Computer vision applications using multispectral UAS imagery: comparing pixel and object-based methods for automatic classification of river landscapes

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I AM HYDRO
INVESTIGATION AND MONITORING OF HYDROSYSTEMS

Background & Motivation

1) UAVs are an efficient option for high-resolution (1-10 cm GSD) **imagery of river landscapes**.

2) Workflows were designed to improve cover and river bed substrate size classification at the reach scale (100 – 1000s m).

3) **New devices = new methods** are needed for rapid and efficient classification of river landscapes.

Research Objectives & Methods

Objective 1:

To establish the utility of UAVs for reach-scale remote sensing.

Method 1:

Create orthoimage using SfM with 1 cm GSD (error 1.3 cm).

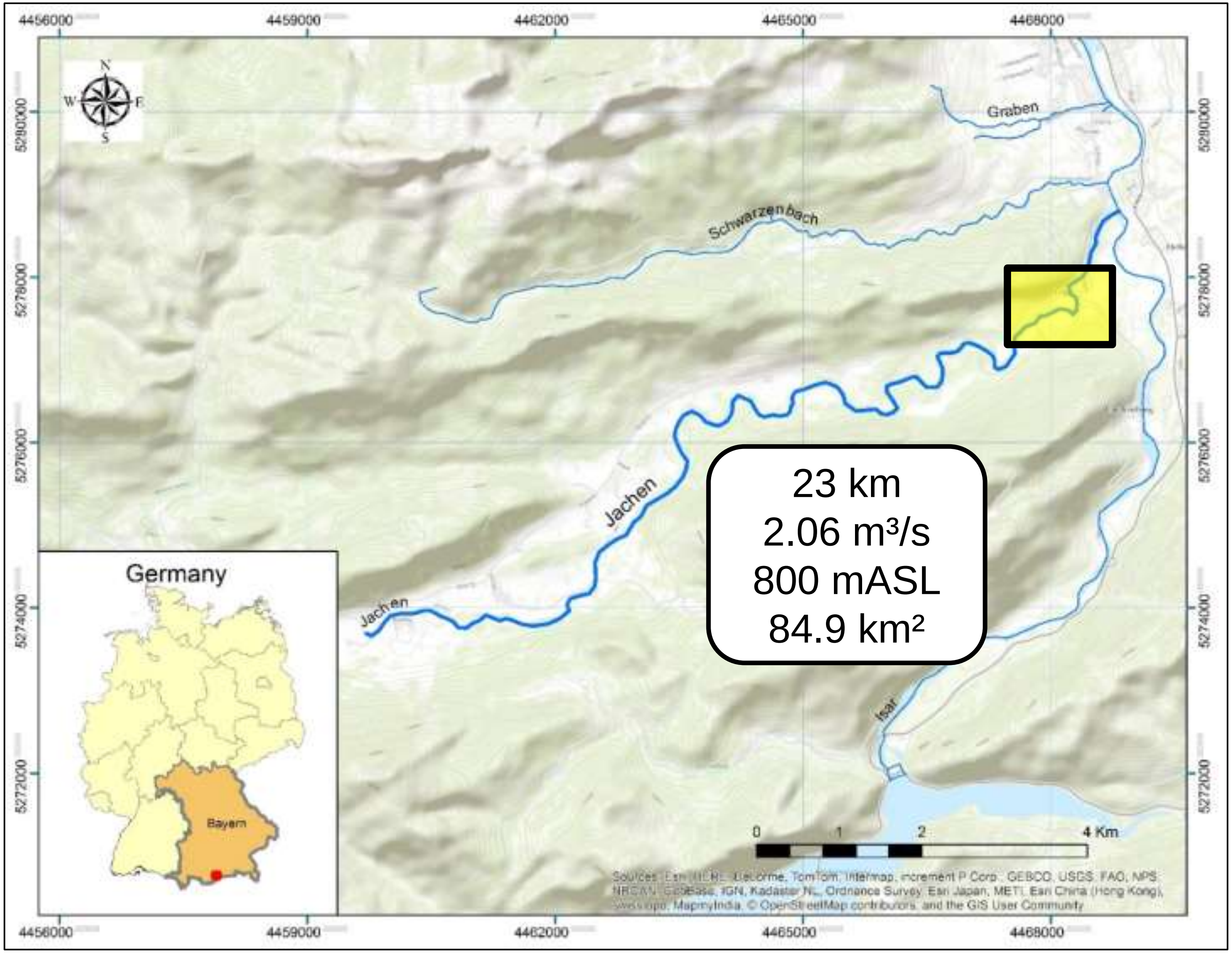
Objective 2:

