Tables Outlining How to Use Remote Sensing for Marine Applications

This section guides you through a standard set of questions to determine the environmental variable (e.g. seagrass cover) to be mapped, and suitable remotely sensed data set(s) and mapping procedure(s). The information you have filled out in the mapping needs table is used to drive this process. A graphic interface is used to link the environmental variable to be mapped and type of environment, to suitable data sets and processing techniques. Completing the questions provides a guide on the data to acquire and steps to follow, to give an idea of the scope and costs for implementing such a project.

The detailed information specified for each application will include:

- data types and their dimensions;
- Environmental / Sensor Restrictions;
- processing techniques and requirements;
- resources (hardware, software and personnel);
- supporting references to related work.

Tables of Remote Sensing Data and Approaches for Mapping Selected Environmental Variables:

Table 1 Seagrass (Presence/absence)

	DATA OPTION 1: Quickbird 2	**DATA OPTION 2: Landsat 7 ETM**
Spatial Dimensions		
Area to cover	12 km x 12 km per scene	185 km x 185 km per scene
Mapping unit	068m panchromatic 4.0 m multi-spectral	15 m panchromatic 30 m multi-spectral
Positional accuracy	Dependent on georef-erencing process	Dependent on Geo-referencing process
Temporal Dimensions		
When	Approx 10.45 am	Approx 9.45 am
How often	Minimum every 4 days	every 16 days
Variable to map	Seagrass (Presence/ absence)	Seagrass (Presence/ absence)
Environmental / Sensor Restrictions	For sub-tidal vegetation to depth limited by water clarity. Inter-tidal and supra-tidal vegetation can have water on top. Not possible for turbid water Clouds, strong winds and breaking waves.	For sub-tidal vegetation to depth limited by water clarity. Inter-tidal and supra-tidal vegetation can have water on top. Not possible for turbid water Clouds, strong winds and breaking waves.
Processing technique **(Output)**	Image classification or feature detection using segmentation and classification (Vegetation type map and target features) Note: The ability to map seagrass will depend on their growth form, percent cover, substrate colour and extent.	Image classification or feature detection using segmentation and classification (Vegetation type map and target features) Note: The ability to map seagrass will depend on their growth form, percent cover, substrate colour and extent.
Resources – Hardware and Software	PC Image processing software GIS with image classification module (e.g.	PC Image processing software GIS with image classification module (e.g. ARCGIS Image Analyst)

	ARCGIS Image Analyst)	
Resource – Personnel	Trained in image classification Experience with high spatial resolution data Knowledge of area to be mapped	Trained in image classification Experience with Landsat data Knowledge of area to be mapped
References: Note these are some example references	(Phinn et al., 2008)	(Roelfsema et al., 2009)

Table 2 Seagrass (Species Composition)

	DATA OPTION 1: Quickbird 2	**DATA OPTION 2: Airborne hyper-spectral data**
Spatial Dimensions		
Area to cover	12 km x 12 km per scene	Up to 1000 km ^{2}
Mapping unit	068m panchromatic 4.0 m multi-spectral	0.5m – 5m
Positional accuracy	Dependent on georef-erencing process	Dependent on Geo-referencing process
Temporal Dimensions		
When	Approx 10.45 am	User defined
How often	Minimum every 4 days	User defined (can be < 1 day)
Variable to map	Seagrass (Species Composition)	Seagrass (Species Composition)
Environmental / Sensor Restrictions	For sub-tidal vegetation to depth limited by water clarity. Inter-tidal and supra-tidal vegetation can have water on top. Not possible for turbid water Clouds, strong winds and breaking waves.	For sub-tidal vegetation to depth limited by water clarity. Inter-tidal and supra-tidal vegetation can have water on top. Not possible for turbid water Strong winds, breaking waves
Processing technique **(Output)**	Image classification or feature detection using segmentation and classification (Vegetation type map and target features) Note: The ability to map specific targets will depend on their growth form, percent cover, substrate colour and extent.	Image classification or feature detection using segmentation and classification (Vegetation type map and target features) Note: The ability to map specific targets will depend on their growth form, percent cover, substrate colour and extent.
Resources – Hardware and Software	PC Image processing software	PC Image processing software with Hyper-spectral analysis

	GIS with image classification module (e.g. ARCGIS Image Analyst)	capabilities, including sub-pixel mapping techniques.
Resource – Personnel	Trained in image classification Experience with high spatial resolution data Knowledge of area to be mapped	Trained in hyper-spectral data processing. Knowledge of area to be mapped
References: Note these are some example references	(Phinn et al., 2008)	(Brando 2004; Phinn et al., 2008)

Table 3 Seagrass (Percent Cover [horizontal projected foliage])

	DATA OPTION 1: Quickbird 2	**DATA OPTION 2: Airborne hyper-spectral data**
Spatial Dimensions		
Area to cover	12 km x 12 km per scene	Up to 1000 km ^{2}
Mapping unit	068m panchromatic 4.0 m multi-spectral	0.5m – 5m
Positional accuracy	Dependent on georef-erencing process	Dependent on Geo-referencing process
Temporal Dimensions		
When	Approx 10.45 am	User defined
How often	Minimum every 4 days	User defined (can be < 1 day)
Variable to map	Benthic (species, cover, biomass)	Benthic (species, cover , biomass)
Environmental / Sensor Restrictions	For sub-tidal vegetation to depth limited by water clarity. Inter-tidal and supra-tidal vegetation can have water on top. Not possible for turbid water Clouds, strong winds and breaking waves.	For sub-tidal vegetation to depth limited by water clarity. Inter-tidal and supra-tidal vegetation can have water on top. Not possible for turbid water Strong winds, breaking waves
Processing technique **(Output)**	Image classification or feature detection using segmentation and classification Empirical model built using field survey data to estimate cover from image pixel values. (Vegetation type map and target features) Note: The ability to map specific targets will depend on their growth form, percent cover, substrate colour	Image classification or feature detection using segmentation and classification Empirical model built using field survey data to estimate cover from image pixel values. (Vegetation type map and target features) Note: The ability to map specific targets will depend on their growth form, percent cover, substrate colour and extent.

	and extent.	
Resources – Hardware and Software	PC Image processing software GIS with image classification module (e.g. ARCGIS Image Analyst)	PC Image processing software with Hyper-spectral analysis capabilities, including sub-pixel mapping techniques.
Resource – Personnel	Trained in image classification Experience with high spatial resolution data Knowledge of area to be mapped	Trained in hyper-spectral data processing. Knowledge of area to be mapped
References: Note these are some example references	(Lathrop et al., 2006; Phinn et al., 2008; Roelfsema et al., 2009)	(Brando 2004; Lathrop et al., 2006; Phinn et al., 2008; Roelfsema et al., 2009)

Table 4 Seagrass (Total (above+below ground Biomass)

	DATA OPTION 1: Quickbird 2	**DATA OPTION 2: Airborne hyper-spectral data**
Spatial Dimensions		
Area to cover	12 km x 12 km per scene	Up to 1000 km ^{2}
Mapping unit	068m panchromatic 4.0 m multi-spectral	0.5m – 5m
Positional accuracy	Dependent on georef-erencing process	Dependent on Geo-referencing process
Temporal Dimensions		
When	Approx 10.45 am	User defined
How often	Minimum every 4 days	User defined (can be < 1 day)
Variable to map	Benthic (species, cover, biomass)	Benthic (species, cover , biomass)
Environmental / Sensor Restrictions	For sub-tidal vegetation to depth limited by water clarity. Inter-tidal and supra-tidal vegetation can have water on top. Not possible for turbid water Clouds, strong winds and breaking waves.	For sub-tidal vegetation to depth limited by water clarity. Inter-tidal and supra-tidal vegetation can have water on top. Not possible for turbid water Strong winds, breaking waves
Processing technique **(Output)**	Image classification or feature detection using segmentation and classification Empirical model built using field survey data to estimate biomass from image pixel values. (Vegetation type map and target features) Note: The ability to map specific targets will depend on their growth form, percent cover, substrate colour	Image classification or feature detection using segmentation and classification Empirical model built using field survey data to estimate biomass from image pixel values. (Vegetation type map and target features) Note: The ability to map specific targets will depend on their growth form, percent cover, substrate colour and extent.

	and extent.	
Resources – Hardware and Software	PC Image processing software GIS with image classification module (e.g. ARCGIS Image Analyst)	PC Image processing software with Hyper-spectral analysis capabilities, including sub-pixel mapping techniques.
Resource – Personnel	Trained in image classification Experience with high spatial resolution data Knowledge of area to be mapped	Trained in hyper-spectral data processing. Knowledge of area to be mapped
References: Note these are some example references	(Phinn et al., 2008)	(Brando 2004; Phinn et al., 2008)

