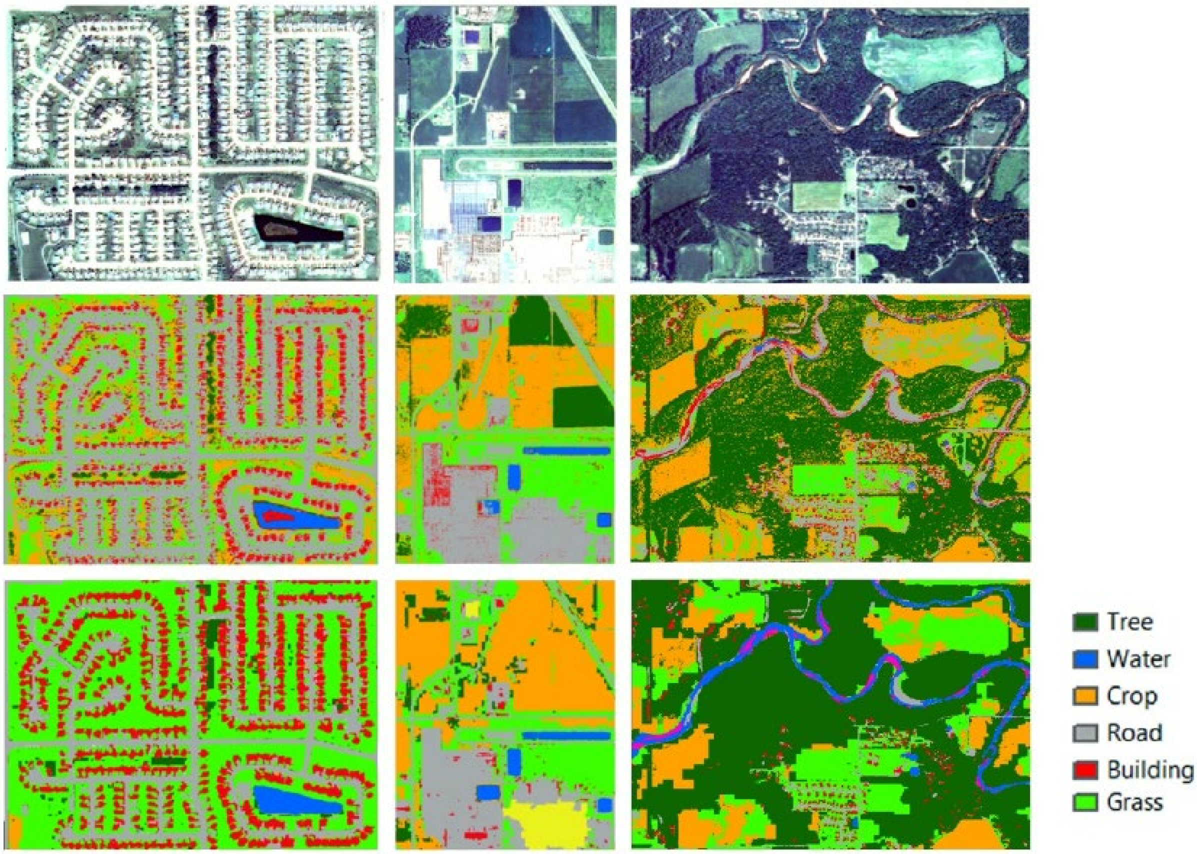

Figure 13. *Taken from Xiaoxiao, L and Guofan, S. (2014). A comparison between pixel-based and object-based classification results. The first row shows the image of original images with RGB band combination display. The second row of images is the pixel-based classification results. The third row of image is the object-based classification results. Each column shows the same location on the map.*

Object-based image analysis adds an extra dimension to image classification by reducing noise and small variation, and by including form of objects, such as skeleton and width, as additional variables. One is no longer so dependent on the actual values in the single pixel giving unique signals. Neighboring pixels tend to be similar even if they have a slightly different combination of values in different bands (image segmentation aims at internal homogeneity and difference to neighboring objects). In deep learning it is thus the composition of pixel values in a larger neighborhood that counts. By using these neighborhoods, it should in principle be easier to find structures or patterns that allow the computer to separate classes such as wetlands through the deep learning process. This is in accordance (Aggarval et al. 2016) which observed that the object-based techniques shows higher accuracy in classification process than the pixel-based technique because pixel based can't satisfy the high resolution satellite data properties and it produced data redundancy

