Spatially-explicit Uncertainty of Remote Sensing Coastal Biodiversity Products using a scalable cloud-based framework in the Google Earth Engine

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DAAD
Deutscher Akademischer Austausch Dienst
German Academic Exchange Service

DLR Deutsches Zentrum für Luft- und Raumfahrt
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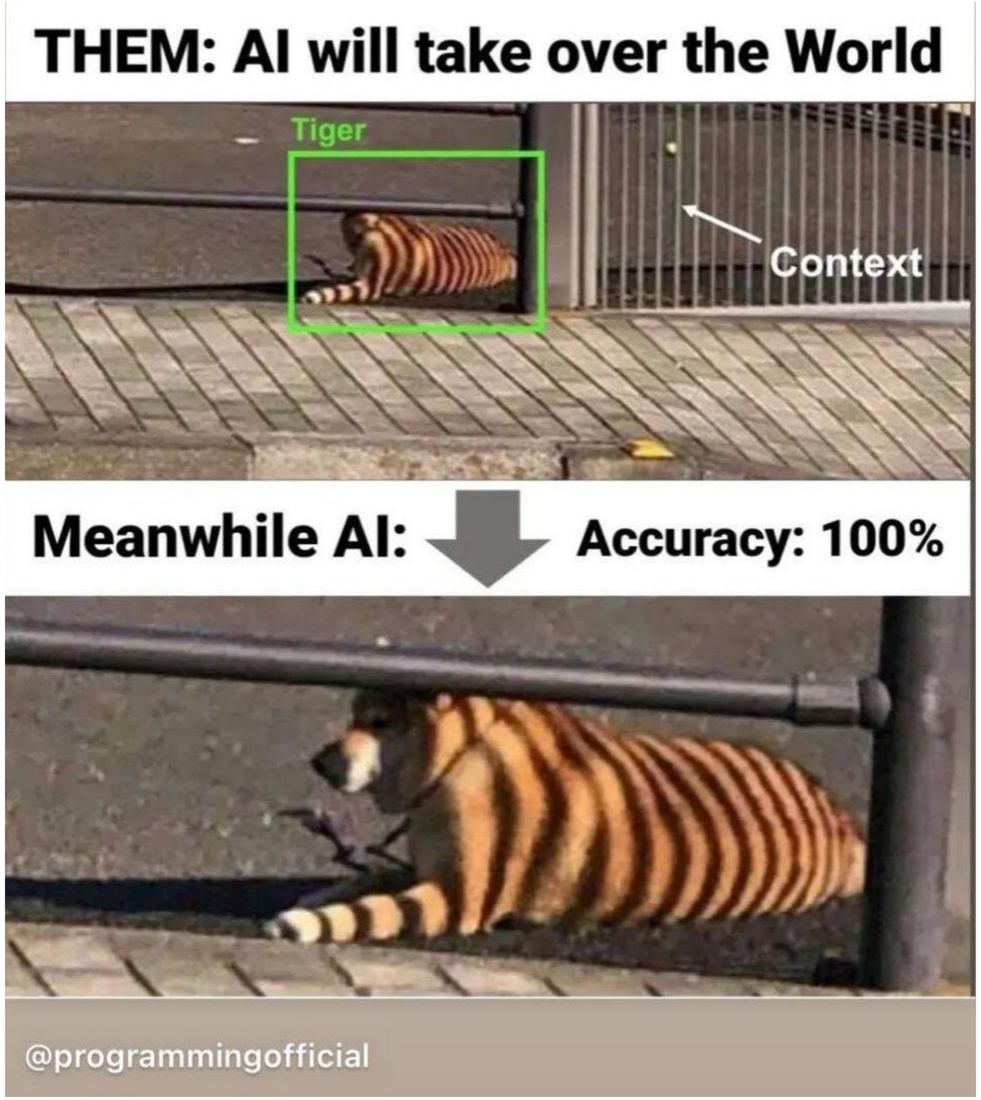
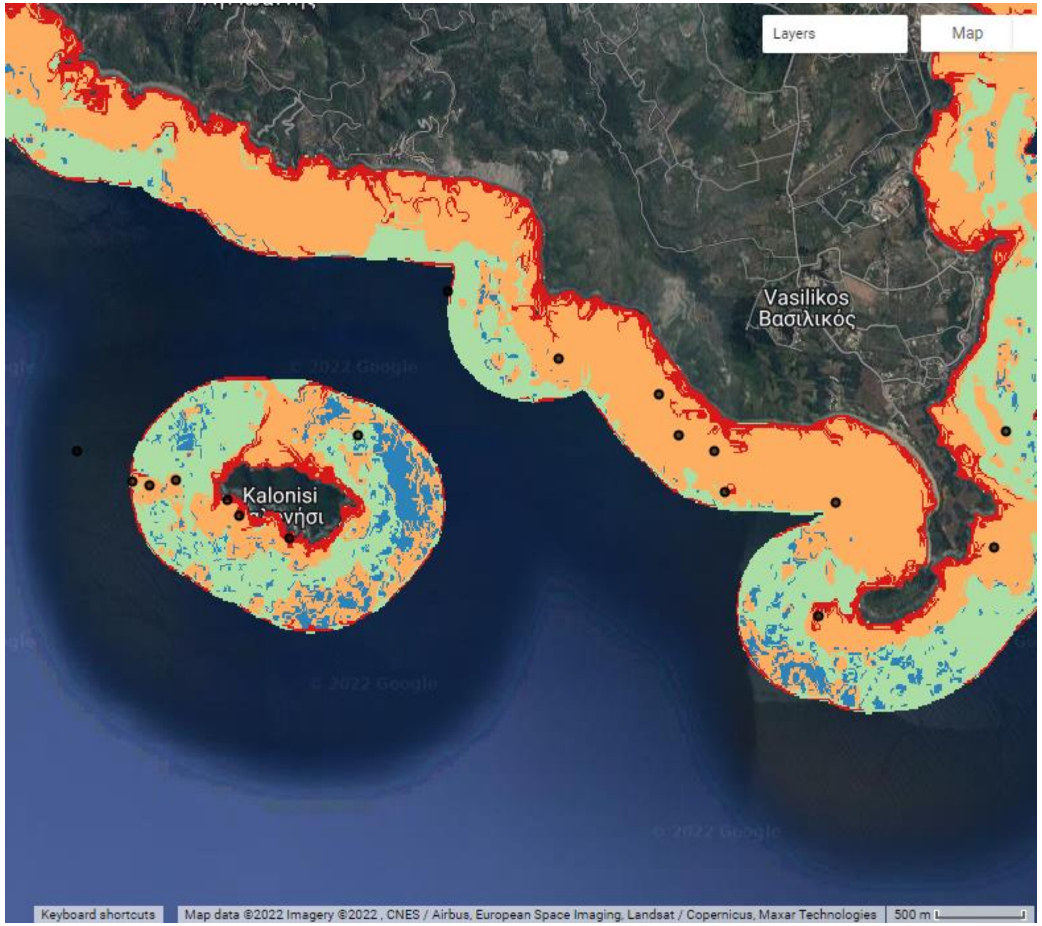
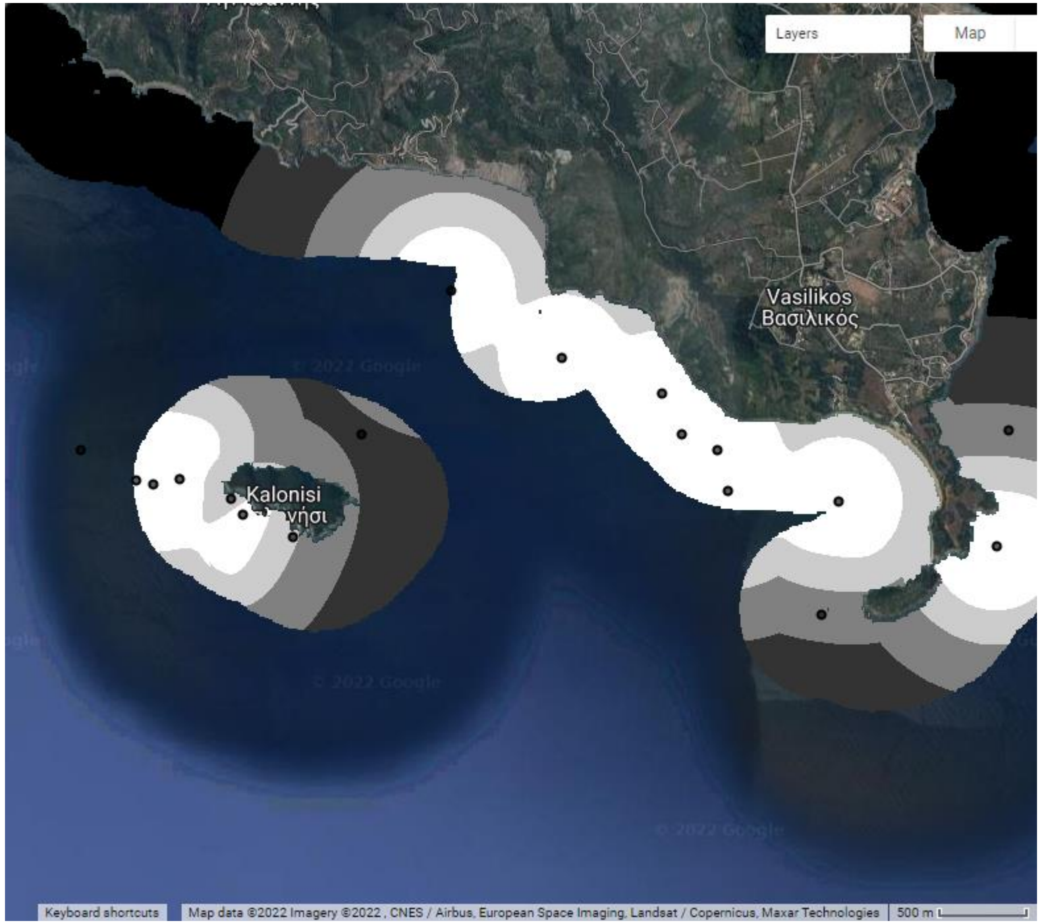
How accurate is a classification, spatially?