Table 5 *Harmful Algal Blooms* Presence/absence *e.g. Lyngbya majuscula*

	DATA OPTION 1: Quickbird 2	**DATA OPTION 2: Landsat ETM**
Spatial Dimensions		
Area to cover	12 km x 12 km per scene	185 km x 185 km per scene Example 250 km ^{2}
Mapping unit	068m panchromatic 4.0 m multi-spectral	15 m panchromatic 30 m multi-spectral
Positional accuracy	Dependent on georef-erencing process	Dependent on Geo-referencing process
Temporal Dimensions		
When	Approx 10.45 am	Approx 9.45 am
How often	Minimum every 4 days	every 16 days
Variable to map	*Harmful algal bloom, benthic form.* (Presence/absence, % Cover)cover	*Harmful algal bloom, benthic form* (Presence/absence, % Cover)
Environmental / Sensor Restrictions	For sub-tidal vegetation to depth limited by water clarity. Inter-tidal and supra-tidal vegetation can have water on top. Not possible for turbid water Clouds, strong winds and breaking waves. % cover of Lyngbya should be higher than 40 %	For sub-tidal vegetation to depth limited by water clarity. Inter-tidal and supra-tidal vegetation can have water on top. Not possible for turbid water Clouds, strong winds and breaking waves. % cover of Lyngbya should be higher than 40 %
Processing technique **(Output)**	Supervised Image classification (Vegetation type map and target features) Note: The ability to map specific targets will depend on their growth form, percent cover, substrate colour and extent.	Supervised Image classification (Vegetation type map and target features) Note: The ability to map specific targets will depend on their growth form, percent cover, substrate colour and extent.
Resources – Hardware and Software	PC Image processing software GIS with image classification module (e.g. ARCGIS Image Analyst)	PC Image processing software GIS with image classification module (e.g. ARCGIS Image Analyst)
Resource – Personnel	Trained in image	Trained in image

	classification Experience with high spatial resolution data Knowledge of area to be mapped	classification Experience with Landsat data Knowledge of area to be mapped
References: Note these are some example references	not tested but expected that possible and higher detail as it is operational with multi spectral sensor with moderate resolution pixels see (Roelfsema et al., 2006)	(Roelfsema et al., 2006)

Table 6 *Harmful Algal Blooms* % Cover (*e.g. Lyngbya majuscula*)

	DATA OPTION 1: Quickbird 2	**DATA OPTION 2: Landsat ETM**
Spatial Dimensions		
Area to cover	12 km x 12 km per scene	185 km x 185 km per scene Example 250 km ^{2}
Mapping unit	068m panchromatic 4.0 m multi-spectral	15 m panchromatic 30 m multi-spectral
Positional accuracy	Dependent on georef-erencing process	Dependent on Geo-referencing process
Temporal Dimensions		
When	Approx 10.45 am	Approx 9.45 am
How often	Minimum every 4 days	every 16 days
Variable to map	*Harmful algal bloom, benthic form.* (Presence/absence, % Cover)cover	*Harmful algal bloom, benthic form* (Presence/absence, % Cover)
Environmental / Sensor Restrictions	For sub-tidal vegetation to depth limited by water clarity. Inter-tidal and supra-tidal vegetation can have water on top. Not possible for turbid water Clouds, strong winds and breaking waves. % cover of Lyngbya should be higher than 40 %	For sub-tidal vegetation to depth limited by water clarity. Inter-tidal and supra-tidal vegetation can have water on top. Not possible for turbid water Clouds, strong winds and breaking waves. % cover of Lyngbya should be higher than 40 %
Processing technique **(Output)**	Supervised Image classification (Vegetation type map and target features) Note: The ability to map specific targets will depend on their growth form, percent cover, substrate colour and extent.	Supervised Image classification (Vegetation type map and target features) Note: The ability to map specific targets will depend on their growth form, percent cover, substrate colour and extent.
Resources – Hardware and Software	PC Image processing software GIS with image classification module (e.g. ARCGIS Image Analyst)	PC Image processing software GIS with image classification module (e.g. ARCGIS Image Analyst)

Resource – Personnel	Trained in image classification Experience with high spatial resolution data Knowledge of area to be mapped	Trained in image classification Experience with Landsat data Knowledge of area to be mapped
References: Note these are some example references	not tested but expected that possible and higher detail as it is operational with multi spectral sensor with moderate resolution pixels see (Roelfsema et al., 2006)	(Roelfsema et al., 2006)

Table 7 *Harmful Algal Blooms e.g. Lyngbya majuscula* (Biomass)

	DATA OPTION 1: Quickbird 2	**DATA OPTION 2: Airborne hyper-spectral data**
Spatial Dimensions		
Area to cover	12 km x 12 km per scene	Up to 1000 km ^{2}
Mapping unit	068m panchromatic 4.0 m multi-spectral	0.5m – 5m
Positional accuracy	Dependent on georef-erencing process	Dependent on Geo-referencing process
Temporal Dimensions		
When	Approx 10.45 am	User defined
How often	Minimum every 4 days	User defined (can be < 1 day)
Variable to map	Benthic (biomass)	Benthic (biomass)
Environmental / Sensor Restrictions	For sub-tidal vegetation to depth limited by water clarity. Inter-tidal and supra-tidal vegetation can have water on top. Not possible for turbid water Clouds, strong winds and breaking waves. % cover of Lyngbya should be higher than 40 %	For sub-tidal vegetation to depth limited by water clarity. Inter-tidal and supra-tidal vegetation can have water on top. Not possible for turbid water Clouds, strong winds and breaking waves. % cover of Lyngbya should be higher than 40 %
Processing technique **(Output)**	Regression Analysis	Regression Analysis
Resources – Hardware and Software	PC Image processing software GIS with image classification module (e.g. ARCGIS Image Analyst)	PC Image processing software with Hyper-spectral analysis capabilities, including sub-pixel mapping techniques.
Resource – Personnel	Trained in image	Trained in hyper-spectral

	classification Experience with high spatial resolution data Knowledge of area to be mapped	data processing. Knowledge of area to be mapped
References: Note these are some example references	No peer reviewed reference	No peer reviewed reference

Table 8 Coral Reef Composition: Reef Extent

	DATA OPTION 1: Landsat ETM	**MODIS**
Spatial Dimensions		
Area to cover	185 km x 185 km per scene	Up to km ^{2}
Example area	Heron Reef	
Mapping unit	15 m panchromatic 30 m multi-spectral	500 – 1000 m
Positional accuracy	Dependent on Geo-referencing process	Dependent on Geo-referencing process
Temporal Dimensions		
When	Approx 9.45 am	Approx 9.45 am
How often	every 16 days	Daily
Variable to map	Where are reefs	Where are reefs
Environmental / Sensor Restrictions	For sub-tidal vegetation to depth limited by water clarity. Inter-tidal and supra-tidal vegetation can have water on top. Not possible for turbid water Clouds, strong winds and breaking waves.	For sub-tidal vegetation to depth limited by water clarity. Inter-tidal and supra-tidal vegetation can have water on top. Not possible for turbid water Clouds, strong winds and breaking waves.
Processing technique **(Output)**	Supervised Image classification or feature detection, Object based analysis or manual delineation	Supervised Image classification
Resources – Hardware and Software	PC Image processing software GIS with image classification module (e.g. ARCGIS Image Analyst)	PC Image processing software with Hyper-spectral analysis capabilities, including sub-pixel mapping techniques.
Resource – Personnel	Trained in image classification Experience with Landsat data Knowledge of reef	Trained in image classification Experience with Landsat

	geomorphology to be mapped When object based analysis then experience with object based analysis software (e.g. Ecognition)	data Knowledge of reef geomorphology to be mapped hyper-spectral
References: Note these are some example references	(Ahmad et al., 1999; Andréfouët et al., 2005; Roelfsema and Phinn 2008; Phinn et al., in press)	(Andréfouët and Claereboudt 2000; Capolsini et al., 2003)

Table 9 Coral Reef Composition: Coarse Spatial Scale (e.g. geomorphic zones)

	DATA OPTION 1: Landsat ETM	**DATA OPTION 2: Quickbird**
Spatial Dimensions		
Area to cover	185 km x 185 km per scene	Up to km ^{2}
Example area	Heron Reef	
Mapping unit	15 m panchromatic 30 m multi-spectral	500 – 1000 m
Positional accuracy	Dependent on Geo-referencing process	Dependent on Geo-referencing process
Temporal Dimensions		
When	Approx 9.45 am	Approx 9.45 am
How often	every 16 days	Daily
Variable to map	Reef Province Reef Type Geomorphic Zones	Reef Province Reef Type Geomorphic Zones
Environmental / Sensor Restrictions	For sub-tidal vegetation to depth limited by water clarity. Inter-tidal and supra-tidal vegetation can have water on top. Not possible for turbid water Clouds, strong winds and breaking waves.	For sub-tidal vegetation to depth limited by water clarity. Inter-tidal and supra-tidal vegetation can have water on top. Not possible for turbid water Clouds, strong winds and breaking waves.
Processing technique **(Output)**	Supervised Image classification or feature detection, Object based analysis or manual delineation	Supervised Image classification
Resources – Hardware and Software	PC Image processing software GIS with image classification module (e.g. ARCGIS Image Analyst), Object based analysis software if using this technique.	PC Image processing software with Hyper-spectral analysis capabilities, including sub-pixel mapping techniques.
Resource – Personnel	Trained in image classification	Trained in image classification