Develop workflow for UAV riverine landcover classification,

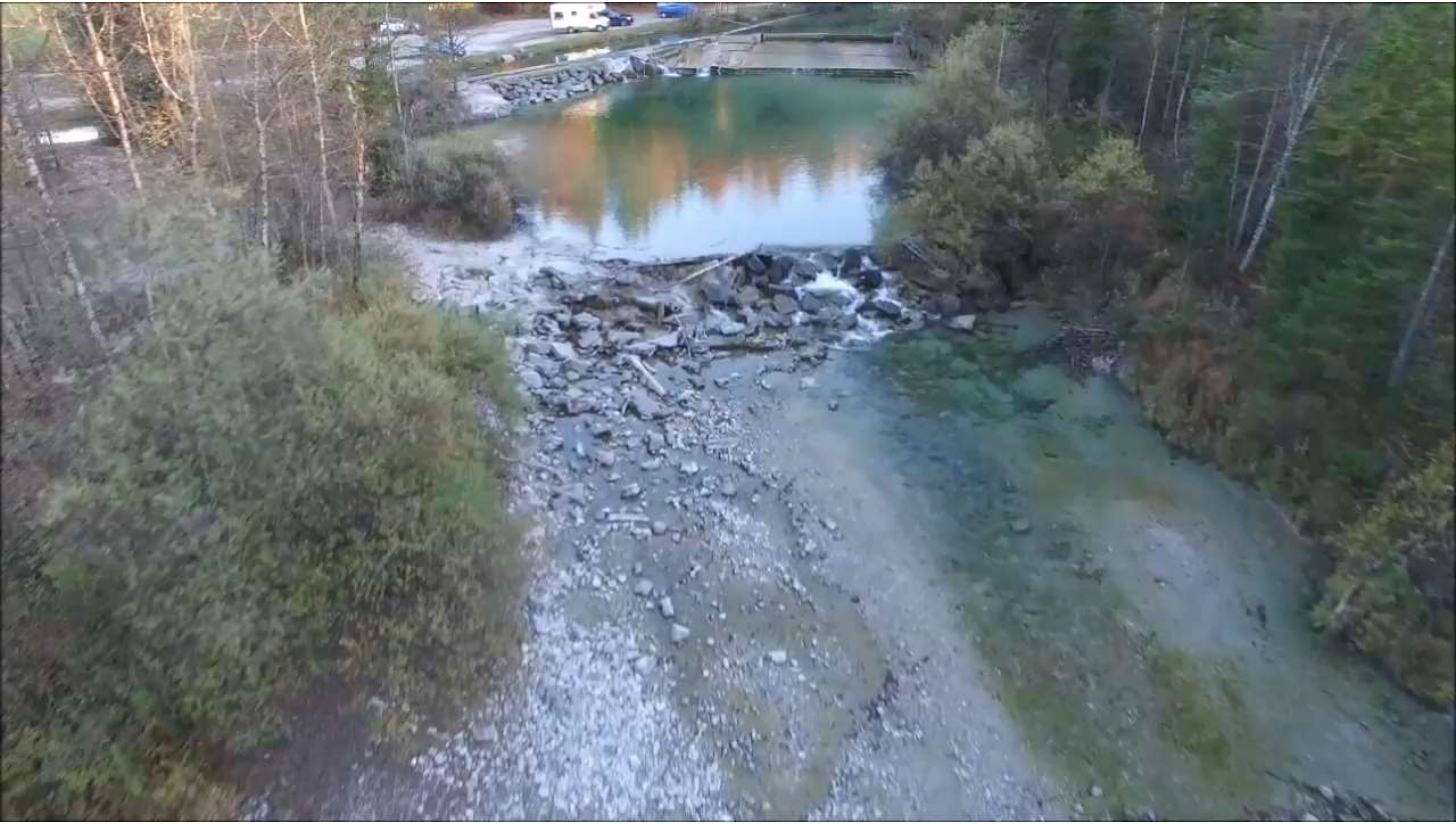
Method 2:

Test object and pixel-based methods, supervised and unsupervised classification, assess performance.

Test Site: River Jachen (DE)

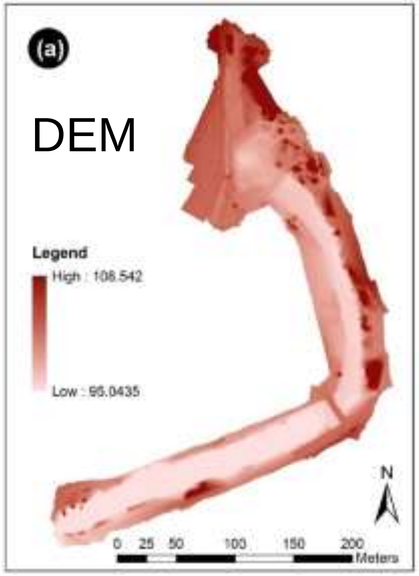


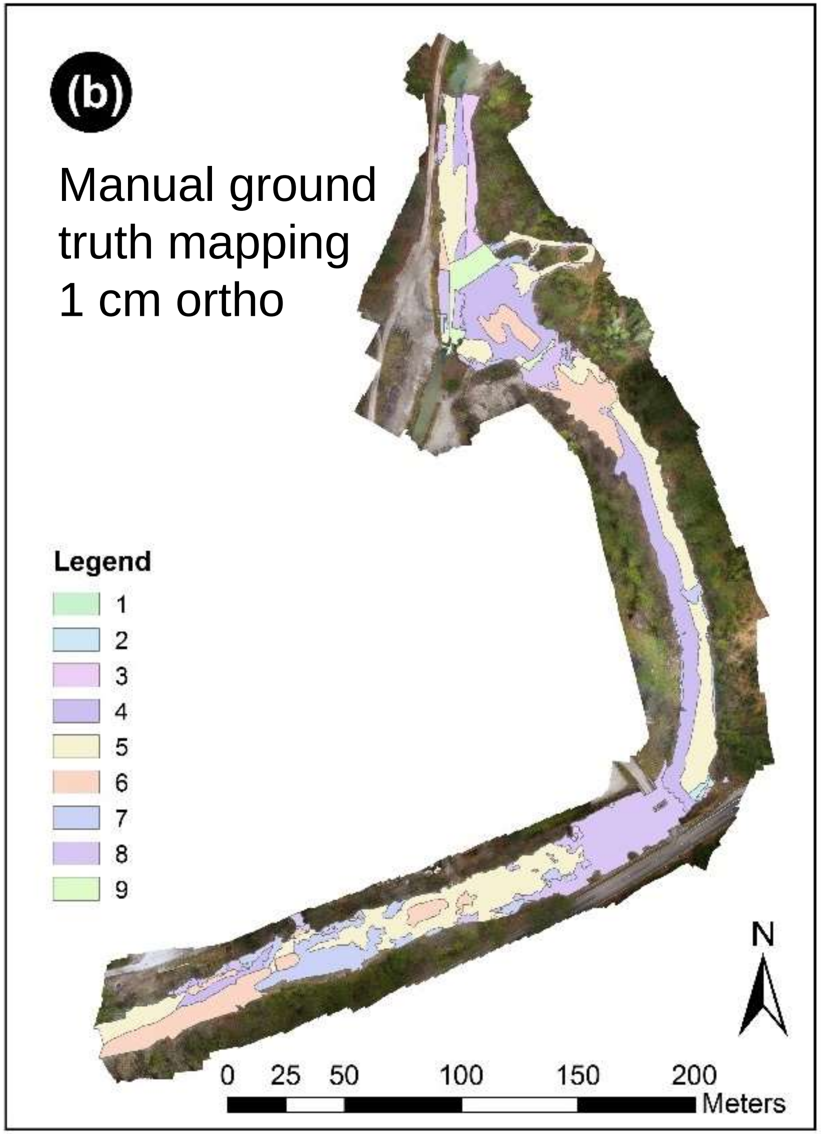
Test Site: River Jachen (DE)