How accurate is a classification, spatially?

Accuracy assessment is spatially bound





Goal of PhD research

- Develop a semi-automated workflow to estimate the spatially explicit uncertainty of classification and regression procedures that take place in coastal ecosystems

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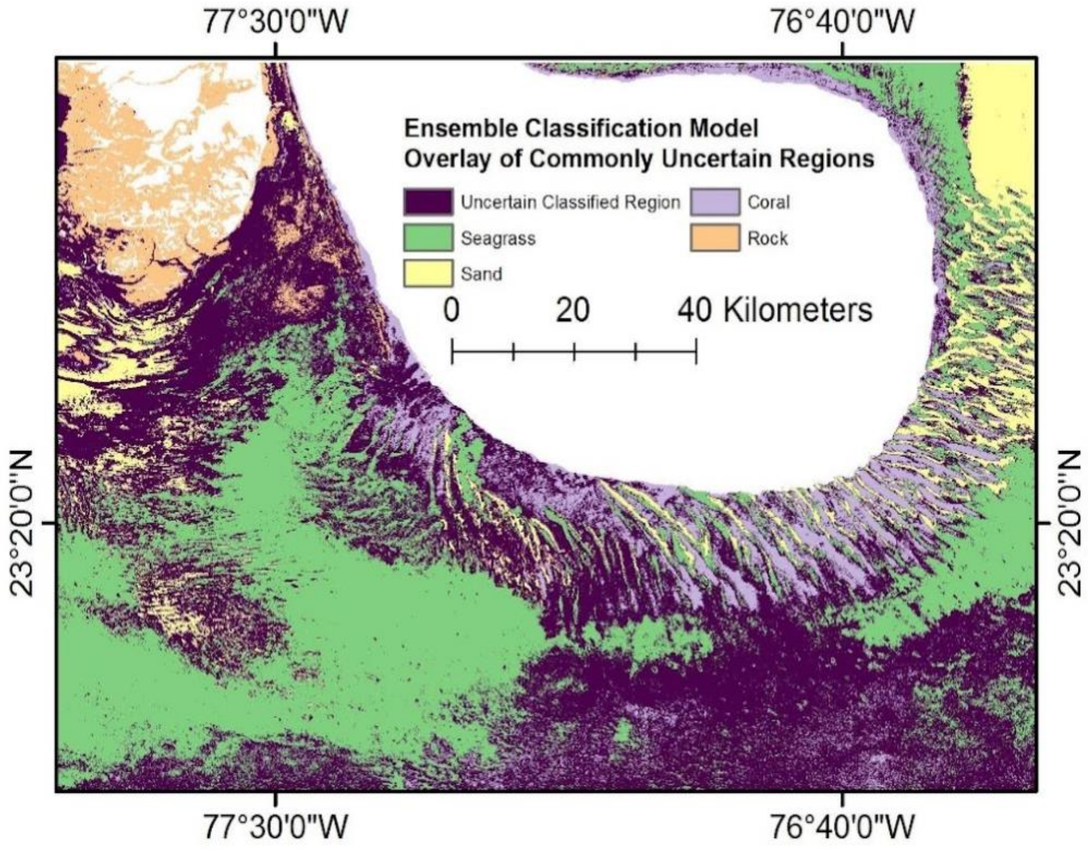
1) Highlight the uncertain areas



Goal of PhD research

- Develop a semi-automated workflow to estimate the spatially explicit uncertainty of classification and regression procedures that take place in coastal ecosystems

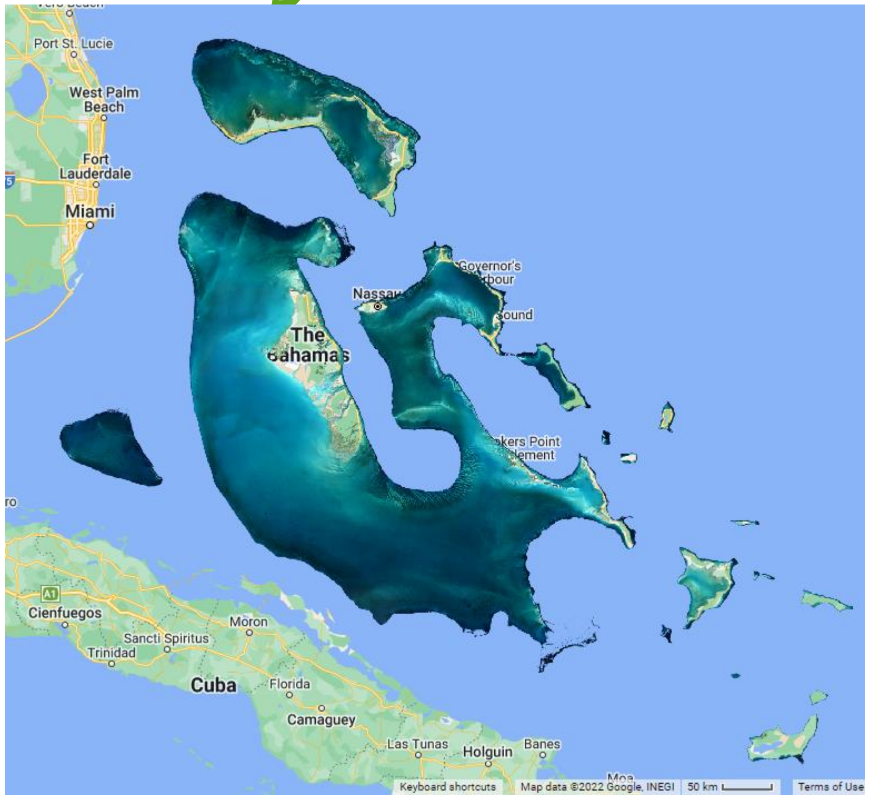
1) Highlight the uncertain areas
2) Acquire training data from uncertain/certain areas and re-train the model