	Experience with Landsat data Knowledge of reef geomorphology to be mapped When object based analysis then experience with object based analysis software (e.g. Ecognition)	Experience with Landsat data Knowledge of reef geomorphology to be mapped hyper-spectral
References: Note these are some example references	(Ahmad et al., 1999; Andréfouët et al., 2005; Roelfsema and Phinn 2008; Phinn et al., in press)	(Andréfouët and Claereboudt 2000; Capolsini et al., 2003)

Table 10 Coral Reef Composition: Fine Spatial Scale (e.g. community zones)

	DATA OPTION 1: Quickbird 2	**DATA OPTION 2: Airborne hyper-spectral**
Spatial Dimensions		
Area to cover	12 km x 12 km per scene	Up to 1000 km ^{2}
Mapping unit	0.68 m panchromatic 2.44 m multi-spectral	0.5m – 5m
Positional accuracy	Dependent on Geo-referencing process	Dependent on Geo-referencing process
Temporal Dimensions		
When	On request	User defined
How often	User defined but minimum every 5 days	User defined (can be < 1 day)
Variable to map	Benthic Community Scale - benthic cover type	Benthic Community Scale - benthic cover type
Environmental / Sensor Restrictions	For sub-tidal vegetation to depth limited by water clarity. Inter-tidal and supra-tidal vegetation can have water on top. Not possible for turbid water Clouds, strong winds and breaking waves.	For sub-tidal vegetation to depth limited by water clarity. Inter-tidal and supra-tidal vegetation can have water on top. Not possible for turbid water Clouds, strong winds and breaking waves.
Processing technique **(Output)**	Image classification or feature detection or object based analysis (Vegetation type map and target features) Note: The ability to map specific targets will depend on their growth form and extent.	Image classification or feature detection (Vegetation type map and target features) Note: The ability to map specific targets will depend on their growth form and extent.
Resources – Hardware and Software	PC Image processing software GIS with image classification module (e.g. ARCGIS Image Analyst) , Object based analysis	PC Image processing software with Hyper-spectral analysis capabilities, including sub-pixel mapping techniques. , Object based analysis
Resource – Personnel	Trained in image classification	Trained in hyper-spectral data processing.

	Experience with Landsat data Knowledge of area to be mapped When object based analysis then experience with object based analysis software (e.g. Ecognition)	Knowledge of area to be mapped When object based analysis then experience with object based analysis software (e.g. Ecognition)
References: Note these are some example references	(Mishra et al., 2006; Phinn et al., in press)	Leiper in press, (Mumby et al., 1997)

Table 11 Coral Reefs: Coral Cover

	DATA OPTION 1: Quickbird 2	**DATA OPTION 2: Airborne hyper-spectral**
Spatial Dimensions		
Area to cover	12 km x 12 km per scene	Up to 1000 km ^{2}
Mapping unit	0.68 m panchromatic 2.44 m multi-spectral	0.5m – 5m
Positional accuracy	Dependent on Geo-referencing process	Dependent on Geo-referencing process
Temporal Dimensions		
When	On request	User defined
How often	User defined but minimum every 5 days	User defined (can be < 1 day)
Variable to map	Benthic Community Scale - % benthic cover	Benthic Community Scale - % benthic cover
Environmental / Sensor Restrictions	For sub-tidal vegetation to depth limited by water clarity. Inter-tidal and supra-tidal vegetation can have water on top. Not possible for turbid water Clouds, strong winds and breaking waves.	For sub-tidal vegetation to depth limited by water clarity. Inter-tidal and supra-tidal vegetation can have water on top. Not possible for turbid water Clouds, strong winds and breaking waves.
Processing technique **(Output)**	Image classification or feature detection or object based analysis (Vegetation type map and target features) Note: The ability to map specific targets will depend on their growth form and extent.	Image classification or feature detection (Vegetation type map and target features) Note: The ability to map specific targets will depend on their growth form and extent.
Resources – Hardware and Software	PC Image processing software GIS with image classification module (e.g. ARCGIS Image Analyst) , Object based analysis	PC Image processing software with Hyper-spectral analysis capabilities, including sub-pixel mapping techniques. , Object based analysis
Resource – Personnel	Trained in image classification Experience with Landsat	Trained in hyper-spectral data processing. Knowledge of area to be

	data Knowledge of area to be mapped When object based analysis then experience with object based analysis software (e.g. Ecognition)	mapped When object based analysis then experience with object based analysis software (e.g. Ecognition)
References: Note these are some example references	(Mishra et al., 2006; Phinn et al., in press)	Leiper in press, (Mumby et al., 1997)

Table 12 Coral Reef – Detect extent and cover Bleaching

	DATA OPTION 1: Quickbird 2	**DATA OPTION 2: Airborne hyper-spectral**
Spatial Dimensions		
Area to cover	12 km x 12 km per scene	Up to 1000 km ^{2}
Mapping unit	0.68 m panchromatic 2.44 m multi-spectral	0.5m – 5m
Positional accuracy	Dependent on Geo-referencing process	Dependent on Geo-referencing process
Temporal Dimensions		
When	On request	User defined
How often	User defined but minimum every 5 days	User defined (can be < 1 day)
Variable to map	Benthic Community Scale - benthic cover type - % benthic cover Benthic Patch Scale	Benthic Community Scale - benthic cover type - % benthic cover Benthic Patch Scale
Environmental / Sensor Restrictions	For sub-tidal vegetation to depth limited by water clarity. Inter-tidal and supra-tidal vegetation can have water on top. Not possible for turbid water Clouds, strong winds and breaking waves.	For sub-tidal vegetation to depth limited by water clarity. Inter-tidal and supra-tidal vegetation can have water on top. Not possible for turbid water Clouds, strong winds and breaking waves.
Processing technique **(Output)**	Image classification or feature detection	Image classification or feature detection
Resources – Hardware and Software	PC Image processing software GIS with image classification module (e.g. ARCGIS Image Analyst)	PC Image processing software with Hyper-spectral analysis capabilities, including sub-pixel mapping techniques.
Resource – Personnel		
References: Note these are some example references		

Table 13 Event Based – Flood Plumes

	DATA OPTION 1: Quickbird 2	**DATA OPTION 2: MODIS**
Spatial Dimensions		
Area to cover	12 km x 12 km per scene	Up to 1000 km ^{2}
Mapping unit	068m panchromatic 4.0 m multi-spectral	0.5m – 5m
Positional accuracy	Dependent on georef-erencing process	Dependent on Geo-referencing process
Temporal Dimensions		
When	Approx 10.45 am	User defined
How often	Minimum every 4 days	User defined (can be < 1 day)
Variable to map	Extent of plume and concentrations of sediments	Extent of plume and concentrations of sediments
Environmental / Sensor Restrictions	For sub-tidal vegetation to depth limited by water clarity. Inter-tidal and supra-tidal vegetation can have water on top. Not possible for turbid water Clouds, strong winds and breaking waves.	For sub-tidal vegetation to depth limited by water clarity. Inter-tidal and supra-tidal vegetation can have water on top. Not possible for turbid water Clouds, strong winds and breaking waves.
Processing technique **(Output)**	Image classification and application empirical or analytical models to estimate sediment concentrations.	Image classification and application empirical or analytical models to estimate sediment concentrations.
Resources – Hardware and Software	PC Image processing software GIS with image classification module (e.g. ARCGIS Image Analyst)	PC Image processing software with Hyper-spectral analysis capabilities, including sub-pixel mapping techniques.
Resource – Personnel	Trained in image classification Experience with high	Trained in hyper-spectral data processing.

	spatial resolution data	
References: Note these are some example references	No examples but should be possible. See Curran and Novo (1988)	Tralli et al. (2005), Shi and Wang (2009), Jiang et al. (2009)

References

Tralli, D. M., Blom, R. G., Zlotnicki, V., Donnellan, A., and Evans, D. L., 2005: Satellite remote sensing of earthquake, volcano, flood, landslide and coastal inundation hazards. *ISPRS Journal of Photogrammetry and Remote Sensing,* 59: 185-198.

Shi, W. and Wang, M., 2009: Satellite observations of flood driven Mississippi River plume in the spring of 2008. *Geophysical Research Letters,* 36: L07607.

Jiang, L., Yan, X., and Klemas, V., 2009: Remote sensing for the identification of coastal plumes: case studies of Delaware Bay. *International Journal of Remote Sensing,* 30: 2033-2048.

Curran, P. and E. Novo, 1988: The relationship between suspended sediment concentration and remotely sensed spectral radiance: a review. *Journal of Coastal Research***,** 351-368.