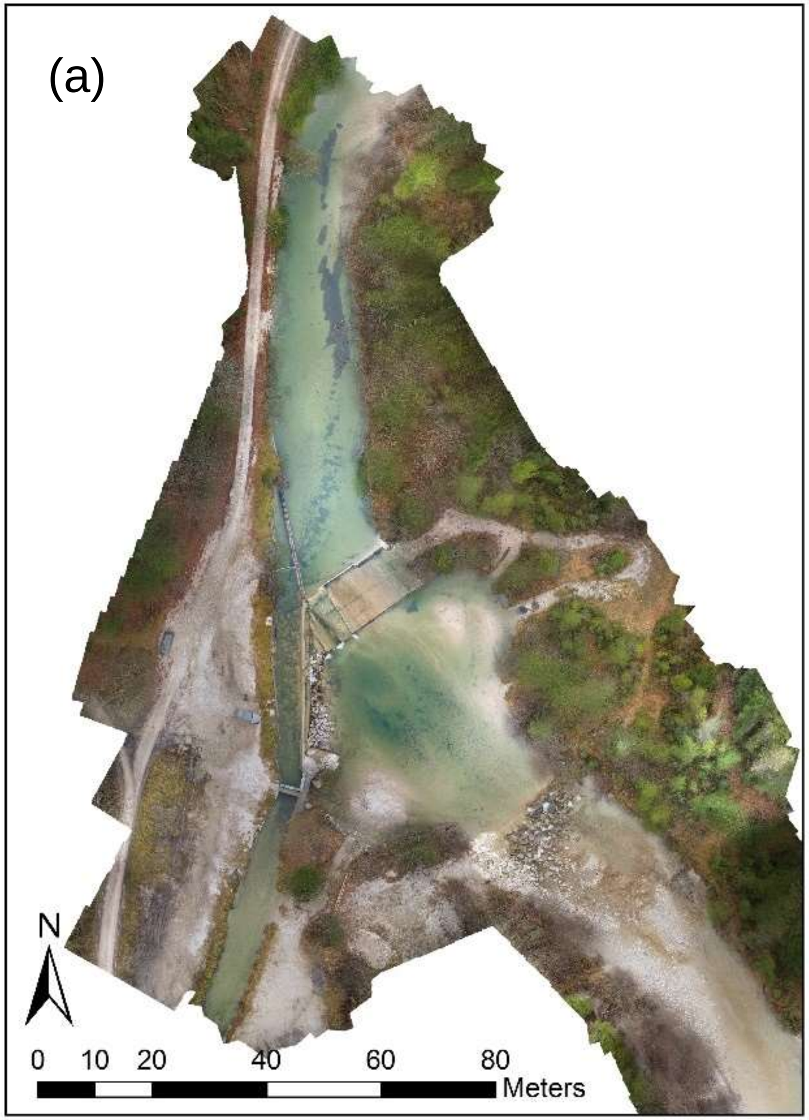
River Substrate Index

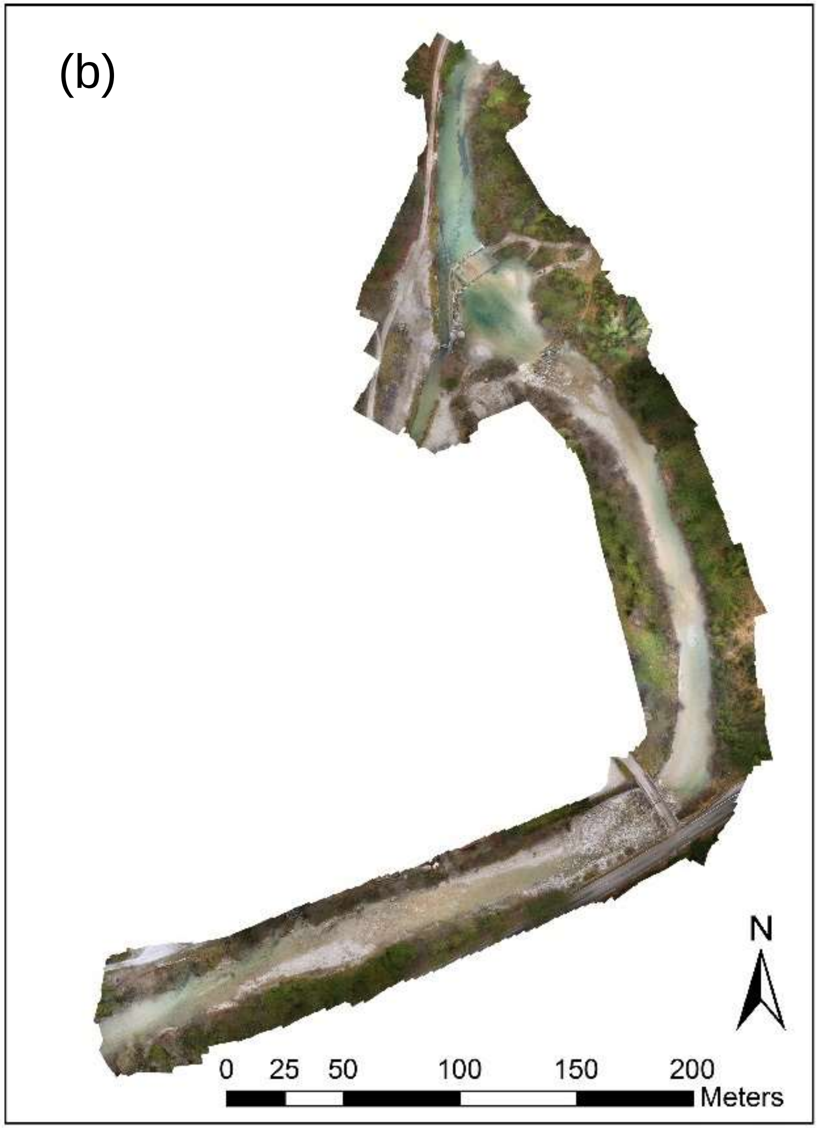
Index	*Color code*	Substrate type
0		Organic material, detritus
1		Silt, clay, loam
2		Sand < 2 mm
3		Fine gravel 2-6 mm
4		Medium gravel 6-20 mm
5		Large gravel 2-6 cm
6		Small stones 6-12 cm
7		Large stones 12-20 cm
8		Boulders > 20 cm
9		Rock