Goal of PhD research

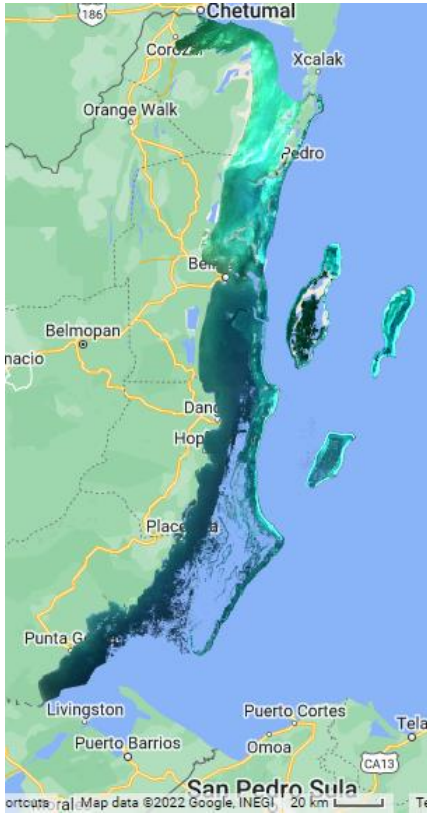
- Develop a semi-automated workflow to estimate the spatially explicit uncertainty of classification and regression procedures that take place in coastal ecosystems

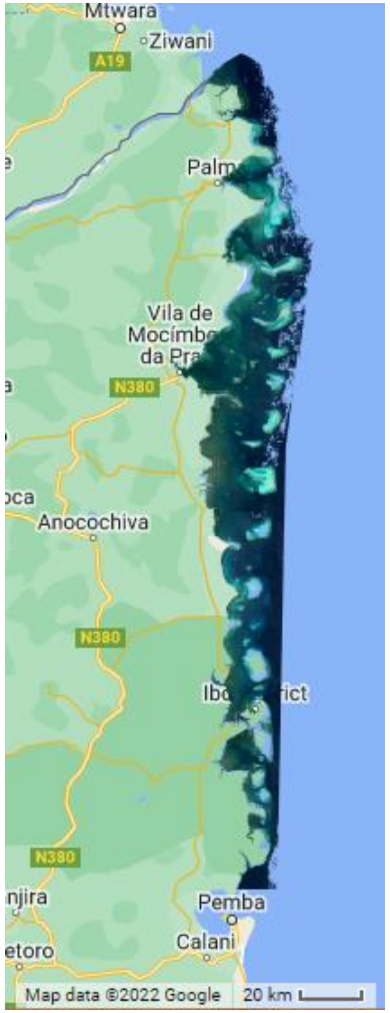
1) Highlight the uncertain areas
2) Acquire training data from uncertain/certain areas and re-train the model
3) Be able to tell how accurate is the classification/regression spatially (EU Habitats Directive)

Study Areas



CLASSIFICATION
Task: Benthic Habitat Classification
Case study: Bahamas,
Satellite Data: Four years timeseries of Sentinel2, lvl 2a data
Validation Points: 300 per class
Training Points: 1000 per Class
(Allen Coral Atlas)

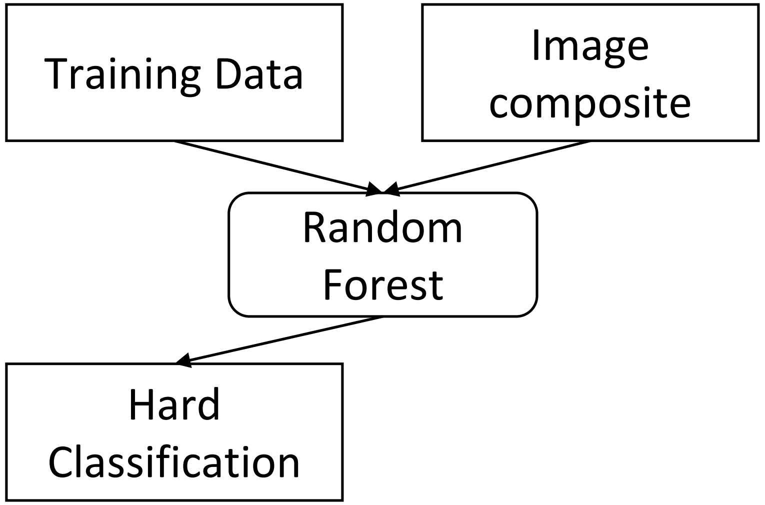


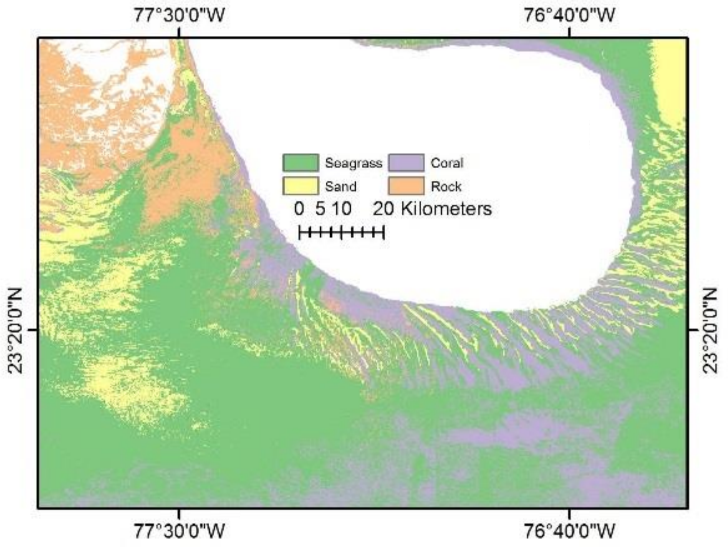


REGRESSION
Task: Satellite Derived Bathymetry
Case study: Belize (Central America), Quirimbas (Mozambique)
Satellite Data Two years timeseries of Sentinel2, lvl 2a data
Validation Points: 800 (777 after rescaling)
Training

Blume, Alina (2021) *Development of cloud-native and scalable algorithms to estimate seagrass composition and related carbon stocks in support of the Nationally Determined Contributions of the Paris Agreement.* Master's, University of Aachen. (https://elib.dlr.de/148787/)
N. Marc Thomas et all., (2020).**SPACE-BORNE CLOUD-NATIVE SATELLITE-DERIVED BATHYMETRY (SDB) MODELS USING ICESat-2 and SENTINEL-2**
https://doi.org/10.1002/essoar.10504452.2