Table 14 Event Based – Ship groundings

	DATA OPTION 1: Quickbird 2	**DATA OPTION 2: Airborne hyper-spectral data**
Spatial Dimensions		
Area to cover	12 km x 12 km per scene	Up to 1000 km ^{2}
Mapping unit	068m panchromatic 4.0 m multi-spectral	0.5m – 5m
Positional accuracy	Dependent on georef-erencing process	Dependent on Geo-referencing process
Temporal Dimensions		
When	Approx 10.45 am	User defined
How often	Minimum every 4 days	User defined (can be < 1 day)
Variable to map	Benthic cover type	Benthic cover type
Environmental / Sensor Restrictions	For sub-tidal vegetation to depth limited by water clarity. Inter-tidal and supra-tidal vegetation can have water on top. Not possible for turbid water Clouds, strong winds and breaking waves.	For sub-tidal vegetation to depth limited by water clarity. Inter-tidal and supra-tidal vegetation can have water on top. Not possible for turbid water Clouds, strong winds and breaking waves.
Processing technique **(Output)**	Image classification or feature detection using segmentation and classification	Image classification or feature detection
Resources – Hardware and Software	PC Image processing software GIS with image classification module (e.g. ARCGIS Image Analyst)	PC Image processing software with Hyper-spectral analysis capabilities, including sub-pixel mapping techniques.
Resource – Personnel	Trained in image classification Experience with high	Trained in hyper-spectral data processing. Knowledge of area to be

	spatial resolution data Knowledge of area to be mapped	mapped
References: Note these are some example references	No specific examples but should be possible	No specific examples but should be possible

References

This paper mentions ship groundings:

Chabanet, P., Adjeroud, M., Andréfouët, S., Bozec, Y., Ferraris, J., Garcìa-Charton, J., and Schrimm, M., 2005: Human-induced physical disturbances and their indicators on coral reef habitats: A multi-scale approach. *Aquatic Living Resources,* 18: 215-230.

Table 15 Event Based –Cyclone

	DATA OPTION 1: Quickbird 2	**DATA OPTION 2: LANDSAT 7 ETM**
Spatial Dimensions		
Area to cover	12 km x 12 km per scene	185 km x 185 km per scene
Mapping unit	068m panchromatic 4.0 m multi-spectral	Heron Reef 15 m panchromatic 30 m multi-spectral
Positional accuracy	Dependent on georef-erencing process	Dependent on Geo-referencing process
Temporal Dimensions		
When	Approx 10.45 am	Approx 9.45 am
How often	Minimum every 4 days	every 16 days
Variable to map	Benthic cover type	Reef Province Reef Type Geomorphic Zones
Environmental / Sensor Restrictions	For sub-tidal vegetation to depth limited by water clarity. Inter-tidal and supra-tidal vegetation can have water on top. Not possible for turbid water Clouds, strong winds and breaking waves.	For sub-tidal vegetation to depth limited by water clarity. Inter-tidal and supra-tidal vegetation can have water on top. Not possible for turbid water Clouds, strong winds and breaking waves.
Processing technique **(Output)**	Image classification or feature detection using segmentation and classification. Object based analysis or manual delineation	PC Image processing software GIS with image classification module (e.g. ARCGIS Image Analyst), Object based analysis software if using this technique.
Resources – Hardware and Software	PC Image processing software GIS with image classification module (e.g. ARCGIS Image Analyst) When object based analysis then experience	Trained in image classification Experience with Landsat data Knowledge of reef geomorphology to be mapped

	with object based analysis software (e.g. Ecognition)	When object based analysis then experience with object based analysis software (e.g. Ecognition)
Resource – Personnel	Trained in image classification Experience with high spatial resolution data Knowledge of area to be mapped	PC Image processing software GIS with image classification module (e.g. ARCGIS Image Analyst), Object based analysis software if using this technique.
References: Note these are some example references	Scopélitis et al (2009)	Klemas (2009)

References

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Table 16 Event Based – Oil Spills

	DATA OPTION 1: Quickbird 2	**DATA OPTION 2: Radarsat or Terrasar**
Spatial Dimensions		
Area to cover	12 km x 12 km per scene	Up to 3600 km ^{2}
Mapping unit	068m panchromatic 4.0 m multi-spectral	5m -60m
Positional accuracy	Dependent on georef-erencing process	Dependent on Geo-referencing processGeo-referencing
Temporal Dimensions		
When	Approx 10.45 am	User defined
How often	Minimum every 4 days	User defined (can be < 1 day)
Variable to map	Extent of oil spill on water surface	Extent of oil spill on water surface
Environmental / Sensor Restrictions	Cloud cover, strong winds and breaking waves.	Strong winds and breaking waves.
Processing technique **(Output)**	Image classification or feature detection using segmentation and classification	Image classification or feature detection using segmentation and classification
Resources – Hardware and Software	PC Image processing software GIS with image classification module (e.g. ARCGIS Image Analyst)	PC Image processing software with radar image analysis capabilities, including sub-pixel mapping techniques.
Resource – Personnel	Trained in image classification Experience with high spatial resolution data Knowledge of area to be mapped	Trained in radar data processing. Knowledge of area to be mapped
References: Note these are some example references	Wettle et al (2009) Hesse and Schmullius (2009)	Brekke and Solberg (2005) Ferraro et al (2010)

References

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Table 17 Mangrove (% cover)

	DATA OPTION 1: Landsat ETM or SPOT XS	DATA OPTION 2: Radarsat, TerrsarX or ALOS Palsar	DATA OPTION 3: Quickbird 2
Spatial Dimensions			
Area to cover	185 km x 185 km per scene	Up to 3600 km ^{2}	12 km x 12 km per scene
Mapping unit	15 m panchromatic 30 m multi-spectral	5 m -60 m	068m panchromatic 4.0 m multi-spectral
Positional accuracy	Depends on level of Geo-referencing	Dependent on Geo-referencing process	Dependent on georef-erencing process
Temporal Dimensions			
When	Approx 9.45 am	Approx 11 am	Approx 10.45 am
How often	every 16 days	Minimum every 4 days	Minimum every 4 days
Variable to map	Mangrove cover (horizontal foliage projected cover)	Mangrove cover (horizontal foliage projected cover	Mangrove cover (horizontal foliage projected cover
Environmental / Sensor Restrictions	Cloud cover Mangrove fringe can be narrow, smaller then pixel size	Mangrove fringe can be narrow, smaller then pixel size Standing water on leaves of mangroves	. Cloud cover Mangrove fringe can be narrow, smaller then pixel size
Processing technique **(Output)**	Image classification or feature detection (Vegetation type map and target features) Note: The ability to map specific targets will depend on their growth form and extent.	Image classification or feature detection (Vegetation type map and target features) Note: The ability to map specific targets will depend on their growth form and extent.	Image classification or feature detection (Vegetation type map and target features) Note: The ability to map specific targets will depend on their growth form and extent.
Resources – Hardware and Software	PC Image processing software GIS with image classification module (e.g. ARCGIS Image Analyst)	PC Image processing software with radar image analysis capabilities, including sub-pixel mapping techniques.	PC Image processing software GIS with image classification module (e.g. ARCGIS Image Analyst)
Resource – Personnel	Trained in image classification Experience with	Trained in radar data processing. Knowledge of area to be	Trained in image classification Experience with high

	Landsat data Knowledge of area to be mapped	mapped	spatial resolution data Knowledge of area to be mapped
References: Note these are some example references	Liu et al (2008) Jensen (1991) Green et al (1998)	Lucas et al (2007) Simard et al (2006)	Held et al. (2003) - CASI Wang et al. (2004)

References

Liu, K., Li, X., Shi, X., and Wang, S., 2008: Monitoring mangrove forest changes using remote sensing and GIS data with decision-tree learning. *Wetlands,* 28: 336-346.

Jensen, J. R., H. Lin, Y. Yang, E. Ramsey, B. A. Davis, and C. W. Thoemke. 1991. The measurement of mangrove characteristics in Southwest Florida using SPOT multispectral data. Geocarto International 2:13–21.

Green, E., C. Clark, P. Mumby, A. Edwards, and A. Ellis, 1998: Remote sensing techniques for mangrove mapping. *International journal of remote sensing*, **19,** 935-956.

Lucas, R., A. Mitchell, A. Rosenqvist, C. Proisy, A. Melius, and C. Ticehurst, 2007: The potential of L-band SAR for quantifying mangrove characteristics and change: case studies from the tropics. *Aquatic conservation: marine and freshwater ecosystems*, 17, 245-264.

Simard, M., K. Zhang, V. Rivera-Monroy, M. Ross, P. Ruiz, E. Castaneda-Moya, R. Twilley, and E. Rodriguez, 2006: Mapping height and biomass of mangrove forests in Everglades National Park with SRTM elevation data. *Photogrammetric engineering and remote sensing*, 72, 299-311.

Held, A., C. Ticehurst, L. Lymburner, and N. Williams, 2003: High resolution mapping of tropical mangrove ecosystems using hyperspectral and radar remote sensing. *International Journal of Remote Sensing*, 24, 2739-2759.

Wang, L., W. Sousa, P. Gong, and G. Biging, 2004: Comparison of IKONOS and QuickBird images for mapping mangrove species on the Caribbean coast of Panama. *Remote Sensing of Environment*, 91, 432-440.