In several of the articles that compare object-based versus pixel bases models, the object based model gives the best result and achieves the highest accuracies (Aggarval et al. 2016, Mahdianpari et al. 2019). No paper stated that the pixel based model was superior of the object based. In a similar literature study of ours, object-based classifications were found to be superior to pixel-based classifications using optical (~6.5% improvement) and SAR (~6% improvements) imagery in comparative cases in the study by (Mahdianpari et al. 2020a). However, the opposite was reported in several other papers. So, the literature is inconclusive when either the one or the other is used. Generally, pixel-based classifications are used on coarse resolution imagery (greater than 30m pixel resolution), but object-based classifications are used on high resolution imagery (lower than 10m pixel resolution). Therefore one would expect object-based classifications to be more accurate when incorporating aerial imagery, drone or LiDAR data, but when using Landsat or Sentinel data, pixel-based classification may be as accurate. This of course depends on the size of the mapping units one is aiming at. If you want to capture small or narrow wetlands, segmentation of 10m pixels will likely be just too coarse. But if you want to get the larger wetland areas at national scale even segmenting 10m pixels can be suitable. Experience so far is that deep learning models give better results than traditional methods, but it must be emphasized that the method is still new in remote sensing contexts (Mahdianpari et al. 2020a).

5.2.6 Classifier

Remote sensing data and ground-truth data are used to train and validate a model which classifies the study area into wetland (or other land cover) classes. There are a range of classifier types used in the literature, but the majority are some type of machine learning model. The most used classifiers are decision tree models, followed by support vector machines and then neural networks (**figure 10**). We noted that the most common singular model used was the Random Forest classifier (Breiman 2001) which is a flexible decision tree model. There is no clear difference in mapping accuracy between these classifiers based on our literature review, however the lack of difference may be confounded by other factors such as the remote sensing data used or the ground-truth data size etc. Nevertheless it is insightful to note that many studies compared different classifiers within their mapping case studies before they generated a final wetland map. It is relatively quick to deploy different modelling frameworks using the same remote sensing and ground-truth data to test the effect on accuracy for your given study area. Furthermore, some modelling frameworks such as Neural Networks and Random Forests can output a heatmap of wetland probability scores per class. This continuous variable output is often more relevant because in reality nature exists on a continuum and not discrete categories. Collection of training data for deep learning models should however consist of neighborhood pixels that are marked ("tagged") with the correct class or area type. Validation ground truths, on the other hand, can be objects or pixel-based as before.

5.2.7 Time consumption of different methods

Most studies did not report on the time it took to create a wetland map, however based on the results from the expert online questionnaire and one study that did describe how long it took, it appears that collecting training data is the most time-consuming part of the process. Mahdianpari et al. (2019) spent 3 field-seasons collecting training data for 1200 wetland and non-wetland sites. A respondent from the expert online questionnaire reported a similar amount of time spent mapping landcover in Antartica. Of the various techniques used to collect training data, in-situ is the most time-consuming, taking up to years to capture sufficient data on the range of wetlands and other land cover types. Image labelling is considerably less time-consuming because it does not require visiting sometimes inaccessible areas. This technique is not season dependent meaning data can be captured at any time of the year since it relies on aerial photographs or high-resolution satellite imagery from dates with ideal conditions. Furthermore, there are many image labelling Software packages that facilitate this task and provide an accuracy assessment of the training data to ensure quality. The time required for image labelling ranges from days to months depending on the size of the study area and the number of classes. The fastest way to collect training data is by using points or polygons extracted from reference maps, however this is often also the lowest quality training data, but yet this depends on collection purpose and how well maintained the dataset is. To compensate for inaccuracies in the reference data, a very large number of training data are required, which makes the classification process including training and tuning, more resource-intensive.

5.2.8 Costs of different methods

Not much information on costs was provided by the literature review because it is uncommon to report such details in academic papers. The answers from the questionary varied significantly, but several emphasized that it is hard to estimate costs for university research involving international collaboration and student theses. Another referred to the fact that this depends dramatically on the request as well as the spatial resolution. One respondent wrote that they did not purchase any data. Only the salary and computer costs of a post doc, were included. A final respondent answered that since the wetlands was only one part of a land cover mapping project, a quick answer could not be given. A respondent's estimate that could be comparable to Norwegian costs indicated 300,000 CHF (Swiss francs) which equals 2,778,941 NOK, while an another Norwegian respondent indicated 400,000 NOK. The overall cost of a wetland mapping project will depend on the amount of existing ground-truth data available and the quality of the data. If new ground-truth data is required or if image interpretation is required to clean and supplement existing data, then project costs can quickly increase significantly. An important factor will also be timeliness required for the analysis. How quick changes in nature will and can occur defines also how often data needs to be updated

