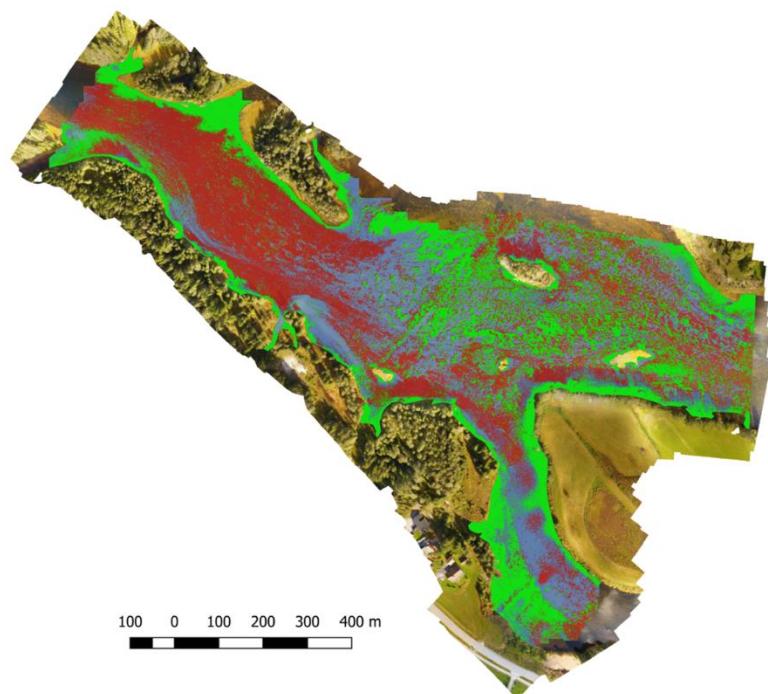


Kartlegging av krypsiv manuelt og med drone - en pilotstudie



NORCE Laboratorium for ferskvannsøkologi og innlandsfiske (LFI)

Laboratorium for ferskvannsøkologi og innlandsfiske (LFI)

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Sammendrag

I denne studien har vi kartlagt krypsiv og fiskehabitater i Otra fra Brokke til Ose. Først ble hele strekningen kartlagt manuelt. Deretter undersøkte vi om det var mulig å bruke drone til å reproduksjonen fra deler av strekningen. Dronene hadde påmontert standard kamera, multispekter kamera og hyperspekter kamera.

Totalt elveareal som ble kartlagt var 4 735 501 m². Krypsiv dekket 50,6 % av strekningen og med størst krypsivforekomster i Rysstadbassenget og rundt Storøy. Alge og mose dekket til sammen 27 % av bunnarealet, mens flotgras (*Sparganium angustifolium*) var den vanligste makrofyten etter krypsiv med 0,8 % dekningsgrad. Sand var det vanligste sedimentet på elvebunnen med 16,4 % dekningsgrad. Områder med potensielt gunstige gyteforhold for fisk med optimalt substrat og strømhastighet ble registrert i flere strekninger.

Bildebehandlingen av dronebilder viste at vegetasjonstypene til en viss grad hadde ulikt fingeravtrykk i form av spektralt signal. Disse forskjellene kom best frem ved bruk av hyperspekter kamera, og til dels også ved bruk av multispekter kamera. Kartlegging ved hjelp av drone førte til at krypsivutbredelsen ble underestimert, og spesielt fordi krypsiv ble feiltolket som alge. Feiltolkningen kan komme av at fargespekeret endres gjennom vannsøylen slik at vegetasjonen får ulike signaler på grunt og på dypt vann, samt refleksjoner i vannet og ugunstige og varierende lysforhold.

Metodene er tidkrevende og vi mener det fremdeles for tidlig med fullskala kartlegging av krypsiv med drone, og spesielt med hyperspekter kamera. Likevel kan metodene vise seg å fungere godt når standard verktøy blir tilgjengelig, og vi mener spesielt at resultatene tyder på at man potensielt kan oppnå gode resultater ved bruk av hyperspekter kamera.

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Forord

På oppdrag fra Krypsivprosjektet på Sørlandet og Miljødirektoratet har Laboratorium for ferskvannsøkologi og innlandsfiske (LFI) ved NORCE kartlagt elvebunnen i Otra mellom Brokke og Ose. Avdelingen NORCE Energi har utført kartlegging ved hjelp av drone. Personalet som utførte kartlegging ved hjelp av drone er fremmedspråklige, og deres del av arbeidet er skrevet på engelsk. Det norske sammendrag er derfor utvidet. Vi vil takke Susanne Claudia Schneider (NIVA), Turid Myklebust Helle (LFI) og Elisabeth Stöger (LFI) for hjelp til å kartlegge i felt, og Susanne Claudia Schneider for hjelp til å artsbestemme makrofytter i felt. Vi vil også takke Norsk Elektro Optikk AS (NEO) som samlet data i felt til hyperspekter kartlegging. Oppdraget har vært administrert av Krypsivprosjektet på Sørlandet.

Med vennlig hilsen



Gaute Velle
Prosjektleader

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1.Utvidet sammendrag

En fortetning og spredning av krypsiv (*Juncus bulbosus*) har ført til problemvekst i mange elver og innsjøer, og spesielt på Sørlandet. Vi mangler likevel et detaljert grunnlag som angir utbredelsen til krypsiv, noe som er et nødvendig kunnskapsgrunnlag for å fastslå fremtidige endringer i utbredelse og vekst, for eksempel om veksten endres ved kalking.

I denne studien ønsker vi å kartlegge krypsiv og fiskehabitater i Otra fra Brokke til Ose manuelt, og å teste bruk av drone og ulike metoder for avansert bildebehandling for å kartlegge krypsiv. Det har skjedd en rask utvikling av droneteknologi de siste årene. Målsettingen med prosjektet var derfor å kartlegge krypsiv og annen vegetasjon med drone, deretter sammenlikne og kalibrere resultatet med resultatene fra den manuelle kartleggingen.

Den manuelle kartleggingen foregikk ved personer iført dykkerdrakt, snorkel og dykkemaske fløt nedover elven og registrerte krypsiv og annen vegetasjon på elvebunnen, samt sedimenter og potensielle gyteområder. Rysstadbassenget ble kartlagt fra båt. Totalt elveareal som ble kartlagt var 4 735 501 m². Utbredelsen til krypsiv er vist i detaljerte kartblad i rapporten. Krypsiv dekket 50,6 % av den kartlagte strekningen der de største forekomstene av krypsiv var i Rysstadbassenget og rundt Storøy. Alge og mose dekket til sammen 27 % av bunnarealet, mens flotgras (*Sparganium angustifolium*) var den vanligste makrofytten etter krypsiv med 0,8 % dekningsgrad. Sand var det vanligste sedimentet på elvebunnen med 16,4 % dekningsgrad. Områder med potensielt gunstige gyteforhold med optimalt substrat (grus) og strømhastighet ble registrert i flere strekninger og er vist i kartblad. Restfeltet fra Hekni ble kartlagt i 2015 og 2016. Her er det først og fremst krypsiv i terskelbassengene, og det totale arealet som er dekket av krypsiv utgjør ca 27 900 m² (5,3 % av elvebunnen på strekningen).

Bruk av drone for kartlegging av krypsiv ble testet ved hjelp av tre ulike kamerateknologier. Den første med en drone påmontert standard kamera, dvs kamera som tar bilde av synlig lys innen bølgelengdene rødt, grønt, blått (RGB). Denne dronen var også påmontert et multispekter kamera. Dette kameraet har fem linser som tar bilde av hver sine bølgelengder av lys, det vil si RGB og to bølgelengder av infrarødt lys. Til slutt brukte vi drone påmontert kamera som tar hyperspekter bilder. Hyperspekter fotografering er en teknologi som kun helt nylig har blitt tilgjengelig for drone. Hyperspekterkameraet som ble brukt i prosjektet tar bilder av 200 ulike bølgelengder av lys. For å kalibrere kameraene ble det tatt bilder av prøver med kjente farger, samt krypsiv. Bilder tatt med multi- og hyperspekter kameraer krever intens bildebehandling, for eksempel for å sy sammen den store datamengden til ett sammensatt bilde.

Multispekter kamera. Først ble bildene fra de fem spektrene satt sammen til ett mosaikkbilde. Deretter testet vi flere metoder for å gjenkjenne vegetasjonstypene i bildene. Metodene som ble testet inkluderer Maximum likelihood classification (ML), Spectral angle

mapper (SAM), Object based image analysis (OBIA) og Object based nearest neighbour classification (NN).

Bildebehandlingen viste at vegetasjonstypene til en viss grad hadde ulikt fingeravtrykk i form av spektralt signal. Disse forskjellene kom bedre frem i multispekterbilder enn i standard RGB-bilder. Metodene klarte derfor til en viss grad å skille mellom vegetasjonstyper under vann hjelpt av drone. Vi fant at OBIA-metoden ga best resultat. Metoden bruker både spektral informasjon og annen relevant informasjon, slik som nærliggende vegetasjon. Metodene var likevel ikke gode nok for nøyaktig kartlegging. Hovedutfordringen er at metodene fører til at krypsivutbredelsen underestimeres, og spesielt fordi krypsiv feiltolkes som alge. En årsak til feiltolkningen kan være at fargespekteret endres gjennom vannsøylen slik at vegetasjonen får ulike signaler på grunt og på dypt vann.

Hyperspekter kamera. Forskjeller i de spektrale signalene mellom ulike vegetasjonstyper indikerer at hyperspekter fotografering har godt potensiale for å brukes til å kartlegge vegetasjon og substrat i vann. Basert på relativt enkle dataanalyser fant vi ulike fargespektra for grus, sand, alge to typer mose og tre typer krypsiv. Det viste seg likevel å være flere utfordringer knyttet til kartlegging ved hjelp av drone påmontert hyperspekter kamera. For det første er det praktiske utfordringer knyttet til bruk av store droner, siden disse har begrenset flytid og krever spesiell sertifisering. For det andre er fotograferingen kresen for stabile og klare værforhold. For det tredje kan det være utfordrende å kalibrere rådataene og korrigere signalene for støy, f.eks fra refleksjon og vanndamp. For det fjerde mangler metode for å kalibrere resultatene for endringer i fargespekteret som skjer gjennom vannsøylen. Utfordringene gjorde at innsamlede data ikke ble fullt utnyttet.

Generelt vil det være en fordel om den manuelle kartleggingen gjennomføres med høyere grad av nøyaktighet og med høyere oppløsning, for eksempel ved bruk av målebånd og GPS. Dette vil føre til et bedre sammenlikningsgrunnlag mellom resultatene fra den manuelle kartleggingen og kartleggingen ved bruk av drone. En slik grad av nøyaktighet er neppe hensiktsmessig for manuell kartlegging av større arealer, men kan brukes i utvalgte mindre områder.

Inntil teknologien er bedre utviklet fører utfordringene til at klassifisering av vegetasjon under vann ved hjelp av både multispekterkamera og hyperspekterkamera er svært tidkrevende. Vi mener det fremdeles for tidlig med fullskala kartlegging av krypsiv med drone, og spesielt ved bruk av hyperspekter kamera. Likevel kan metodene vise seg å fungere godt når standard verktøy blir tilgjengelig, og vi mener spesielt at resultatene tyder på at man potensielt kan oppnå gode resultater ved bruk av hyperspekter kamera.

2. Bakgrunn og hensikt

Utbredelsen og tettheten av planter i ferskvann øker over store deler av verden (Brundu, 2015; Hussner et al., 2017; Verhofstad et al., 2017; Kagami et al., 2019). Det er mange arter som øker, for eksempel krypsiv (*Juncus bulbosus*). Krypsiv er en plante i sivfamilien (Juncaceae) som har naturlig utbredelse i ferskvann og på land i Europa og Nord Amerika (Brandrud & Roelofs, 1995; Proćkow, 2008). I løpet av de siste 30-40 årene har utbredelsen av krypsiv økt, og planten er nå spredt i Norge, Finland, Sverige, Storbritannia, Nederland, Australia, New Zealand, Chile, USA, Canada and Russland (Brandrud, 2002; Roelofs, 1983; Rose, 2007; Aulio, 1987; Svedang, 1992; www.discoverlife.org). Krypsiv er vidt utbredt i Norge, og særlig i kystnære og næringsfattige vassdrag på Sørlandet. Her har fortetning ført til problemvekst i elver og innsjøer. Under problemvekst kan tett vegetasjon dekke store områder. Vanlig vekstform av krypsiv har 10-20 cm lange skudd, men under gunstige forhold kan skuddene nå 3 meter og danne tette tepper som vokser fra bunnen og opp til vannoverflaten.

Problemveksten av krypsiv hindrer tradisjonelle friluftsaktiviteter, slik som fiske og bading, og kan føre til redusert fremkommelighet for båt og tette inntaksrister til vannkraftverk. I tillegg endrer krypsivet strømregimet i elver, noe som fører til en akkumulering av mudder. Når det gjelder effekter på fisk og bunndyr ser det ut til at moderate mengder krypsiv kan være positivt for ungfishproduksjonen i mosaikkhabitater med grus og krypsiv (Velle et al., 2014). Det er fordi krypsiv gir gode skjulmuligheter og godt næringsgrunnlag.

Utbredelsen av krypsiv har tidligere vært kartlagt ved hjelp av flyfoto (Reither og Kansen 2012). Kartlegging basert på flyfoto overestimerer i midlertid utbredelsen av krypsiv (Velle et al., 2014). Vi mangler dermed en oversikt over utbredelsen av krypsiv i sørlandsvassdragene, noe som er et nødvendig kunnskapsgrunnlag for å fastslå fremtidige endringer i utbredelse og vekst. En kartlegging gir også relevant informasjon om status for krypsiv i forbindelse med den planlagte kalkingen av Otra ved Brokke. Det er uttrykt en bekymring for at kalking kan føre til økt vekst og utbredelse av krypsiv. For å kunne evaluere potensielle effekter av kalking på krypsiv vil det være nødvendig med en kartlegging av status før kalkingen starter. Når vi samtidig kartlegger fiskehabitater vil det også være mulig å fastslå mulige effekter som både krypsiv og kalking har på fisken, der bleka er en laksefisk av særlig interesse (Barlaup m. fl. 2018).

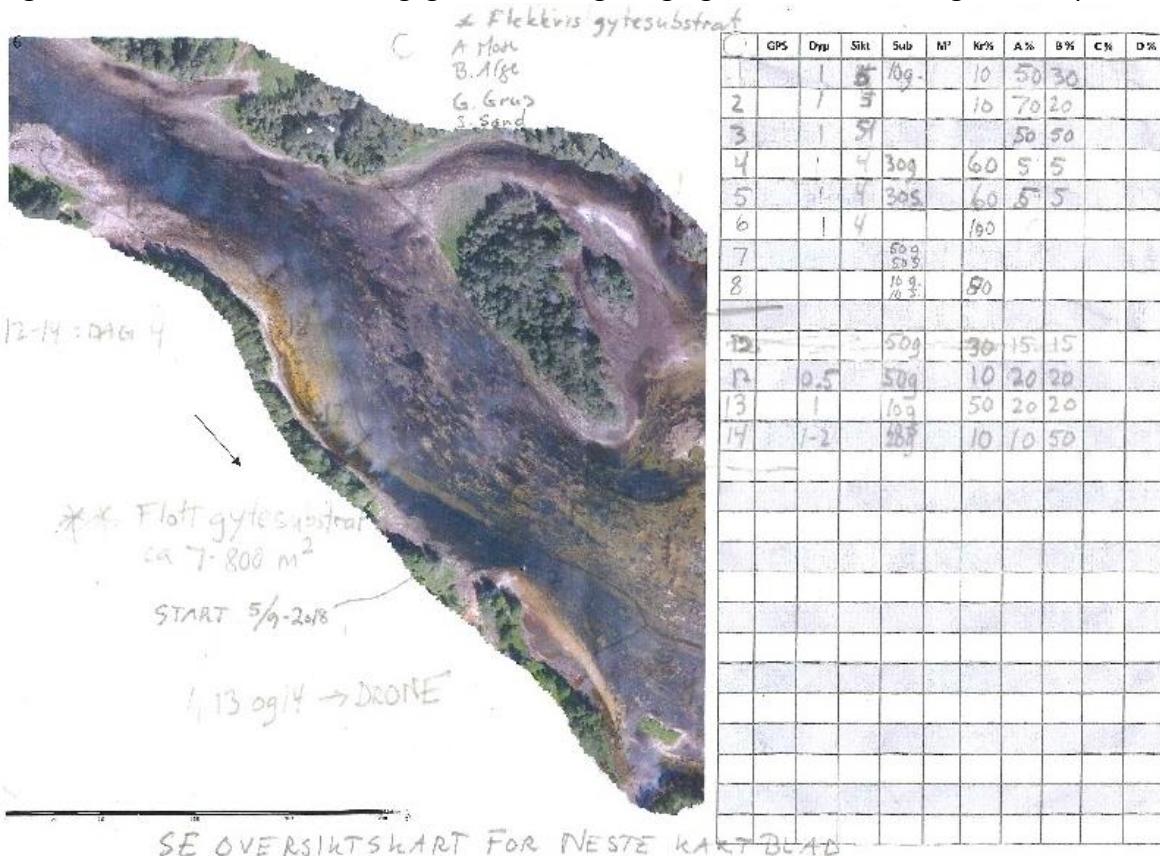
Hensikten med denne studien er todelt. For det første ønsket vi å kartlegge krypsiv og fiskehabitater i Otra fra Brokke til Ose, og for det andre ønsket vi å teste bruk av drone og ulike metoder for avansert bildebehandling for å kartlegge krypsiv i utvalgte testflater. Det har skjedd en rask utvikling av droneteknologi de siste årene. Vi har testet kartleggingsmetoder ved hjelp av droner som er påmontert multispekter kamera eller hyperspekter kamera. Enkelte av metodene tar bruk av flere parametere samtidig for å gjenkjenne bunnforholdene, og der lag med informasjon kan legges oppå hverandre i GIS. Droner påmontert multispekter kamera eller hyperspekter kamera tar mange bilder samtidig der bildene registrerer ulike bølgelengder av lys. Bildene sys deretter sammen under bildebehandlingen.

Hensiktene krever forskjellige metoder og kunnskap. Vi har derfor valgt å dele rapporten i to. Det er likevel klart at delrapportene henger sammen; den manuelle kartleggingen var nødvendig for å evaluere kartleggingen som ble utført ved hjelp av drone.

3. Manuell kartlegging

3.1 Metoder

Kartlegging av elvebunnen ble utført 8. til 12. September 2018 ved at tre personer iført tørrdrakt, snorkel og dykkemaske fløt nedover elven fra Brokke til innløpet ved Hækni, og fra utløpet fra Hækni og til Ose. Krypsiv i strekningen i restfeltet fra innløpet til Hækni ved Tjurmodammen og til utløpet av Hækni (ca 7,8 km) ble kartlagt i 2015 og 2016 (Barlaup m fl. 2018). Dykkerne artsbestemte all bunnvegetasjon og substrat som ikke var dekket av vegetasjon, og anslo deres prosentvise fordeling. Dette ble gjort i hele elvens bredde. Synlig substrat ble kartlagt etter dekningsgrad av kategoriene organisk gyttja, sand, grus, stein, blokk og fast fjell. En person satt i tillegg i gummibåt for å samle informasjonen fra dykkerne og danne et oversiktsbilde av begroingen og bunnforholdene. Rysstadbassenget ble i sin helhet kartlagt fra båt. All informasjon ble notert direkte i ortofoto av elven der det ble tegnet polygoner med relativt homogene bunnforhold (Figur 1). Informasjonen ble deretter digitalisert i ArcGIS, der dekningsgraden av begroing og substrat ble inntegnet i shape-filer.



Figur 1. Otra ved Stråøne. Elvebunnen ble kartlagt ved at polygoner ble tegnet rundt områder med uniform dekningsgrad av ulike vannplanter og substrat. Polygonene ble deretter digitalisert.

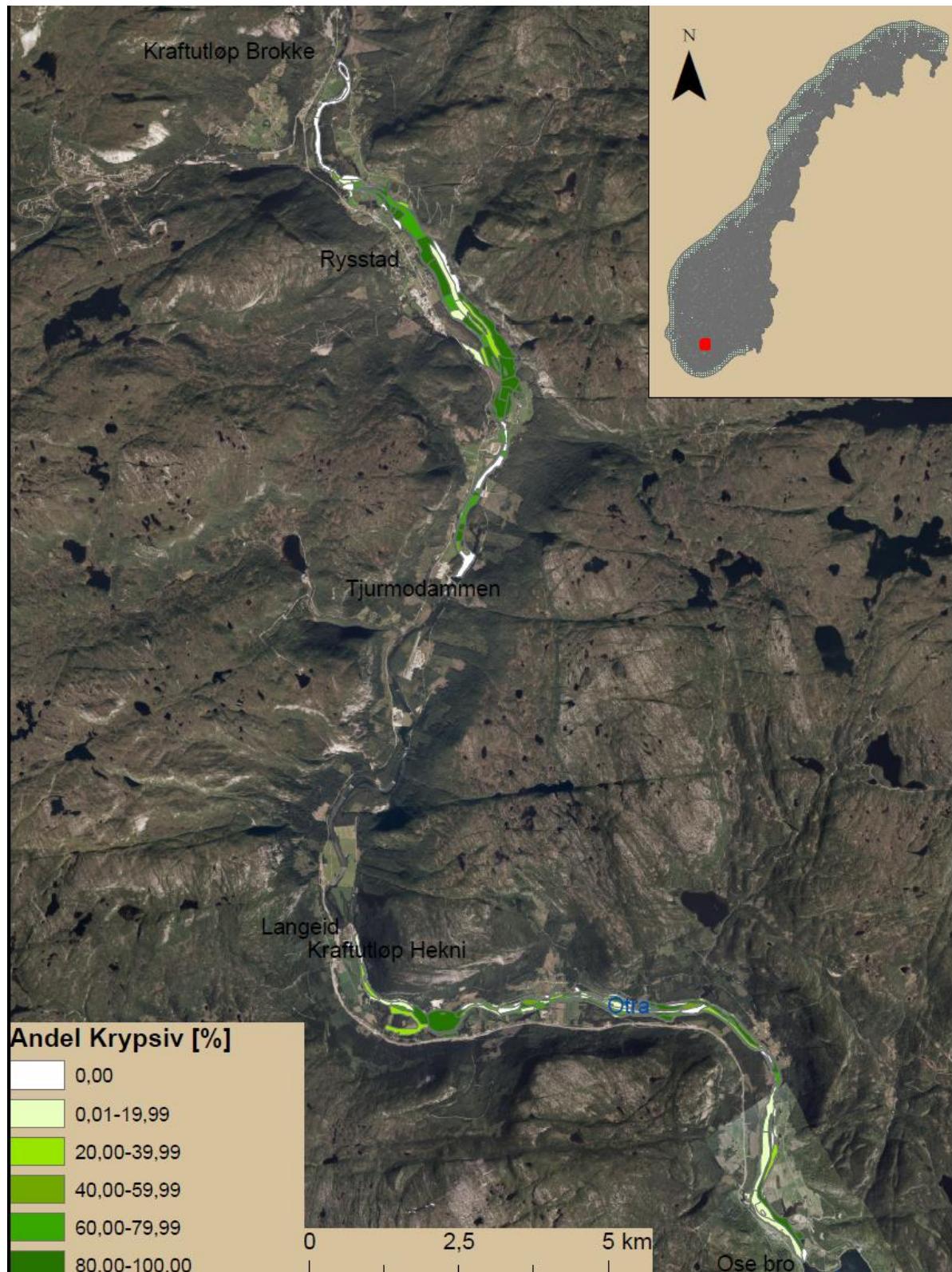
3.2 Resultater

Sikten i vannet under kartleggingen var 5-6 m. Det var ikke mulig å kartlegge enkelte områder med dybde over 6 m ved Straumsfossen og forbi Helle camping, samt ved Tjurmodammen. Totalt elveareal som ble kartlagt var 4 735 501 m² (utenom restfeltet fra Hækni). Krypsiv dekket 2 394 319 m² av arealet, noe som tilsier at 50,6% av den kartlagte strekningen var dekket av krypsiv (Figur 2 og 3, Tabell 1). De største forekomstene av krypsiv er i Rysstadbassengen og området ved Storøy. I tillegg er store deler av elven med vanndyp mindre enn ca 4 meter dekket av krypsiv. Dersom en går ut ifra av krypsivskuddene i gjennomsnitt rekker 80-100 cm opp i vannsøylen (ca lengde på skuddene: rosetter 25 cm, enkeltsåter 50 cm og såtevekst 100-120 cm), tilsvarer volumet av krypsiv ca 2 200 000 m³. Alge og mose dekket til sammen 27% av bunnarealet, mens flotgras (*Sparganium angustifolium*) var den vanligste makrofyten etter krypsiv med 0,8% dekning (Tabell 1, Figur 4). Sand var det vanligste sedimentet på elvebunnen (Figur 5). Elvearealet i restfeltet fra Tjurmodammen og til utløpet av Hækni kraftverk utgjør ca 527 631 m². Av dette arealet var ca 27 900 m² (5,3 %) dekket av krypsiv, som for det meste vokste i terskelbassengene.