Uncertainty in Benthic Habitat Classification





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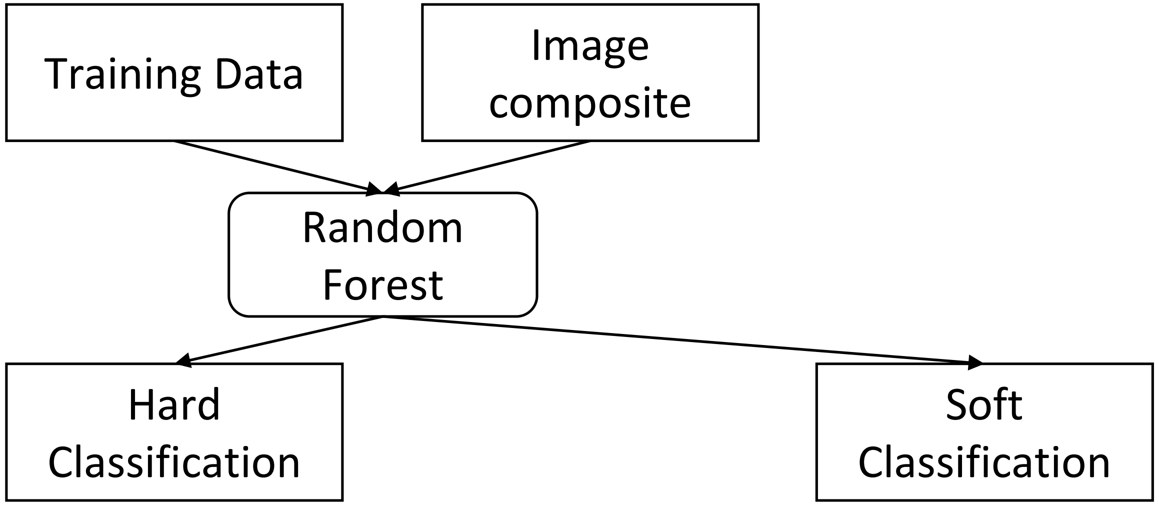
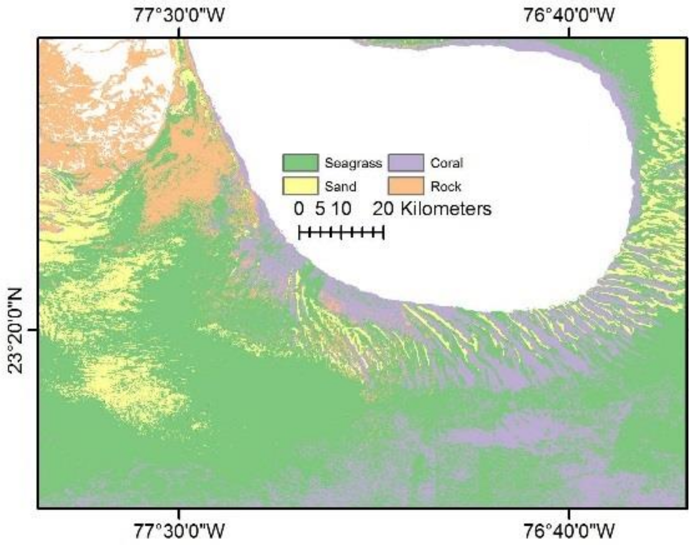
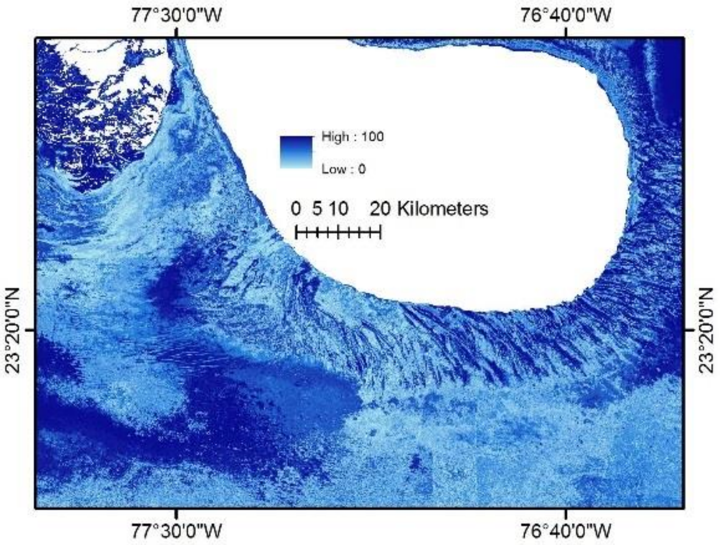
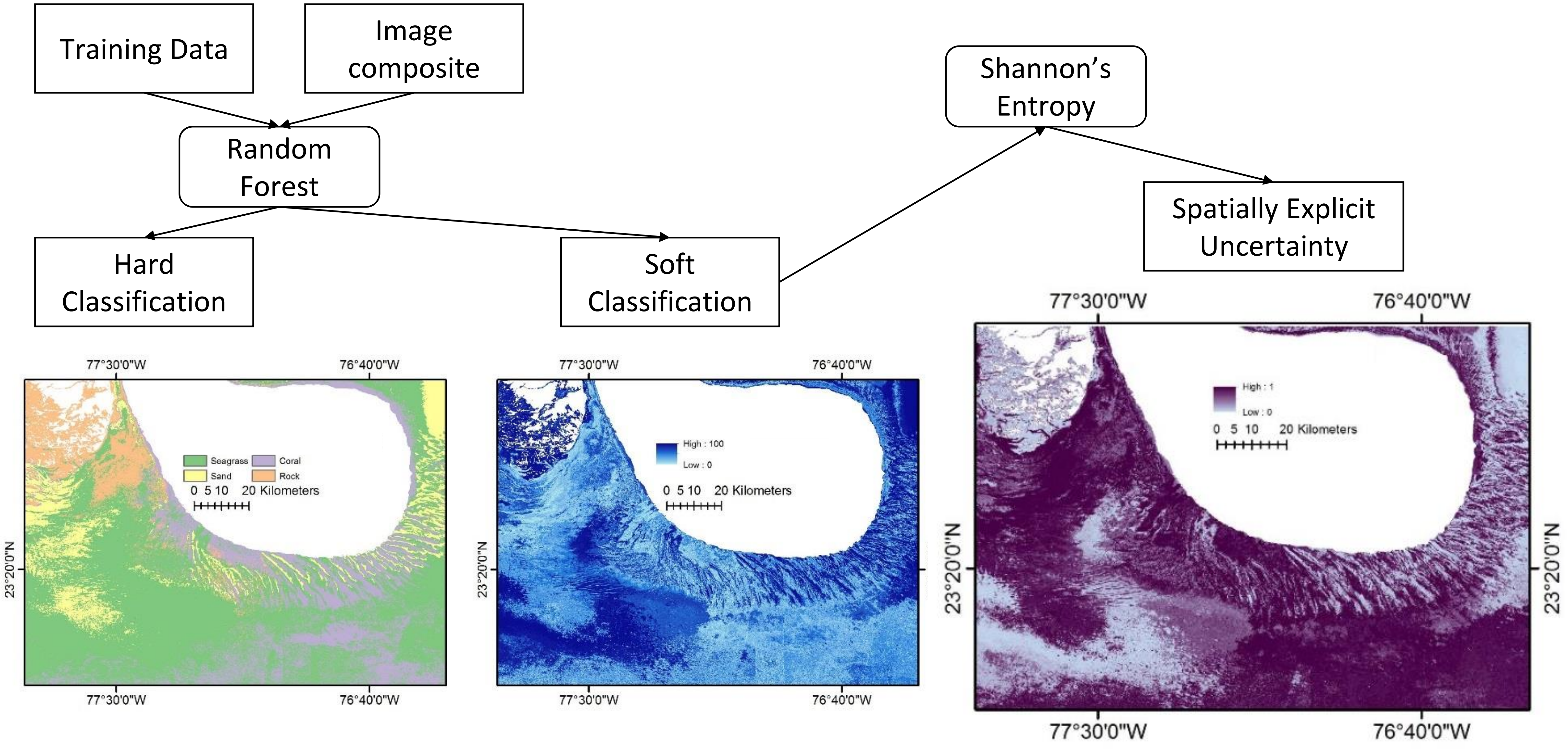