Costing of satellite data will also vary substantially over time given market fluctuations and technological advancements, however, we have attempted to provide a rough overview of costs in **figure 8C**. In summary, satellite data at spatial resolutions of 10m or coarser (I.e. Sentinel and

Landsat) are free, but very high resolution satellite data (< 5m) and airborne remote sensing is very expensive at a national scale. In the future, is a possibility that Norway can access this type of data via Copernicus. However, in Norway LiDAR and Orthophotos are available for the country for mapping and research purposes so it may be feasible to incorporate them into national mapping. However, they are supposed to be in every fifth year and the question is if this is frequent enough for operational monitoring. Lyndstad & Davidsen (2021) mapped wetlands using visual interpretation of stereo aerial photographs. However, this approach suffers from the same problem of not being able to monitor operationally over time because it is expensive for larger areas. They report that they can map areas at a rate of between 20 and 50km^2 per hour. Given that Norway covers approx. 380 000 km^2, this manual approach would take about 70 person months to generate a complete map of bogs over the country. Financial budgets of that magnitude could rather be directed to purchasing 3-5m satellite imagery from companies like Planet. Norway's Ministry of Climate and Environment recently awarded an international contract to Kongsberg Satellite Services for 405M NOK to provide Planet satellite imagery over tropical forests. If Norway can direct similar funds to purchasing imagery over Norway itself, then there are many more possibilities for ecosystem mapping and monitoring.

5.2.9 Ecological condition and influencing factors

Few studies in our literature review measured the ecological condition of wetlands or their influencing factors. Rather, most studies focussed on mapping the wetland extent alone. It therefore appears as though remote sensing of wetland condition and its influencing factors is still in its infancy and there is scope for more research in this direction. This is particularly important given the strong coupling between climate and ecosystem disturbance from anthropogenic development. By mapping infrastructure development and wetland disturbance over time, we can more accurately quantify carbon emissions and the effects on climate change.

In order to map and monitor the condition or dynamics of the wetland (e.g. vegetation productivity, vegetation stress or nutrient cycles) the biochemical and biophysical properties of the wetland are needed (Adam et al. 2010). Leaf water content and biomass are amongst the most important biochemical and biophysical properties of wetland vegetation. Biomass is directly linked to plant productivity and carbon sequestration. It has been estimated using the near-infrared band and spectral indices. A study by Moreau et al. (2003) found that the growing season is the best time to estimate biomass using remote sensed data. There has been very little research on estimating water stress on vegetation in wetlands because it is very challenging to distinguish between vegetation water content and atmospheric vapour, however Adam et al. (2010) describe studies that show potential for using red-edge data, NDWI (normalised difference water index) or WI (water band index). The Leaf Area Index (LAI) is an important indicator of photosynthesis, evapotranspiration, primary productivity and respiration (Adam et al. 2010). Vegetation indices, such as NDVI have a strong linear relationship with LAI and can therefore be used to estimate carbon sequestration (Xue & Su 2017).

Only five studies actually quantified human impact on wetland ecosystems through remote sensing. This was done by mapping the change in wetland extent over time and the agent of change was defined based on the land-use replacement (e.g. wetland conversion to cropland is an anthropogenic disturbance). Breili et al (2020) used LiDAR data in Norway to map flood risk along the coastline – an example of mapping the human-nature interface. Although this was not focussed on wetlands, a similar approach may be applied to mapping wetland condition or the impact of human infrastructure on wetland flooding dynamics. However, they report a root-mean-square error of 26cm for the LiDAR data which may introduce too much uncertainty in some wetland cases where water level changes are smaller than this. The report by Blumentrath et al. (2019) contains a simple and relative reliable example of identifying ditches in LiDAR terrain models.

5.2.10 Area estimates and time series

Wetlands may cover as much as 9% of the Earth's surface. Peatlands may represent up to one-third of the world's wetlands, occupying more than 400 million hectares. Ten countries have over 2 million hectares of peatlands alone, with Canada leading at nearly 130 million hectares (representing about 18% of the country) followed by the former USSR at 83 million hectares (Tiner 2009). demonstrates the area of Canada occupied by different wetland and non-wetland classes. Amani et al. (2019) estimated however in their study by using remote sensing that 36% and 64% of the total area of Canada (3,650,798 km^2 and 6,459,990 km^2, respectively) are covered by wetlands and non-wetlands, respectively. The most dominant wetland classes were marsh and swamp covering approximately 12% and 8% of Canada, respectively. Peatlands (i.e., bog and fen), which are important for carbon storage, also cover a large portion of Canada (about 10%). Lidberg et al. (2020) state that comparisons between field data and available maps show that 64% of wet areas in the boreal landscape in Sweden are missing on current maps, and that forested wetlands and wet soils near streams and lakes are those primarily missing .