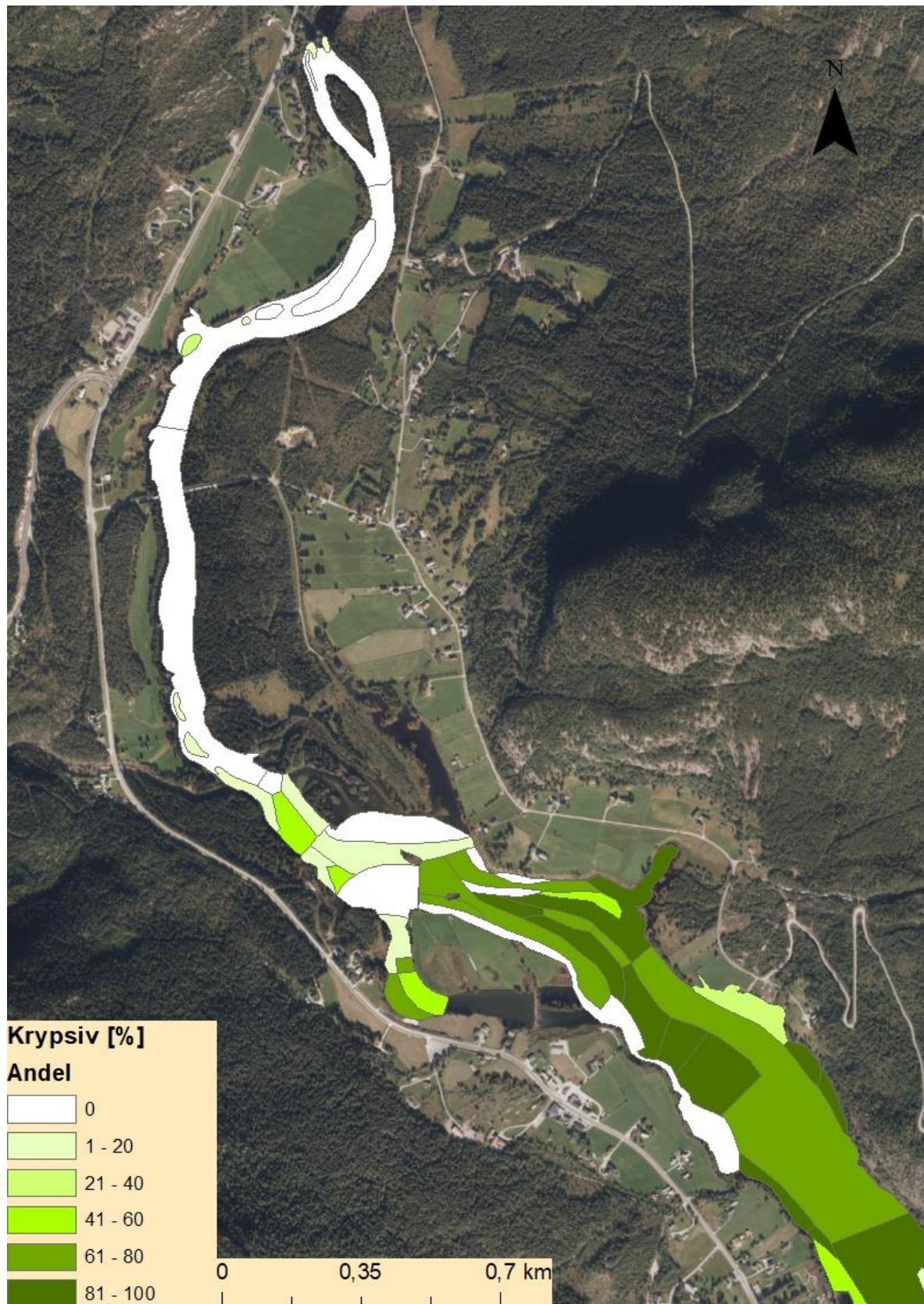
Ca 6 % av elvebunnen var dekket grus. Ikke all grusen er egnet som gytesubstrat for fisk siden gyteforholdene også er avhengig av vannføring. Større områder med potensielt gode gyteforhold ble registrert i flere strekninger. Områdene er tegnet inn i kart sammen med tidligere kjente gyteområder og danner en oversikt over gytehabitater i elvestrekningen (Figur 6, se også Barlaup m fl. 2018 for gytehabitater i restfeltet fra Hækni) Gyting forekommer ikke i alle områdene, for eksempel forventer vi liten gyteaktivitet rett nedstrøms Brokke kraftverk (Figur 6, kartblad 1) pga gassovermetning. Gyting kan også forekomme andre steder i elven som ikke er markert i kartet, spesielt i mosaikkliknende habitater i kanaler mellom krypsivvekst der det er gunstig vannføring og substrat. Vi kartla ikke slike mindre forekomster av gytesubstrat.

Tabell 1. Dekningsgrad av vegetasjon og sedimenter på elvebunnen, sortert etter synkende dekningsgrad.

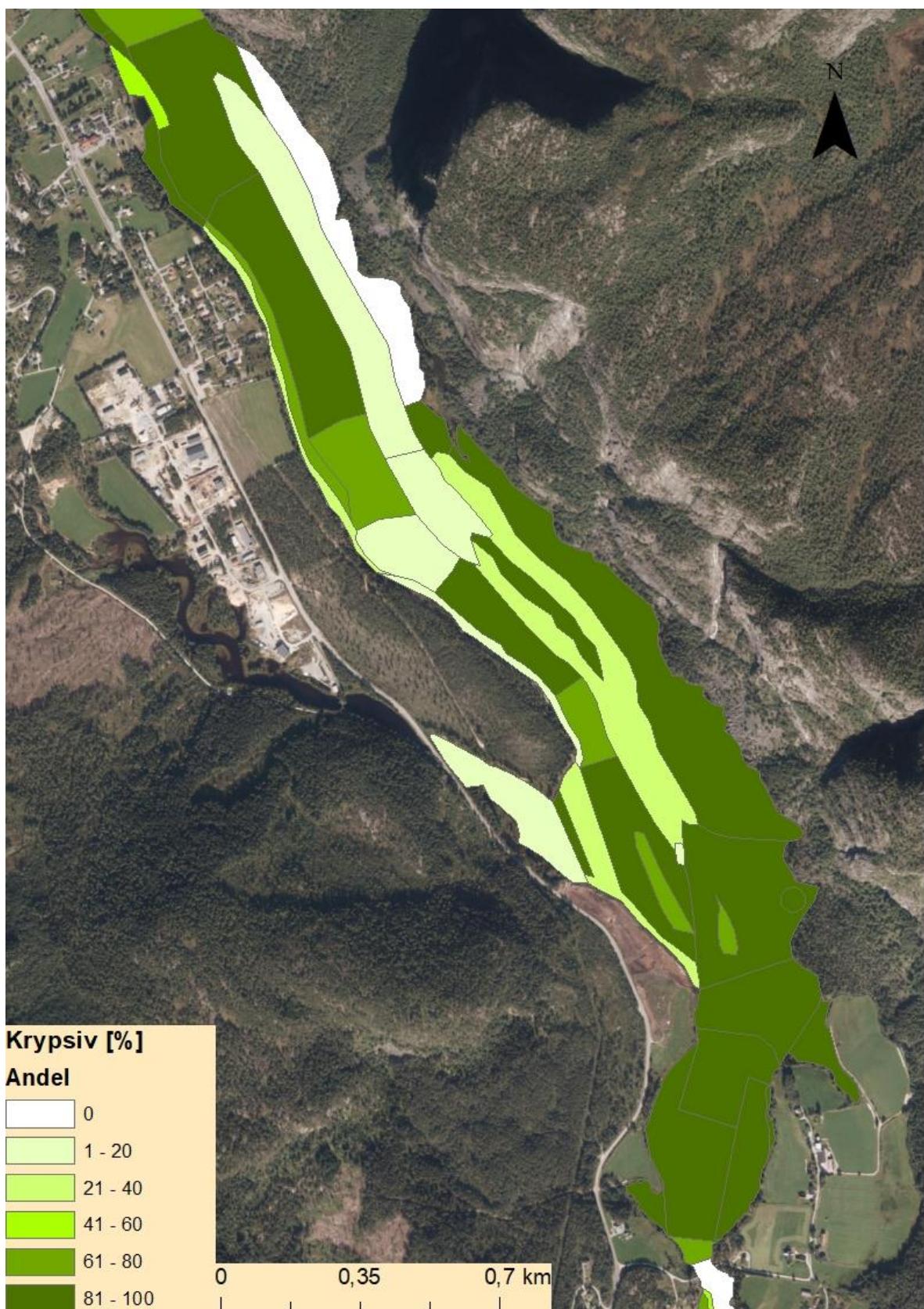
	Antall m ² dekning	Prosentvis dekning
Krypsiv (<i>Juncus bulbosus</i>)	2 394 319	50,6
Sand	778 414	16,4
Alge	488 312	10,3
Mose	472 542	10,0
Grus	291 174	6,1
Organisk gyttja	147 488	3,1
Stein	54 640	1,2
Flotgras (<i>Sparganium angustifolium</i>)	37 638	0,80
Blokk	33 592	0,71
Silt	7012	0,15
Tjønnaks (<i>Potamogeton</i>)	2374	0,050
Gress (Poaceae)	582	0,012
Tusenblad (<i>Myriophyllum</i>)	530	0,011
Bukkeblad (<i>Menyanthes trifoliata</i>)	112	0,0024
Fast fjell	41	0,0009



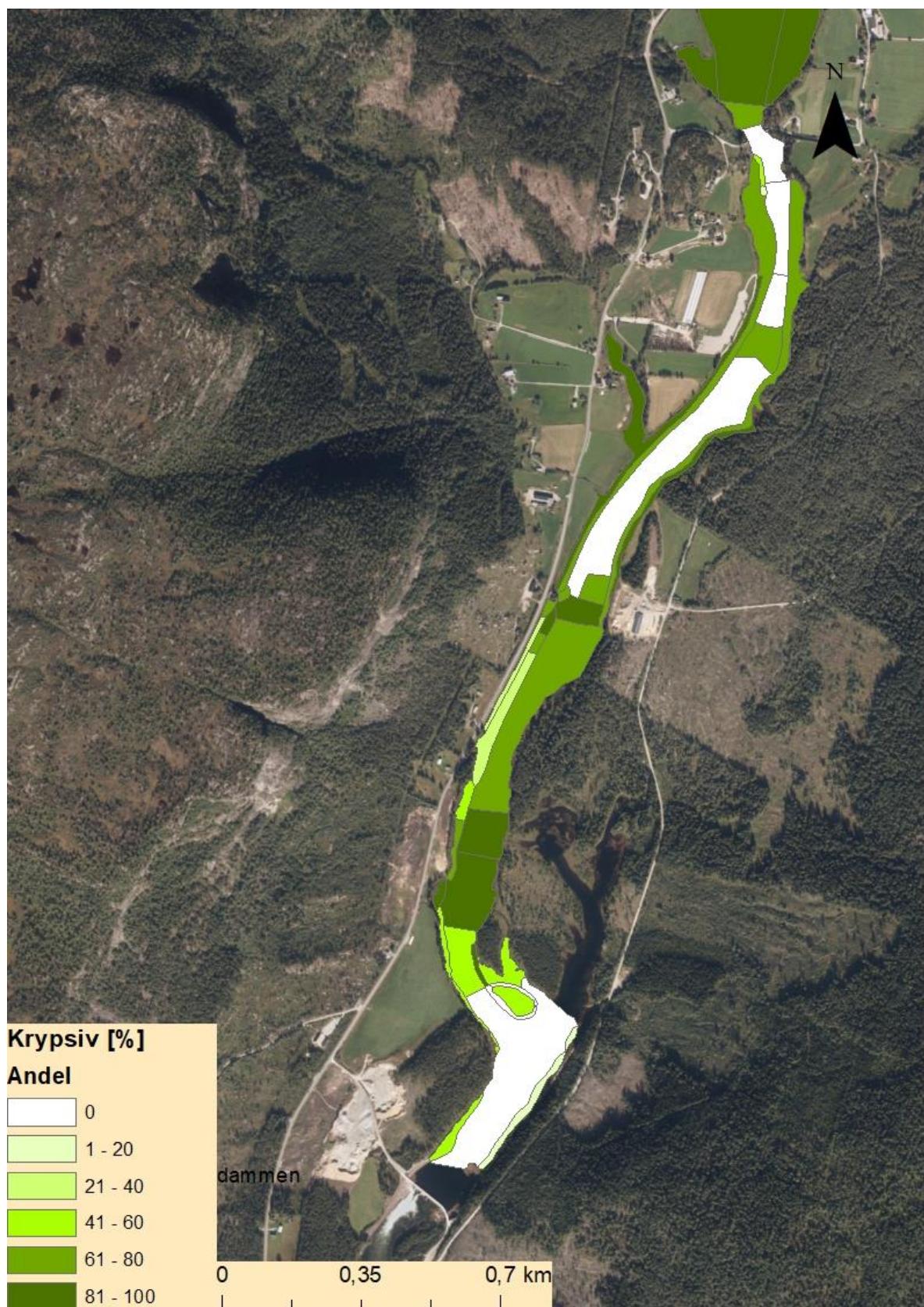
Figur 2. Oversiktsbilde som viser dekningsgrad av krypsiv i Otra mellom Brokke og Ose (utenom strekningen i restfeltet fra innløpet til Hækni kraftverk ved Tjurmodammen og til utløpet av Hækni kraftverk).



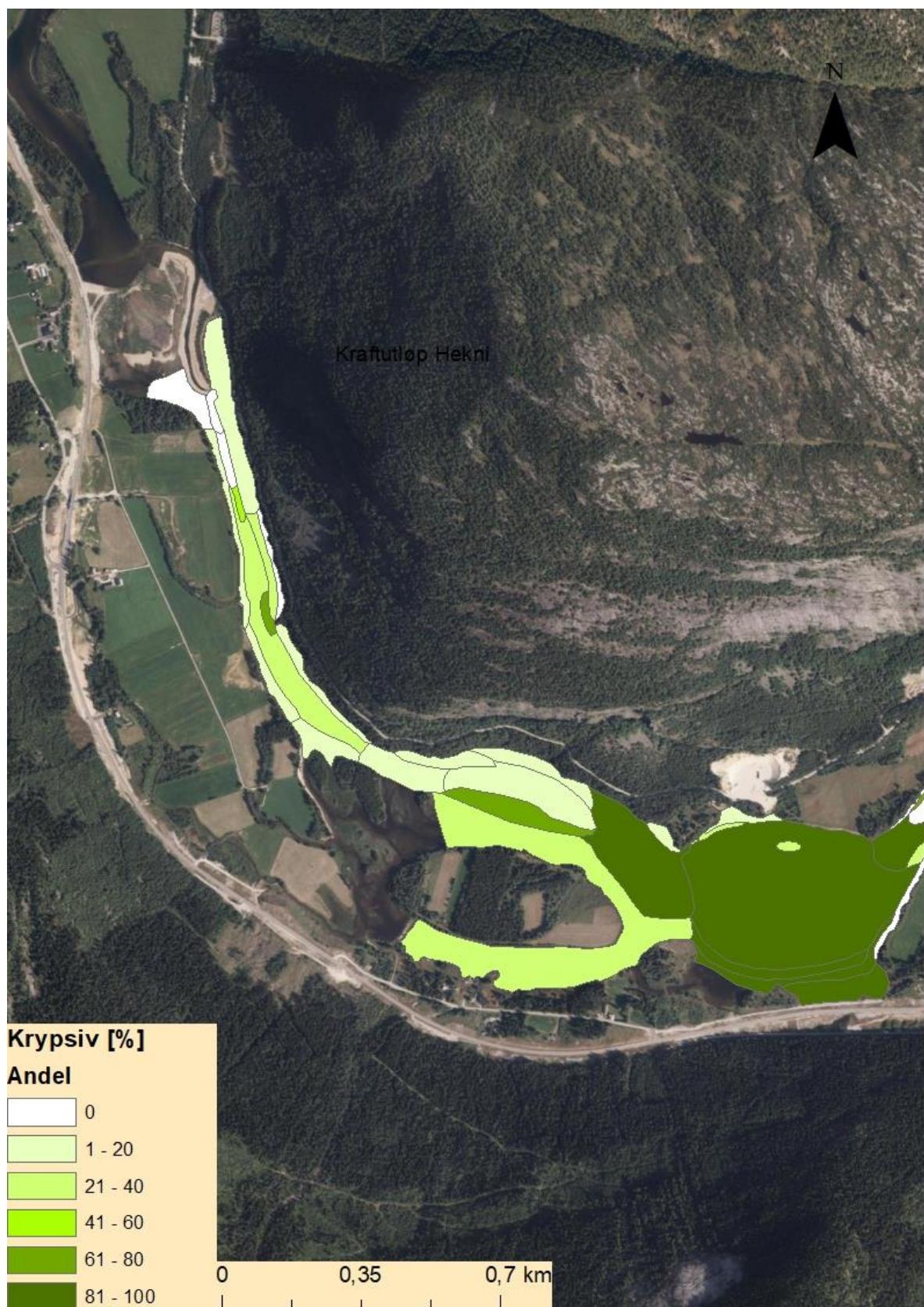
Figur 3. Dekningsgrad av krypsiv, kartblad 1: fra utløpet av Brokke kraftverk og til Rysstadbassenget.



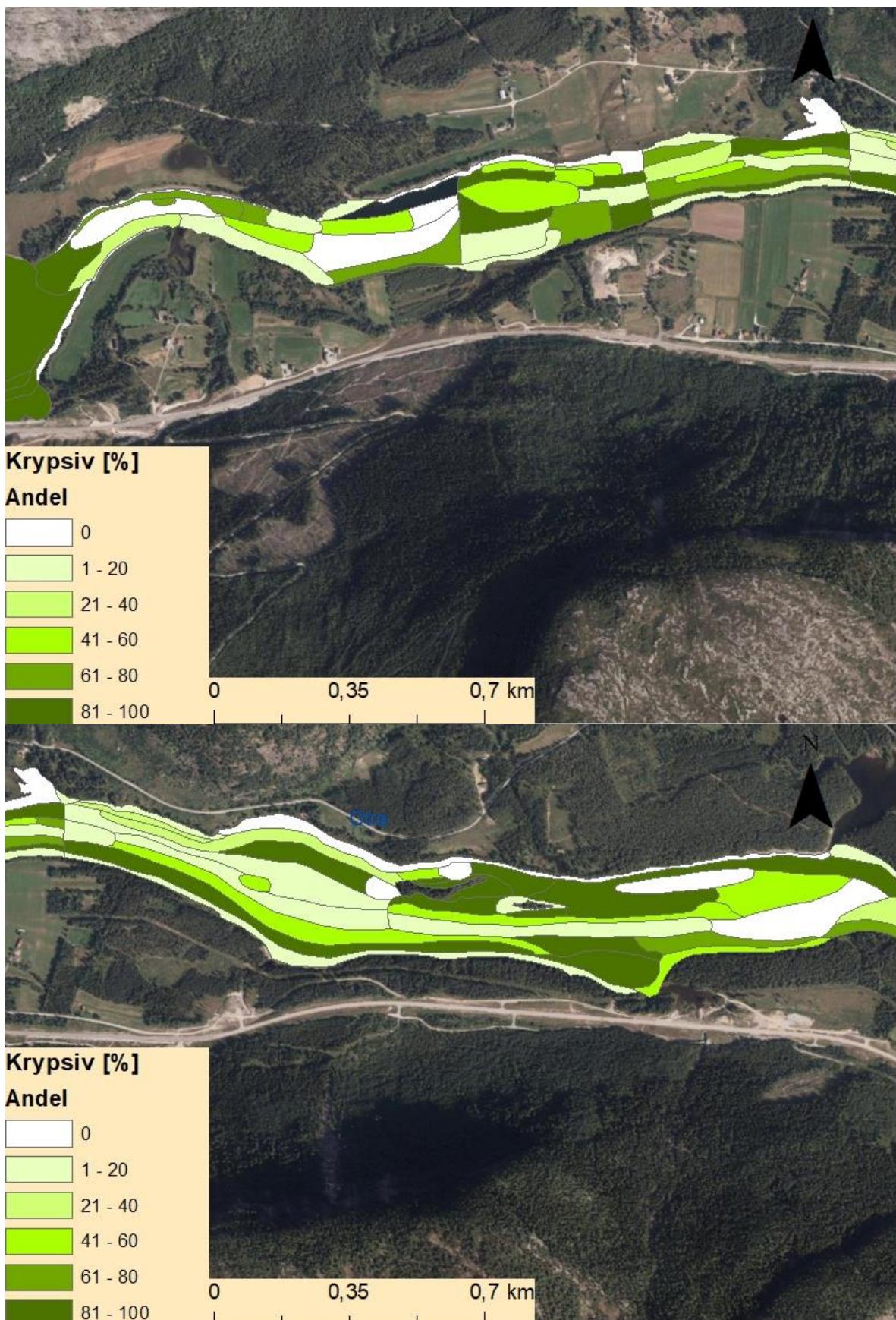
Figur 3 (forts.). Dekningsgrad av krypsiv, kartblad 2. Rysstadbassenget.



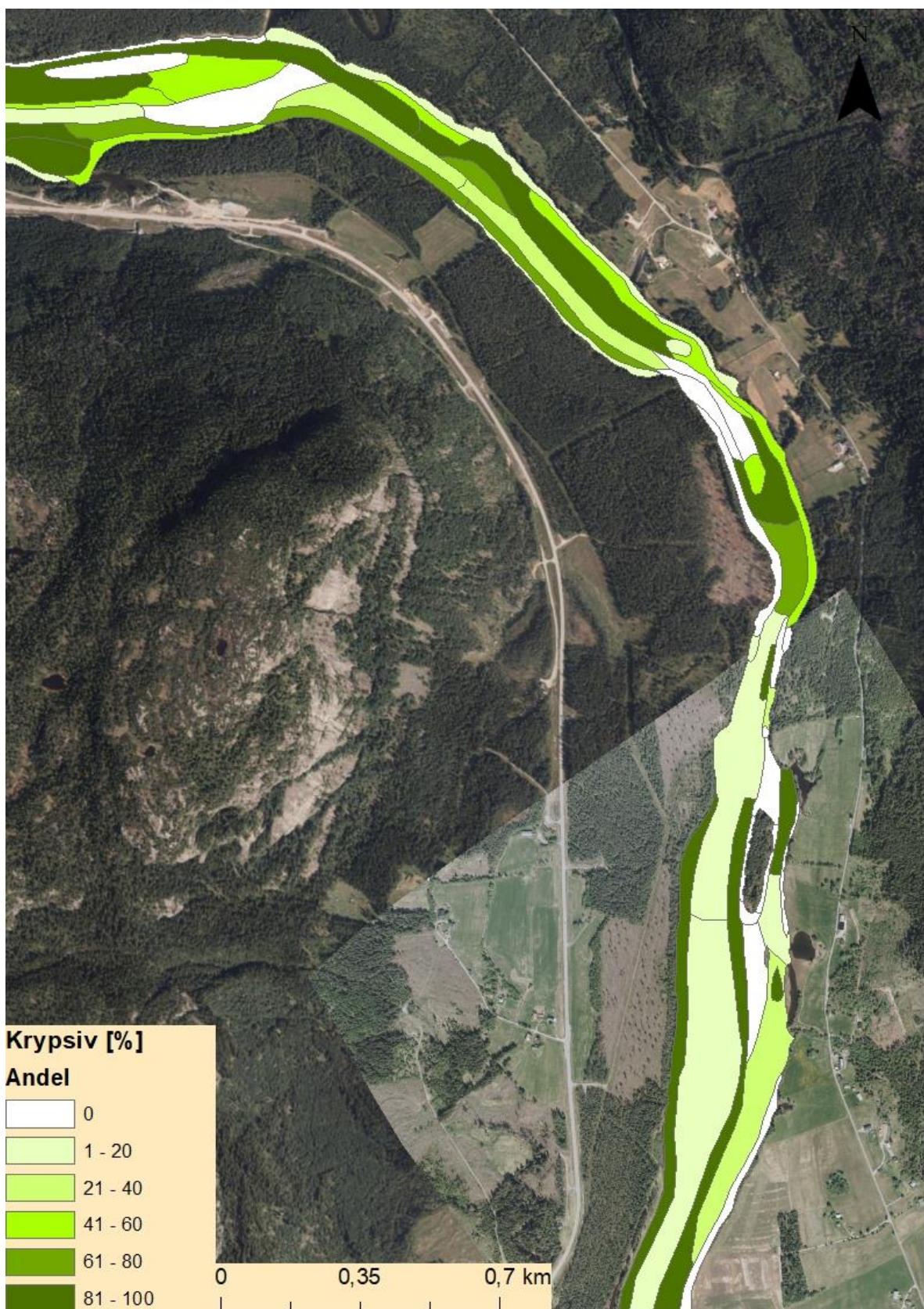
Figur 3 (forts.). Dekningsgrad av krypsiv, kartblad 3: fra Straumsfossen til Tjurmodammen. Deler av strekningen hadde dyp større enn sikt, og ble ikke kartlagt.