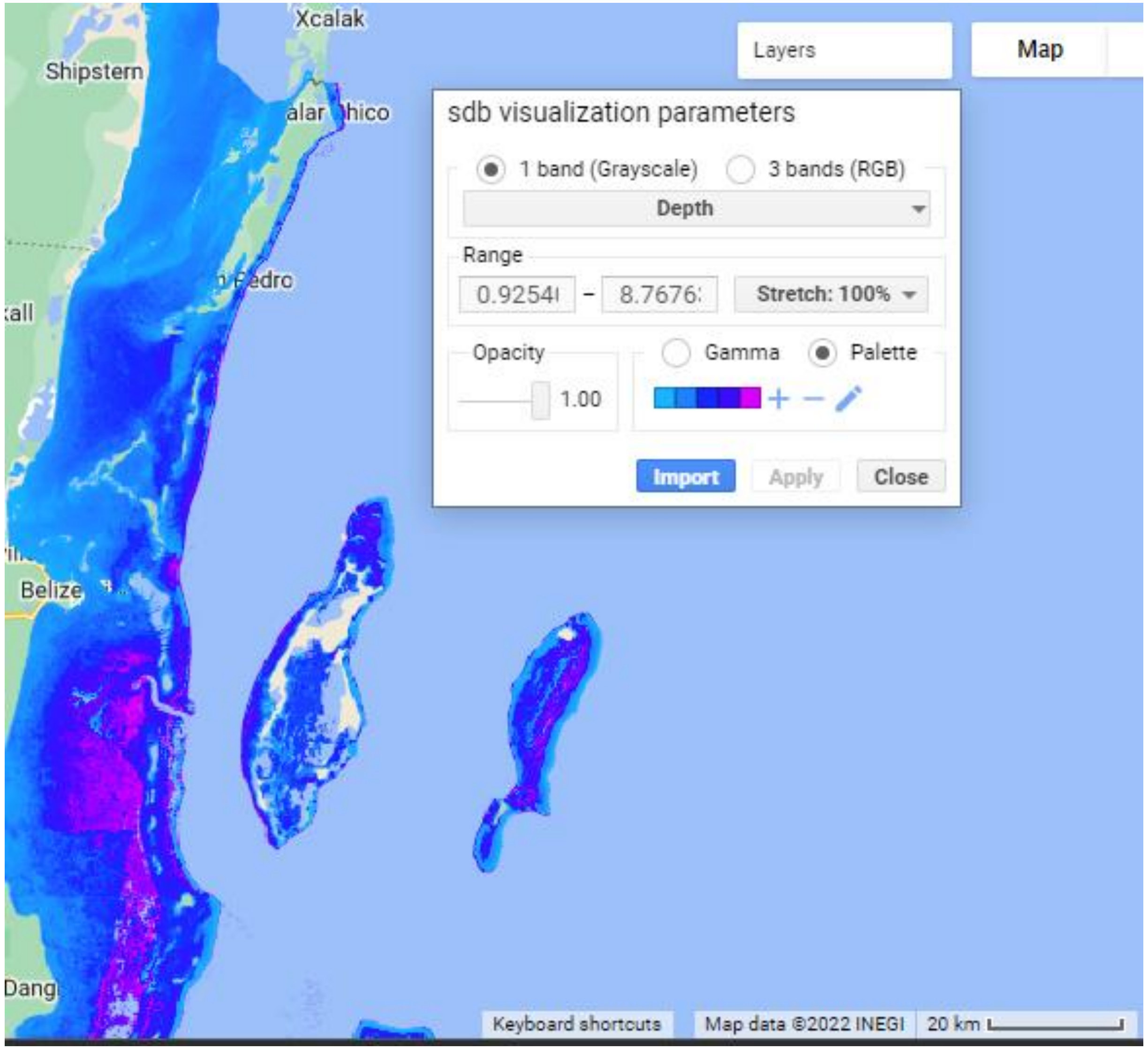


Uncertainty in Benthic Habitat Classification

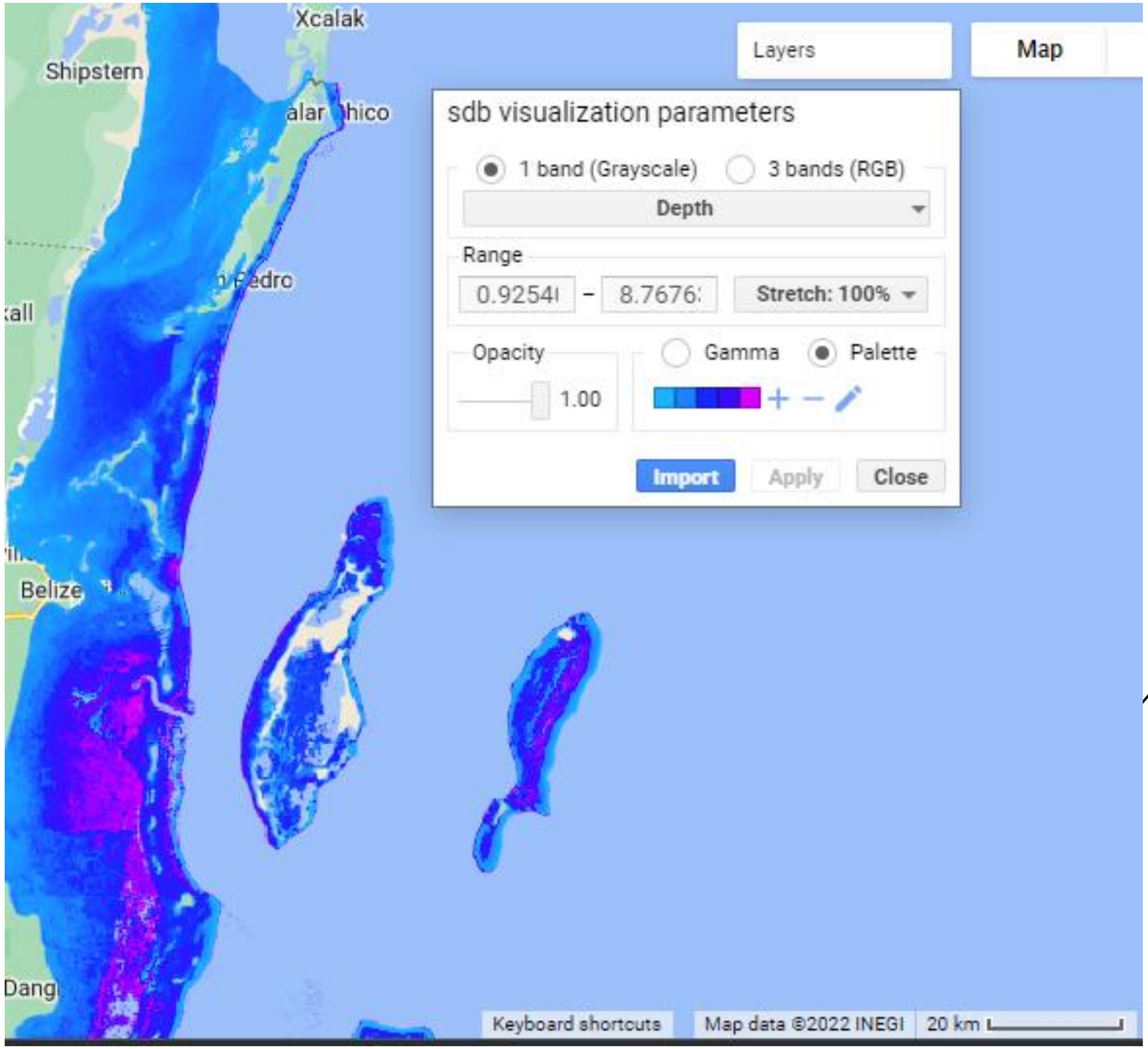


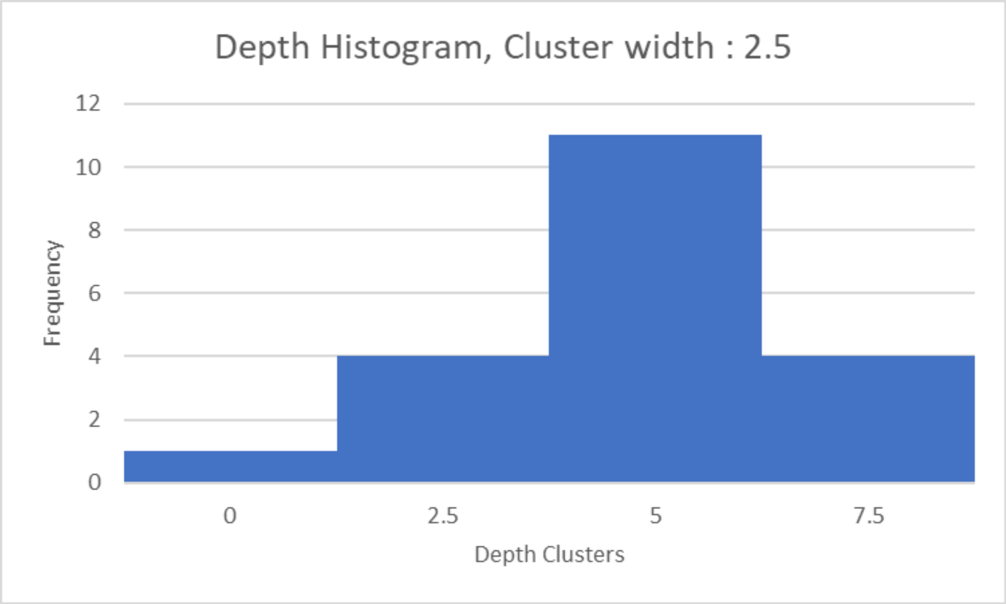
Uncertainty in Satellite Derived Bathymetry