Coverage of wetlands over Norway remains uncertain because different data source used (e.g. AR5 vs N50 vs AR18X18) ends up with different percentage estimates. It is though a common understanding that also wetland coverage (10 %) in Norway are underestimated, particular in the mountains and on the west coast.

A time-series trend analysis performed by Nhamo et al. (2017) on the delineated wetlands in South Africa shows a declining tendency from 2000 to 2015, which could worsen in the coming few years if no remedial action is taken. Wetland area declined by 19% in the study area over the period under review. A time series investigation by Mahdianpari et al. (2020b) showed that bog, followed by swamp and fen, were the most common wetland classes across all time periods generally, and marsh wetlands were the least common wetland classes across all time periods respectively. Wulder et al. (2017) combined a time series of land cover maps derived from Landsat data at 30-m resolution to inform on spatial and temporal changes to non-treed and treed wetland extents over Canada's forested ecosystems (>650 million ha) from 1984 to 2016. Overall, for the period, 1984 to 2016, they found the extent of wetlands in Canada's forested ecosystems to be stable, with some regional variability, often resulting from offsetting decreases and increases within a given ecozone

5.3 Grey and overlooked literature

We reviewed some grey literature Norwegian reports: Kylling et al. (2021), Lyngstad & Davidsen (2021), Joosten et al. (2015) and Lauknes et al. (2012). In addition we added on Swedish paper that was not covered by our literature search.

Kylling et al. (2021) explores what opportunities that Sentinel-5P can provide to develop products for annual national coverage maps with area estimates with emphasis on the greenhouse gas methane. The possibility of detecting emissions from three systems was assessed: wetlands (bogs), areas in the Arctic with permafrost, and oil and gas activities on land and in the sea. With the sensitivity of the Sentinel-S5P, they conclude it will only be possible to observe large individual discharges in connection with accidents at land-based oil and gas operations given favorable observation conditions. Generation of annual national coverage maps for methane was considered possible. Lyngstad & Davidsen mapped raised bogs in the Nordland county of Norway by digitizing them from aerial photographs in stereo model on screen. While this approach does use remote sensing imagery, it is a manual classification which is very time consuming. Nevertheless, such methodologies can be used to supplement field-based ground truth data for training and calibrating machine learning models. Joosten et al. (2015) did a review of the possibilities of monitoring greenhouse gas fluxes from remote sensing. They concluded back in 2015 that sensors used in remote sensing did not yet have good enough resolution to monitor greenhouse gas flux accurately. However they stated that rapid improvements were expected, but so far neither instruments nor planned instruments were good enough. Lauknes et al. (2012) did a pilot study on using remote sensing including aerial photographs, high resolution satellite imagery and synthetic aperture radar imagery for monitoring of palsa peatlands in northern Norway. They found the method useful and showed changes in different palsa formations (e.g. reduced area of palsas and increased number of water ponds). New palsas could also be detected, but they might also be confused with ordinary lawn fens.

A study by Ågren et al. 2014 'Evaluating digital terrain indices for soil wetness mapping – a Swedish case study' did not show up among the papers in our literature review. They use digital terrain indices from high resolution LiDAR digital elevation models to predict soil wetness. The found that topographic wetness index (TWI) and the newly developed cartographic depth-to-water index (DTW) were the best soil wetness predictors. This is potential very useful ecological base map for mapping wetlands in Norway as well because Norway also has good coverage of LiDAR data. However, as the LiDAR data is seldom updated which make this approach less useful for time series predictions.

Also a study by Lidberg et al. (2021) was overlooked. They modelled missing wet areas in Sweden from high-resolution digital elevation models, using indices such as topographical wetness index and depth to water. By using soil moisture data from the National Forest Inventory of Sweden as a training dataset, they showed that it was possible to combine information from several indices and thresholds, using machine learners, to improve the mapping of wet soils (kappa = 0.65). In addition, the national wetland inventory of Sweden (VMI) has during a 25 year period surveyed the wetlands of Sweden below the mountain range (Gunnarsson and Löfroth 2014). They found that in Sweden only about 20% of the wetlands are untouched. In the whole country 11% of the wetlands were assigned to the highest nature conservation class (class 1), 24% to class 2 (high nature conservation values), 51% to class 3 (from high to low nature conservation values) and 14% to class 4 (low values). A changed hydrology caused by drainage systems are the most common impact on wetlands, followed by clear-cuttings and road constructions.