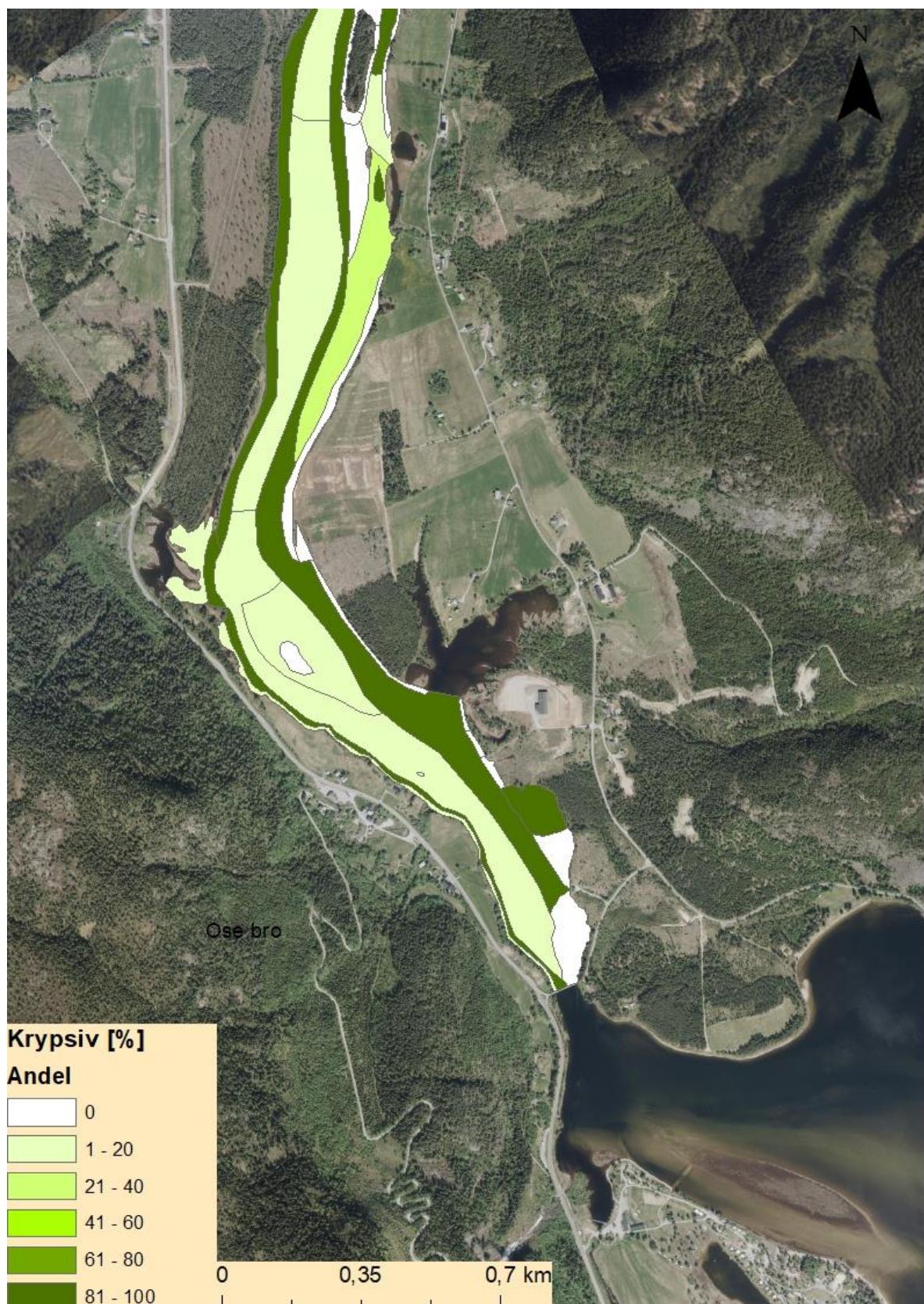
Figur 3 (forts.). Dekningsgrad av krypsiv, kartblad 4: fra utløp Hækni til Nedre Hegland.



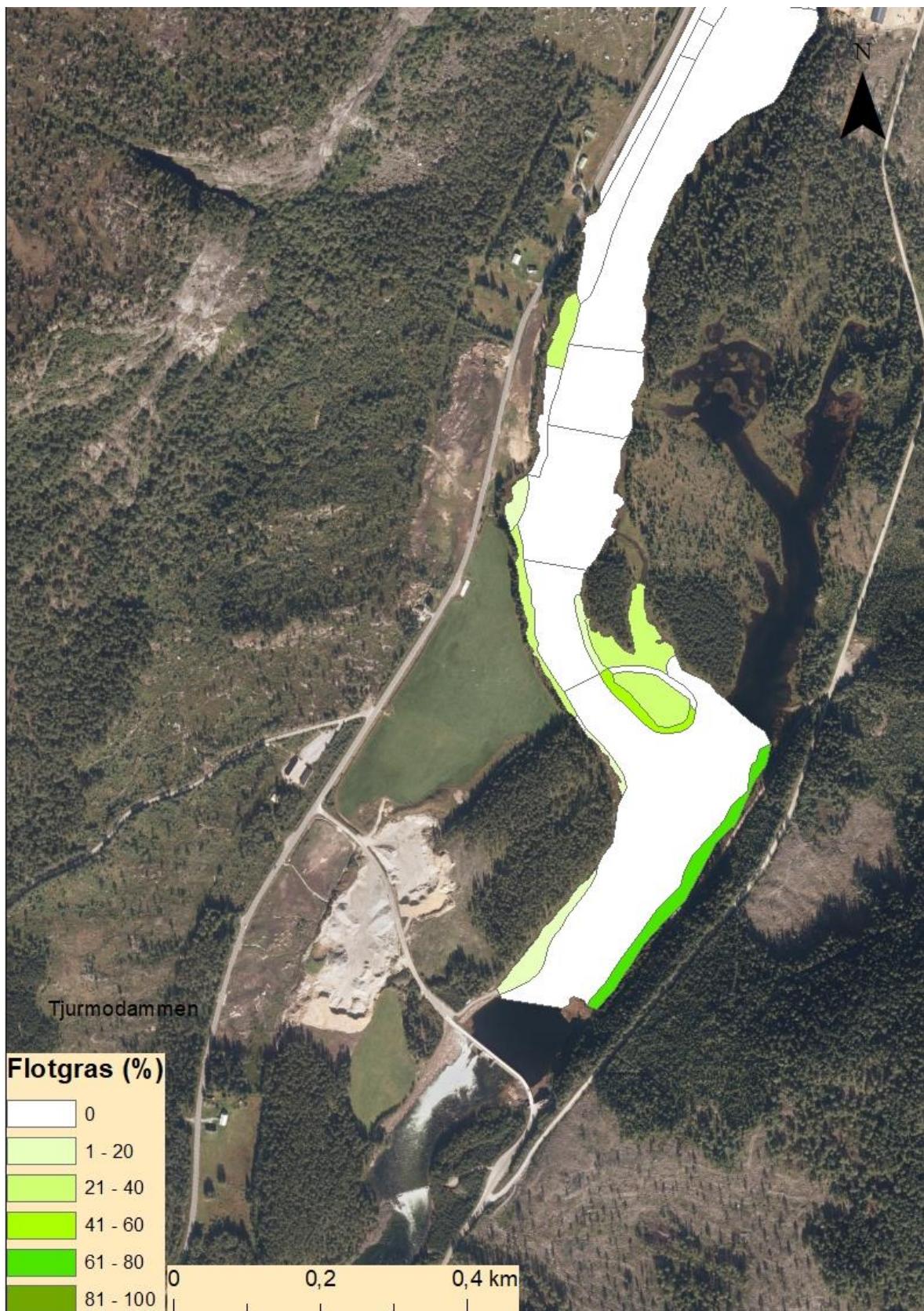
Figur 3 (forts.). Dekningsgrad av krypsiv, kartblad 5: fra Nedre Hegland og 6: fra Austad Kyrkje.



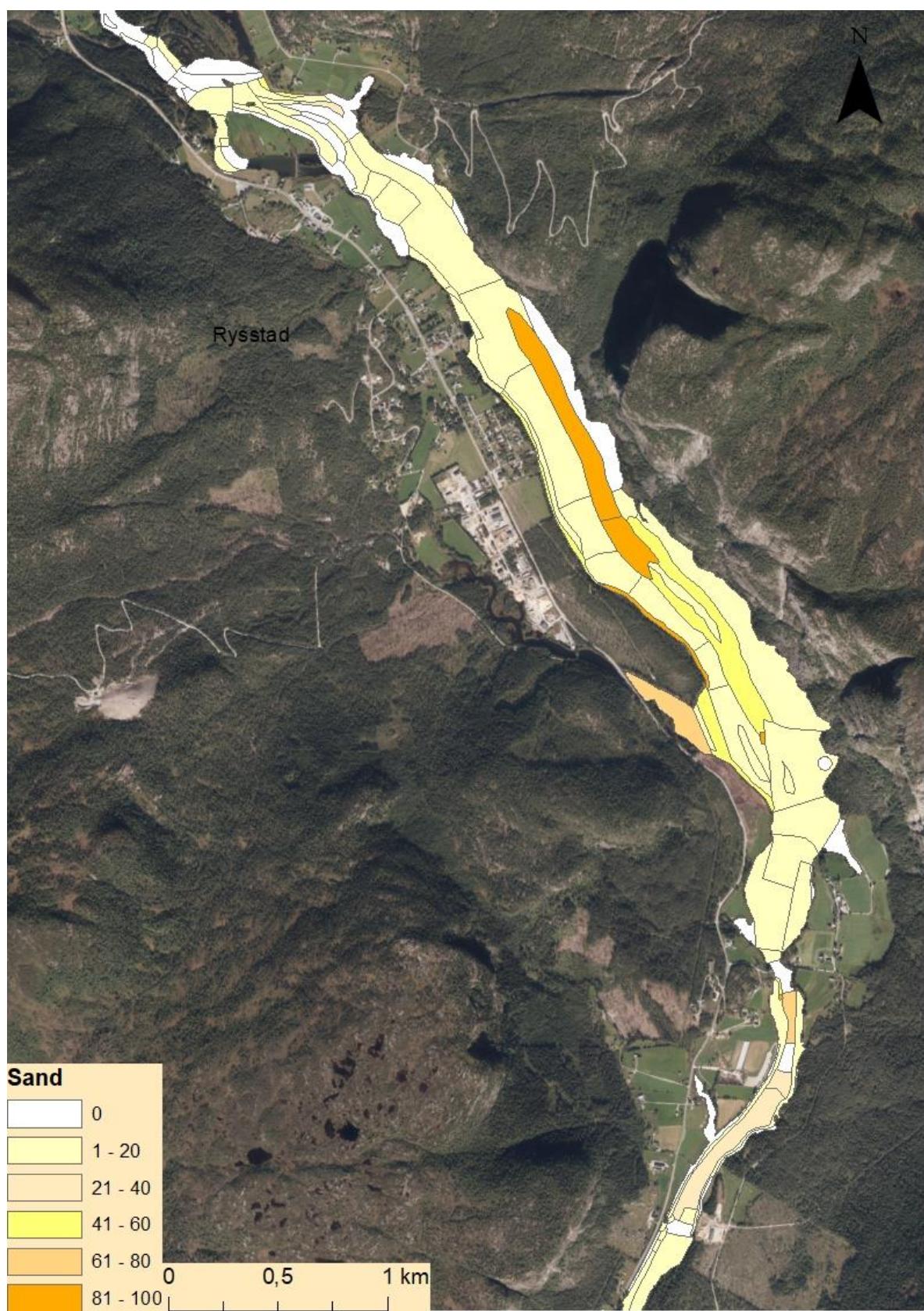
Figur 3 (forts.). Dekningsgrad av krypsiv, kartblad 7: fra Odden via Heistad til Austad.



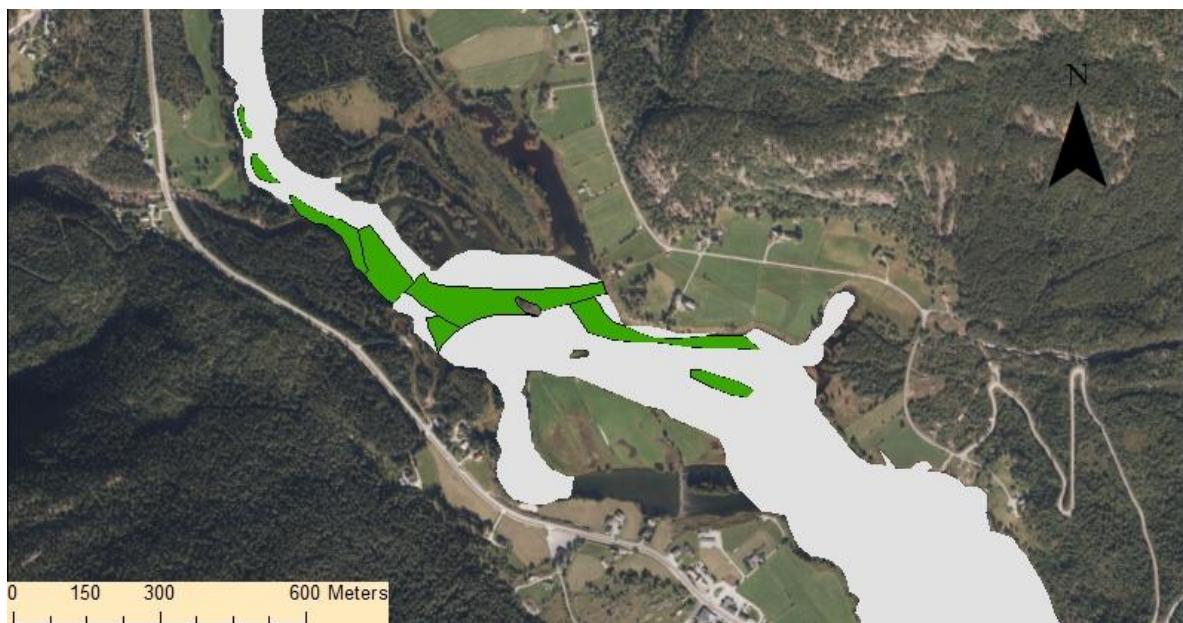
Figur 3 (forts.). Dekningsgrad av krypsiv, kartblad 8. fra Glomsøyni via Austad til Ose.



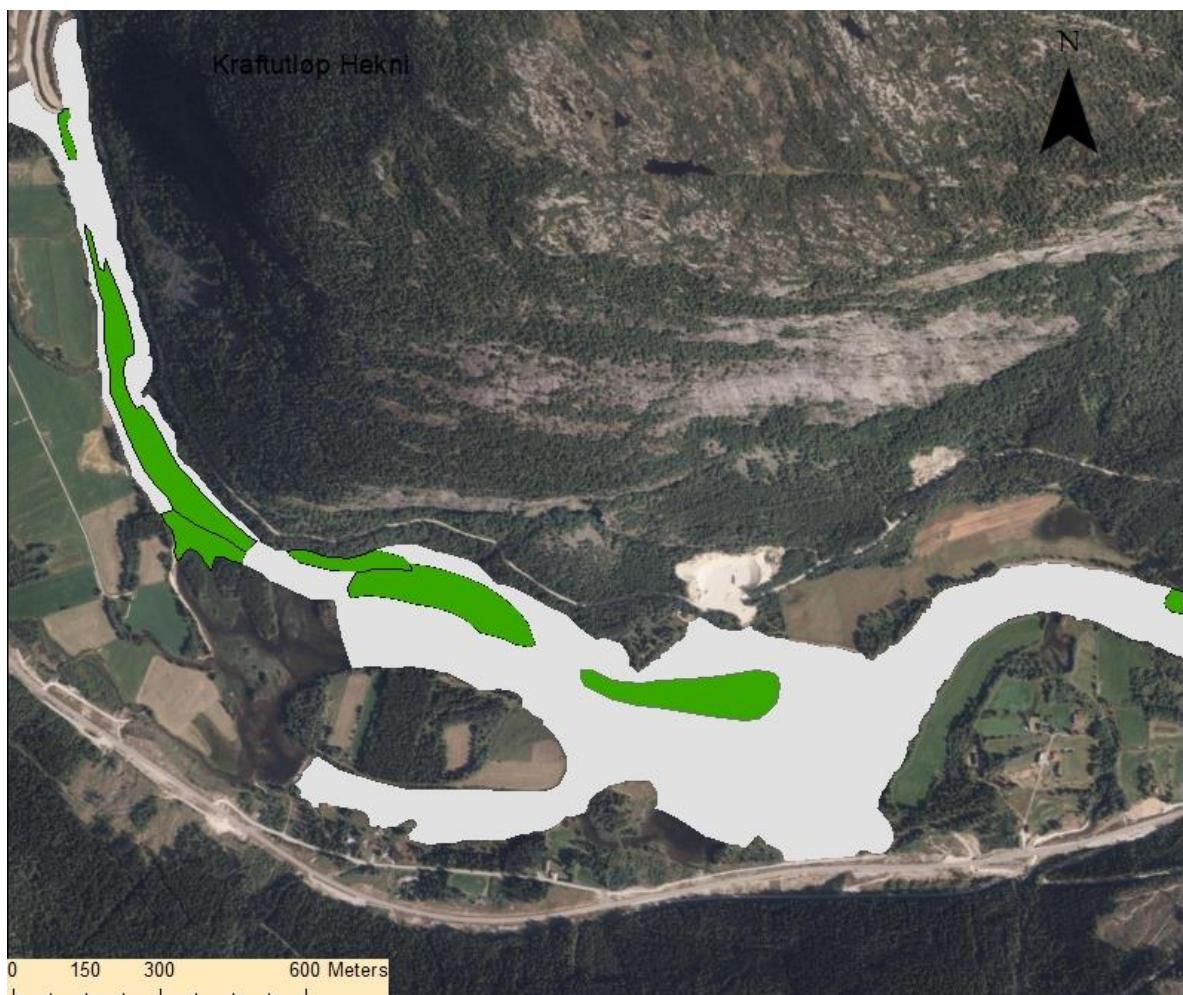
Figur 4. Det var høyest tetthet av flotgras rett oppstrøms Tjurmodammen.



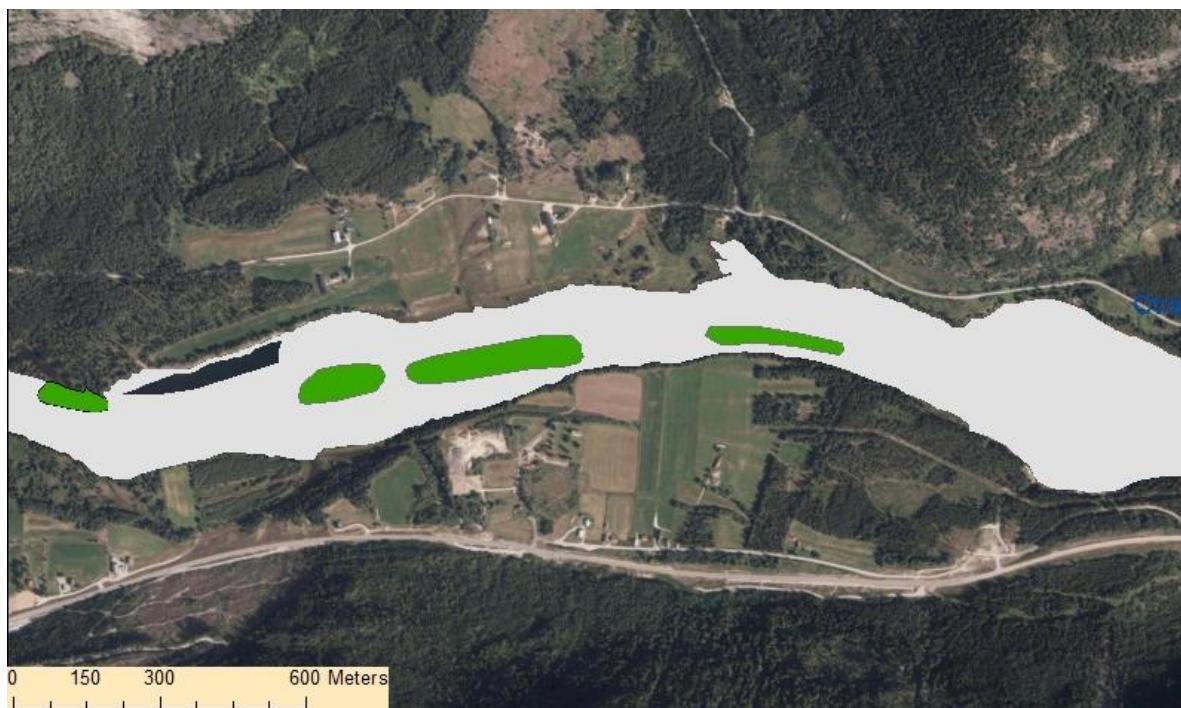
Figur 5. Dekningsgrad (%) av sand i Rysstadbassenget.