Table 18 Mangroves (Extent)

	DATA OPTION 1: Landsat ETM	**DATA OPTION 2: Airborne hyper-spectral data**	**DATA OPTION 3: Quickbird 2**
Spatial Dimensions			
Area to cover	185 km x 185 km per scene	Up to 1000 km ^{2}	12 km x 12 km per scene
Mapping unit	15 m panchromatic 30 m multi-spectral	0.5m – 5m	068m panchromatic 4.0 m multi-spectral
Positional accuracy	Depends on level of Geo-referencing	Dependent on Geo-referencing process	Dependent on georef-erencing process
Temporal Dimensions			
When	Approx 9.45 am	User defined	Approx 10.45 am
How often	every 16 days	User defined (can be < 1 day)	Minimum every 4 days
Variable to map	Mangrove (species, cover, biomass)	Mangrove (species, cover, biomass)	Mangrove cover
Environmental / Sensor Restrictions	Cloud cover Mangrove fringe can be narrow, smaller then pixel size	Strong winds, Cloud cover	Cloud cover Mangrove fringe can be narrow, smaller then pixel size
Processing technique **(Output)**	Image classification or feature detection (Vegetation type map and target features) Note: The ability to map specific targets will depend on their growth form and extent.	Image classification or feature detection (Vegetation type map and target features) Note: The ability to map specific targets will depend on their growth form and extent.	Image classification or feature detection (Vegetation type map and target features) Note: The ability to map specific targets will depend on their growth form and extent.
Resources – Hardware and Software	PC Image processing software GIS with image classification module (e.g. ARCGIS Image Analyst)	PC Image processing software with Hyper-spectral analysis capabilities, including sub-pixel mapping techniques.	PC Image processing software GIS with image classification module (e.g. ARCGIS Image Analyst)
Resource – Personnel	Trained in image classification Experience with Landsat data Knowledge of area to be mapped	Trained in hyper-spectral data processing. Knowledge of area to be mapped	Trained in image classification Experience with high spatial resolution data Knowledge of area to be mapped
References:	Liu et al (2008)	Lucas et al (2007)	Held et al (2003)

Note these are some example references	Jensen (1991) Green et al (1998)	Simard et al (2006)	Wang et al (2004)

Liu, K., Li, X., Shi, X., and Wang, S., 2008: Monitoring mangrove forest changes using remote sensing and GIS data with decision-tree learning. *Wetlands,* 28: 336-346.

Jensen, J. R., H. Lin, Y. Yang, E. Ramsey, B. A. Davis, and C. W. Thoemke. 1991. The measurement of mangrove characteristics in Southwest Florida using SPOT multispectral data. Geocarto International 2:13–21.

Green, E., C. Clark, P. Mumby, A. Edwards, and A. Ellis, 1998: Remote sensing techniques for mangrove mapping. *International journal of remote sensing*, **19,** 935-956.

Lucas, R., A. Mitchell, A. Rosenqvist, C. Proisy, A. Melius, and C. Ticehurst, 2007: The potential of L-band SAR for quantifying mangrove characteristics and change: case studies from the tropics. *Aquatic conservation: marine and freshwater ecosystems*, 17, 245-264.

Simard, M., K. Zhang, V. Rivera-Monroy, M. Ross, P. Ruiz, E. Castaneda-Moya, R. Twilley, and E. Rodriguez, 2006: Mapping height and biomass of mangrove forests in Everglades National Park with SRTM elevation data. *Photogrammetric engineering and remote sensing*, 72, 299-311.

Held, A., C. Ticehurst, L. Lymburner, and N. Williams, 2003: High resolution mapping of tropical mangrove ecosystems using hyperspectral and radar remote sensing. *International Journal of Remote Sensing*, 24, 2739-2759.

Wang, L., W. Sousa, P. Gong, and G. Biging, 2004: Comparison of IKONOS and QuickBird images for mapping mangrove species on the Caribbean coast of Panama. *Remote Sensing of Environment*, 91, 432-440.

Table 19 Mangroves (Species)

	DATA OPTION 1: Landsat ETM	DATA OPTION 2: Airborne hyper-spectral data	DATA OPTION 3: Quickbird 2
Spatial Dimensions			
Area to cover	185 km x 185 km per scene	Up to 1000 km ^{2}	12 km x 12 km per scene
Mapping unit	15 m panchromatic 30 m multi-spectral	0.5m – 5m	068m panchromatic 4.0 m multi-spectral
Positional accuracy	Depends on level of Geo-referencing	Dependent on Geo-referencing process	Dependent on georef-erencing process
Temporal Dimensions			
When	Approx 9.45 am	User defined	Approx 10.45 am
How often	every 16 days	User defined (can be < 1 day)	Minimum every 4 days
Variable to map	Mangrove (species, cover, biomass)	Mangrove (species, cover, biomass)	Mangrove cover
Environmental / Sensor Restrictions	Cloud cover Mangrove fringe can be narrow, smaller then pixel size	Strong winds, Cloud cover	Cloud cover Mangrove fringe can be narrow, smaller then pixel size
Processing technique **(Output)**	Image classification or feature detection (Vegetation type map and target features) Note: The ability to map specific targets will depend on their growth form and extent.	Image classification or feature detection (Vegetation type map and target features) Note: The ability to map specific targets will depend on their growth form and extent.	Image classification or feature detection (Vegetation type map and target features) Note: The ability to map specific targets will depend on their growth form and extent.
Resources – Hardware and Software	PC Image processing software GIS with image classification module (e.g. ARCGIS Image Analyst)	PC Image processing software with Hyper-spectral analysis capabilities, including sub-pixel mapping techniques.	PC Image processing software GIS with image classification module (e.g. ARCGIS Image Analyst)
Resource – Personnel	Trained in image classification Experience with Landsat data Knowledge of area to	Trained in hyper-spectral data processing. Knowledge of area to be mapped	Trained in image classification Experience with high spatial resolution data Knowledge of area to be

	be mapped		mapped
References: Note these are some example references	Green et al (1998)	Lucas et al (2007) Held et al (2003)	Wang et al (2004) Kovacs et al (2005)

Green, E., C. Clark, P. Mumby, A. Edwards, and A. Ellis, 1998: Remote sensing techniques for mangrove mapping. *International journal of remote sensing*, **19,** 935-956.

Lucas, R., A. Mitchell, A. Rosenqvist, C. Proisy, A. Melius, and C. Ticehurst, 2007: The potential of L-band SAR for quantifying mangrove characteristics and change: case studies from the tropics. *Aquatic conservation: marine and freshwater ecosystems*, 17, 245-264.

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Held, A., C. Ticehurst, L. Lymburner, and N. Williams, 2003: High resolution mapping of tropical mangrove ecosystems using hyperspectral and radar remote sensing. *International Journal of Remote Sensing*, 24, 2739-2759.

Table 20 Mangroves (Biomass)

	DATA OPTION 1: Radarsat, TerrsarX or ALOS Palsar
Spatial Dimensions	
Area to cover	Up to 3600 km ^{2}
Mapping unit	5m -60mm
Positional accuracy	Dependent on Geo-referencing process
Temporal Dimensions	
When	Approx 11 am
How often	Minimum every 4 days
Variable to map	Mangrove cover (horizontal foliage projected cover
Environmental / Sensor Restrictions	Mangrove fringe can be narrow, smaller then pixel size Standing water on leaves of mangroves
Processing technique **(Output)**	Image classification or feature detection (Vegetation type map and target features) Note: The ability to map specific targets will depend on their growth form and extent.
Resources – Hardware and Software	PC Image processing software with radar image analysis capabilities, including sub-pixel mapping techniques.
Resource – Personnel	Trained in radar data processing. Knowledge of area to be mapped
References:	

Note these are some example references	Lucas et al (2007) Simard et al (2006) Held et al (2003)

Simard, M., K. Zhang, V. Rivera-Monroy, M. Ross, P. Ruiz, E. Castaneda-Moya, R. Twilley, and E. Rodriguez, 2006: Mapping height and biomass of mangrove forests in Everglades National Park with SRTM elevation data. *Photogrammetric engineering and remote sensing*, 72, 299-311.

Lucas, R., A. Mitchell, A. Rosenqvist, C. Proisy, A. Melius, and C. Ticehurst, 2007: The potential of L-band SAR for quantifying mangrove characteristics and change: case studies from the tropics. *Aquatic conservation: marine and freshwater ecosystems*, 17, 245-264.

Held, A., C. Ticehurst, L. Lymburner, and N. Williams, 2003: High resolution mapping of tropical mangrove ecosystems using hyperspectral and radar remote sensing. *International Journal of Remote Sensing*, 24, 2739-2759.