5.4 Limitations and opportunities for further research

Due to time and budget constraints, we took a pragmatic approach to the literature review and questionnaire survey by focussing on wetland mapping studies since 2015 that passed a number of exclusion criteria outlined in **table 3**. As a result, we did not cover the literature focussing specifically on mapping ecological condition (e.g. carbon storage) or influencing factors (e.g. technical interventions / infrastructure). To adequately cover these topics one would need to perform a separate literature review for each, where the search terms are focussed on concepts including infrastructure, buildings and roads, trenching / drainage, overgrowth and woody plant encroachment, cultivation, fertilization and variables relevant to the assessment of climate change impacts. Concerning ecological status variables there was little information to gain from the current literature regarding assessments of which ones of these that can be implemented immediately: biomass and volume above ground, water saturation, shrub and wood layers.

Another pragmatic decision we made was to replicate the literature search terms adopted by Mahdianpari et al (2020a) so that we could build on to their meta-analysis dataset from North America. However, we acknowledge that their search terms specifically included “Landsat” and “Sentinel” which may have biased our results to having less representation of other satellite or airborne sensors.

Due to the variety of wetland classification systems, it is difficult to translate them directly to the suggested classes summed up in Magnussen et al. (2018) or into NiN (Halvorsen et al. 2020). But it is possible that this can be done when designing a remote sensing project in Norway using, for example, the Canadian typology as a guideline for what level of classification detail is realistic to map.

It is also worth noting that we excluded studies that mapped mangrove forests and coastal wetlands due to time constraints and the fact that they are not as relevant to the Norwegian context as inland peatlands. Coastal wetlands in Norway were also recently covered by Haarpainter et al. (2020). However, a further reading of this literature may be beneficial because, for example, methods to map inundation in mangrove wetlands using radar satellites may be useful for mapping wetlands in Norway that are overgrown by trees. It is also worth mentioning that the habitat classification system Nature in Norway includes 13 main wetland habitat types. This is about double the median number of classes in found in our literature study. So our literature study does not provide much information on how to deal with such a large variety of wetland sub-classes which are likely to have very similar spectral signatures and therefore be difficult to map accurately.

Finally, we did not perform a systematic screening of the grey literature. This is perhaps why we did not find many wetland mapping studies from Norway

5.5 Recommendations for Norway

Based on the literature review, expert online questionnaire, and personal experience as researchers at NINA, we provide recommendations for a Norwegian wetland inventory. It is important to note that these recommendations may change significantly depending on the exact specifications of the mapping project (e.g. budget, accuracy requirement etc.).

- The wetland typology used should be a fusion of the NiN system and international standard systems such as the Cowardian system. The decision on the typology should be made in collaboration between botanists and remote sensing practitioners. Botanists will ensure the theoretical integrity of the classification, and remote sensing practitioners will advise on what is/isn't possible to distinguish with satellite imagery. Based on the frequency of wetland classes used in the literature (**figure 5**), it appears as though it is possible to distinguish fens ("jordvannsmyr" på norsk), marsh, swamp ("sump"), and bog ("nedbørsmyr"). It may therefore be unrealistic to try map more detailed hierarchies as defined in NiN.
- Fusing optical and radar data will not only provide complementary data on the spectral, structural, textural and dielectric characteristics, but also compensate for the frequent cloud-cover in Norway.
- Sentinel-1 and Sentinel-2 are open-source data, available at 10m spatial resolution. As both are polar-orbiting satellites, the repeat time is much less for countries near the Polar regions. While these satellites do not have a long historical record (launched in 2014 and 2015), they do have a long future ahead, making them useful for monitoring wetlands.
- Sentinel-1 data should be acquired in dual polarization mode (HH/HV) with both high and low incidence angles, where possible. HH and HV measure the horizontal and vertical radar waves returned by the earth's surface. The information in each is different. Surfaces like trees, shrubs, dry and rough soils are likely to cause change in polarization are often characterized by volume scattering. The distribution of volume scattering over the image can be compared with HH and HV. The incidence angle can significantly affect the response in HH and HB particularly for vertically oriented structures like trees or mountains. Given the above, it is important to collect information in HH and HV at multiple incidence angles so that the machine learning algorithm has enough information to "learn" what a wetland "looks like" from a SAR sensor. This will improve the classification accuracy.
- The national LiDAR and orthophoto datasets in Norway have not yet reached full coverage and also excludes some high alpine areas which may contain wetlands. Furthermore, the LiDAR and orthophoto data is not updated annually, however though regularly, and therefore does not allow annual operational monitoring. Therefore, these high resolution datasets should be used to clean, quality-check, and possibly contribute additional ground-truth data, but cannot be used in the overall classification model. In the case that the Norwegian Environment Agency want a single baseline wetland map of Norway that is not regularly updated, then they can consider using the LiDAR and orthophotos within the classification model.
- Remote sensing data should ideally be processed in a cloud-based platform because of the scale of the map and the amount of data, especially when fusing multitemporal and multisensor approaches which require processing of a significant amount of data. Using GEE as the processing platform is advantageous because it already hosts Sentinel data and private-access copies of the Kartverket LiDAR data have been uploaded and are ready for processing. GEE can be used for generating a pilot national wetland map, however operational monitoring into the future would require evaluating the GEE commercial programme as a sustainable solution. GEE is meant for research and development purposes and it may not be used in an operational manner for commercial purposes. However, GEE is developing a commercial programme which may allow for adoption in the governmental and private sectors. Alternatively other cloud-based remote sensing platforms should be considered.