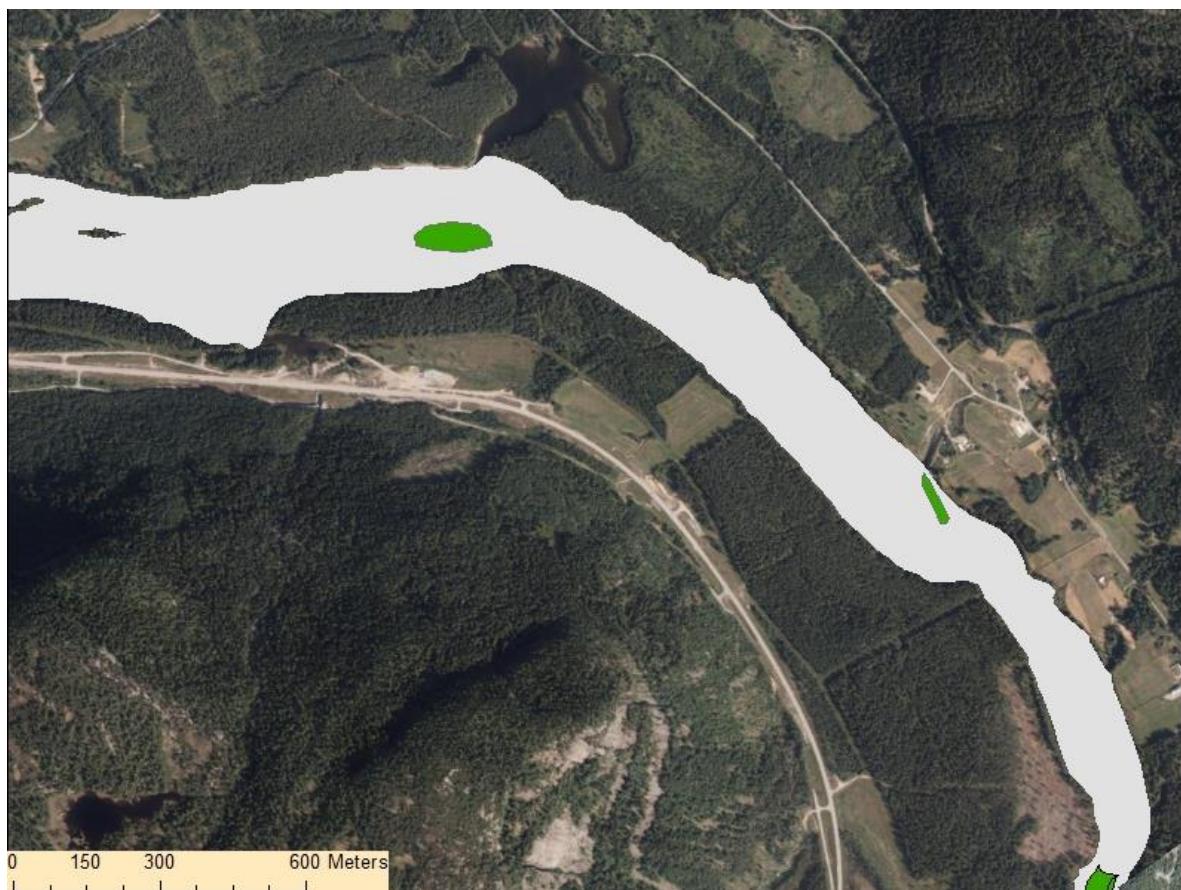
Figur 6. Potensielt godt gytehabitat (markert i grønt), kartblad 1: fra Faremo og forbi Skarpøy.



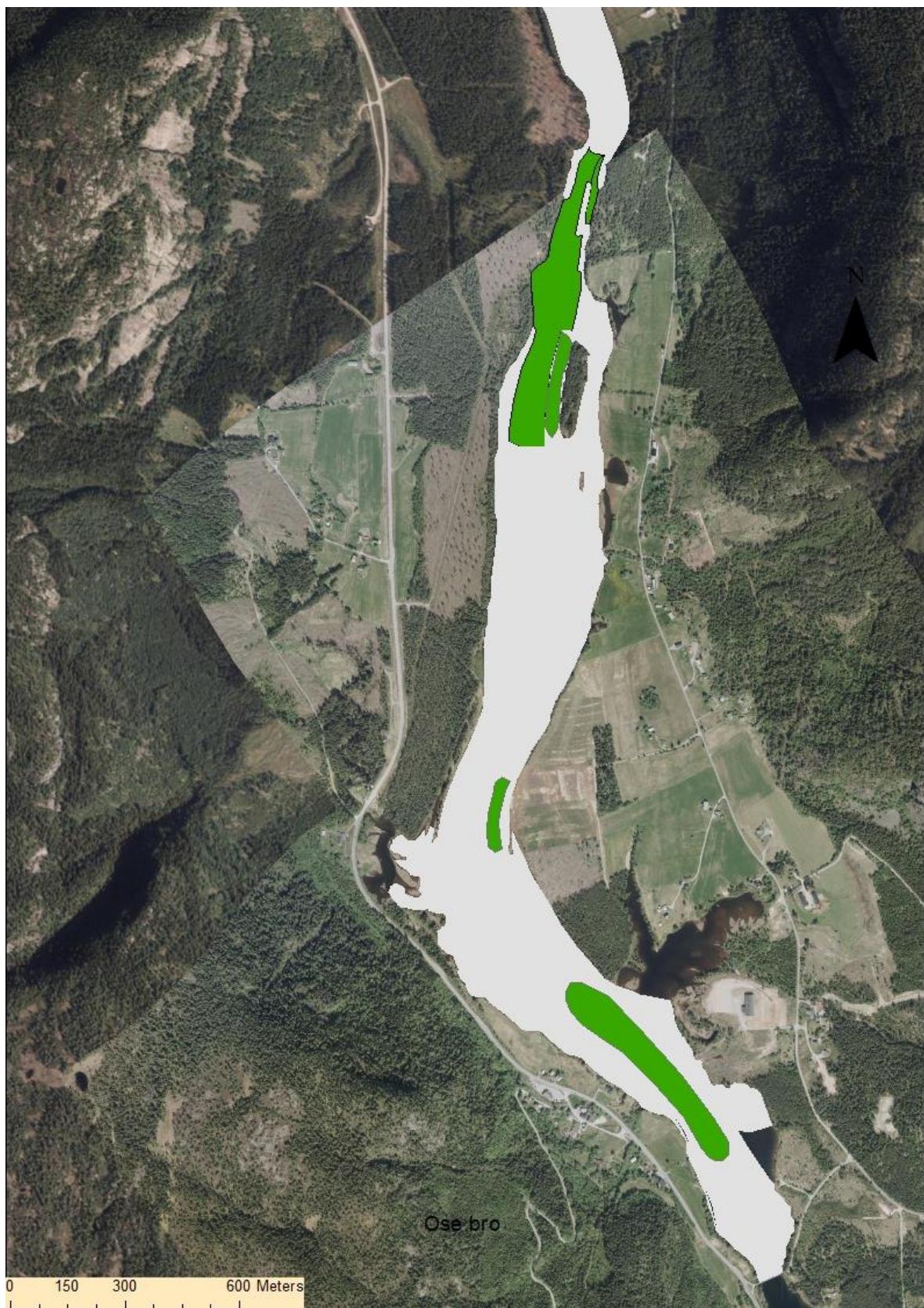
Figur 6 (forts.). Potensielt godt gytehabitat (markert i grønt), kartblad 2: fra utløp Hækni og forbi Storøy.



Figur 6 (forts.). Potensielt godt gytehabitat (markert i grønt), kartblad 3: fra utløp Hækni til Nedre Hegland.



Figur 6 (forts.). Potensielt godt gytehabitat (markert i grønt), kartblad 4: fra Heisevja til Heistad.



Figur 6 (forts.). Potensielt godt gytehabitat (markert i grønt), kartblad 5: fra Heistad til Ose.

4. Kartlegging ved hjelp av drone

4.1 Test sites

Three test sites (Figur 7) with differing conditions were chosen to represent material- and environmental properties, such as krypsiv distribution, other vegetation types, substrate, water depth or moving and non-moving water. Another aspect was easy accessibility of the test sites. The sizes were also adjusted to available flying time of the hyperspekter drone, which is limited by the number of available batteries and the time for battery charging.

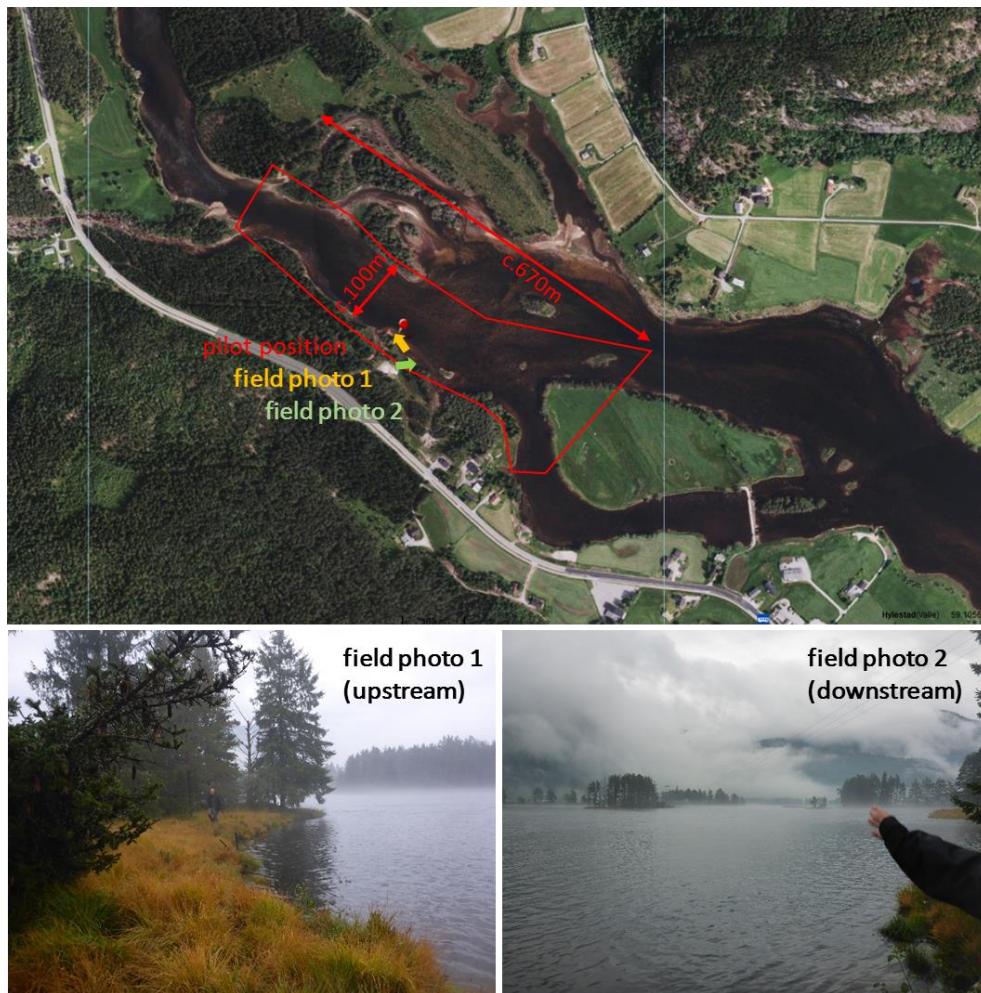
Area 1 (Figur 8) shows, from up to down-stream, a gradual increase of krypsiv distribution from non, over patchy to 80% krypsiv coverage. Other green vegetation types are moss and algae. This area represents relatively shallow water from zero to c. 5 m water depth with flowing and non-flowing water. Due to the material variation and gradual krypsiv coverage, this area was the focus for the method testing.



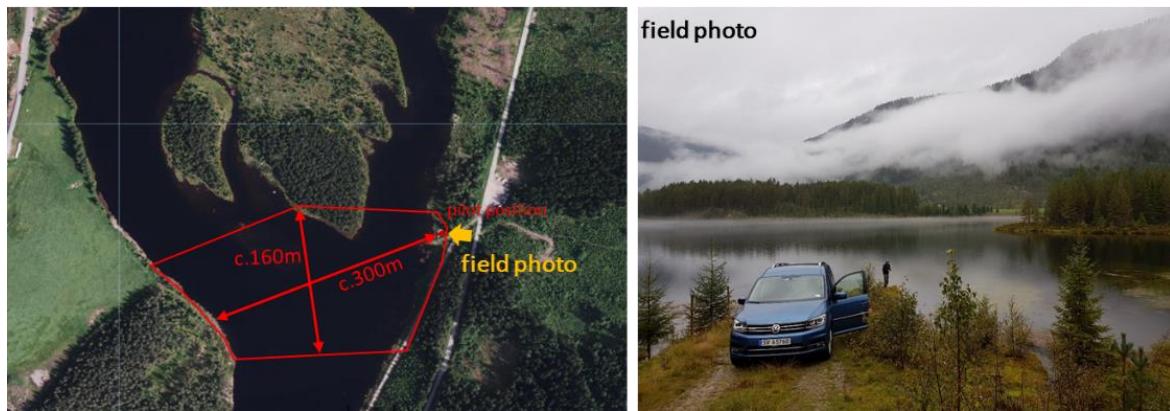
Figur 7. Positions of the test sites 1, 2 and 3. River Otra, between Brokke and Ose, Valle and Bugland Commune in Aust-Agder Fylke.

Area 2 (Figur 9) shows krypsiv and other vegetation types, in addition “dead” vegetation floating at the water surface in an abandoned meander. Water depth varies from shallow to ca 5 m depth. This area was mainly chosen to evaluate to what water depth spectral mapping might be applicable.

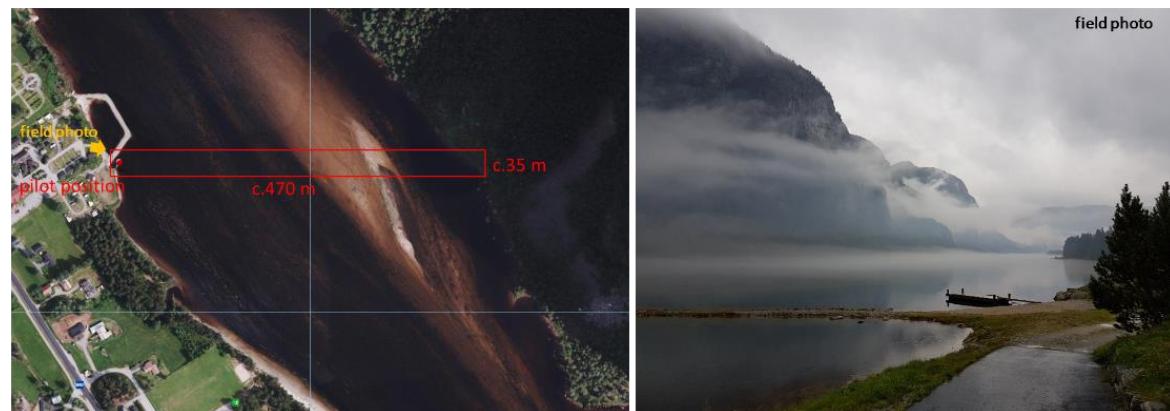
Area 3 (Figur 10) was chosen as reference area with nearly 100% krypsiv coverage. However, this area does not show much contrast to other vegetation types. Since krypsiv was growing in shallow water close to shore, we collected samples from this area to scan as reference material with the multi- and the hyperspectral cameras.



Figur 8. Area 1, c. 1 Km NW from Hylestad.



Figur 9. Area 2, c. 350 m NNE of Tjurmodammen.



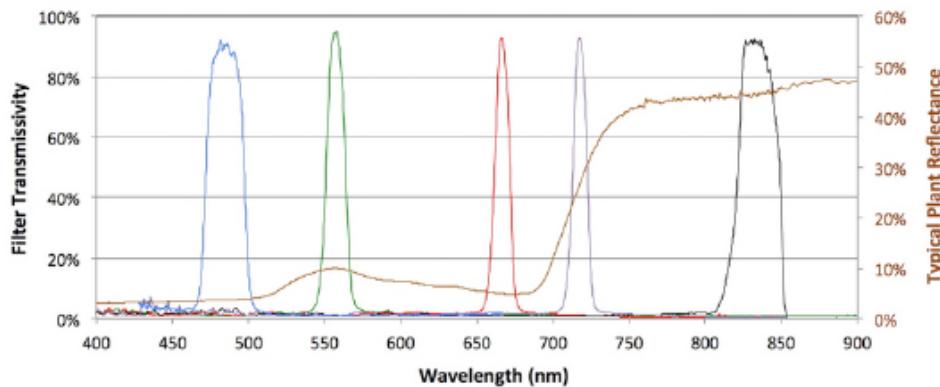
Figur 10. Area 3, Sølvgarden hotel and camp ground.

4.2 Multispectral mapping

Multispectral camera

The multispectral data was acquired using a MicaSense RedEdge™ 3 multispectral camera. This camera is designed particularly for agriculture application, and provides beside the three RGB bands two spectral bands within the near infrared (NIR) spectral range (Figur 11). Band 5 centres at 717nm which represents the “RedEdge” spectral range which provides diagnostic spectral information for vegetation analysis due to chlorophyll absorption. The multispectral bands allow extracting different types of vegetation indices for further analysis (Xue and Su, 2017).

The MicaSense RedEdge™ multispectral camera operates as a frame camera. However, the spectral bands are acquired as separate images with separate lenses. Post-processing is required to register the separate bands into a multi-band image. The camera provides a ground sample distance of 8.2cm/pixel (per band) at a range of 120m (e.g. flying height).



Band Number	Band Name	Center Wavelength (nm)	Bandwidth FWHM (nm)
1	Blue	475	20
2	Green	560	20
3	Red	668	10
4	Near IR	840	40
5	Red Edge	717	10

Figur 11. Spectral band specifications MicaSense RedEdge™ 3 multispectral camera (from RedEdge 3 User Manual, 2015).

Drone and camera mount

The multispectral camera was mounted on a DJI Phantom 4 drone (unmanned aerial vehicle, UAV), which has an in-build gimbal mounted RGB camera (Figur 12). This drone belongs to drone category RO1 (Luftfartstilsynet, 2015). After some initial mounting tests, it was decided to purchase a MicaSense RedEdge™ mounting kit to provide a more stable nadir view during drone moving and to compensate for vibration. Furthermore, the mounting kit provides customised accessories such as batteries, GPS receiver and cables, which minimises the payload. Whereas the flying time of the DJI Phantom 4 can be up to 25 minutes with one battery (depending on various parameters, such as battery condition, temperature and wind), the flying time was reduced to less than 15 minutes with the additional payload of the multispectral camera system. A reduced flying time can be compensated by a flight-planning program and autopilot operation, in addition to efficient charge of batteries.

The drone was operated in auto-pilot mode using the flight planning program DroneDeploy to ensure most stable flying conditions and constant flying height for image acquisition. The MicaSense camera was set to auto exposure and image acquisition period of 2 seconds. The system, camera settings and data processing workflow were tested before the field campaign.

Since two cameras are used with the drone, two data sets are created:

- I. RGB photo imagery from the DJI Phantom 4 in-build camera, providing a slightly higher pixel resolution and complemented with photos from different view angles and altitudes.
- II. Multispectral imagery from the MicaSense RedEdge camera (with five frame images per shot), proving spectral information within the NIR.



Figur 12. MicaSense RedEdge 3 camera mounted at a DJI Phantom 4.

Data acquisition

The multispectral data was collected on 15th September 2018. After a hazy morning with some fog over the river, the weather cleared and provided good visibility and almost cloud-free, sunny conditions and little wind. Area 1 was collected at the highest solar altitude, which provided good light conditions. The data collection at area 2 was hampered by failure of the autopilot software. Consequently, areas 2 and 3 were not collected with direct solar illumination (Tabell 2).

Tabell 2. Multispectral data acquisition overview.

	Area 1	Area 2	Area 3
Appr. dimension	830 x 350 m	380 x 360 m	465 x 160 m
Appr. covered ground area	233 300 m ²	107 500 m ²	75 000 m ²
Flying height	70m / (60m)*	70 m	70 m
Number of images MicaSense camera	9469	15486	2270
Number of images RGB camera	1611	851	423
Ground sample distance of MicaSense camera cm/pixel	c. 4.7cm / (c. 4.1cm)*	c. 4.7cm	c. 4.7cm
Ground sample distance of cm/pixel RGB camera	c.3.0cm / (c.2.6cm)*	c.3.0cm	c.3.0cm
Acquisition time	09:00 -> 09:50	13:10 -> 15:30	16:25 -> 16:35
Illumination conditions	No clouds, high solar altitude, direct sun	No clouds, low sun, indirect sun	No clouds, low sun, indirect sun

* A subarea was scanned a second time with lower flying height for high resolution data.

Calibrating targets (optical standards with known reflection properties) used for spectral correction were scanned before and after each drone flight in all three testing areas (Figure 13). For this, we included krypsiv material from area 3.



Figur 13. Calibration targets and reference material as used for multispectral imaging, shown from area 1. Some plastic material was placed and scanned as reference material to allow method assessment for plastic mapping from drones in other pilot projects.

Multispectral data processing

We tested different workflows to process the multispectral- and RGB images. Compared to common drone RGB camera data, the processing of the MicaSense RedEdge imagery differs in two main aspects:

- i. Generate single multispectral images from the spectral five bands. This was done after mosaicking each spectral band separately.
- ii. Applying spectral correction.

Digital Elevation Models (DEM) and mosaic extraction in Agisoft Photoscan

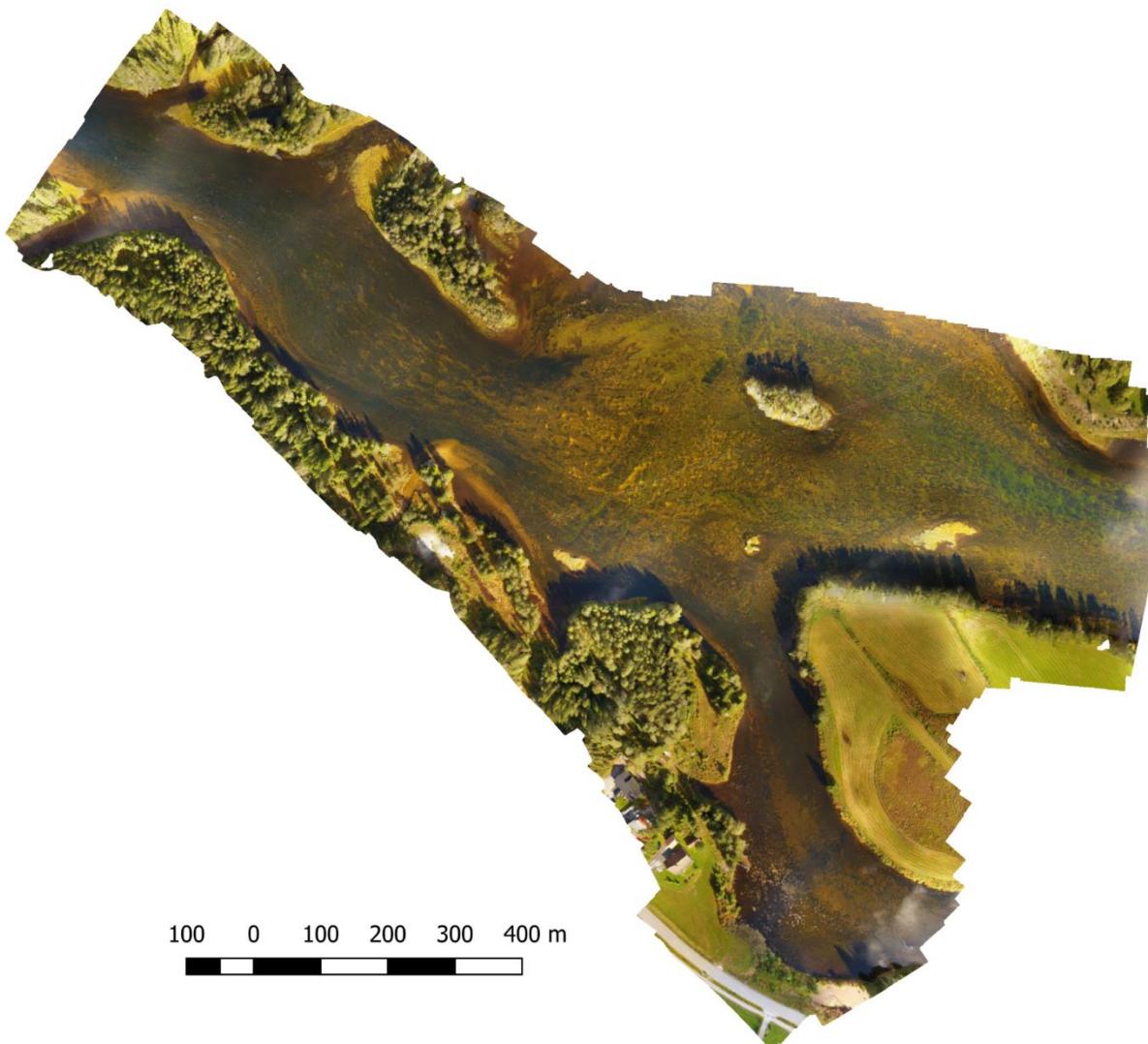
The Phantom RGB imagery as well as the RedEdge imagery were loaded into a single project in Agisoft Photoscan a Structure-from-Motion (SfM) photogrammetry software. Loading both data sets in a single project utilizes redundant image information, which is benefiting in SfM approaches, particularly for areas with challenging texture surfaces, such as water

surfaces. The subsequent workflow follows the common workflow for drone RGB imagery with the main processing steps. This was applied to all 3 test sites:

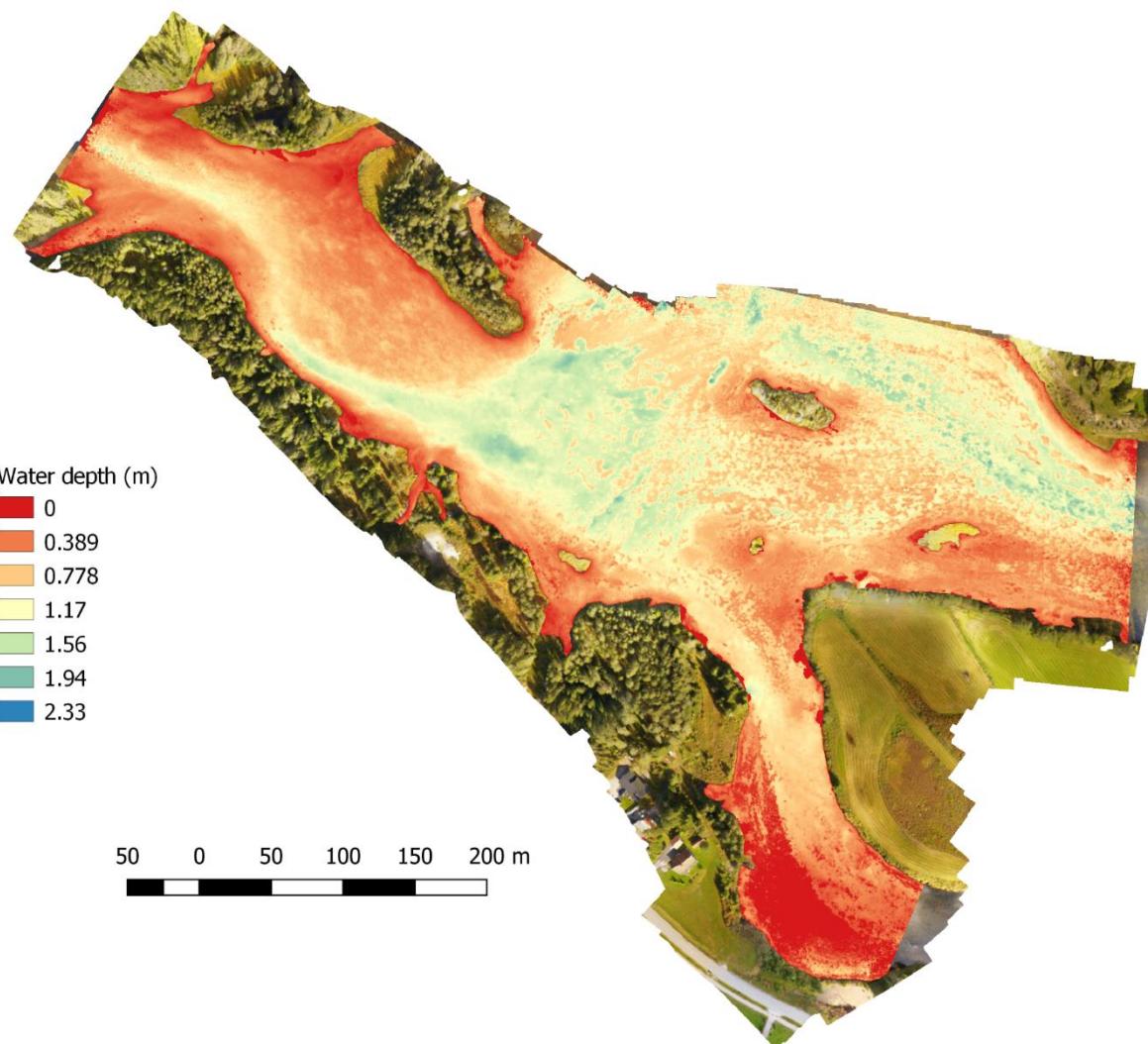
1. Image alignment and alignment optimisation
2. DEM building
3. Photo ortho-rectification
4. Mosaic building
5. Geo-referencing

Some alignment issue appears in areas where the riverbed is not visible due to water depth or water surface reflection. The resulted products are:

1. Georeferenced DEM
2. RGB mosaic (georeferenced) extracted from the Phantom RGB camera (Figure 14)
3. Five separate spectral mosaics (georeferenced) for each spectral band of the RedEdge camera.



Figur 14. Area1 RGB mosaic extracted from Phantom RGB camera imagery

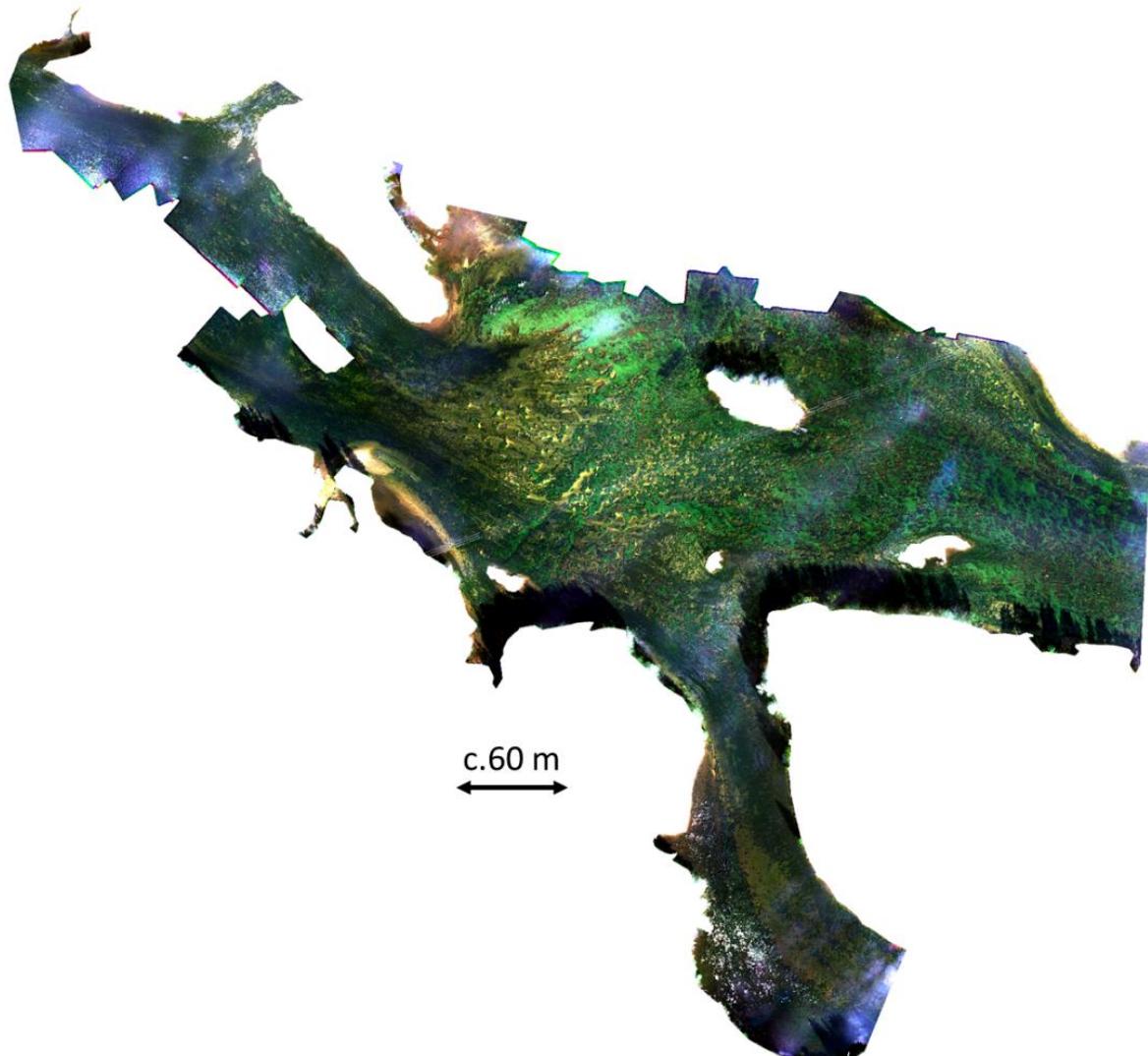


Figur 15. Water depth of area 1 superimposed on a RGB mosaic image. Depth represents water depth to top of the canopy for vegetated areas.

For area 1, the DEM information was used to extract water depth (Figur 15). For improved visualisation purposes, areas not representing riverbed were masked. The spectral correction in Agisoft Photoscan was tested. However, Agisoft Photoscan provides only a simple spectral correction approach, which does not consider camera internal parameters.

RedEdge imagery processing using Pix4D

Pix4D provides a specialised and automated processing workflow for MicaSense RedEdge drone data. Besides DEM extraction and mosaicking per spectral band, the workflow includes sophisticated spectral correction using internal camera parameters, as well as the opportunity to calculate several vegetation indices. However, the resulted DEM and spectral band mosaics were less complete in the upstream area compare to the DEM and mosaic generated with Agisoft Photoscan (Figur 16). In this area, image alignment failed due to insufficient image textures. Visualisation of spectral bands in the RedEdge and NIR band indicated material variation of the river bed (Figur 17 og Figur 18). Due to improved spectral correction, more details can be observed from these coloured band images compare to the Agisoft Photoscan outcome. Figur 19 and 20 shows the Phantom RGB and MicaSense RedEdge mosaics from test areas 2 and 3.

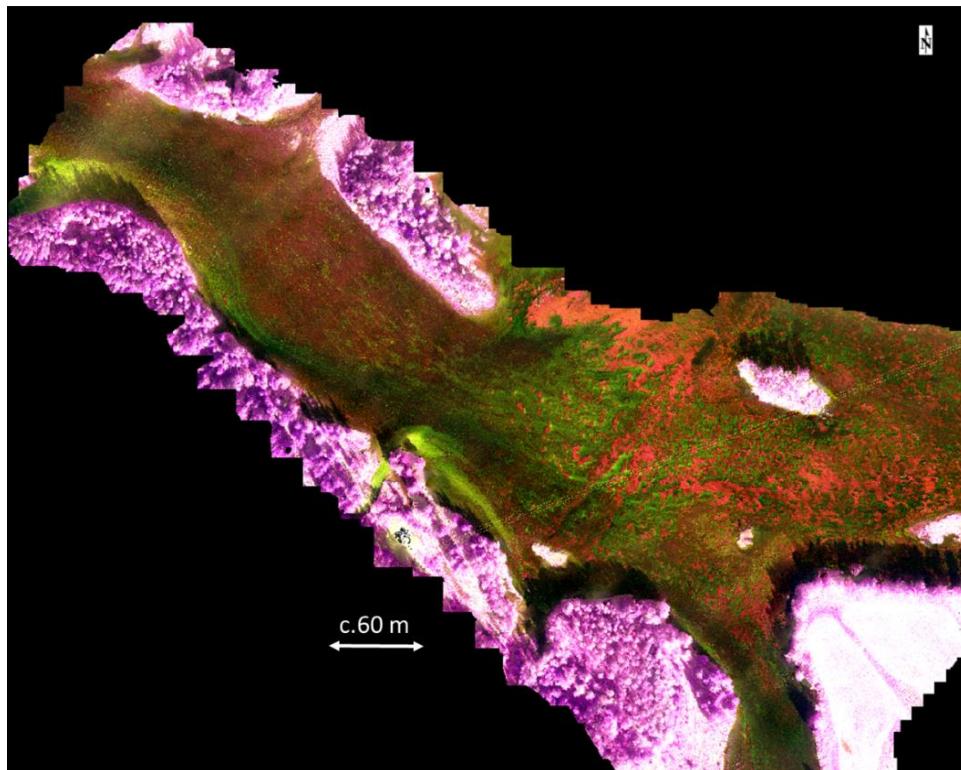


Figur 16 Area1 MicaSense RedEdge mosaic. Bands Red, Green and Blue visualised in RGB. Areas outside the riverbed is masked for improved visualisation.

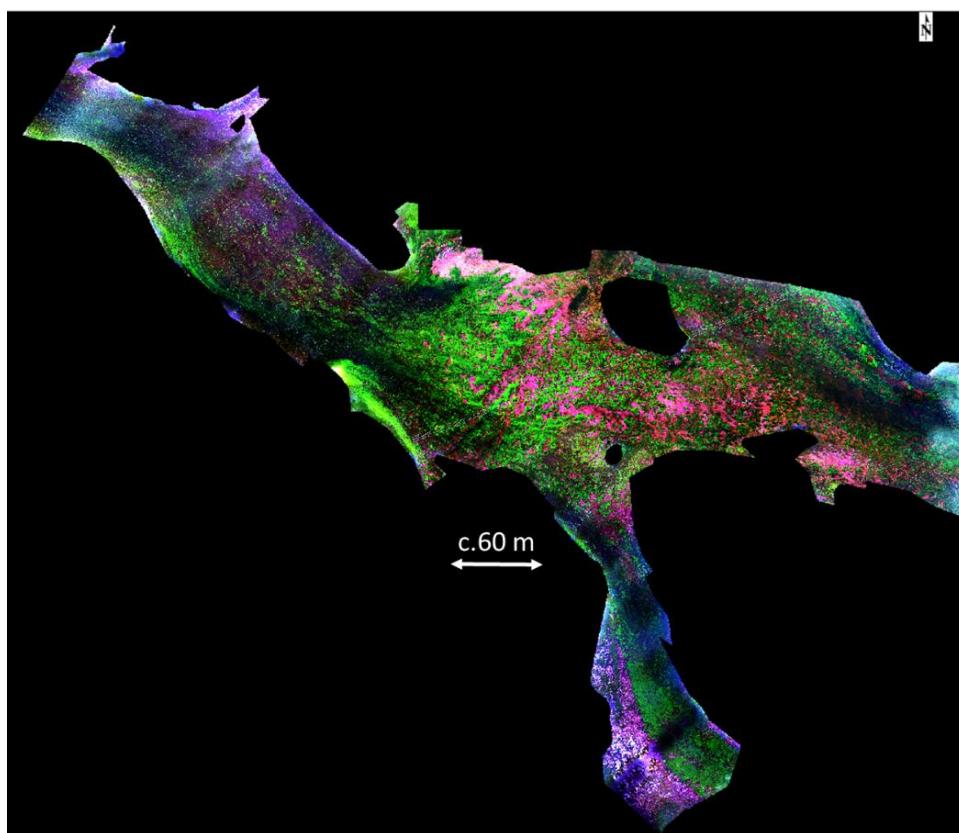
Spectral mapping

Different unsupervised and supervised classification approaches have been tested using software solutions with focus at GIS programs which providing better opportunities for co-visualisation with other spatial information such as parameters from the manual krysiv mapping. Classification have been tested on spectral bands but also other products, such as Normalised Difference Vegetation Index (NDVI; an indicator of plant health from images). Classification approaches includes besides others:

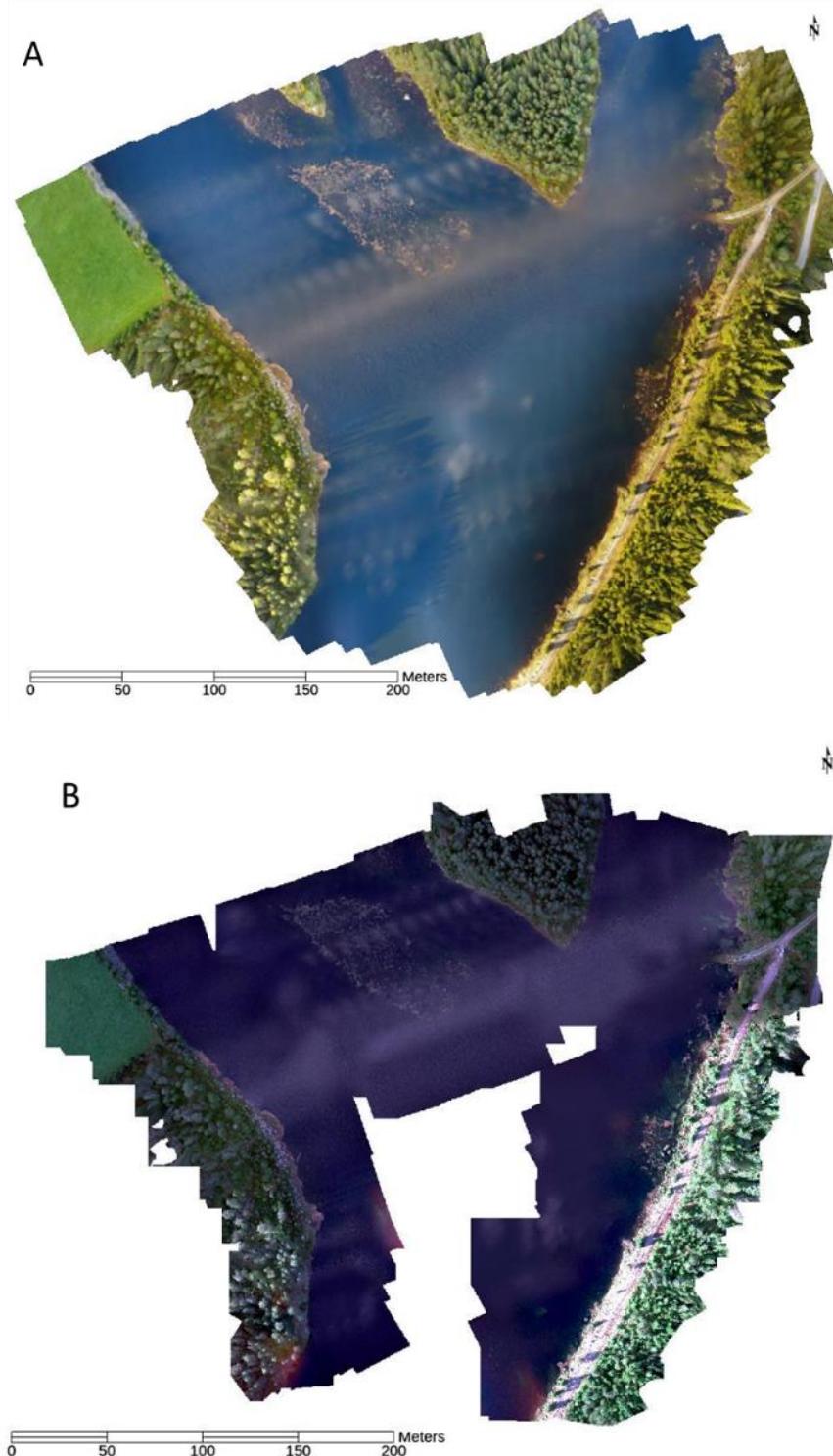
- Maximum Likelihood classification (ML), available e.g. in SAGA GIS
- Spectral Angle Mapper (SAM), available e.g. in SAGA GIS
- Object Based Image Analysis (OBIA), available e.g. in SAGA GIS
- Object Based Nearest Neighbour classification (NN), available in eCognition Developer



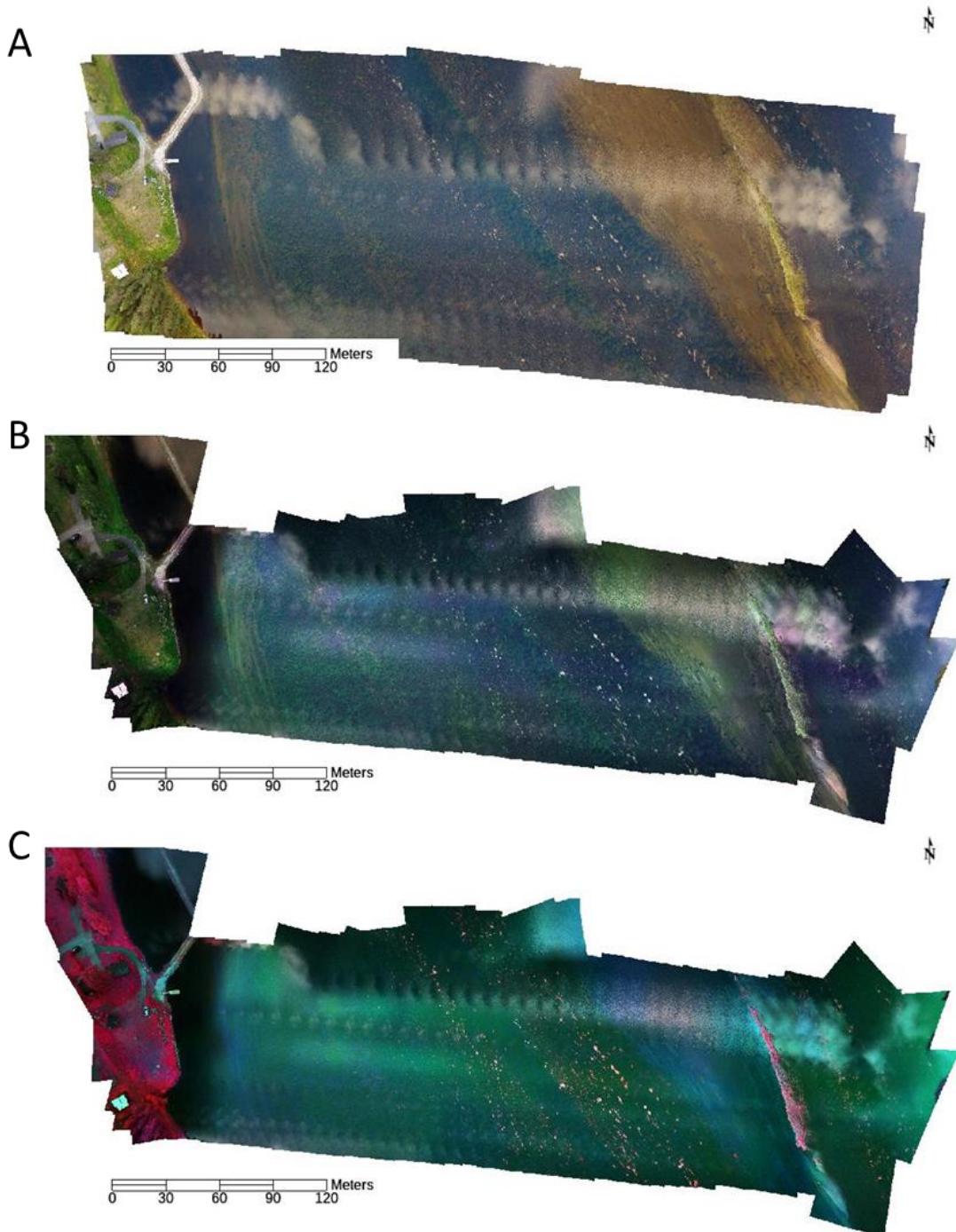
Figur 17 Area1 MicaSense RedEdge mosaic. False coloured image multispectral bands RedEdge, Red, NIR visualised in RGB.



Figur 18 Area1 MicaSense RedEdge mosaic. False coloured image multispectral bands RedEdge, Red, NIR visualised in RGB. Areas outside the riverbed is masked for improved visualisation.



Figur 19 Area 2, A) Phantom RGB mosaic, B) MicaSense RedEdge mosaic, bands Red, Green, Blue, visualised in RGB, processed in Argisoft Photoscan.



Figur 20 Area 3, A) Phantom RGB mosaic, B) MicaSense RedEdge mosaic, bands Red, Green, Blue, visualised in RGB. C) MicaSense RedEdge mosaic, bands RedEdge, Green, Blue, visualised in RGB.