Table 21 Saltmarsh (% Cover)

	DATA OPTION 1: Landsat ETM	**DATA OPTION 2: Quickbird 2**
Spatial Dimensions		
Area to cover	185 km x 185 km per scene	12 km x 12 km per scene
Mapping unit	15 m panchromatic 30 m multi-spectral	068m panchromatic 4.0 m multi-spectral
Positional accuracy	Depends on level of Geo-referencing	Dependent on georef-erencing process
Temporal Dimensions		
When	Approx 9.45 am	Approx 10.45 am
How often	every 16 days	Minimum every 4 days
Variable to map	Saltmarsh cover.	Saltmarsh cover
Environmental / Sensor Restrictions	Cloud cover Saltmarsh fringe can be narrow, smaller then pixel size Standing water levels	Cloud cover Saltmarsh fringe can be narrow, smaller then pixel size Standing water levels
Processing technique **(Output)**	Image classification or feature detection (Vegetation type map and target features) Note: The ability to map specific targets will depend on their growth form and extent.	Image classification or feature detection (Vegetation type map and target features) Note: The ability to map specific targets will depend on their growth form and extent.
Resources – Hardware and Software	PC Image processing software GIS with image classification module (e.g. ARCGIS Image Analyst)	PC Image processing software GIS with image classification module (e.g. ARCGIS Image Analyst)
Resource – Personnel	Trained in image classification Experience with Landsat data Knowledge of area to be mapped	Trained in image classification Experience with high spatial resolution data Knowledge of area to be mapped
References: Note these are some	Jano et al (1998) Zhang et al (1997)	Belluco et al (2006)Gilmore et al (2008)

example references	Jefferies et al. (2006)	

Jano, A., Jefferies, R., and Rockwell, R., 1998: The detection of vegetational change by multitemporal analysis of LANDSAT data: the effects of goose foraging. *Journal of Ecology*: 93-99.

Zhang, M., Ustin, S., Rejmankova, E., and Sanderson, E., 1997: Monitoring Pacific coast salt marshes using remote sensing. *Ecological Applications,* 7: 1039-1053.

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Gilmore, M. S., Wilson, E. H., Barrett, N., Civco, D. L., Prisloe, S., Hurd, J. D., and Chadwick, C., 2008: Integrating multi-temporal spectral and structural information to map wetland vegetation in a lower Connecticut River tidal marsh. *Remote Sensing of Environment,* 112: 4048-4060.

Jefferies, R., Jano, A., and Abraham, K., 2006: A biotic agent promotes large-scale catastrophic change in the coastal marshes of Hudson Bay. *Ecology,* 94: 234-242.

Table 22 Saltmarsh (Species)

	DATA OPTION 1: Landsat ETM	**DATA OPTION 2: Quickbird 2**
Spatial Dimensions		
Area to cover	185 km x 185 km per scene	12 km x 12 km per scene
Mapping unit	15 m panchromatic 30 m multi-spectral	068m panchromatic 4.0 m multi-spectral
Positional accuracy	Depends on level of Geo-referencing	Dependent on georef-erencing process
Temporal Dimensions		
When	Approx 9.45 am	Approx 10.45 am
How often	every 16 days	Minimum every 4 days
Variable to map	Saltmarsh (extent, species composition and above-ground biomass)	Saltmarsh (extent, species composition and above-ground biomass)
Environmental / Sensor Restrictions	Cloud cover Saltmarsh fringe can be narrow, smaller then pixel size Standing water	Cloud cover Saltmarsh fringe can be narrow, smaller then pixel size. Standing water
Processing technique **(Output)**	Image classification or feature detection (Vegetation type map and target features) Note: The ability to map specific targets will depend on their growth form and extent.	Image classification or feature detection (Vegetation type map and target features) Note: The ability to map specific targets will depend on their growth form and extent.
Resources – Hardware and Software	PC Image processing software GIS with image classification module (e.g. ARCGIS Image Analyst)	PC Image processing software GIS with image classification module (e.g. ARCGIS Image Analyst)
Resource – Personnel	Trained in image classification Experience with Landsat data Knowledge of area to be mapped	Trained in image classification Experience with high spatial resolution data Knowledge of area to be mapped
References:	Bartlett and Klemas	Gilmore et al (2008)

Note these are some example references	(1980) Zhang et al. (2008)	Belluco et al (2008) Silvestri et al (2008)

Gilmore, M. S., Wilson, E. H., Barrett, N., Civco, D. L., Prisloe, S., Hurd, J. D., and Chadwick, C., 2008: Integrating multi-temporal spectral and structural information to map wetland vegetation in a lower Connecticut River tidal marsh. *Remote Sensing of Environment,* 112: 4048-4060.

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Silvestri, S., Marani, M., and Marani, A., 2003: Hyperspectral remote sensing of salt marsh vegetation, morphology and soil topography. *Physics and Chemistry of the Earth, Parts A/B/C,* 28: 15-25.

Bartlett, D. and Klemas, V., 1980: Quantitative assessment of tidal wetlands using remote sensing. *Environmental Management,* 4: 337-345.

Zhang, L., Gao, Z., Armitage, R., and Kent, M., 2008: Spectral characteristics of plant communities from salt marshes: A case study from Chongming Dongtan, Yangtze estuary, China. *Frontiers of Environmental Science & Engineering in China,* 2: 187-197.

Table 23 Saltmarsh (Biomass)

	DATA OPTION 1: Radarsat, TerrsarX or ALOS Palsar	**DATA OPTION 2: Quickbird 2**
Spatial Dimensions		
Area to cover	Up to 3600 km ^{2}	12 km x 12 km per scene
Mapping unit	5m -60mm	068m panchromatic 4.0 m multi-spectral
Positional accuracy	Dependent on Geo-referencing process	Dependent on georef-erencing process
Temporal Dimensions		
When	Approx 11 am	Approx 10.45 am
How often	Minimum every 4 days	Minimum every 4 days
Variable to map	Saltmarsh (above-ground biomass)	Saltmarsh (above-ground biomass)
Environmental / Sensor Restrictions	Saltmarsh fringe can be narrow, smaller then pixel size Standing water on leaves of Saltmarsh	Cloud cover Saltmarsh fringe can be narrow, smaller then pixel size. Standing water
Processing technique **(Output)**	Image classification or feature detection (Vegetation type map and target features) Note: The ability to map specific targets will depend on their growth form and extent.	Image classification or feature detection (Vegetation type map and target features) Note: The ability to map specific targets will depend on their growth form and extent.
Resources – Hardware and Software	PC Image processing software with radar image analysis capabilities, including sub-pixel mapping techniques.	PC Image processing software GIS with image classification module (e.g. ARCGIS Image Analyst)
Resource – Personnel	Trained in radar data processing. Knowledge of area to be mapped	Trained in image classification Experience with high spatial resolution data Knowledge of area to be

		mapped
References: Note these are some example references	Refer to Lucas, Simard, Wang etc papers for SAR Kasischke et al (1997)	Belluco et al (2006)

Belluco, E., Camuffo, M., Ferrari, S., Modenese, L., Silvestri, S., Marani, A., and Marani, M., 2006: Mapping salt-marsh vegetation by multispectral and hyperspectral remote sensing. *Remote Sensing of Environment,* 105: 54-67.

Kasischke, E. and L. Bourgeau-Chavez, 1997: Monitoring South Florida wetlands using ERS-1 SAR imagery. *Photogrammetric engineering and remote sensing*, **63,** 281-291.

Table 24 Mean High and Low Water Lines

	DATA OPTION 1: Satellite Multi-spectral	DATA OPTION 2: Satellite Imaging Radar	DATA OPTION 3: Airborne Laser Altimetry
Spatial Dimensions			
Area to cover	12 km x 12 km per scene	Up to 1000 km ^{2}	User defined
Mapping unit	068m panchromatic 4.0 m multi-spectral	0.5m – 5m	0.5 m – 2.5 m
Positional accuracy	Dependent on georef-erencing process	Dependent on Geo-referencing process	Sub metre vertical and horizontal
Temporal Dimensions			
When	Approx 10.45 am	User defined	User defined
How often	Minimum every 4 days	User defined (can be < 1 day)	User defined (can be < 1 day)
Variable to map	Water body – dry land	Water body – dry land	Water body – dry land
Environmental / Sensor Restrictions	Clouds		Clouds
Processing technique **(Output)**			
Resources – Hardware and Software	PC Image processing software	PC Image processing software with radar analysis capabilities,	PC Image processing software
Resource – Personnel	Trained in image classification Experience with high spatial resolution data Knowledge of area to be mapped	Trained in radar data processing.	Trained in lidar data processing.
References: Note these are some example references	Hiroya and SLATS Gorman et al (2008)	No Reference found	Mason et al (2000) Moore et al (2006)

References

Gorman, L., A. Morang, and R. Larson, 1998: Monitoring the coastal environment; part IV: mapping, shoreline changes, and bathymetric analysis. *Journal of Coastal Research*, 14, 61-92.

Mason, D., C. Gurney, and M. Kennett, 2000: Beach topography mapping—a comparsion of techniques. *Journal of Coastal Conservation*, 6, 113-124.

Moore, L., P. Ruggiero, and J. List, 2006: Comparing Mean High Water and High Water Line Shorelines: Should Proxy-Datum Offsets be Incorporated into Shoreline Change Analysis? *Journal of Coastal Research*, 22, 894-905.