ROI



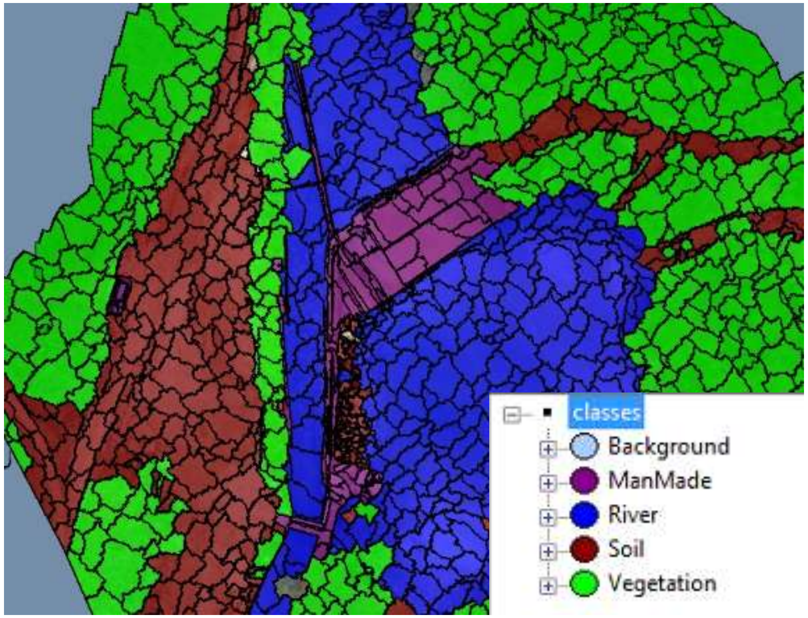


Objective 2: Workflows

1) Classification of river landcover types

(ERDAS signature editor, supervised classification)