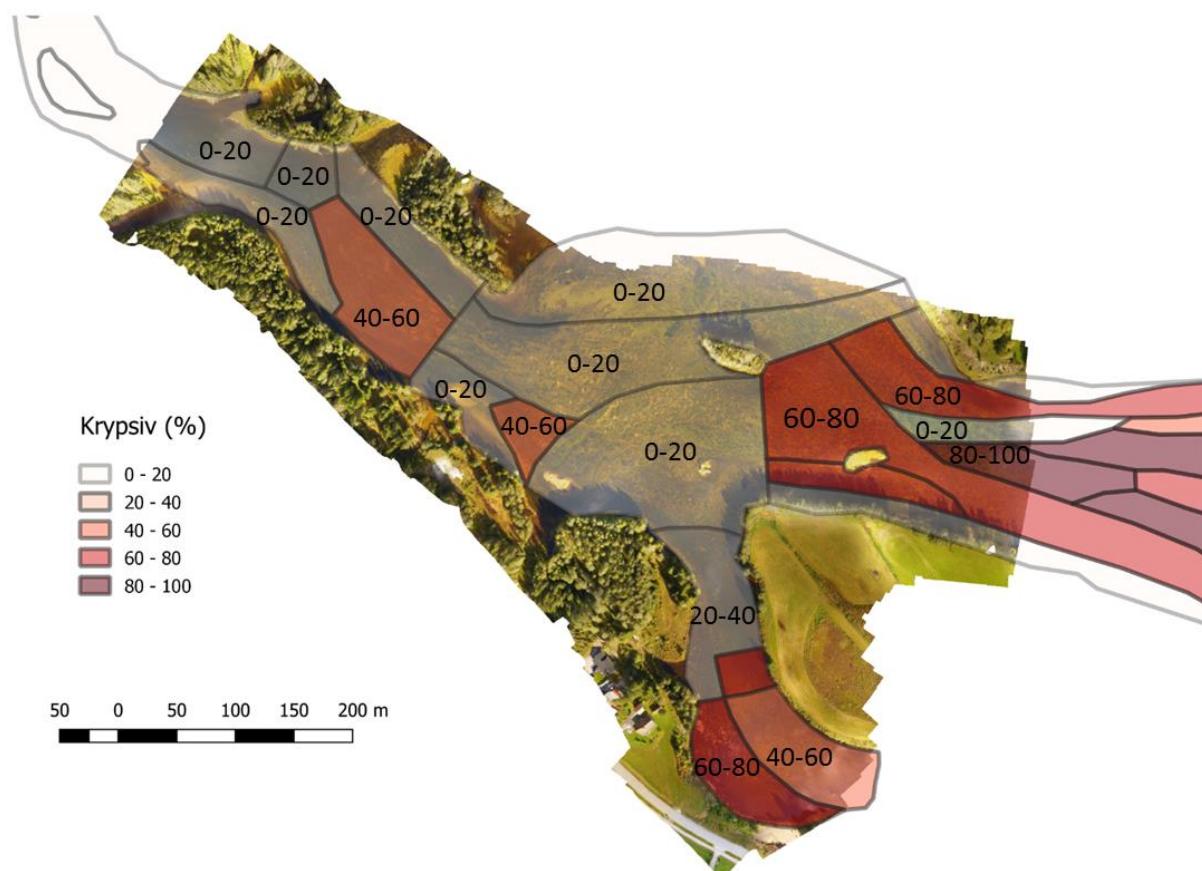
Multispectral mapping results and outcomes

Figur 21 shows the krypsiv distributions in area 1 as mapped from snorkelling observations. Figur 22 og Figur 23 show examples of NDVI products, which are indicative for green vegetation and chlorophyll. Furthermore, Figur 24, Figur 25, Figur 26 and Figur 27 show a selection of different classification attempts. Classification results were qualitatively compared with the snorkelling observations (Figur 21), and with the RGB mosaics (Figur 16)

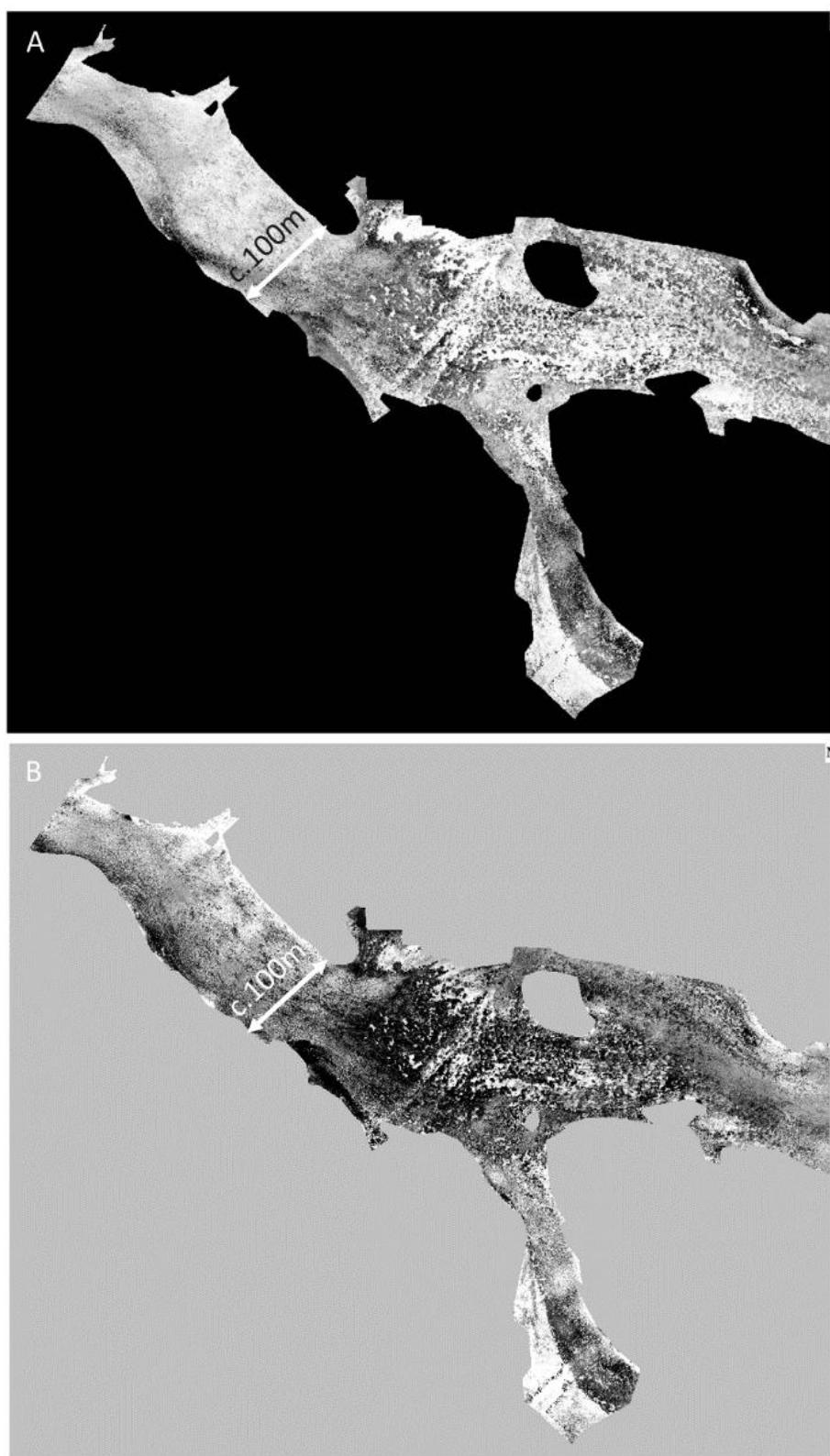
on which vegetation distribution to some extent can be seen. However, differences in mapping resolutions, lack of exact measurements of the polygon positioning and material mixtures hampered comparison with the manual krypsiv map. Due to time limitation, no quantitative evaluation of classification results was performed.

The multispectral mapping results indicate that green sub-water vegetation can be mapped and quantified. RGB and false coloured images, as well as NDVI products, indicate variations within the vegetation, which might allow a differentiation between krypsiv and moss/algae. Field observations confirmed that the classification to some extent represented the krypsiv distribution. However, in some areas, such as in the NE river channel with deeper water and in the SE river channel with very shallow water, classifications seems to underestimate krypsiv. The underestimation of krypsiv might be also caused by mixture effects due to association of krypsiv with algae, for example in shallow water in the SE river channel. Furthermore, the multispectral data was not corrected for water column attenuation, which hampers classification performances.

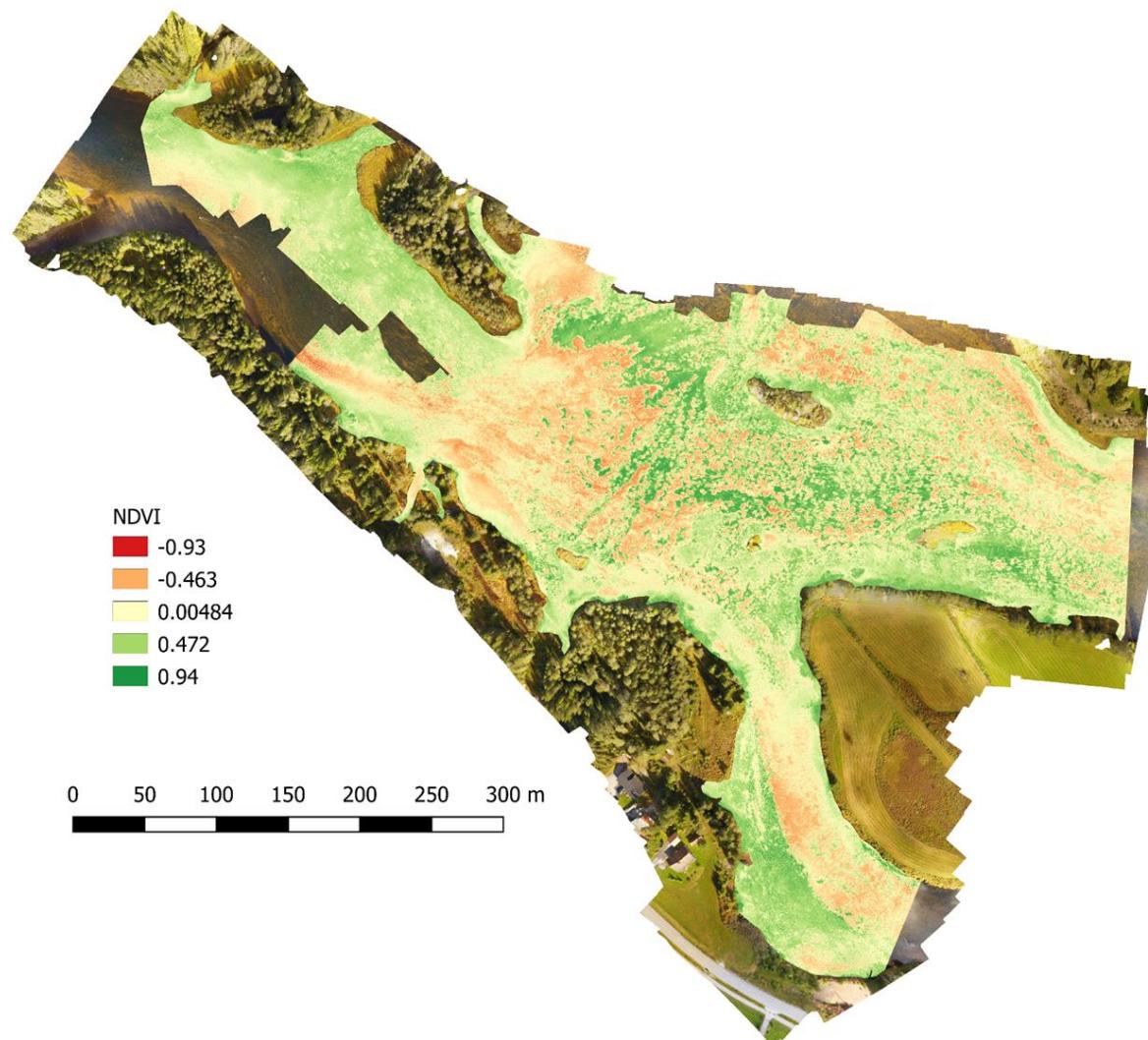
Test sites area 2 and 3 have a lower data quality due to unfavourable illumination conditions (Figur 19 og Figur 20). In addition, in some sections of area 2, image alignment fails due to insufficient texture of the water surface resulting in an incomplete mosaic (Figur 20). Due to time limitation, data from areas 2 and 3 are not fully exploited.



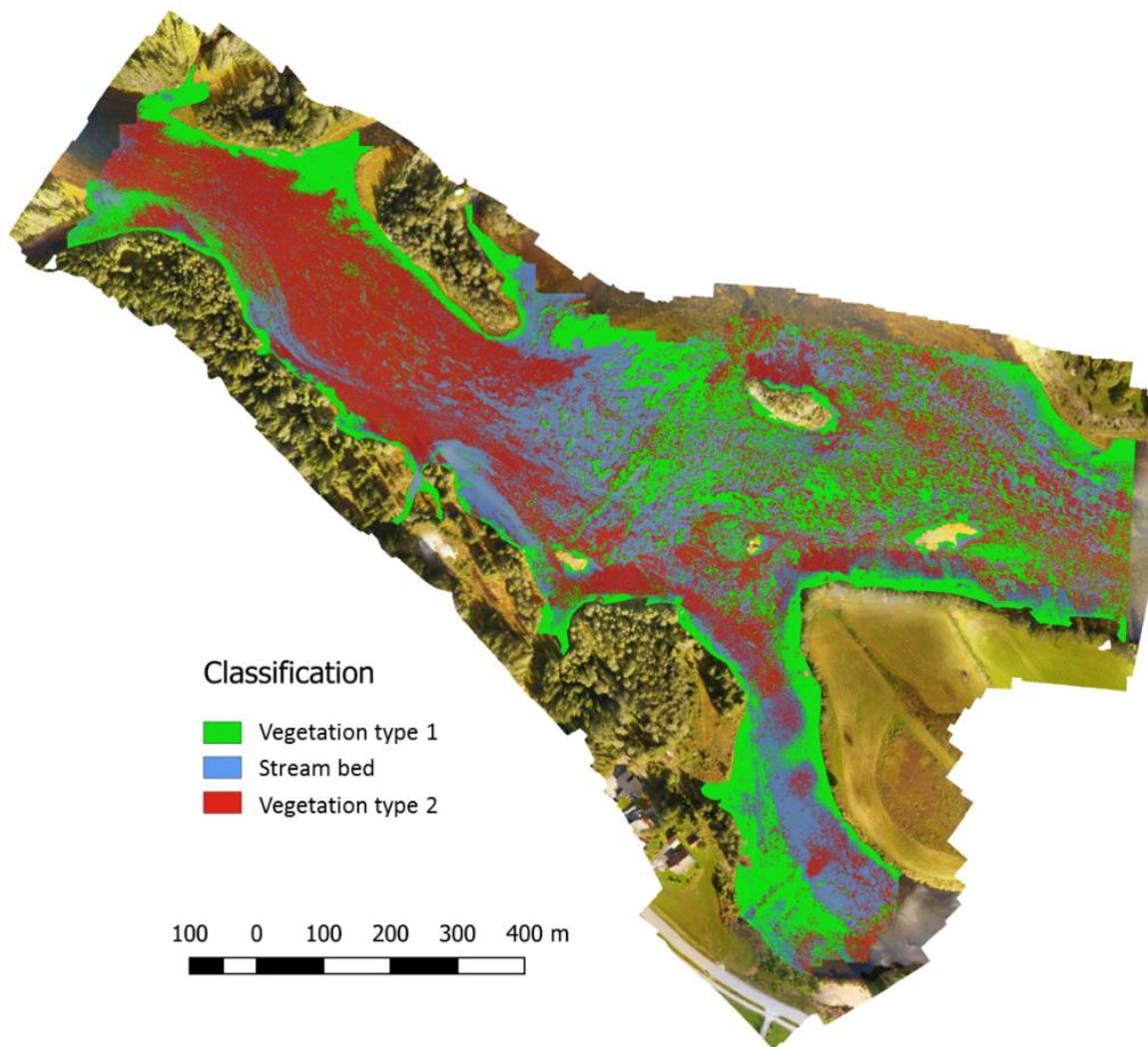
Figur 21 Manual krypsiv map from Area 1 based on diving observations. Tha map is superimposed on a RGB mosaic.



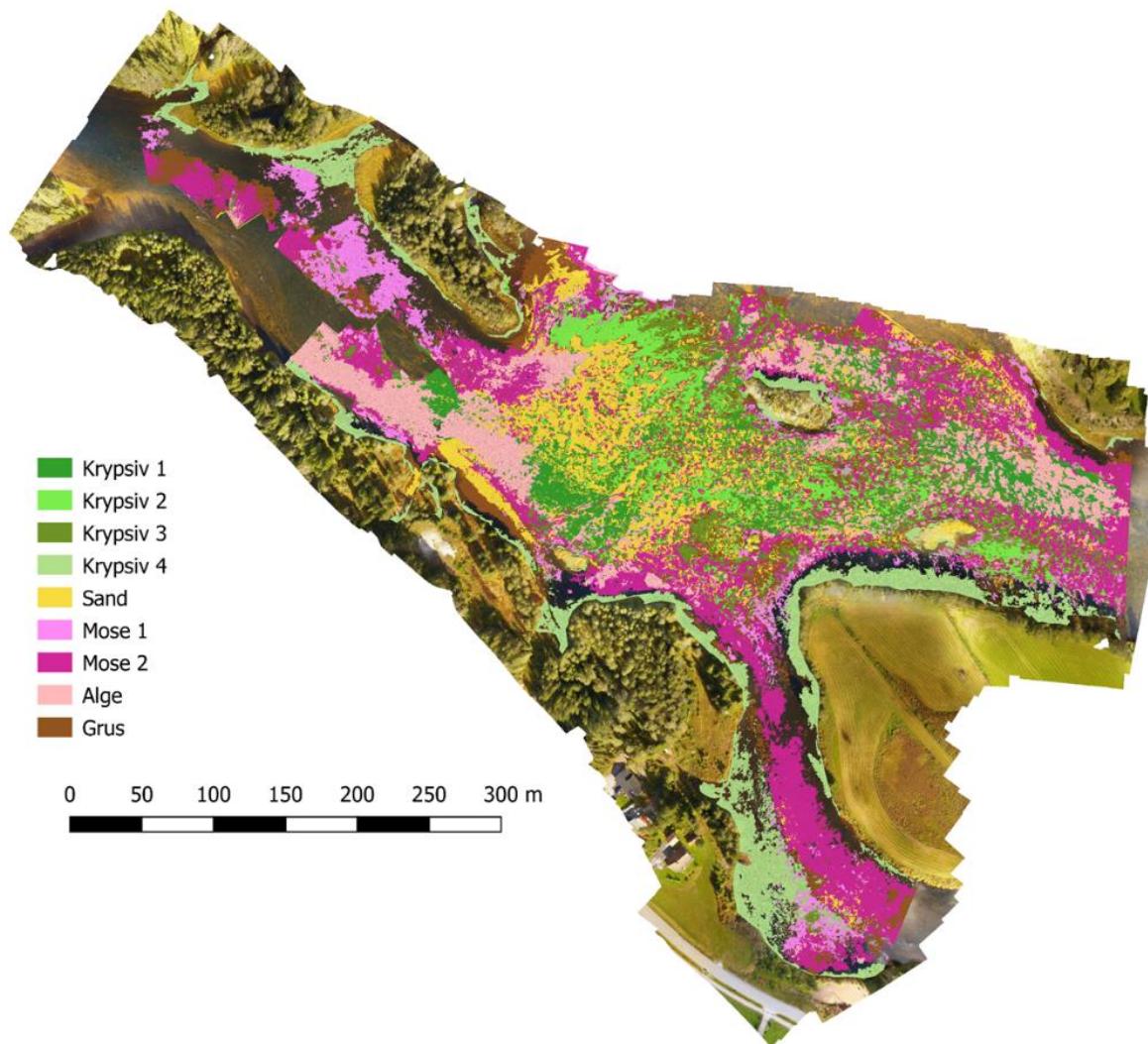
Figur 22 Area1 Normalised Difference Vegetation Index (NDVI) derived from spectral corrected MicaSense RedEdge mosaic. A) NDVI calculated with band NIR1, B) NDVI calculated with band RedEdge. Areas outside the riverbed is masked for improved visualisation.



Figur 23 Area 1, Normalised Difference Vegetation Index (NDVI) map (calculated with RedEdge band) derived from spectral corrected MicaSense RedEdge mosaic. NDVI values ranges between -1 and 1, high values are indicative for green vegetation due to chlorophyll absorption. The NDVI map is superimposed on a RGB- mosaic.



Figur 24 Area 1, initial Maximum Likelihood classification processed in SAGA GIS. The classification is superimposed on a RGB- mosaic.

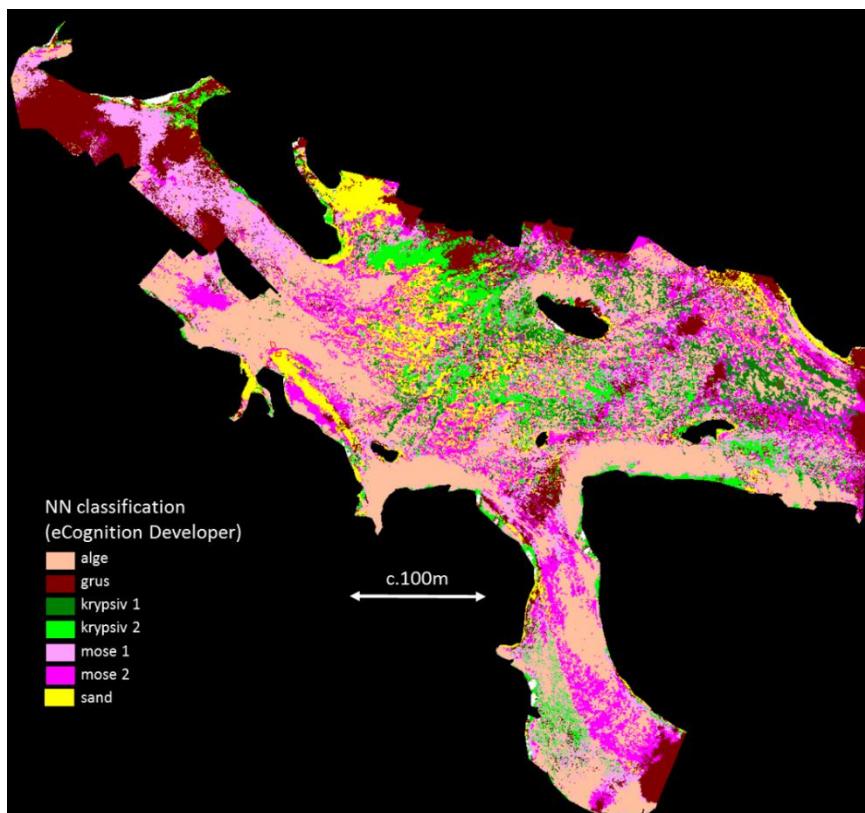


Figur 25 Area 1, Object Based Image Analysis (OBIA) classification processed in SAGA GIS. The classification is superimposed on a RGB- mosaic. Krypsiv and mose have been measured from different training areas. Multiply training areas from the same material class can help to map material variation caused e.g. by mixture effects or different water depth.