Table 25 Bathymetry

	DATA OPTION 1: Airborne Laser Scanning	**DATA OPTION 2: QuickBird (or other satellite multi-spectral)**
Spatial Dimensions		
Area to cover	Can be up to 1000 km^2	12 km x 12 km per scene
Mapping unit	0.5m to 10m – depends on sample intensity	068m panchromatic 4.0 m multi-spectral
Positional accuracy	????	Dependent on georef-erencing process
Temporal Dimensions		
When	User controlled	Approx 10.45 am
How often	User controlled	Minimum every 4 days
Variable to map	Sea surface and seafloor height	Sea surface and seafloor height
Environmental / Sensor Restrictions	Not possible for turbid water Clouds, strong winds and breaking waves.	Not possible for turbid water Clouds, strong winds and breaking waves
Processing technique	Ocean surface and seafloor return extraction, interpolation and ground and canopy mapping.	Inversion of radiative transfer model to estimate depth. Or Empirical estimate of depth using Beer's Law
(Output)	Raster or image surface with each pixel containing an absolute elevation.	
Resources – Hardware and Software	PC Image processing software GIS with image analysis capabilities.	PC Image processing software GIS with image classification module (e.g. ARCGIS Image Analyst)
Resource – Personnel	Trained and with experience in ALS mapping. Knowledge of area	Trained in image classification Experience with high spatial resolution data

	to be mapped	Knowledge of area to be mapped
References: Note these are some example references	Gao (2009)	Lyzenga (1978) Stumpf et al (2003)

References

Gao, J., 2009: Bathymetric mapping by means of remote sensing: methods, accuracy and limitations. *Progress in Physical Geography*, **33,** 103.

Lyzenga, D., 1978: Passive remote sensing techniques for mapping water depth and bottom features. *Applied Optics*, **17,** 379-383.

Stumpf, R., K. Holderied, and M. Sinclair, 2003: Determination of water depth with high-resolution satellite imagery over variable bottom types. *Limnology and Oceanography*, **48,** 547-556.

Table 26 Bathymetric Roughness - Rugosity

	DATA OPTION 1: Airborne Laser Scanning	**DATA OPTION 2: QuickBird (or other satellite multi-spectral)**
Spatial Dimensions		
Area to cover	Can be up to 1000 km ^{2}	12 km x 12 km per scene
Mapping unit	0.5m to 10m – depends on sample intensity	068m panchromatic 4.0 m multi-spectral
Positional accuracy	????	Dependent on georef-erencing process
Temporal Dimensions		
When	User controlled	Approx 10.45 am
How often	User controlled	Minimum every 4 days
Variable to map	Bathymetric Roughness - Rugosity	Bathymetric Roughness - Rugosity
Environmental / Sensor Restrictions	Not possible for turbid water Clouds, strong winds and breaking waves	Not possible for turbid water Clouds, strong winds and breaking waves
Processing technique **(Output)**	Ocean surface and seafloor return extraction, interpolation and ground and canopy mapping. Raster or image surface with each pixel containing an absolute elevation.	Inversion of radiative transfer model to estimate depth. Or Empirical estimate of depth using Beer's Law
Resources – Hardware and Software	PC Image processing software GIS with image analysis capabilities.	PC Image processing software GIS with image classification module (e.g. ARCGIS Image Analyst)
Resource – Personnel	Trained and with experience in ALS mapping. Knowledge of area to be mapped	Trained in image classification Experience with high spatial resolution data Knowledge of area to be mapped
References: Note these are some example references	Zawada et al. (2009) Wedding et al (2009)	Hogrefe et al. (2008)

References

Zawada, D. and J. Brock, 2009: A Multiscale Analysis of Coral Reef Topographic Complexity Using Lidar-Derived Bathymetry.

Wedding, L., A. Friedlander, M. McGranaghan, R. Yost, and M. Monaco, 2008: Using bathymetric lidar to define nearshore benthic habitat complexity: Implications for management of reef fish assemblages in Hawaii. *Remote Sensing of Environment*, 112, 4159-4165.

Hogrefe, K., D. Wright, and E. Hochberg, 2008: Derivation and Integration of Shallow-Water Bathymetry: Implications for Coastal Terrain Modeling and Subsequent Analyses. *Marine Geodesy*, 31, 299-317.

Table 27 Water Quality Parameters – Cyano bacterial bloom (other then Lyngbya)

ALGAL BLOOMS	DATA OPTION 1: Landsat ETM	DATA OPTION 2: MODIS/MERIS
Spatial Dimensions		
Area to cover	185 km x 185 km per scene	Swath width 572 km
Mapping unit	15 m panchromatic 30 m multi-spectral	300 m
Positional accuracy	Dependent on Geo-referencing process	Dependent on Geo-referencing process
Temporal Dimensions		
When	Approx 9.45 am	1030 hrs
How often	every 16 days	Every 3 days
Variable to map	Surface Algal boom presence and thickness.	Algal boom presence and thickness.
Environmental / Sensor Restrictions	Clouds, strong winds, breaking waves	Clouds, strong winds, breaking waves
Processing technique **(Output)**	Image classification or feature detection	Image classification, empirical or analytical
Resources – Hardware and Software	PC Image processing software GIS with image classification module (e.g. ARCGIS Image Analyst)	PC Image processing software with Hyper-spectral analysis capabilities, including sub-pixel mapping techniques.
Resource – Personnel	Trained in image classification Experience with Landsat data Knowledge of area to be mapped	Trained in hyper-spectral data processing. Knowledge of area to be mapped
References: Note these are some example references	Kutser et al (2006)	Dekker et al CRC report Kutser et al (2006)

References

Kutser, T., L. Metsamaa, N. Strömbeck, and E. Vahtmäe, 2006: Monitoring cyanobacterial blooms by satellite remote sensing. *Estuarine, Coastal and Shelf Science*, 67, 303-312.

Table 28 Water Quality - Suspended Sediment Concentration

	DATA OPTION 1: MERIS	**DATA OPTION 2: Landsat ETM**
Spatial Dimensions		
Area to cover	Swath width 572 km	185 km x 185 km per scene
Mapping unit	300 m	15 m panchromatic 30 m multi-spectral
Positional accuracy	Dependent on Geo-referencing process	Depends on level of Geo-referencing
Temporal Dimensions		
When	1030 hrs	Approx 09:45 am
How often	Every 3 days	every 16 days
Variable to map	Suspended sediment concentrations	Suspended sediment concentrations
Environmental / Sensor Restrictions	Optically shallow areas	Optically shallow water
Processing technique **(Output)**	Image based deterministic (inversion of radiative transfer model). (Map showing suspended sediment concentration in mg/m^3 in each pixel)	Image modelling using empirical or process radiative transfer models.
Resources – Hardware and Software	PC Image processing software with Hyper-spectral analysis capabilities, including sub-pixel mapping techniques.	PC Image processing software GIS with image classification module (e.g. ARCGIS Image Analyst)
Resource – Personnel	Trained in hyper-spectral data processing. Knowledge of area to be mapped	Trained in image modelling Experience with Landsat data Knowledge of area to be mapped
References: Note these are some example references	Dekker et al CRC report	Dekker et al CRC report

Table 29 Water Quality – Coloured Dissolved Organic Matter (CDOM) Concentration

	DATA OPTION 1: MERIS	**DATA OPTION 2: Lansat ETM**
Spatial Dimensions		
Area to cover	Swath width 572 km	185 km x 185 km per scene
Mapping unit	300 m	15 m panchromatic 30 m multi-spectral
Positional accuracy	Dependent on Geo-referencing process	Depends on level of Geo-referencing
Temporal Dimensions		
When	1030 hrs	Approx 09:45 am
How often	Every 3 days	Every 16 days
Variable to map	Coloured Dissolved Organic Matter concentrations	Coloured Dissolved Organic Matter concentrations
Environmental / Sensor Restrictions	Optically shallow areas Clouds, strong winds, breaking waves	Optically shallow water bodies Clouds, strong winds, breaking waves
Processing technique **(Output)**	Image based deterministic (inversion of radiative transfer model). (Map showing CDOM concentration in each pixel)	Image modelling using empirical or process radiative transfer models.
Resources – Hardware and Software	PC Image processing software with Hyper-spectral analysis capabilities, including sub-pixel mapping techniques.	PC Image processing software GIS with image classification module (e.g. ARCGIS Image Analyst)
Resource – Personnel	Trained in hyper-spectral data processing. Knowledge of area to be mapped	Trained in image modellling Experience with Landsat data Knowledge of area to be mapped
References: Note these are some example references	Dekker et al CRC report	Dekker et al CRC report

Table 30 Water Quality – Chlorophyll concentration (Suspended Organic Matter Concentration)

	DATA OPTION 1: MERIS	**DATA OPTION 3: Landsat ETM**
Spatial Dimensions		
Area to cover	Swath width 572 km	185 km x 185 km per scene
Mapping unit	300 m	15 m panchromatic 30 m multi-spectral
Positional accuracy	Dependent on Geo-referencing process	Dependent on Geo-referencing process
Temporal Dimensions		
When	1030 hrs	Approx 9.45 am
How often	3 days	every 16 days
Variable to map	Chlorophyll A concentrations	Chlorophyll A concentrations
Environmental / Sensor Restrictions	Optically shallow areas Clouds, strong winds and breaking waves.	Optically shallow areas Clouds, strong winds and breaking waves. Unable to detect low levels of chlorophyll concentration
Processing technique **(Output)**	Image based deterministic (inversion of radiative transfer model). (Map showing Chl a concentration in mg/m^3 in each pixel)	Image based deterministic (inversion of radiative transfer model). (Map showing Chl a concentration in mg/m^3 in each pixel)
Resources – Hardware and Software	PC Image processing software with Hyper-spectral analysis capabilities, including sub-pixel mapping techniques.	PC Image processing software GIS with image classification module (e.g. ARCGIS Image Analyst)
Resource – Personnel	Trained in hyper-spectral data processing. Knowledge of area to be mapped	Trained in image classification Experience with Landsat data Knowledge of area to be mapped
References:	Gons et al (2002)	Ekstrand (1992)

Note these are some example references		

References

Gons, H., M. Rijkeboer, and K. Ruddick, 2002: A chlorophyll-retrieval algorithm for satellite imagery (Medium Resolution Imaging Spectrometer) of inland and coastal waters. *Journal of Plankton Research*, **24,** 947.