- Ground-truth data for wetlands in Norway exists in the form of NiN, ANO, AR5 and N50, however the wetland definitions and data qualities vary substantially. Therefore one will need to invest significant time into harmonizing these ground-truth datasets and quality checking them using very high resolution orthophotos (Norge i bilder, norgeibilder.no) and satellite imagery. If budget is available, fieldwork should be performed to visit a number of wetlands sites to verify the accuracy of these photo-interpreted datasets.
- Spectral indices, such as NDVI, NDWI and NDMI are recommended for distinguishing between wetland types and for assessing the condition of wetlands. More importantly, spectral-temporal indices (e.g. standard deviation in NDVI over the year) give information on the phenology and seasonality of land cover which is an important factor in distinguishing wetlands.
- We recommend testing several classifiers before performing the wetland inventory, a technique that is not computationally intensive and is often done in other studies. Particularly, we recommend testing both Random Forest decision trees and Fully Convolutional Neural Networks. These are two of the most progressive models currently used in the literature and are thus most likely to yield best results. Note that model training and tuning is usually quite time consuming when done carefully.
- Sufficient training data should be collected such that a portion can be kept aside and only used for final validation of the wetland map.
- We recommend following the Canadian wetland classifiction: fen ("jordvannsmyr" på norsk), marsh, swamp ("sump"), and bog ("nedbørsmyr") (see example from Canada in **figure 14**).
- For ecological condition and influencing factors we recommend that we need more research before they can be mapped at a national extent. Importantly, Norway need to invest in collecting ground-truth data on ecological condition parameters.