2) Segmentation, classification of dominant substrate types

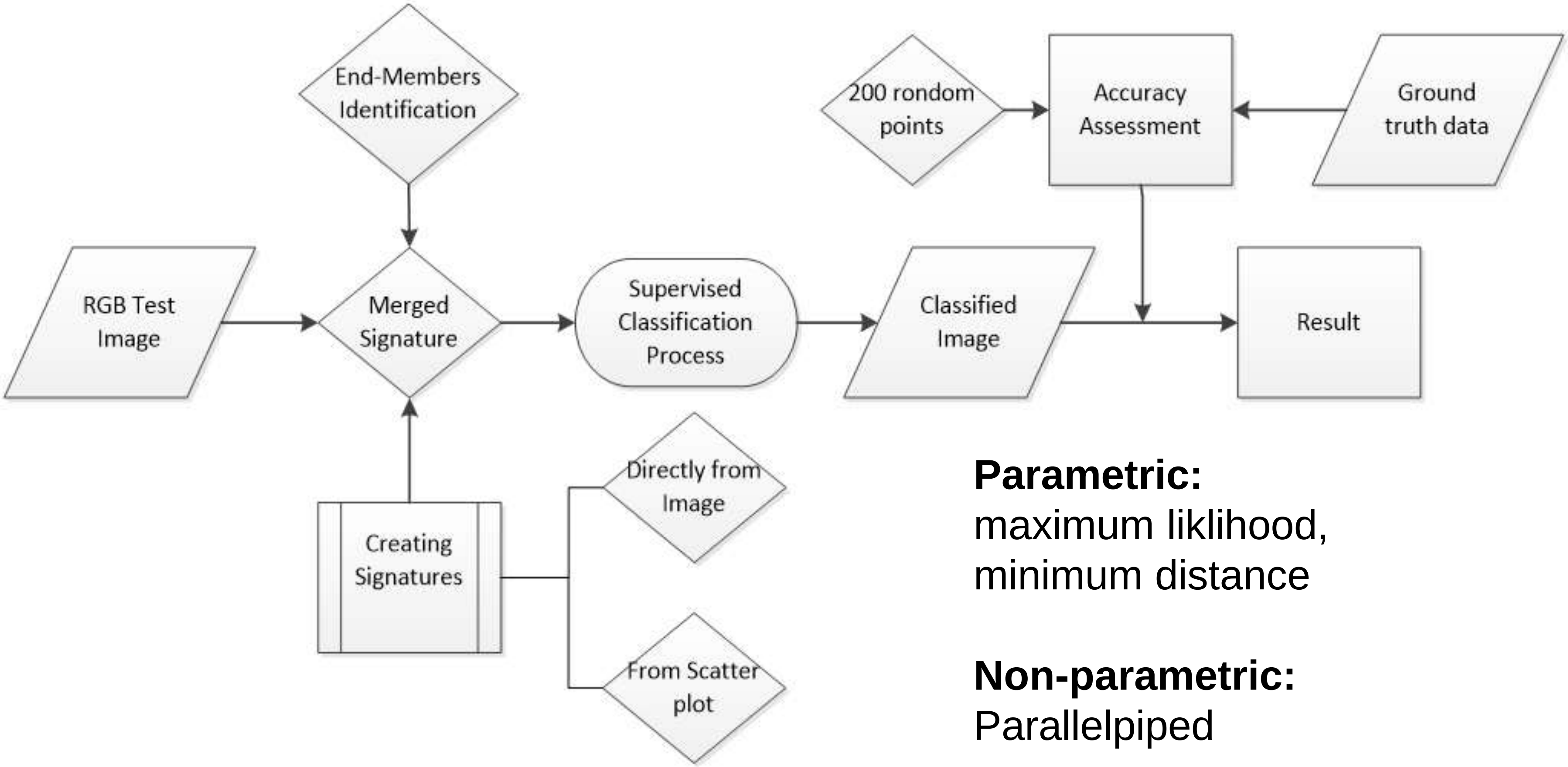


Landcover type

River sub-classes:
Dry, exposed
Shallow, wet
Deep, exposed

Substrate types:
(GCLM image texture)
0 – 9 Index

Classification ERDAS

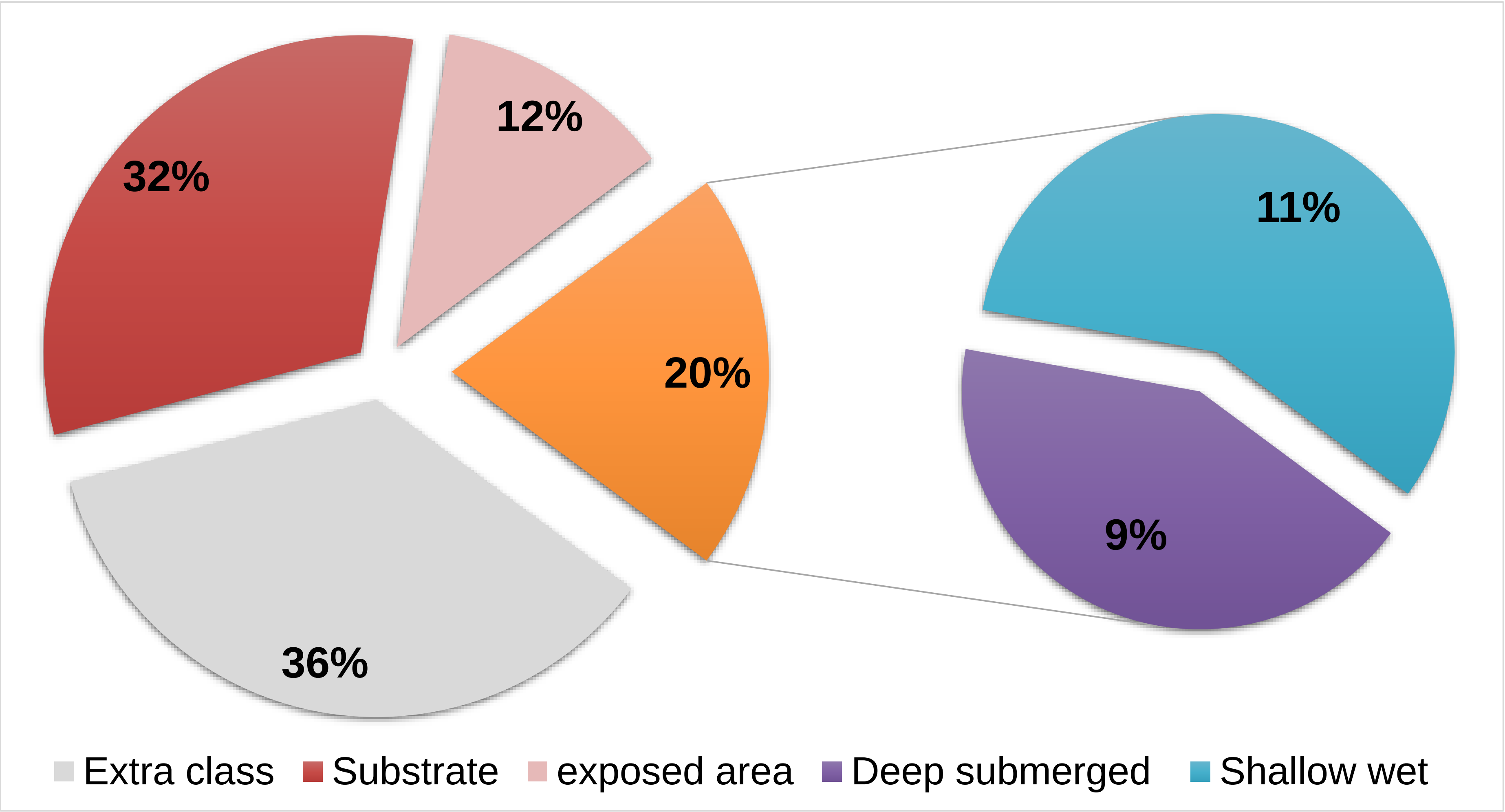


Parametric:
maximum liklihood,
minimum distance

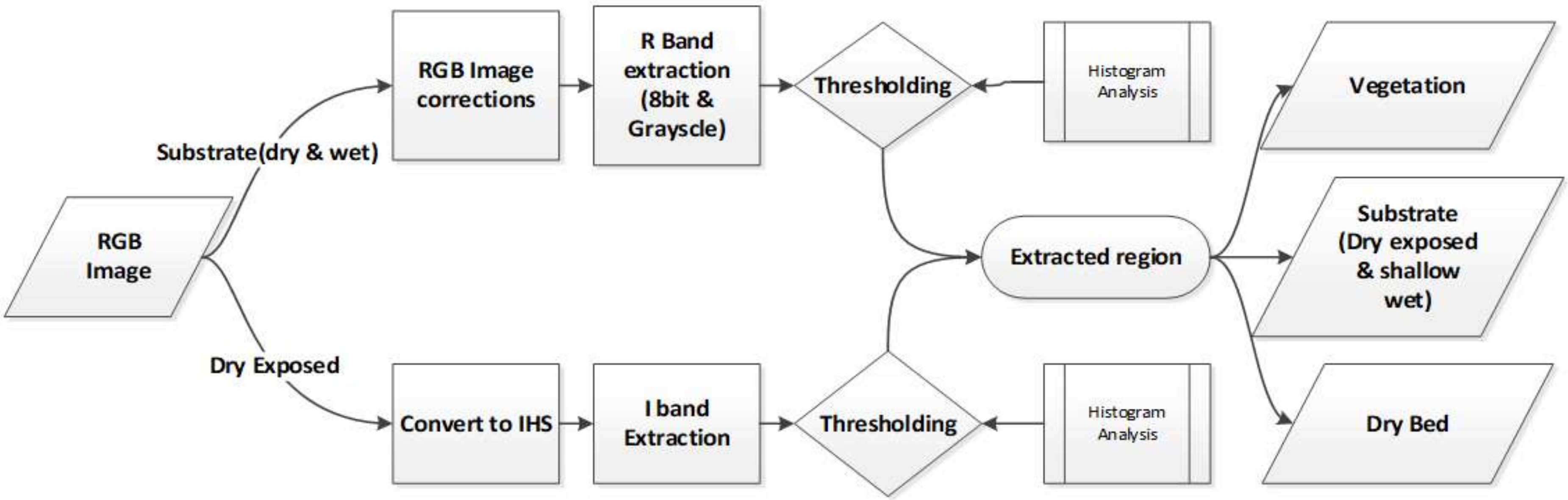
Non-parametric:
Parallelpiped

Unsupervised:
K-means

Classification by Region Type



Classification by Region Type



Importance of Thresholding

Red band

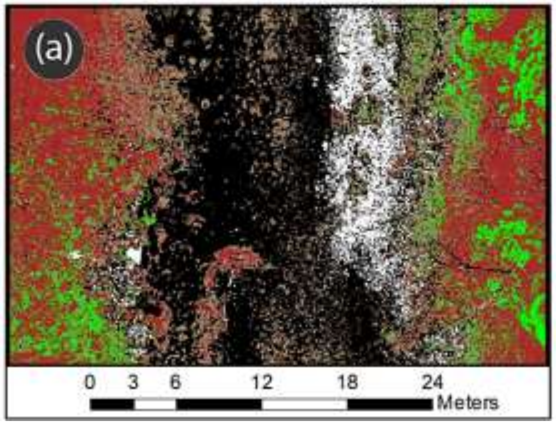
Substrate: wet and dry

I band (IHS)