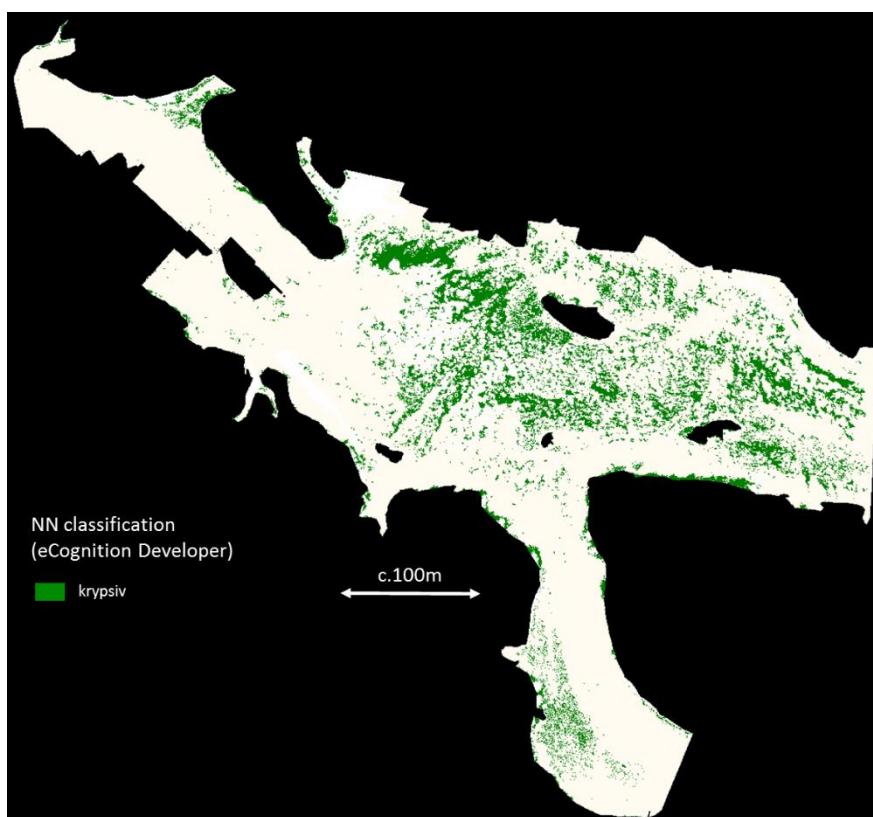
Multispectral mapping conclusions

Potential for krypsiv quantification

At this stage, reliable krypsiv quantification from multispectral drone imaging could not be acquired within the framework of this small-scale pilot study. The classifications approaches were tested but the data is not utilized to full potential. The classification results indicate that particularly the Object Based Nearest Neighbour approach might provide more robust. In contrast to pixel based classifications (e.g. SAM), object based approaches uses spectral and also spatial and contextual local image information which significantly can improve the differentiation between image objects. Further work is required to determine appropriate input statistics and input data (e.g. NDVI bands or topography band) to improve classification performance. The initial results in eCognition Developer was promising; however, more data editing is required to prepare spatial and context information for classification input.



Figur 26 Area 1, Object Based Nearest Neighbour (NN) processed in eCognition Developer.



Figur 27 Area 1, Krypsiv class (krypsiv 1 and 2 combined) from Object Based Nearest Neighbour (NN) classification processed in eCognition Developer (see Figur 26).

Multispectral drone imaging can be considered as established method with of-the-shelf solution for data collection and processing (e.g. Boon and Tesfamichael, 2017). However exploiting multispectral imagery for sophisticated applications, such as mapping of vegetation species in sub-water environment, is not yet easily available. Especially, we expect that the classification performance can be improved by addressing the following:

1. Improving spectral correction by compensation for water column attenuation.
2. Improving understanding of spectral properties and mixture behaviour, and also spatial and context properties of relevant materials and objects.
3. Improving representative trainings / reference data for classification input.
4. More intensive testing of sophisticated classification approaches, such as object based classifications or machine learning algorithms.

Different multispectral products have clearly shown the benefit of additional spectral information within the NIR spectral range compare to simple RGB imagery. Spectral variation within sub-water green vegetation was clearly indicated in our study. However, more work is required to evaluate if this spectral variation is reliable, especially in areas with several plant groups, such as krypsiv, moss and algae.

Practicalities

This pilot project has gained experiences in respect to the practicalities for using multispectral drone imaging in routine applications. The main experiences can be summarised as follow:

- Suitable weather and illumination conditions are required for high data quality, however, requirements are not as restricted as for hyperspectral imaging.
- Photogrammetric processing of water surfaces might be hampered by insufficient surface texture.
- Off-the-shelf hardware solutions are available with cameras designed for agriculture and environmental application and allow reasonable flying time over a day.
- Costs for data collection is similar to conventional RGB drone imagery (e.g. costs for camera, drone, pilot licence, field logistics, time etc.).
- Data processing is highly automated (specialised software required).
- Collecting ground truth and spectral reference data needs more complete sampling and better characterisation for spectral/spatial properties.
- Sub-water mapping is possible but is influenced by water column attenuation and water surface reflection.

4.3 Hyperspectral mapping

Hyperspectral instrumentation and data acquisition

Hyperspectral imaging is conventionally used from maned aircrafts. With the rise of compact hyperspectral imager systems over the last decade, close range applications, e.g. tripod mounted, have been established (e.g. Kurz et al. 2013). Drone-ready hyperspectral imager is the newest generation of hyperspectral sensors. Norsk Elektro Optikk AS (NEO) is one of the few manufactures for high performance hyperspectral imagers. NEO released the drone-ready HySpex MJOLNIR V-1240 imager in 2017. This instrument covers the visible and near infrared light up to a wavelength of 1000 nm, and is therefore suitable for vegetation applications (Tabell 3). Since no service provider for Hyperspectral drone data collection could be found for our project, NEO agreed to collect the data within one-day field campaign. However, NEO is more rigged to collect small-scale data sets during instrumentation demonstrations and is not a commercial provider for data collection. The hyperspectral camera was mounted on a Camflight FX8HL drone (UAV) platform (Figur 28 and Figur 29) with a double quadcopter that provides a stable drone platform for scanning. This is a category RO2-drone that requires an extra drone pilot license (Luftfartstilsynet, 2015).

Tabell 3. Main specifications of HySpex MJOLNIR V-1240 pushbroom camera.

Spectral range	400-1000 nm
Spatial pixel	1240
Ground sample distance at 120m flying height	3.3 cm/pixel
Spectral sampling (200 band mode)	c. 3 nm
Number of spectral channels	200
Field of view	20°
Swath width at 120m flying height	40 m
Bit resolution (raw data)	12 bit
Drone	Camflight FX8HL
Size of drone	140 cm x 50,5 cm (4 kg weight, max. payload 25 kg)



Figur 28 HySpex MJOLNIR V-1240 pushbroom camera mounted on a Camflight FX8HL drone.



Figur 29. Pilot base field setup at area 1. Hazy morning required waiting until the weather cleared.

The hyperspectral data collection had a number of constraints which had to be considered and which made the field campaign challenging:

- Appropriate weather and solar illumination condition
- Contemporary data collection with manual krypsiv mapping from diving observations and within the seasonal vegetation period
- Limited availability of NEO during late summer/ early autumn in 2018

The original plan, collecting the hyperspectral drone data simultaneously with the manual krypsiv mapping and multispectral data, was not possible due to availability and weather issues. A long rainy period in September 2019 caused several delays. The data was finally collected on the 18. September 2018 (Figur 29 og Figur 30). Although light clouds were forecasted for the morning, it was decided to proceed with the data acquisition; otherwise, no data could have been collected in 2018. The morning was hazy, with some fog over the

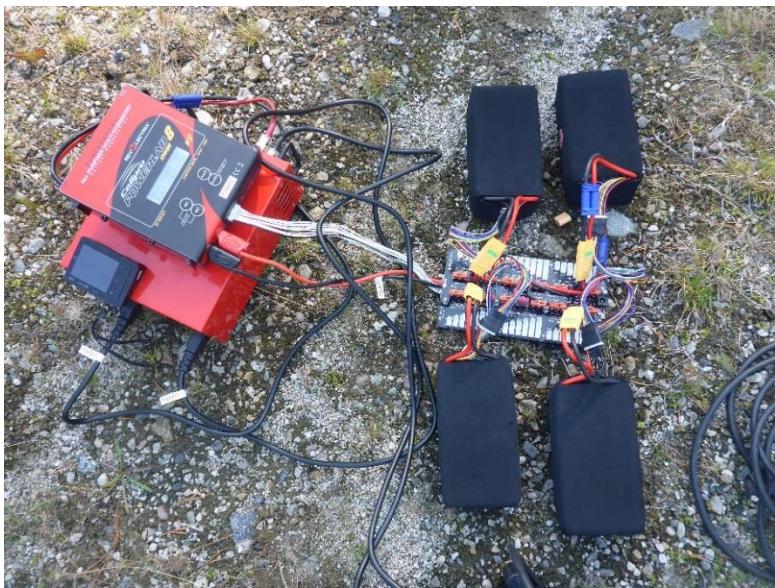
river and some clouds. At lunchtime, the light conditions improved for a few hours, and it was decided to start flying.

The data collection was further hampered by limited flying time due to limited sets of batteries and limited capacity to recharge the batteries (Figur 31). This resulted in longer waiting time for battery recharging than intended and therefore less available flying time. The data collection in area 2 was therefore delayed. Although some data from area 2 collected, the cloud free periods were short and did not provide appropriate illumination condition. No data was collected from area 3.

The hyperspectral data was collected at an altitude of 120 m above ground, which is the maximal allowed altitude for drones without extra permission (Luftfartstilsynet, 2015). This flying altitude results in a ground sample resolution of 3.3 cm at a 40 m swath. The flying speed was chosen at 1.6 m/s (5.8 Km/h). The flying speed is chosen according to illumination and exposure time. However, speed and exposure were chosen based on the assumption of optimal illumination condition. During the pre-processing of the data, NEO reported data quality issues and mentioned that the data should have been collected with lower flying speed and longer exposure time. As for the multispectral data, calibration targets used for spectral correction were scanned (Figur 13).



Figur 30. Screenshot flight plan from area 1.



Figur 31. Charging of one battery set. Since NEO brought the wrong charging equipment, the two sets of batteries could be only charged sequentially and not contemporaneously.

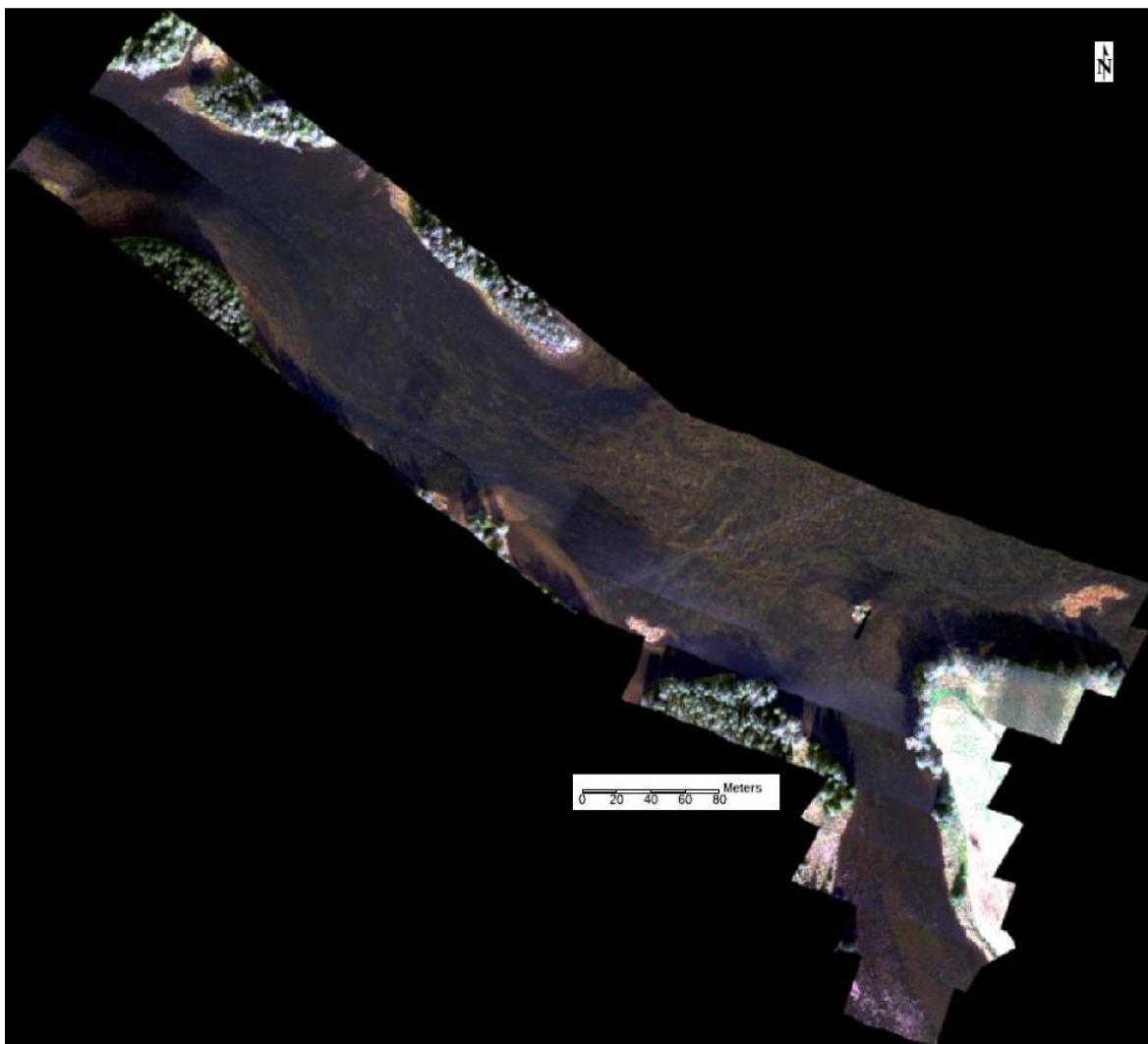
Hyperspectral data processing

The hyperspectral data was pre-processed by NEO in terms to correct for platform movement, image geo-referencing, generating a hyperspectral mosaic image of area 1 and transferring the raw data into radiance values. To improve the signal to noise ratio, the data was spatially re-sampled to c. 15 cm/pixel ground sample size. NEO reported a peak signal to noise ratio between 30-40 for water pixels at 15 cm/pixel ground sample size. Furthermore, NEO reported that the navigation system was changed right before the field campaign and that the sensor bore sighting required recalibration to ensure precision in the rectification. The boresight calibration issues caused a delay in data pre-processing. The final pre-processed hyperspectral mosaic has a dimension of c. 680x180 m, covering ca 180 400 m² (Figur 32 and Figur 33). The hyperspectral mosaic show artefacts due to imprecise swath registration and brightness inhomogeneity due to varying illumination conditions during the data collection. Due to delayed delivery of the hyperspectral data, data processing for artefacts and inhomogeneity correction, as well as detailed data exploitation, were limited towards the end of the study.

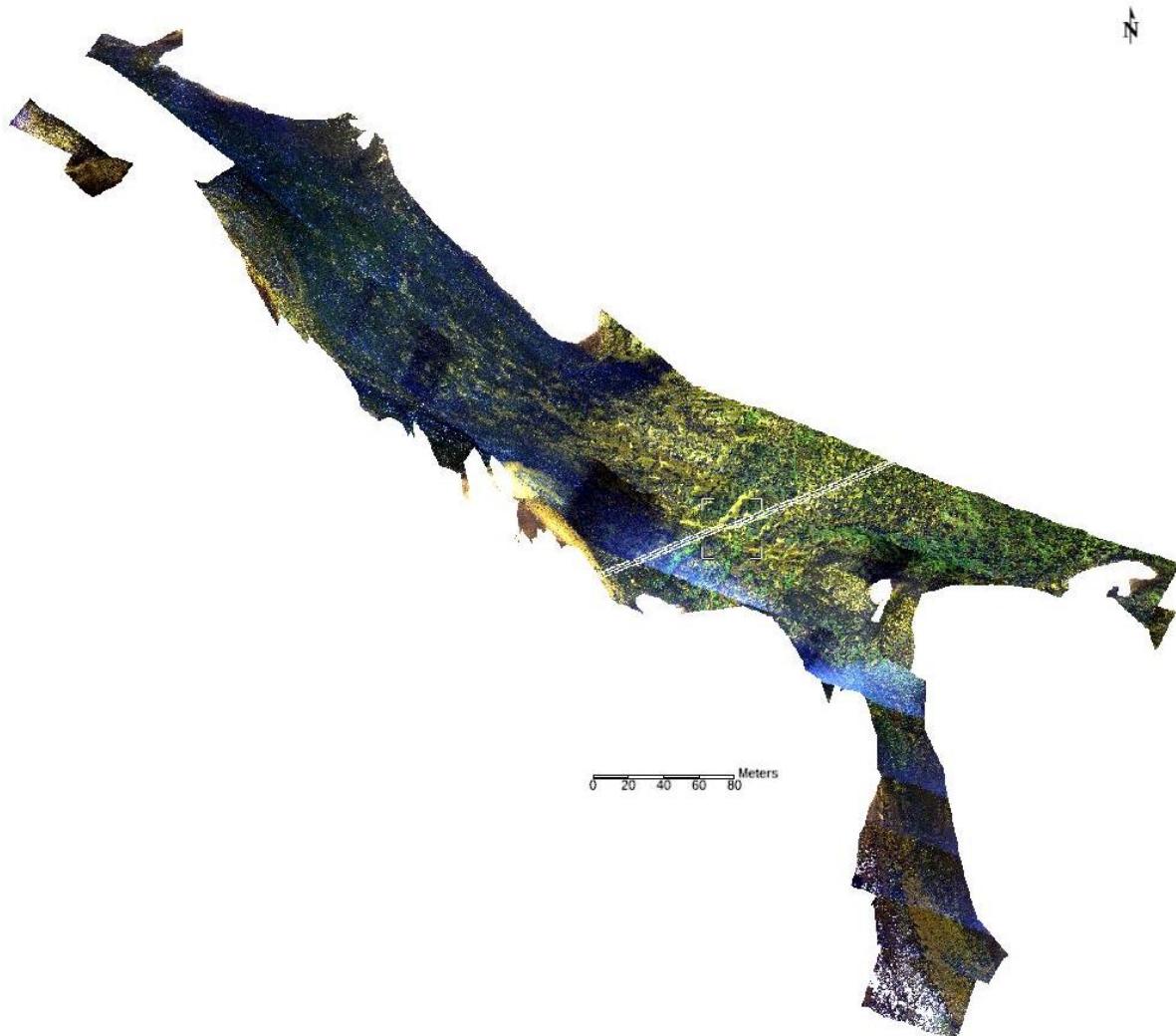
The single band used to test spectral correction was based on radiance transfer modelling using the FLAASH spectral correction tool in Envi (Harris Corporation). The FLAASH software is designed for conventional airborne/spaceborne remote sensing data and estimates many parameters from the data, such as water vapour and other atmospheric gases, allowing fairly automated spectral correction without additional ground information. However, the results did not show reasonable outcomes. According to the technical support, FLAASH cannot handle the high ground sample resolution of drone data. Alternatively, Empirical Line correction (Smith and Milton, 1999) using the calibration targets at the ground can be used for radiometric correction and to transfer the radiance image into reflectance images. However, locating reference measurements, such as calibration targets or the krypsiv sample, was hampered by the lower ground sample resolution of 15 cm. Despite numerous demand notes, NEO did not deliver the original higher resolution imagery.

The sub-water surface reflectance varies with depth and requires correction to improve spectral mapping results. Although various methods have been suggested (e.g. Zoffoli et al. 2014), no standards have been established and off-the-shelf correction tools are not yet available. Therefore, appropriate correction for water column attenuation must be programmed, which was not possible within this pilot study. However, a simple correction was performed by applying Empirical Line correction utilizing the krypsiv reference sample at land and measuring the spectral response of krypsiv at maximum water depth. This allows compensating for water attenuation with a simple linear interpolation. Such a correction for water depth seems to enhance the RedEdge shape of sub-water vegetation spectra, but introduces artefacts at land spectra.

The vegetation was classified using Spectral Angle Mapper (SAM) and Maximum Noise Fraction Transformation (MNF, Green et al. 1988). MNF is an image transformation tool for hyperspectral data that suppress noise and highlighting material differences. MNF bands and RGB images are used as initial image interpretation and to define the training area.



Figur 32. Area 1, hyperspectral reflectance image mosaic. Bands 632 nm, 542 nm and 454 nm visualised in red, green and blue (RGB).



Figur 33. Area1, hyperspectral reflectance image mosaic. Bands 632 nm, 542 nm and 454 nm visualised in RGB. Areas not representing the riverbed or with strong shadow have been masked for improved visualisation.

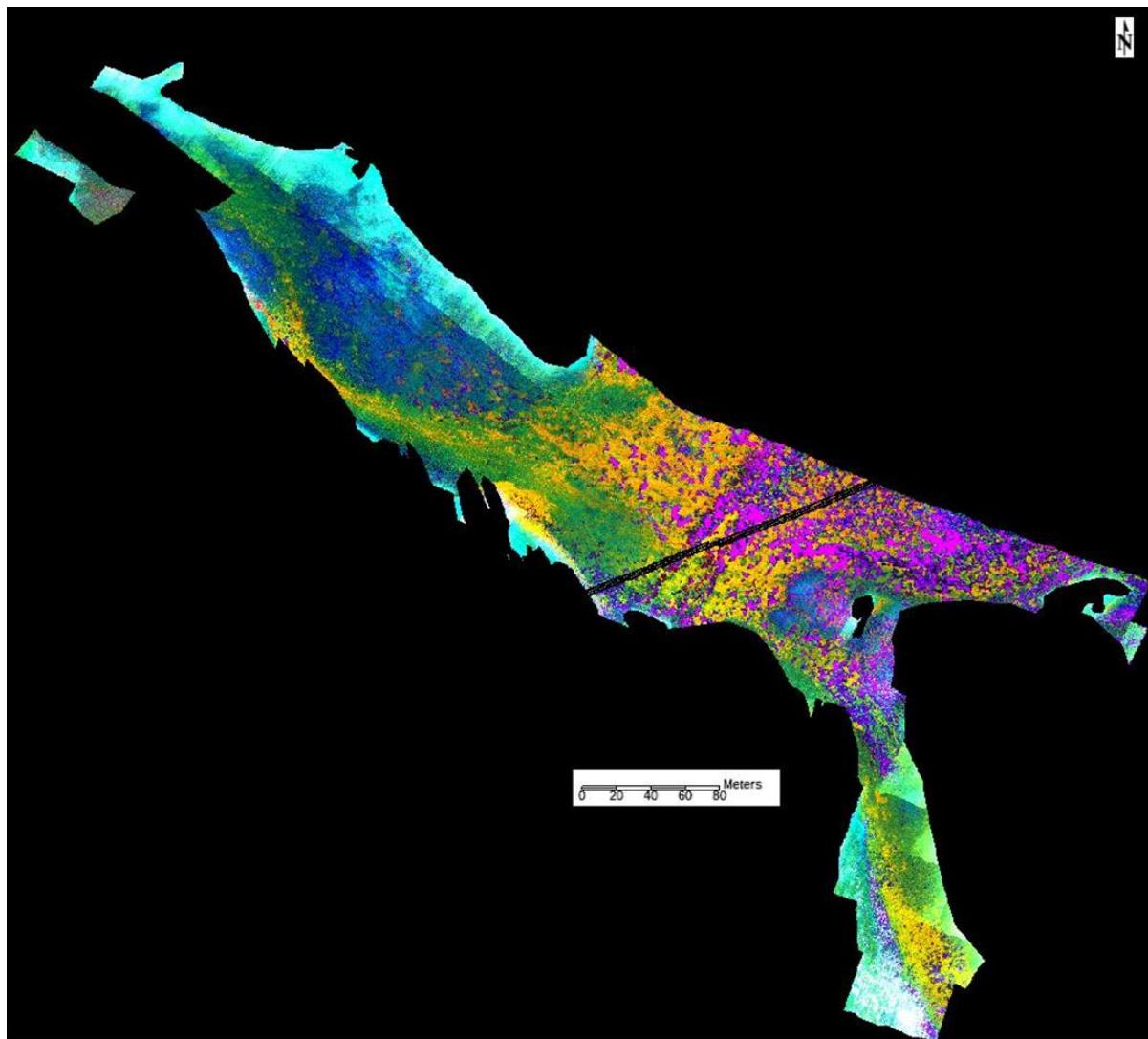
Hyperspectral mapping results and outcomes

Figur 34, Figur 35 and Figur 36 show some hyperspectral results. The MNF image (Figur 34) highlights material differences. Although the MNF is not a classification, similar colour shades indicate material similarities and allows initial image interpretation. Reddish colures is indicative for krypsiv in this MNF band combination. Figur 35 shows spectra measured from reference areas of relevant material. The spectra can be clearly divided into 3 groups:

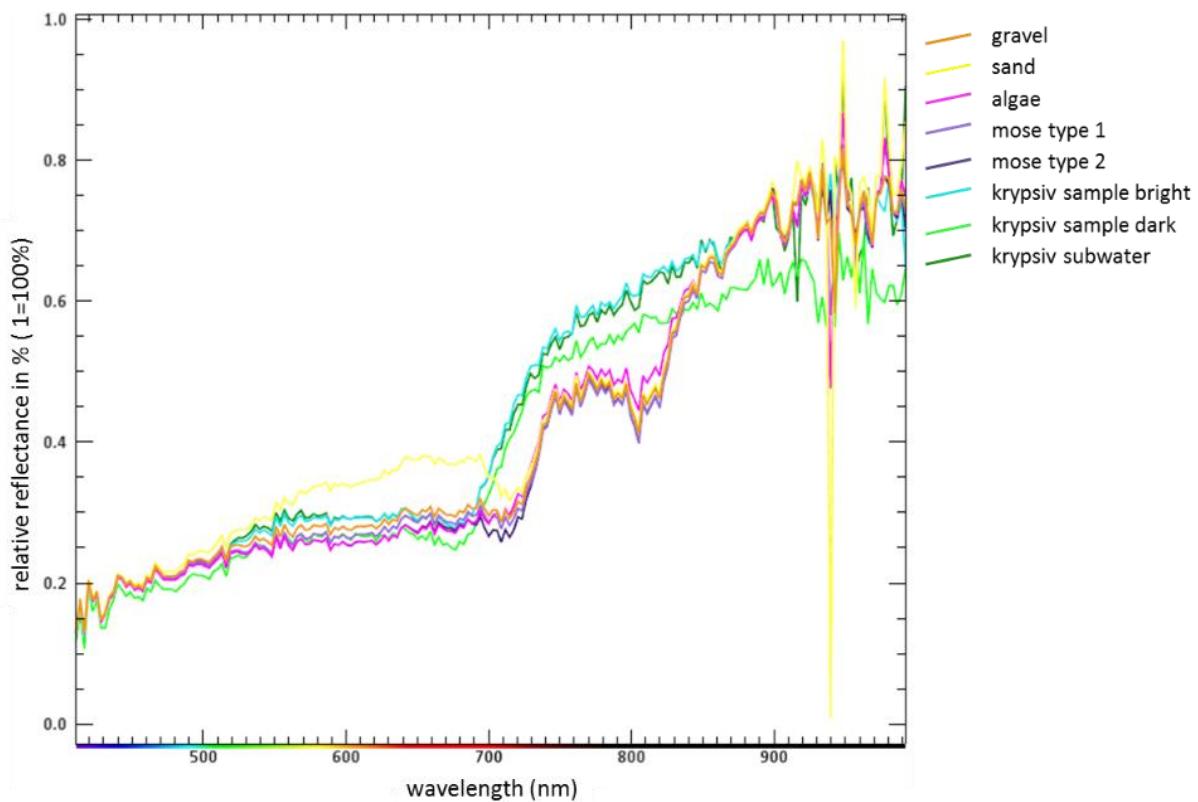
- i) krypsiv
- ii) algae, moss, (gravel)
- iii) sand

The krypsiv group seems to be characterised by the strong “red-edge jump” between 675-750nm. Gravel appears similar to algae/moss, which might be explained by a thin cover of algae and moss on the gravel. Figur 36 shows an initial classification result. A visualisation of the krypsiv classes (Figur 37) indicate that the overall krypsiv distribution is represented as observed in the field with an gradual increase in krypsiv distribution downstream. In

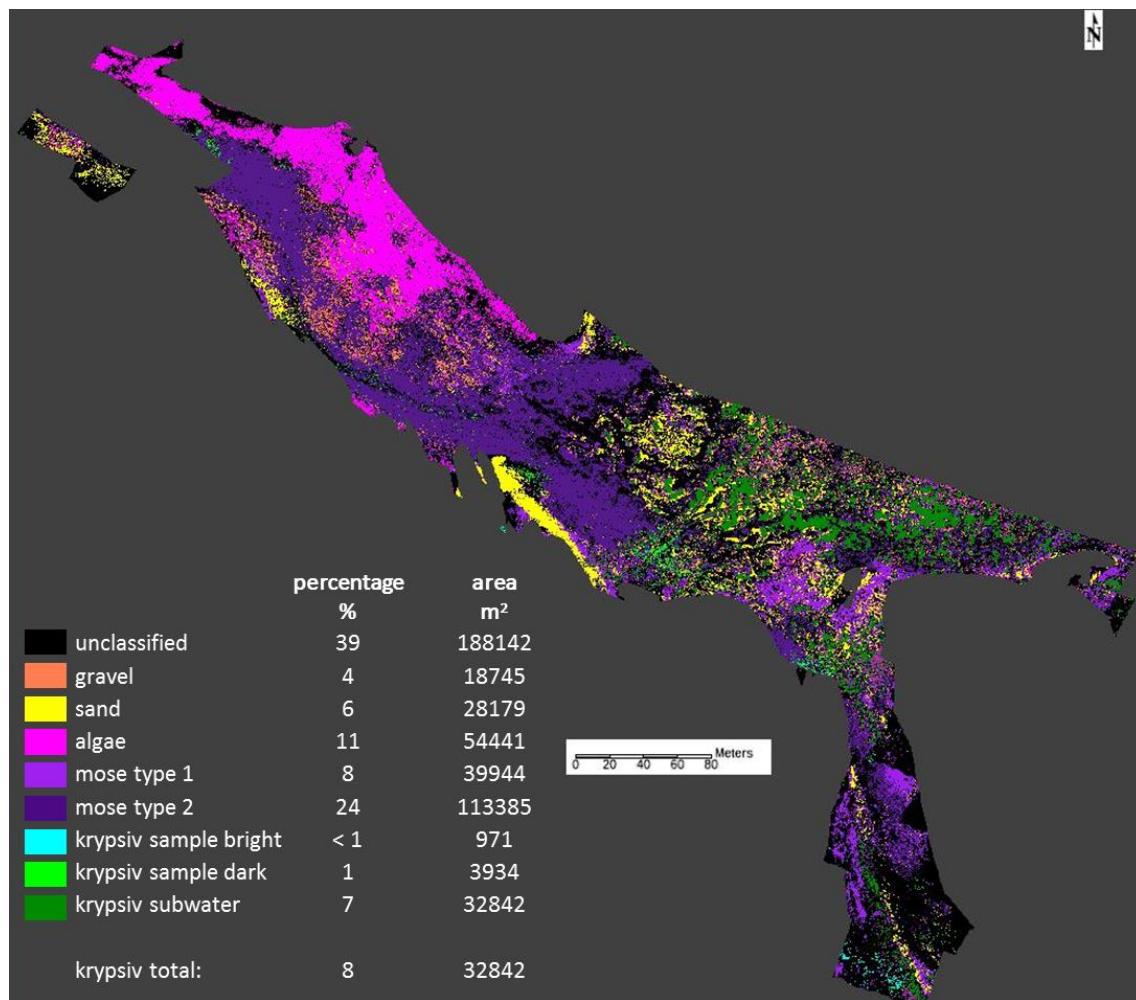
comparison with the manual krysiv map from diving observation (Figur 38), krypsiv might be underestimated, particularly in the shallow water in the SE river channel.



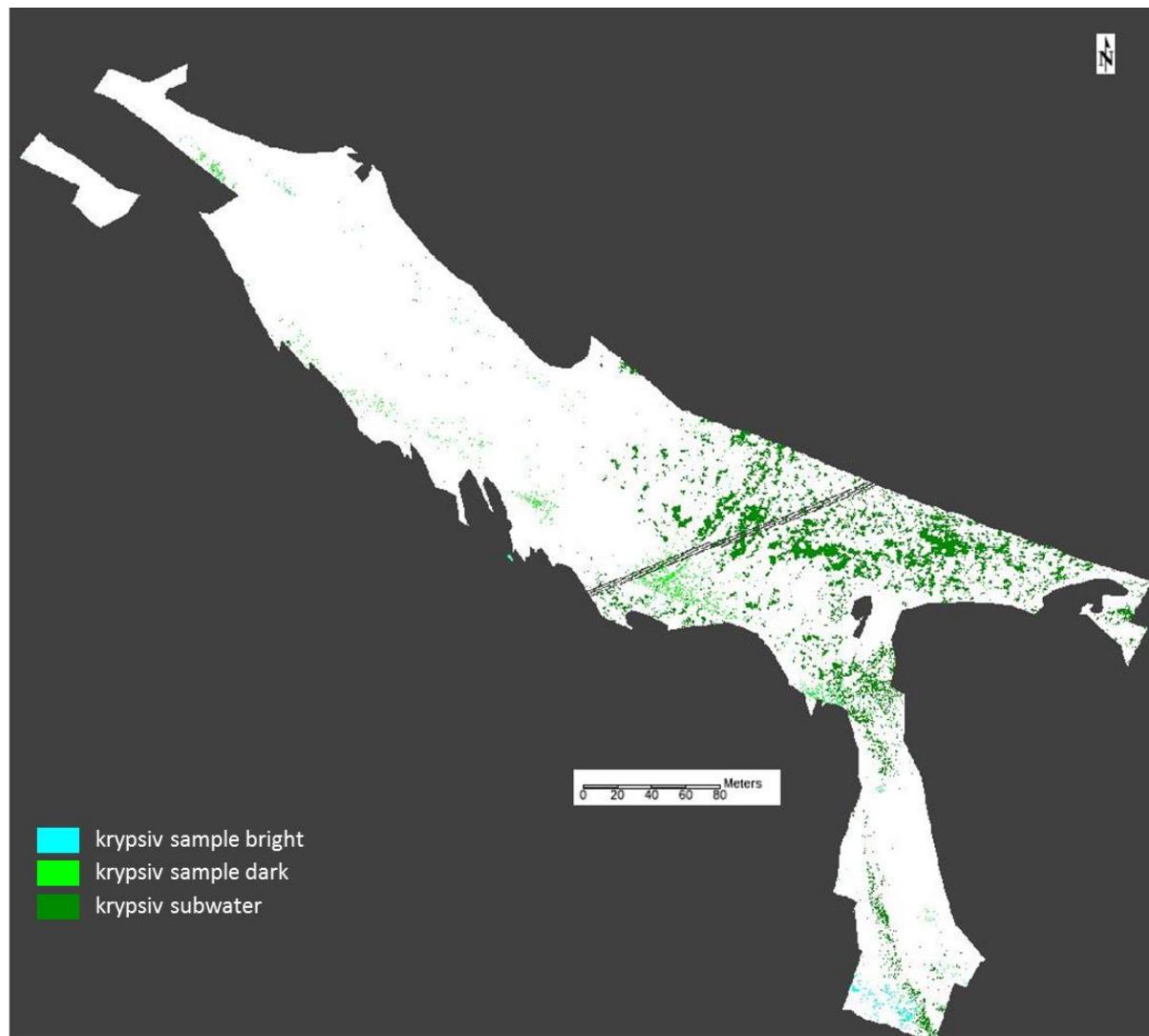
Figur 34. Area1 Hyperspectral MNF image. MNF bands 3, 2, and 1 visualised in RGB. Areas not representing the riverbed or with strong shadow have been masked.



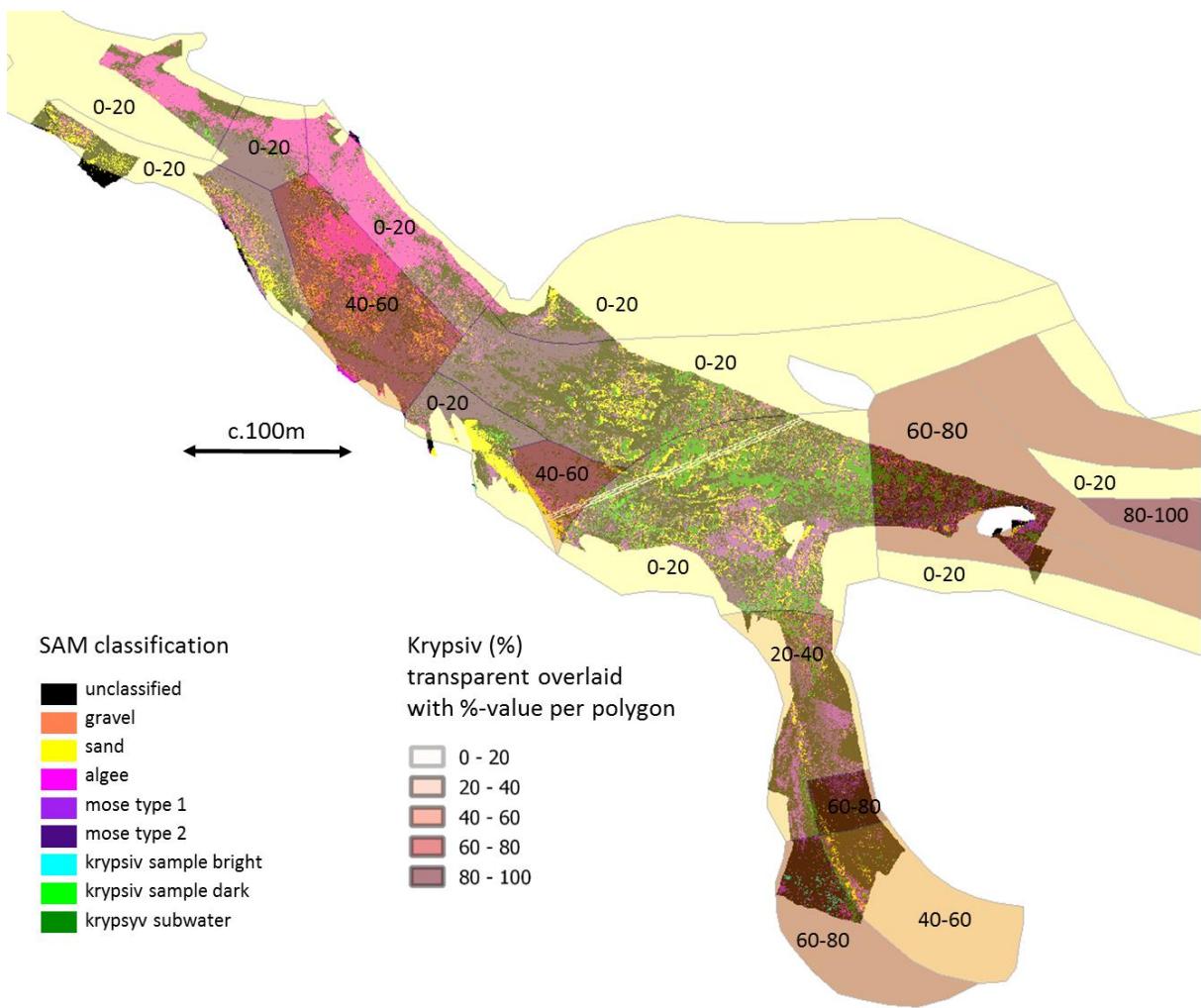
Figur 35. Area 1, material spectra.



Figur 36. (previous page). Area 1 Initial Spectral Angle Mapper (SAM) hyperspectral classification with class quantification based on Maximum Noise Fraction Transformation (MNF) bands. Multiply trainings areas from the same material class can help to map material variation caused e.g. by mixture effects or different water depth in this data set. Areas not representing the river bed or with strong shadow have been masked. 100% refers to non-mask input pixels representing non-shadowed areas of the river bed.



Figur 37. Area1 Kryspsiv class distributions exclusively representing the krysiv classes visualised from Spectral Angle Mapper (SAM) classification, as shown in Figur 36.



Figur 38. Area 1, initial Spectral Angle Mapper (SAM) classification from Figur 36 overlaid results from the manual krypsiv mapping of Figur 21.

Hyperspectral mapping conclusions

Potential for krypsiv quantification

Significant spectral differences among reference spectra strongly indicate that hyperspectral data provides inherent information than can be used to differentiate between subtle material differences of sub-water vegetation and other riverbed substrates. The hyperspectral data have not yet fully processed and exploited. For example, spectral unmixing, a common spectral mapping method for hyperspectral data, was not applied. Spectral unmixing utilising the entire spectral signal and allows sub-pixel material estimation, which can compensate for spatial mixing effects. In addition, other classification methods, such as object-based approaches or machine learning algorithm, was not tested within this small scale pilot study. Object-based approaches, as tested on the multispectral data, often outperforms pixel-based classification of high resolution imagery.

Based on qualitative comparison with the ground truth map and diving observations, the initial hyperspectral classification results did not represent krypsiv distribution in a

satisfactory manner. For quantitative comparison, the polygons of the ground truth data must be adjusted to the size of the hyperspectral mosaic to calculate krypsiv percentage from the hyperspectral classification for each polygon. This was not done within this project. The mapping from the diving might require further evaluation, quality check and editing for better comparability with spectral image classification. Comparability might be hampered by imprecise polygon positioning from diving observations and different mapping resolutions between the drone mapping and the manual mapping. A higher ground truth grid resolution is desired for method establishing and performance assessment of spectral mapping results. More work is required for objective method assessment including:

1. Reducing noise and artefacts, such is brightness inhomogeneity due to illumination variation (e.g. Hakala et al. 2013)
2. Improving spectral correction
3. Compensation for water column attenuation (e.g. Zoffoli et al. 2014)
4. Evaluation of more sophisticated spectral mapping approaches, such as spectral unmixing methods, object based nearest neighbour classification or machine learning algorithms
5. Improving understanding of spectral/spatial properties and mixture behaviour of relevant materials
6. Improving representative trainings / reference data for classification input
7. Improving ground truth information for mapping validation

Practicability

Hyperspectral drone imaging is a new technology, highlighting the importance of sharing some of the experiences that we have gained.

Availability: Neither professional providers nor other research groups could be found for data collection. This was unexpected and the reasons for this may be related to: i) the technology being new, ii) hardware and operation costs (e.g. pilot license RO2 required), iii) lack of software, and iv) specialized expertise required for data collection, processing and exploitation. Accessibility will be improved in the future; however, costs and specialized expertise might remain a limiting factor for this method.

Weather conditions: Hyperspectral imaging in general has more restrictions when it comes to weather and illumination condition to ensure high data quality. Other limiting factors might be caused by low sun altitude, and especially during non-summer seasons at higher latitudes. This makes the planning of field campaigns challenging. High flexibility in respect to availability of personnel and equipment is required.

Drone platforms and flight time: Various suitable drone platforms are available and will be improved in the near future with advances in drone technology. The choice of optimal drone is mainly determined by i) required payload, ii) costs, iii) platform stability during data collection, iv), flying time, and v) logistical aspects such as portability, shipment, and operation restriction as prescribed by regulations. As this project has demonstrated, flight time is crucial for efficient coverage of reasonable- sizes areas. If flying time per battery is

limited, flying time over the day can be extended with addition sets of batteries and charging facilities. It should be noted that the entire flight time per battery cannot be used for data collection, instead the available flight time have to be disposed for: i) launching, landing and flying to/from data collection positions, ii) instrumentation calibration, iii) data collection, and iv) safety buffer.

Coverage of larger areas within shorter time can also be achieved by higher flight altitudes, at the costs of lower ground sample resolution. For many applications, lower ground sample size might be acceptable. However, the maximal flight altitude for drones is regulated at 120 m. With the correct pilot license, it is possible to apply for exceptions. Alternatively, drones with significant longer flying time (e.g. turbine powered providing hours of flying time) are available at a significantly higher cost.

5. Referanser

Aulio, K. (1987) Rapid decline of mass occurrences of *Juncus bulbosus* in a deacidified freshwater reservoir. *Memoranda Societatis pro Fauna et Flora Fennica*, 63, 41-44.

Barlaup BT, Skoglund H, Pulg U, Halvorsen GA, Velle G, Isaksen TE, Stranzl S, Postler C, Vollset KW, Birkeland I, Gabrielsen SE, Helle T, Johannessen A, Lehmann GB, Espedal EO, Normann ES, Skår B, Wiers T, Höglund E, Høgberget R, Hobæk A, Skancke LB, Kleiven E, Kaste Ø (2018) Blekeprosjektet 2014-2018. Bergen: Norce LFI-rapport nr. 317, 132.

Boon, M. A., Tesfamichael, S., 2017. Wetland vegetation integrity assessment with low altitude Multispectral UAV imagery. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, Volume XLII-2/W6, 2017. International Conference on Unmanned Aerial Vehicles in Geomatics, 4–7 September 2017, Bonn, Germany

Brandrud, T. E. (2002) Effects of liming on aquatic macrophytes, with emphasis on Scandinavia. *Aquatic Botany*, 73, 395-404.

Brandrud, T. E., & Roelofs, J. G. M. (1995) Enhanced growth of the macrophyte *Juncus bulbosus* in S Norwegian limed lakes. A regional survey. *Water Air and Soil Pollution*, 85, 913-918.

Brundu, G. (2015) Plant invaders in European and Mediterranean inland waters: profiles, distribution, and threats. *Hydrobiologia*, 746, 61-79.

Green A. A., Berman M., Switzer P., Craig M. D. 1988. A transformation for ordering multispectral data in terms of image quality with implications for noise removal. *IEEE Transactions on Geoscience and Remote Sensing* 26, pp 65-74.

Hakala, T, Honkavaara, E., Saari, H., Mäkinen, J., Kaivosoja, J., Pesonen, L., Pölönen. 2013. Spectral imaging from UAVs under varying illumination conditions. *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, Volume XL-1/W2, 2013 UAV-g2013, 4 – 6 September 2013, Rostock, Germany.

Hussner, A., Stiers, I., Verhofstad, M. J. J. M., Bakker, E. S., Grutters, B. M. C., Haury, J., . . . Hofstra, D. (2017) Management and control methods of invasive alien freshwater aquatic plants: A review. *Aquatic Botany*, 136, 112-137.

Kurz, T.H., Buckley, S.J. and Howell, J.A. 2013. Close-range hyperspectral imaging for geological field studies: workflow and methods. *International Journal of Remote Sensing* 34(5), pp 1798-1822.

Luftfartstilsynet 2015. Forskrift om luftfartøy som ikke har fører om bord. Luftfartstilsynet, Publisert I 2015 heft 13, ikrafttredelse 01.01.2016, Lovdata.

Kagami, M., Nishihiro, J., & Yoshida, T. (2019) Ecological and limnological bases for management of overgrown macrophytes: introduction to a special feature. *Limnology*, 20, 1-2.

MicaSense RedEdgeTM 3 Multispectral Camera User Manual, 2015. MicaSense, Seattle, WA, PDF, pp27.

Smith M.G., Milton J.E. 1999. The use of the empirical line method to calibrate remotely sensed data to reflectance. *International Journal of Remote Sensing* 20, pp 2653-2662.

¹www: www.micasense.com, accessed January 2019

²www: https://skyflightrobotics.com, accessed January 2019

Proćkow, J. (2008) What is *Juncus bulbosus* subsp. *kochii* (Juncaceae) and does it really exist? A taxonomic revision of bulbous rush subspecies. *Botanical Journal of the Linnean Society*, 156, 501-512.

Roelofs, J. G. M. (1983) Impact of acidification and eutrophication on macrophyte communities in soft waters in The Netherlands I. Field observations. *Aquatic Botany*, 17, 139-155.

Rose, N. L. (2007) Lochnagar : the natural history of a mountain lake, Springer, Dordrecht, the Netherlands.

Svedang, M. U. (1992) Carbon dioxide as a factor regulating the growth dynamics of *Juncus bulbosus*. *Aquatic Botany*, 42, 231-240.

Velle, G., Skoglund, H., Skår, B., & Barlaup, B. (2014) Påvirkning av krypsiv på anadrom fisk og biologisk mangfold av bunndyr. Uni Research, LFI rapport nr. 231, Bergen.

Verhofstad, M. J. J. M., Alirangues Núñez, M. M., Reichman, E. P., Van Donk, E., Lamers, L. P. M., & Bakker, E. S. (2017) Mass development of monospecific submerged macrophyte vegetation after the restoration of shallow lakes: Roles of light, sediment nutrient levels, and propagule density. *Aquatic Botany*, 141, 29-38.

Xue, J., Su, S. 2017. Significant Remote Sensing Vegetation Indices: A Review of Developments and Applications. Review article. *Journal of Sensors*. Article ID 1353691, pp 17.

Zoffoli, M.L., Frouin, R., Kampel, M., 2014. Water column correction for coral reef studies by remote sensing. Review paper, Sensor, 14, 16881-16931, doi:10.3390/s140916881