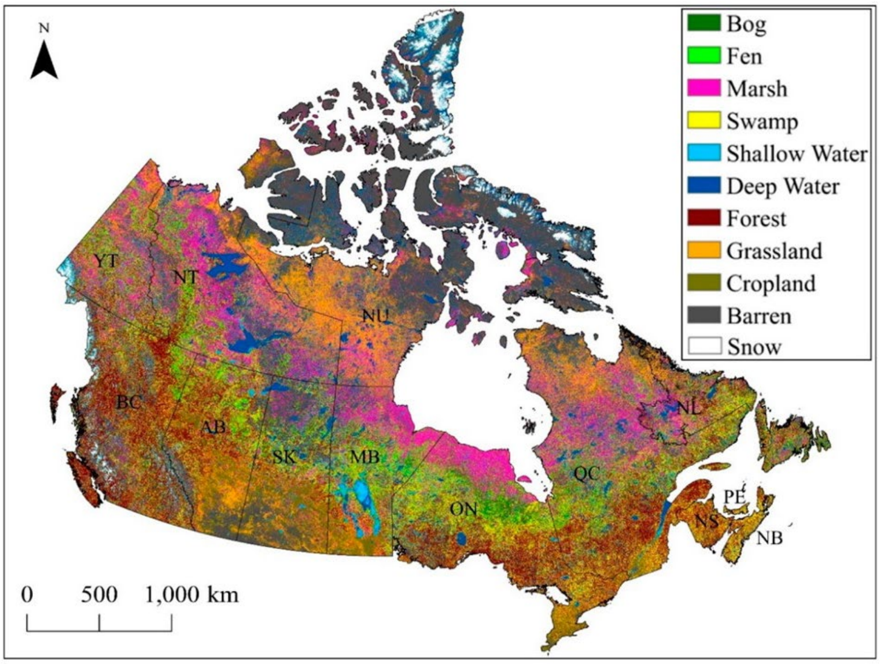

Figure 14. *First Canada-wide wetland map (taken from Amani et al. 2019).*

6 Conclusion

Wetland remote sensing at national to continental extents is still in its infancy. The literature is largely focused on methods development at landscape scales with little information on operational mapping solutions. However, we synthesize information from the literature and expert online questionnaire to provide recommendations for developing a national wetland map of Norway. As a disclaimer, we emphasize that our recommendations may change significantly depending on the specifications of the mapping project. The remote sensing methodologies used are largely dependent on the project budget, spatial scale, desired accuracy and intended use (baseline map vs operational monitoring). Therefore our recommendations are generalizations informed both by the consensus in the literature and the experience of NINA researchers. In the case of a wetland baseline map, our recommendations would be to combine Sentinel 1 and 2, together with LiDAR and possibly aerial photography to form the basis (a ‘stack’) for classification of a single time-point base map of wetlands in Norway. In the case of an operational and annually updateable wetland mapping, we recommend only including Sentinel 1 and 2 data in the classification due to their spatial and temporal availability and consistency. However, aerial photos will be required to collect sufficient ground truth data and to clean and quality assure existing field inventory data from AR5, NiN and N50. Landsat and historical aerial photos can be used for information about historical wetland coverage, however accuracies will be reduced for this retrospective analysis and conclusions drawn about ecological condition (e.g. carbon emissions or storage) will need to be done with caution. We recommend using Google Earth Engine as a processing platform, at least for prototyping a production workflow, although there are many alternative platforms available on the market. Recommended inputs to machine learning models include optical bands, radar backscatter and indices such as NDVI, NDWI and NDMI. A resolution of 10m can be ideal for a nationwide model for wetlands in Norway such that smaller wetlands can be detected. It is recommended to use both pixel-based and object-based methods in combination in order to leverage the advantages of each. The pixel-based methods can be used to 'remove' area types that are not related to wetlands such as snow, ice, bare rock and so on. Object-based methods can be used to separate wetlands from the remaining area types. Surface models from LiDAR can be used, among other things, to separate wooded areas from open areas. LiDAR data can also be used to create derived terrain variables such as slope and terrain aspect which can be important predictors, especially in mountain areas.

The lack of studies in Scandinavia means that there is little experience with mapping of wetlands by using remote sensing in Norway. This also applies to studies on the observation of ecological condition and human disturbances from remote sensing. More research needs to be performed in this direction before remote sensing methods can be adopted to operationally monitor these factors at a national extent.