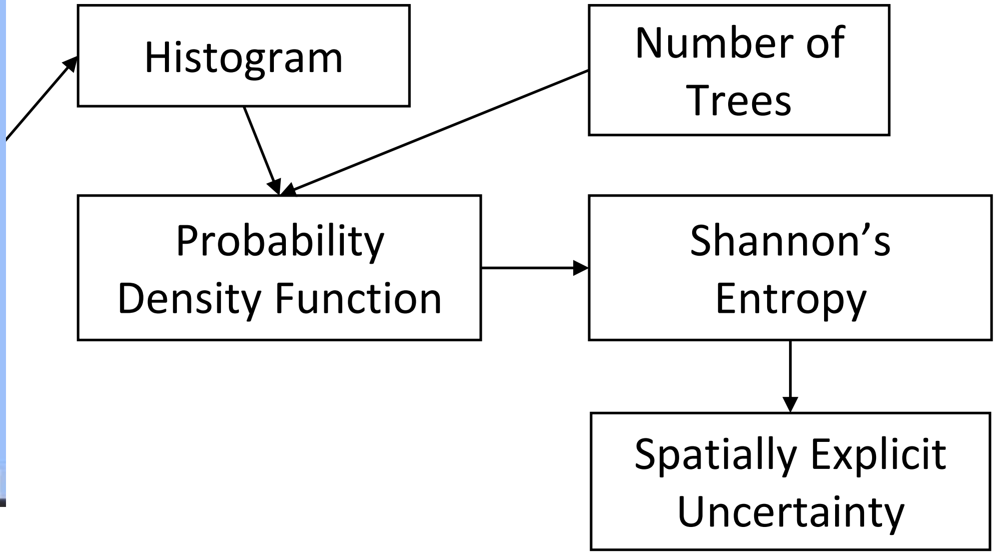
Bathymetry regression with Random Forest classifier of 20 trees



Uncertainty in Satellite Derived Bathymetry



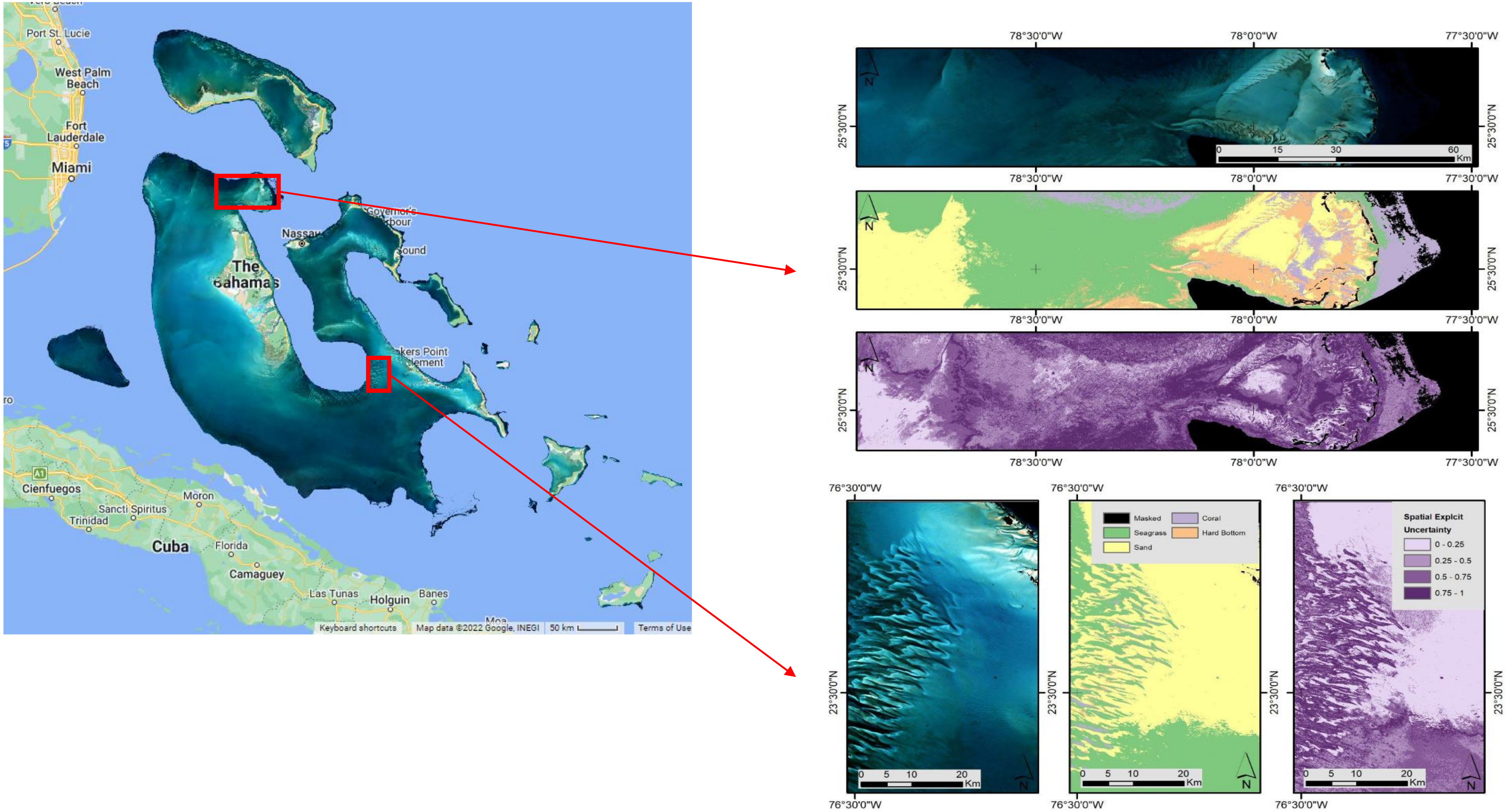




Results: Accuracy Assessment in Classification

OBIA			
	Initial Classification	**Retrained from Uncertain Areas lt(0.25)**	**Accuracy Gain**
Overall Accuracy	57.83%	62.08%	4.25%
User's Accuracy	53.82%	60.30%	6.48%
Producer's Accuracy	54.00%	67.33%	13.33%