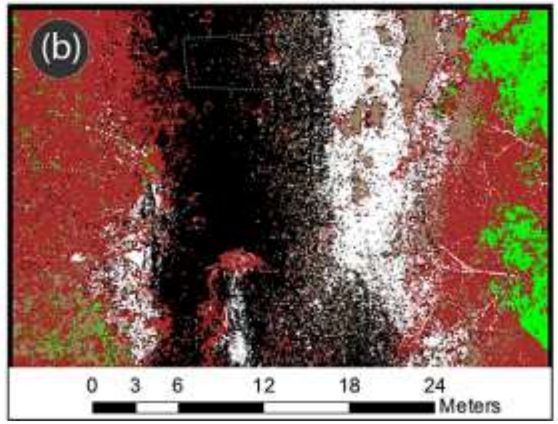
Substrate: dry, exposed

Classification by Region Type

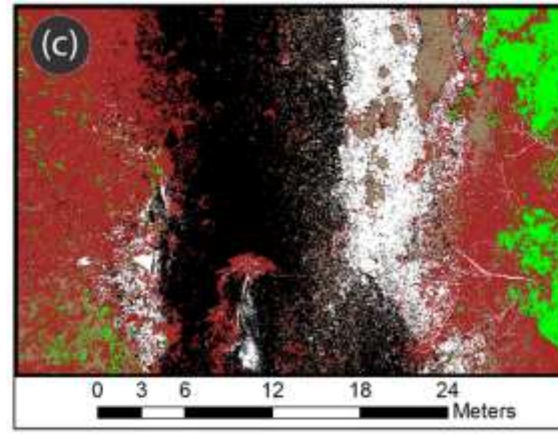
Supervised



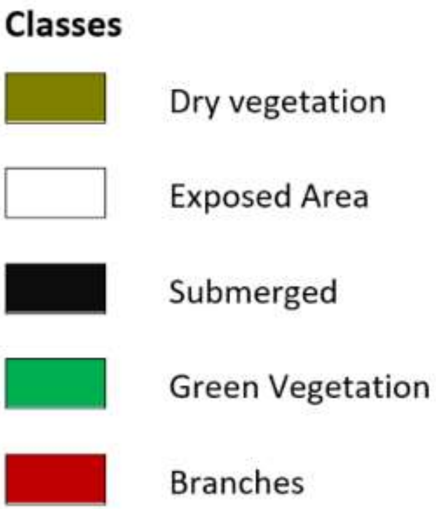
Minimum distance



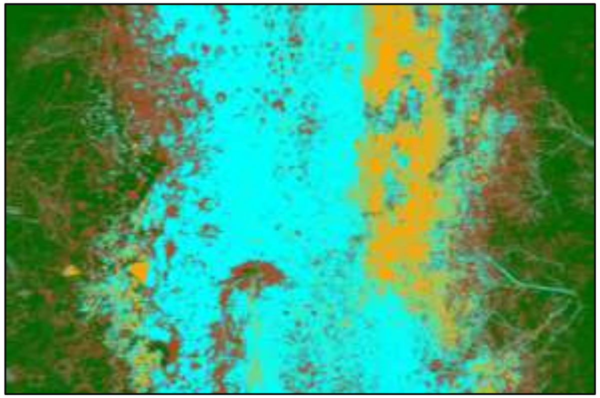
Maximum likelihood



Parallelpiped

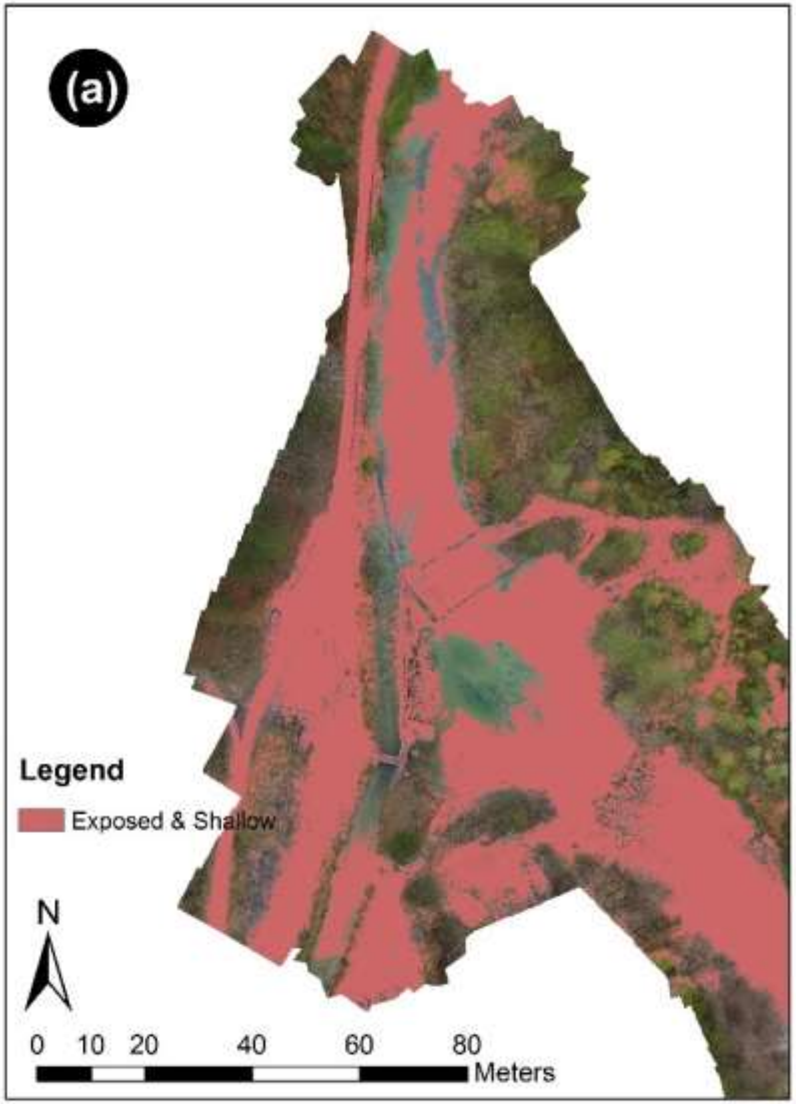


Unsupervised



K-means

Re-Classification by Region Type

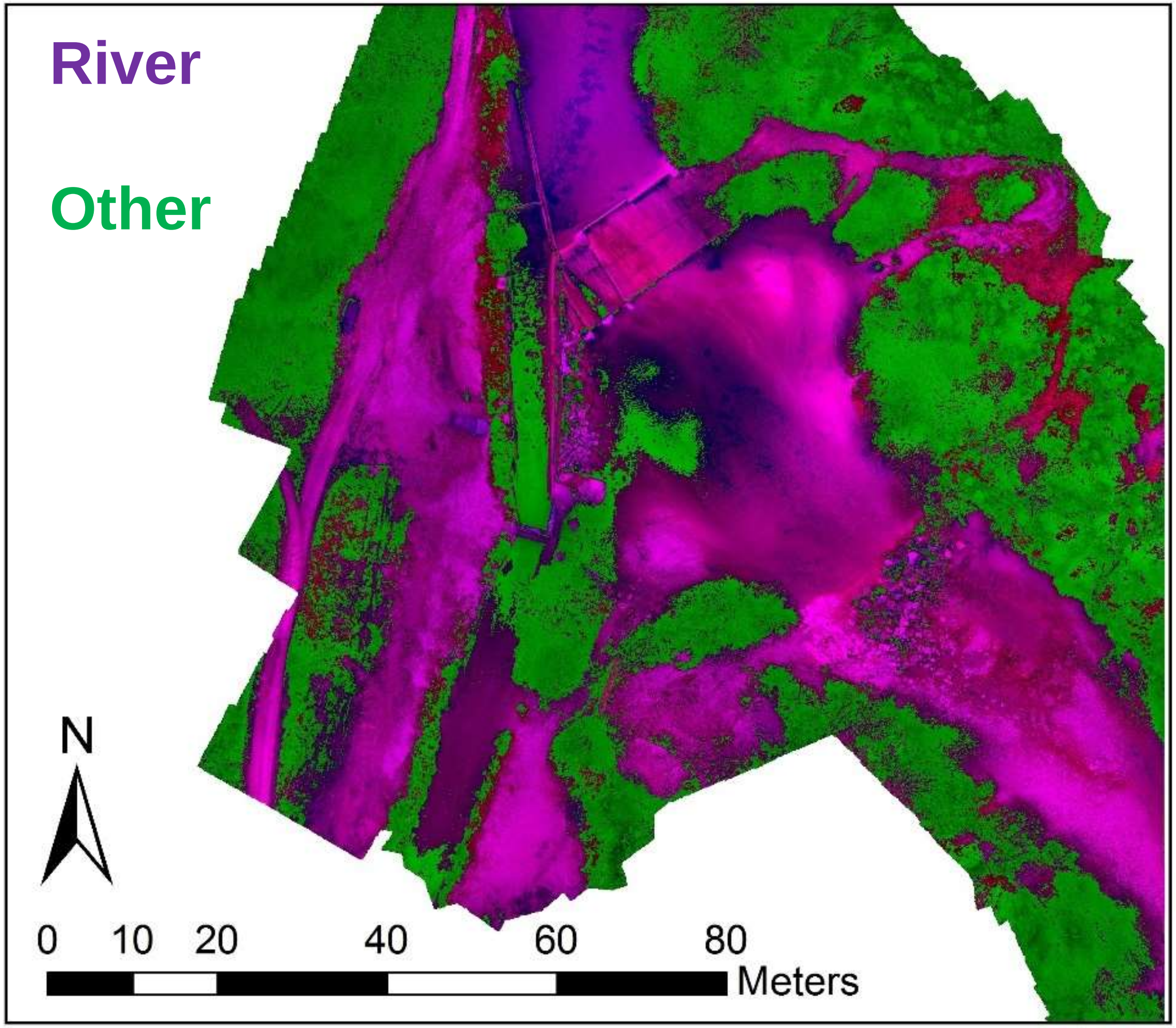


1) Two-level river classifier

2) Faster segmentation

3) Seasonal comparison of wetted regions

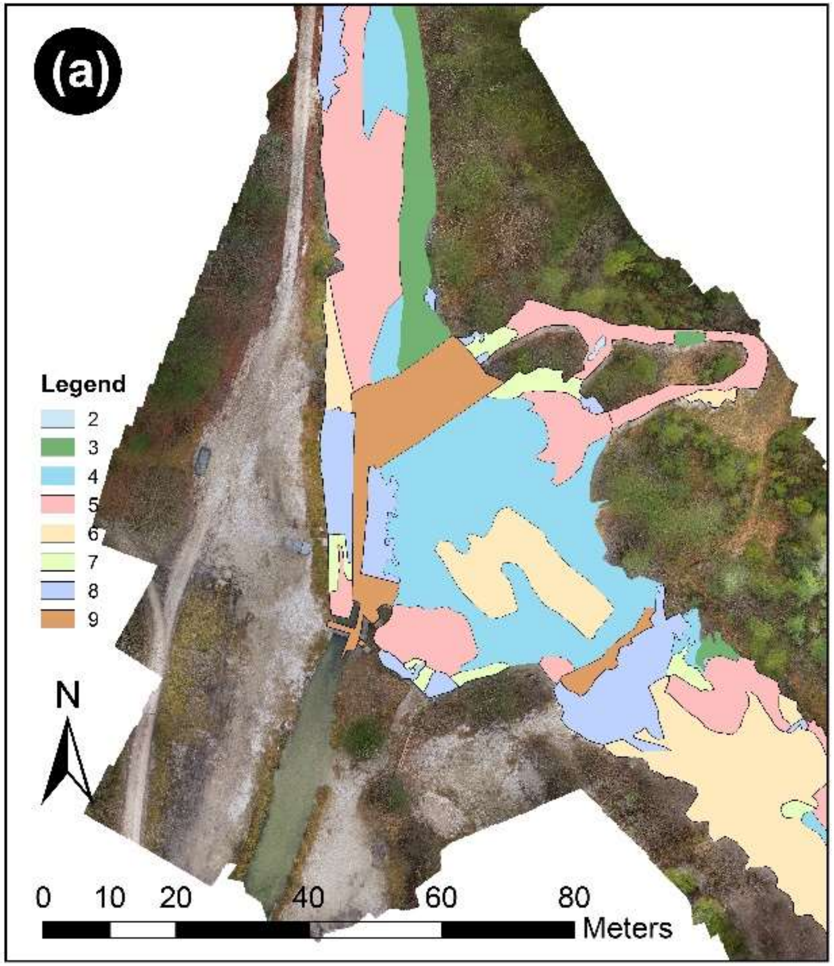
Merging Classes



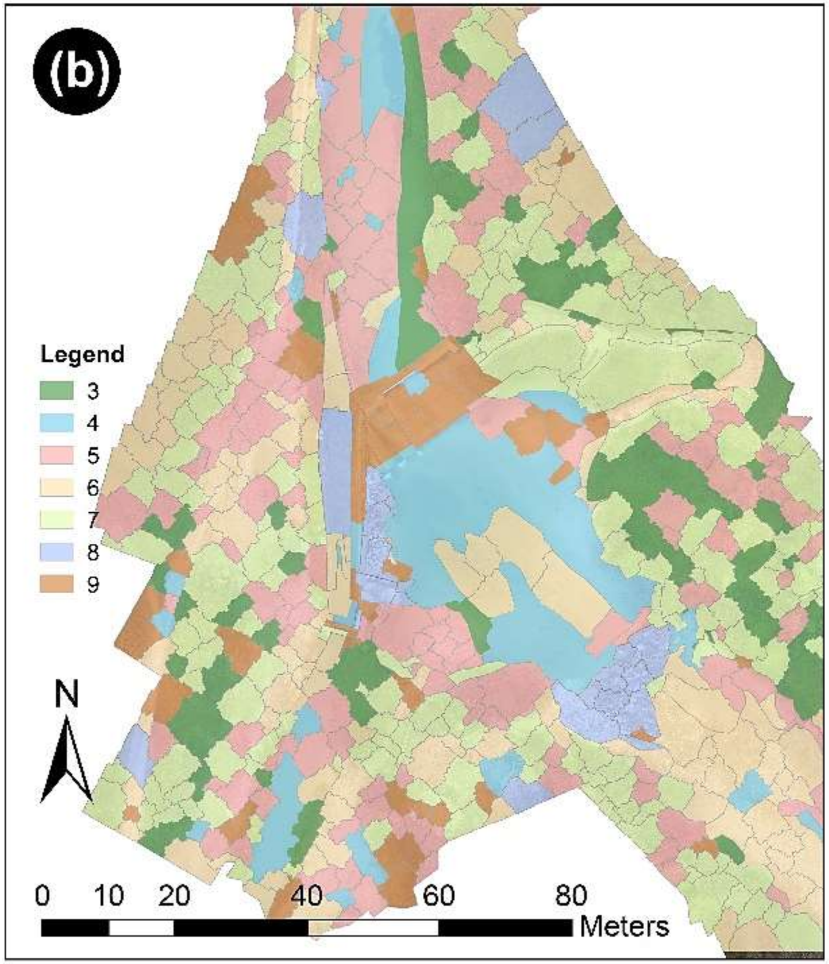
Results: Accuracy

Class Name	Distributed SRP / reference points Reference Totals	Classified Totals	Number Correct	Producers Accuracy
Non-Substrate	61	50	49	-
Substrate	77	88	76	98 %
Totals	138	138	125	

Results: Substrate Classification



Manual substrate mapping



Segmented substrate mapping

Results: Substrate Accuracy

Class Name	Distributed SRP / reference points			Producers accuracy	Users accuracy
	Reference Total	Classified Totals	Number correct		
Class 3	6	4	4	66 %	66 %
Class 4	20	14	12	60 %	85 %
Class 5	11	9	7	63 %	78 %
Class 6	10	20	10	100 %	50 %
Class 7	3	5	2	66 %	40 %
Class 8	8	7	7	87 %	100 %
Class 9	9	8	6	67 %	75 %
Unclassified	69	69	69	100 %	100 %
Totals	136	136	117	-	-

Human ~80% accurate

Results: Computing Time

Intel i7 3.4 GHz, 8 GB RAM

No.	Application tree	Approximate run time (minutes)	Area / Pixels	Dependency