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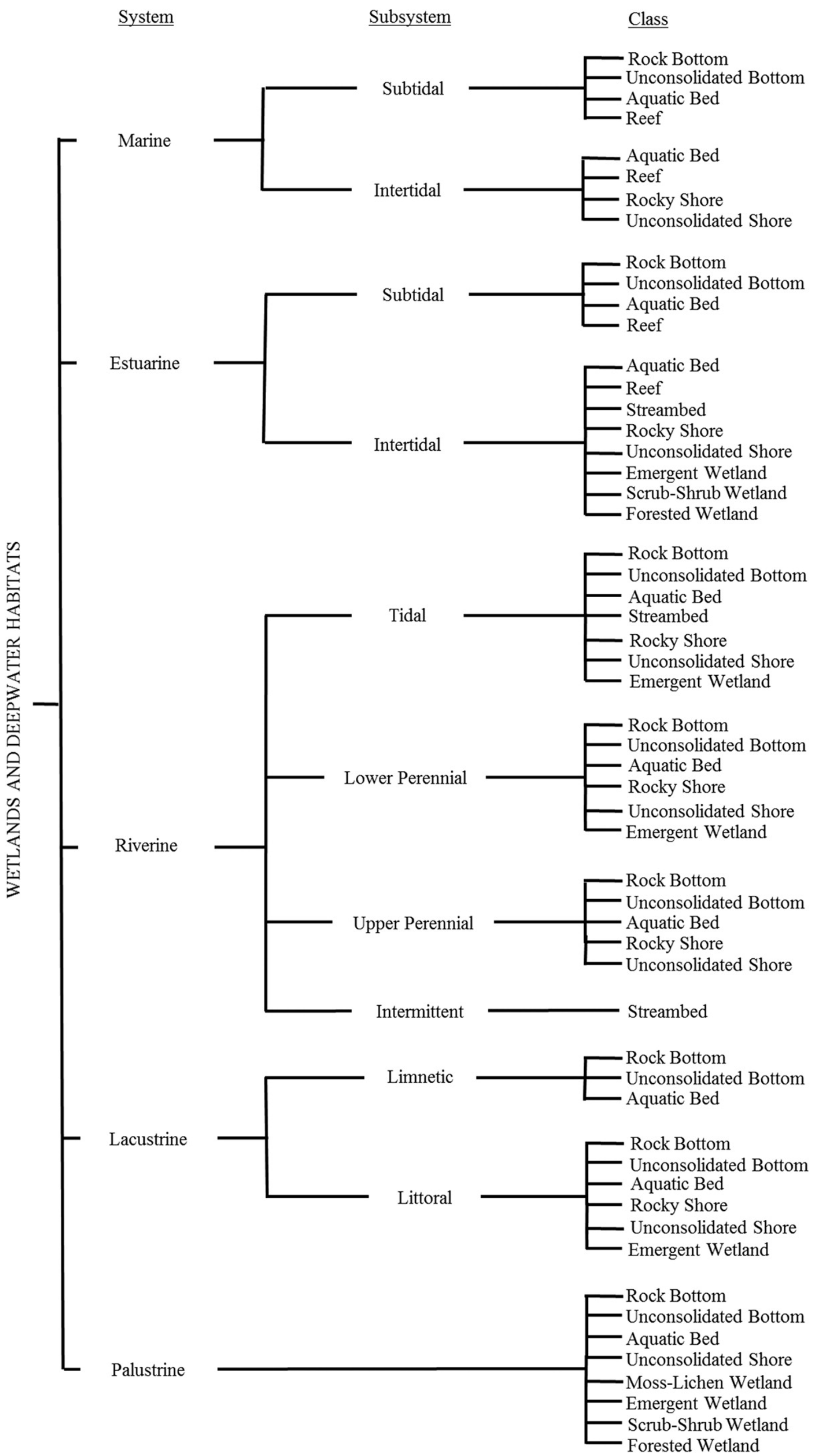
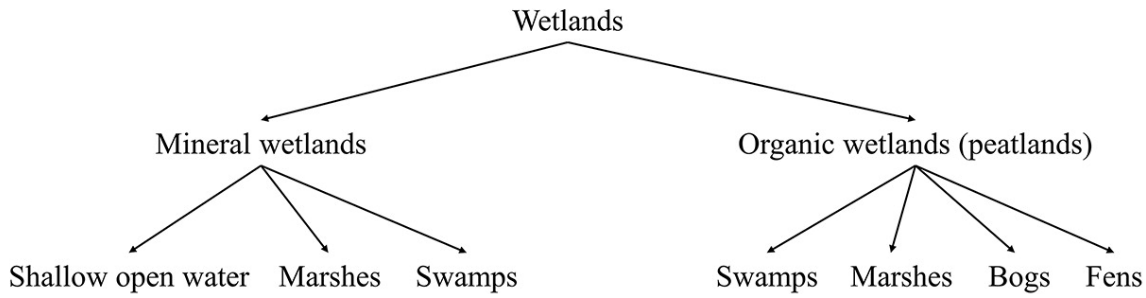
8 Appendix



Appendix A. Description of the Cowardin classification system used in the USA (1979). The figure is takes from the review of remote sensing for wetland classification by Mahdavi et al. (2017).



Appendix B. The Canadin Wetland Classification System (CWCS, 2017) taken from Mahdavi et al. (2017).

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2014

NINA Rapport

Norsk institutt for naturforskning, NINA,
er en uavhengig stiftelse som forsker på natur og samspillet natur–samfunn.

NINA ble etablert i 1988. Hovedkontoret er i Trondheim, med avdelingskontorer i Tromsø, Lillehammer, Bergen og Oslo. I tillegg driver NINA Sæterfjellet avlsstasjon for fjellrev på Oppdal, og forskningsstasjonen for vill laksefisk på Ims i Rogaland.

NINAs virksomhet omfatter både forskning og utredning, miljøovervåking, rådgivning og evaluering. NINA har stor bredde i kompetanse og erfaring med både naturvitere og samfunnsvitere i staben. Vi har kunnskap om artene, naturtypene, samfunnets bruk av naturen og sammenhenger med de store drivkreftene i naturen.

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Norsk institutt for naturforskning
NINA Hovedkontor
Postadresse: Postboks 5685 Torgarden, 7485 Trondheim
Besøks-/leveringsadresse: Høgskoleringen 9, 7034 Trondheim
Telefon: 73 80 14 00, Telefaks: 73 80 14 01
E-post: firmapost@nina.no
Organisasjonsnummer 9500 37 687
http://www.nina.no

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