Results: Uncertainty in Classification

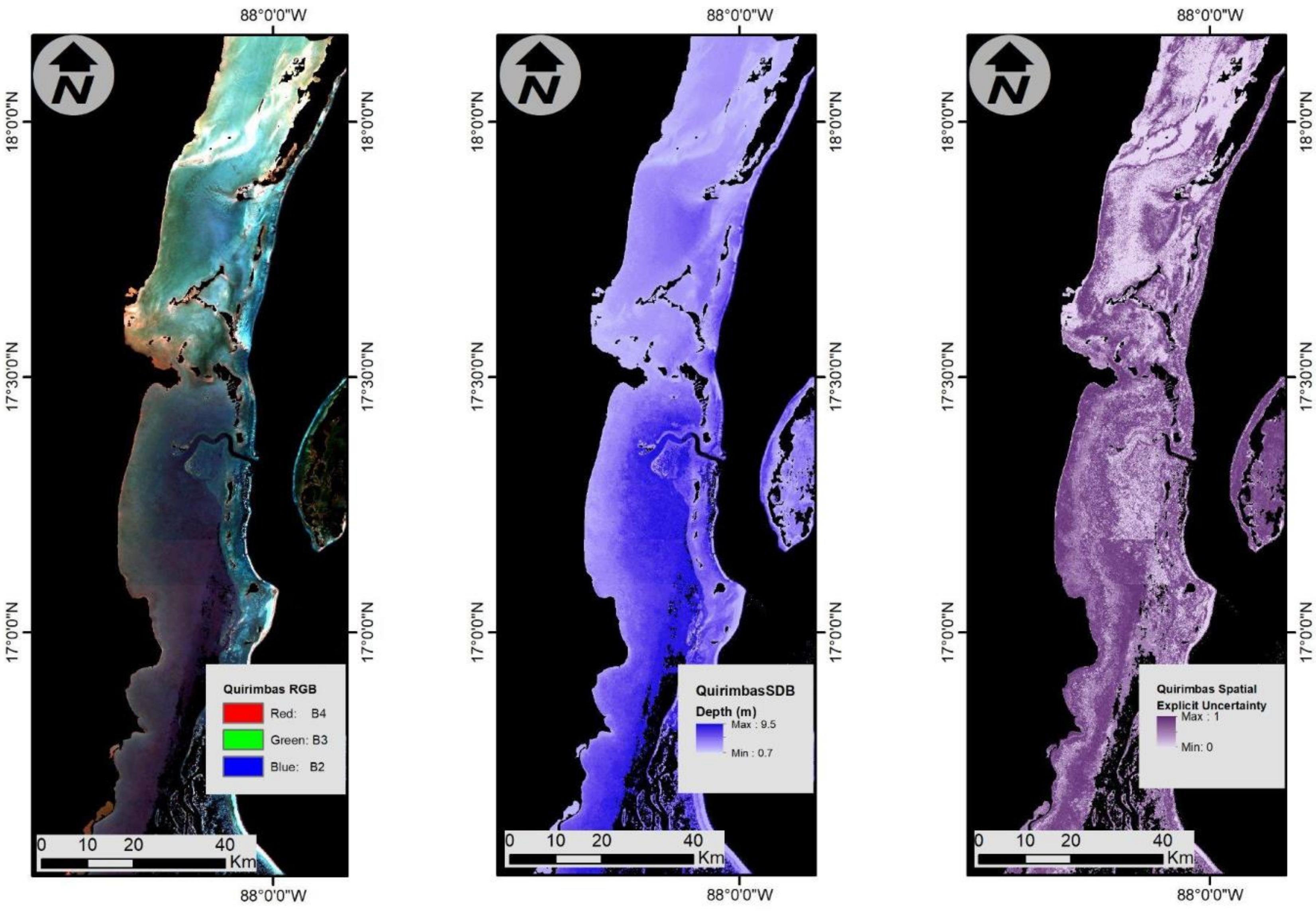


Results: Accuracy Assessment in Regression

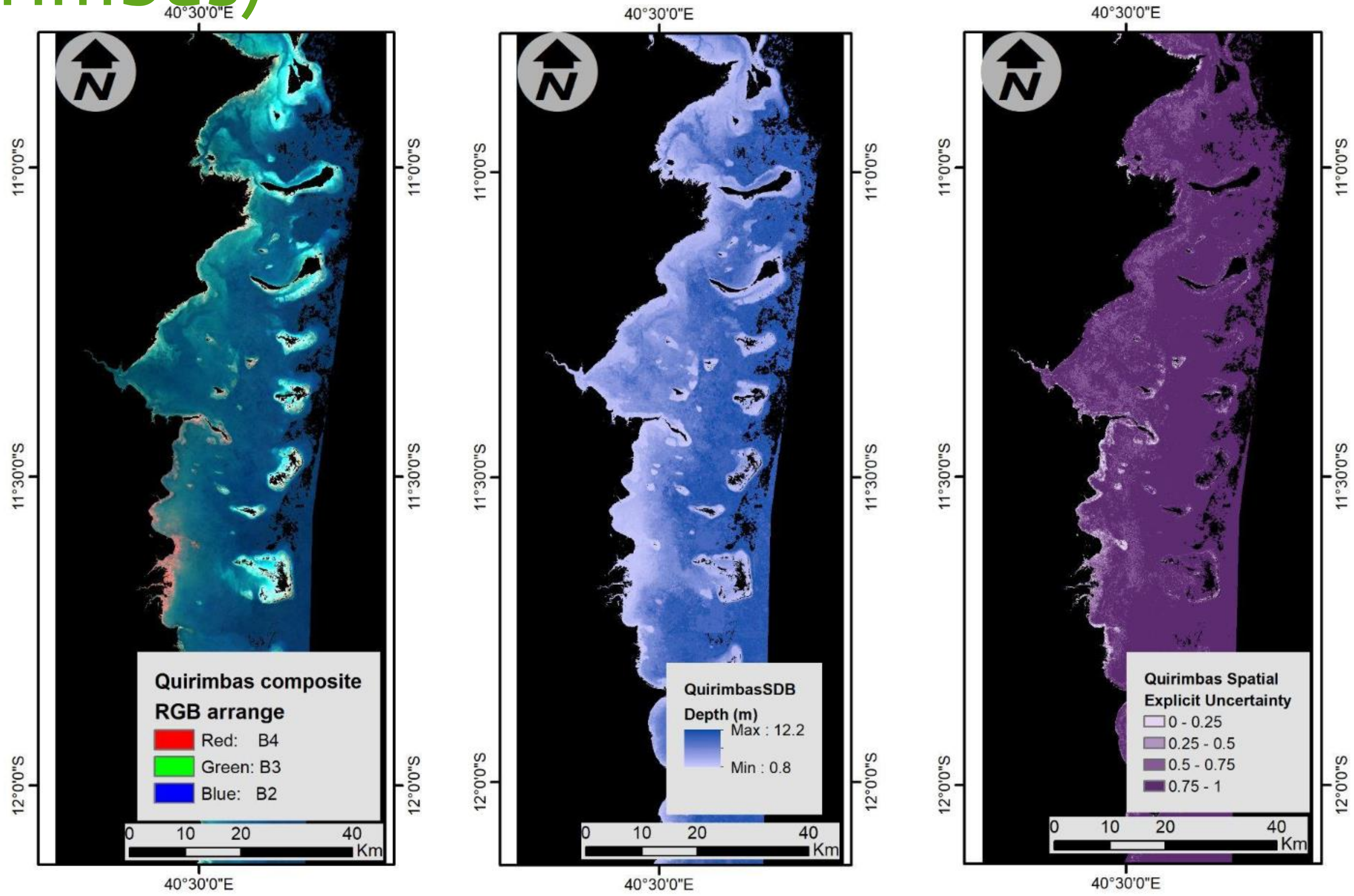
QUIRIMBAS			
model	Initial Regression	Retrained from Uncertain Areas lt(0.25)	Accuracy Gain
MeanSqr Error	2.6328	2.1955	0.4373
r_sqr	0.6289	0.6162	0.0127

BELIZE			
model	Initial Regression	Retrained from Uncertain Areas lt(0.25)	Accuracy Gain
MeanSqr Error	1.2306	1.1479	0.0827
r_sqr	0.6104	0.6026	0.0078

Results: Uncerainty in Regression (Belize)



Results: Uncerainty in Regression (Quirimbas)



Takeaways and Next Steps

- Spatially Explicit Uncertainty shows promise to improve the remote sensing products and especially marine habitat classifications

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- In turn, better maps could support more effective policy making, field data collection and real world impact

- Use of Spatially Explicit Uncertainty for a data driven data creation workflow for modelling instead of using field data

Thank you for your time!

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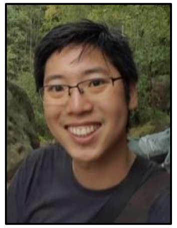
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PhD candidate


Spyros Christofilakos
PhD candidate

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Shannon's Entropy (Predicted Entropy)

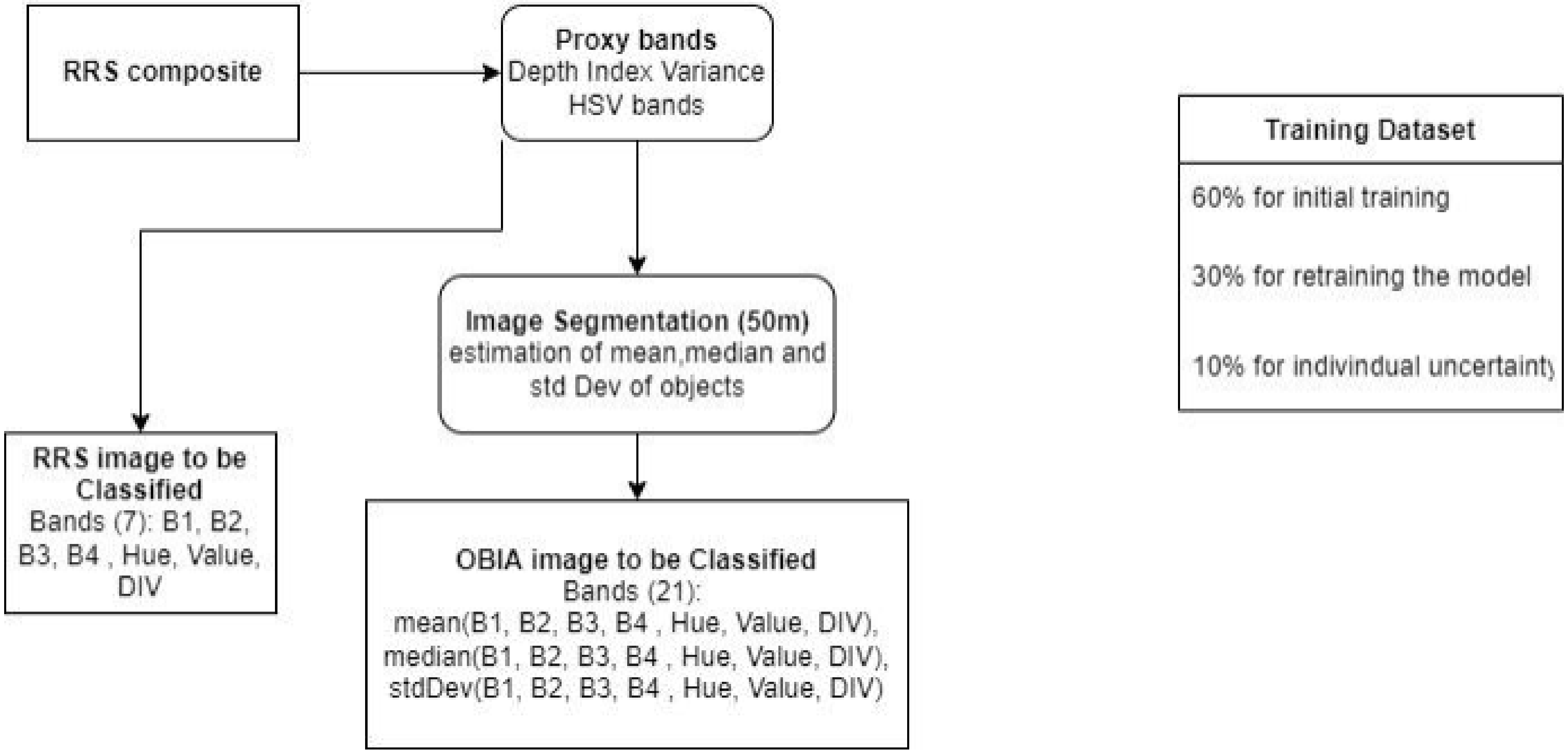
- 1) Possible outcome: Head , Tails
- 2) Probabilities of the outcome:

  P(H)= 50%

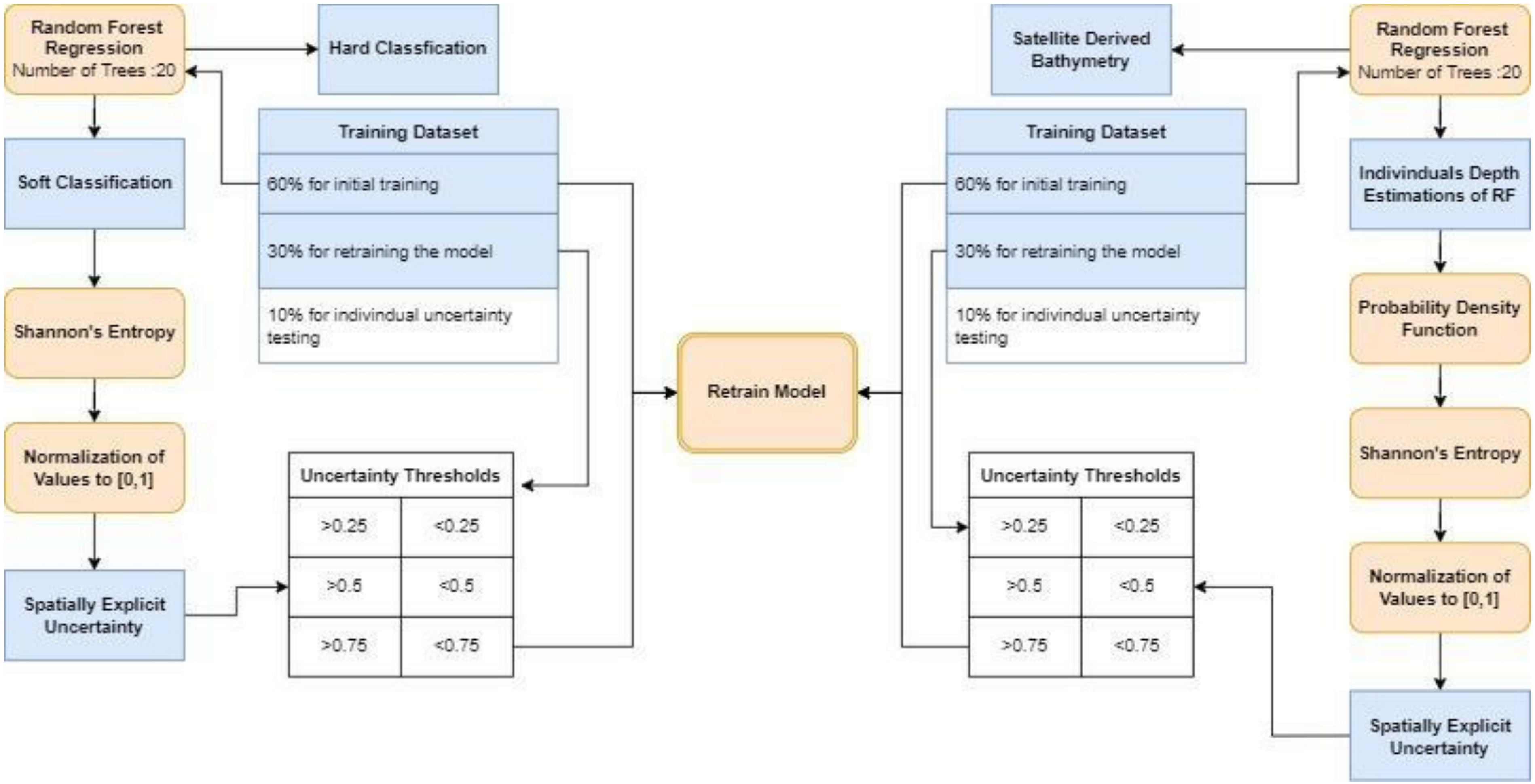
  P(T)=50%
- 3) Shannon's Entropy

$$E(x) = -\sum_{i=1}^{N} P(x_i) * \log_2 P(x_i)$$

Data Pre-processing



Data Processing



Results: Accuracy Assessment in Classification

OBIA	lt: Less than	gt: Greater than						
model	**Retrained from Uncertain Areas lt(0.25)**	**Initial Classification**	**Retrained from Uncertain Areas lt(0.5)**	**Retrained from Uncertain Areas lt(0.75)**	**Retrained from Uncertain Areas gt(0.25)**	**Retrained from Uncertain Areas gt(0.5)**	**Retrained from Uncertain Areas gt(0.75)**	**Classification with 90% of Data**
Overall Accuracy	62.08%	57.83%	60.92%	58.83%	59.58%	60.42%	58.83%	59.17%
	Percentage Gain	4.25%	1.17%	3.25%	2.50%	1.67%	3.25%	2.92%
User's Accuracy	60.30%	53.82%	58.86%	55.56%	53.94%	56.01%	57.19%	56.37%
	Percentage Gain	6.48%	1.44%	4.74%	6.36%	4.29%	3.11%	3.93%
Producer's Accuracy	67.33%	54.00%	62.00%	61.67%	61.67%	59.00%	61.67%	59.00%
	Percentage Gain	13.33%	5.33%	5.67%	5.67%	8.33%	5.67%	8.33%

Results: Accuracy Assessment in Classification

RGB	lt: Less than	gt: Greater than						
model	**Retrained from Uncertain Areas lt(0.5)**	**Initial Classification**	**Retrained from Uncertain Areas lt(0.25)**	**Retrained from Uncertain Areas lt(0.75)**	**Retrained from Uncertain Areas gt(0.25)**	**Retrained from Uncertain Areas gt(0.5)**	**Retrained from Uncertain Areas gt(0.75)**	**Classification with 90% of Data**
Overall Accuracy	59.33%	56.92%	56.75%	56.83%	57.17%	57.67%	58.25%	57.25%
	Percentage Gain	2.42%	2.58%	2.50%	2.17%	1.67%	1.08%	2.08%
User's Accuracy	48.35%	44.62%	45.08%	44.44%	45.28%	46.73%	47.73%	47.19%
	Percentage Gain	3.74%	3.27%	3.91%	3.07%	1.62%	0.62%	1.16%
Producer's Accuracy	58.67%	48.33%	47.33%	48.00%	46.33%	50.00%	49.00%	47.67%
	Percentage Gain	10.33%	11.33%	10.67%	12.33%	8.67%	9.67%	11.00%