1.	Multiresolution Segmentation	180:00	-	bands weight, scale factor, number of bands etc.
2.	Multiresolution based on thematic layers	238:15	-	bands weight, thematic layers weight and format, scale factor, number of bands etc.
3.	Region margin	23:00	-	Number of regions and objects
4.	Sample selection	15:28 for each class	-	Number of classes
5.	Texture measure application on sample	386:13	-	Texture measures direction and number selected and types, number of classes, bands, weights of bands , objects,
6.	Classification	288:56	-	Number of classes, number of measure of texture, and type of texture measures.
7.	Total	1110:00 minutes	ROI	

Human ~480 minutes

Results: Cover, Pixel-Based

Error Matrix	2	3	5	9	10	11	12	13	Total Classified	User Accuracy [%]
2. Shallow Water	7	2	0	0	0	0	0	0	9	77.78
3. Superficial Water	3	27	0	0	0	0	0	0	30	90.00
5. Grasss	0	1	8	0	1	0	0	0	10	80.00
9. Deciduos and Stubble	2	1	2	30	1	5	2	0	45	66.67
10.Trees	0	0	3	1	3	2	0	0	9	33.33
11. Bushes	0	0	0	0	6	13	0	0	19	68.42
12. River Bed	0	4	0	0	0	0	10	0	14	71.43
13. Water (Reflectance)	0	3	0	0	0	0	0	2	5	40.00
Total Reference	12	38	13	40	11	20	15	2	128	182
Producer Acuracy [%]	58.33	71.05	61.54	75.00	27.27	65.00	66.67	100	182	70.33

Results: Cover, Object-Based

Matrix Error	3	4	6	7	10	11	14	17	18	19	**Total Classified**	**User Accuracy [%]**
3. Bushes	2	0	0	0	0	0	0	0	1	0	3	66.67
4. Deciduos	0	35	1	0	0	0	0	1	2	0	39	89.74