Ekstrand, S., 1992: Landsat TM based quantification of chlorophyll-a during algae blooms in coastal waters. *International journal of remote sensing*, **13,** 1913-1926.

Table 31 Hydro- optical Properties - Attenuation Coefficients

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	DATA OPTION 1: MERIS	**DATA OPTION 2: Landsat ETM**
Spatial Dimensions		
Area to cover	Swath width 572 km	185 km x 185 km per scene
Mapping unit	300 m	15 m panchromatic 30 m multi-spectral
Positional accuracy	Dependent on Geo-referencing process	Depends on level of Geo-referencing
Temporal Dimensions		
When	1030 hrs	Approx 09:45 am
How often	Every 3 days	Every 16 days
Variable to map	Attenuation includes: direct, diffuse and total.	Attenuation includes: direct, diffuse and total.
Environmental / Sensor Restrictions	Optically shallow areas Clouds, strong winds and breaking waves.	Optically shallow areas Clouds, strong winds and breaking waves.
Processing technique **(Output)**	Image based deterministic (inversion of radiative transfer model).	Image based deterministic (inversion of radiative transfer model).
Resources – Hardware and Software	PC Image processing software with Hyper-spectral analysis capabilities, including sub-pixel mapping techniques.	PC Image processing software GIS with image classification module (e.g. ARCGIS Image Analyst)
Resource – Personnel	Trained in hyper-spectral data processing. Knowledge of area to be mapped	Trained in image modellling Experience with Landsat data Knowledge of area to be mapped
References: Note these are some example references	Kratzer et al (2008)	Palandro et al (2004)

References

Kratzer, S., Brockmann, C., and Moore, G., 2008: Using MERIS full resolution data to monitor coastal waters—A case study from Himmerfjärden, a fjord-like bay in the northwestern Baltic Sea. *Remote Sensing of Environment,* 112: 2284-2300.

Palandro, D., Hu, C., Andrefouet, S., and Muller-Karger, F., 2004: Synoptic water clarity assessment in the Florida Keys using diffuse attenuation coefficient estimated from Landsat imagery. *Hydrobiologia,* 530: 489-493.

Table 32 Hydro-optical Properties - Euphotic Depth

	DATA OPTION 1: MERIS	**DATA OPTION 2: Lansat ETM**
Spatial Dimensions		
Area to cover	Swath width 572 km	185 km x 185 km per scene
Mapping unit	300 m	15 m panchromatic 30 m multi-spectral
Positional accuracy	Dependent on Geo-referencing process	Depends on level of Geo-referencing
Temporal Dimensions		
When	1030 hrs	Approx 09:45 am
How often	Every 3 days	Every 16 days
Variable to map	Euphotic Depth	Euphotic Depth
Environmental / Sensor Restrictions	Optically shallow areas Clouds, strong winds and breaking waves.	Optically shallow areas Clouds, strong winds and breaking waves.
Processing technique **(Output)**	Image based deterministic (inversion of radiative transfer model). (Map showing CDOM concentration in each pixel)	Image based deterministic (inversion of radiative transfer model).
Resources – Hardware and Software	PC Image processing software with Hyper-spectral analysis capabilities, including sub-pixel mapping techniques.	PC Image processing software GIS with image classification module (e.g. ARCGIS Image Analyst)
Resource – Personnel	Trained in hyper-spectral data processing. Knowledge of area to be mapped	Trained in image modellling Experience with Landsat data Knowledge of area to be mapped
References: Note these are some example references	Kratzer et al (2003)	Kratzer et al (2003)

References

Kratzer, S., Håkansson, B., and Sahlin, C., 2003: Assessing secchi and photic zone depth in the Baltic Sea from satellite data. *AMBIO: A Journal of the Human Environment,* 32: 577-585.

Table 33 Hydro-optical Properties - Secchi Depth

	DATA OPTION 1: MERIS	**DATA OPTION 2: Lansat ETM**
Spatial Dimensions		
Area to cover	Swath width 572 km	185 km x 185 km per scene
Mapping unit	300 m	15 m panchromatic 30 m multi-spectral
Positional accuracy	Dependent on Geo-referencing process	Depends on level of Geo-referencing
Temporal Dimensions		
When	1030 hrs	Approx 09:45 am
How often	Every 3 days	Every 16 days
Variable to map	Secchi	Secchi
Environmental / Sensor Restrictions	Optically shallow areas Clouds, strong winds and breaking waves.	Optically shallow areas Clouds, strong winds and breaking waves.
Processing technique **(Output)**	Image based deterministic (inversion of radiative transfer model).	Image based deterministic (inversion of radiative transfer model).
Resources – Hardware and Software	PC Image processing software with Hyper-spectral analysis capabilities, including sub-pixel mapping techniques.	PC Image processing software GIS with image classification module (e.g. ARCGIS Image Analyst)
Resource – Personnel	Trained in hyper-spectral data processing. Knowledge of area to be mapped	Trained in image modellling Experience with Landsat data Knowledge of area to be mapped
References: Note these are some example references	Phinn et al CRC Report	Phinn et al CRC Report

Table 34 Sea Surface Temperature

	Data type #1 **NOAA AVHRR**	**Data type #2** **MODIS SST**
Spatial Dimensions		
Area to cover	2400 x 6400 kilometers	2000 km wide segments
Mapping unit	1 km	1 km for level 2 daily product
Positional accuracy	Depends on level of Geo-referencing	Depends on level of Geo-referencing
Temporal Dimensions		
When **How often**	Approx. 1030hrs and 2230hrs Twice daily	Approx. 1030hrs and 2230hrs Twice daily (AQUQ and TERRA)
Variable to map	Sea surface temperature	Sea surface temperature
Environmental / Sensor Restrictions	Clouds, strong winds and breaking waves.	Clouds, strong winds and breaking waves.
Processing technique **(Output)**	Image cover slicing and colour coding Map of SST variation	Image cover slicing and colour coding Map of SST variation
Resources – Hardware and Software	PC Image processing software	PC Image processing software
Resource – Personnel	Trained in image analysis and experience with AVHRR thermal data Knowledge of area to be mapped	Trained in image analysis and experience with MODIS thermal data Knowledge of area to be mapped
References: Note these are some example references	McClain et al (1985) Walton et al (1998)	Brown et al (1999)

References

McClain, E., Pichel, W., and Walton, C., 1985: Comparative performance of AVHRR-based multichannel sea surface temperatures. *Journal of Geophysical Research,* 90: 11.

Walton, C., Pichel, W., Sapper, J., and May, D., 1998: The development and operational application of nonlinear algorithms for the measurement of sea surface temperatures with the NOAA polar-orbiting environmental satellites. *Journal of Geophysical Research,* 103: 27,999-928,012.

Brown, O., Minnett, P., Evans, R., Kearns, E., Kilpatrick, K., Kumar, A., Sikorski, R., and Závody, A., 1999: MODIS Infrared Sea Surface Temperature Algorithm Algorithm Theoretical Basis Document Version 2.0. *University of Miami, NAS5-31361*.

Table 35 Photosynthetically Active Radiation (PAR)

	Data type #2 **MODIS PAR**
Spatial Dimensions	
Area to cover	2000 km wide segments
Mapping unit	1 km for level 2 daily product
Positional accuracy	Depends on level of Geo-referencing
Temporal Dimensions	
When	Approx. 1030hrs and 2230hrs
How often	Twice daily
Variable to map	Photosynthetic Active Radiation (PAR)
Environmental / Sensor Restrictions	Clouds, strong winds and breaking waves.
Processing technique **(Output)**	
Resources – Hardware and Software	PC Image processing software
Resource – Personnel	Trained in image analysis and experience with MODIS thermal data Knowledge of area to be mapped
References: Note these are some example references	Gower et al (2004) Van Laake and Sanchez-Azofeifa (2005)

Gower, J., Brown, L., and Borstad, G., 2004: Observation of chlorophyll fluorescence in west coast waters of Canada using the MODIS satellite sensor: Remote sensing and resource management in nearshore and inland waters. *Canadian journal of remote sensing,* 30: 17-25.
Van Laake, P. E. and Sanchez-Azofeifa, G. A., 2005: Mapping PAR using MODIS atmosphere products. *Remote Sensing of Environment,* 94: 554-563.