6. Dry Grass	0	1	20	1	0	0	0	0	0	0	22	90.91
7. Green Grass	0	0	0	3	0	0	0	0	0	0	3	100.00
10. River	1	2	1	0	9	0	0	0	0	0	15	60.00
11. Roads	0	0	1	0	0	0	0	0	0	0	10	90.00
14. Soil	0	0	1	0	0	0	9	0	0	0	12	75.00
17. Superficial	0	3	0	0	0	0	0	34	0	0	42	80.95
18. Trees	0	5	1	0	0	0	0	0	24	0	30	80.00
19. Unclassified	0	3	0	0	0	0	0	0	0	0	3	--
Total Reference	3	51	25	4	9	8	9	35	27	0	182	220
Producer Accuracy [%]	66.67	68.63	80.00	75.00	100.00	100.00	100.00	97.14	88.89	--	220	82.73

Conclusions & Outlook

1. A UAV **can provide** sufficient image quality for river landscape cover and substrate classification.
2. Orthophoto - functional, not ideal (missing NIR).
3. River landscape classifcation: better overall performance using objects. Due to **filtering of landscape segments?**
4. Advantages – similar to manual substrate mapping.
5. Disadvantages – time-consuming workflows.
6. Future direction – ML approaches including DEM, SfM point cloud data in addition to the imagery.

Acknowledgements

Image Processing – Shafi Mohammad:

Arif, M. S. M., Gülch, E., Tuhtan, J. A., Thumser, P., & Haas, C. (2017). An investigation of image processing techniques for substrate classification based on dominant grain size using RGB images from UAV. International journal of remote sensing, 38(8-10), 2639-2661.

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Ethics Statement:

No animal or human experimentation was carried out as part of this research.