Application of aerial photography with visible atmospherically resistant index by using unmanned aerial vehicles for seagrass bed classification in Kung Krabaen Bay, Thailand

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Abstract

The aim of this research was to study seagrass classification by using aerial photography with Visible Atmospherically Resistant Index (VARI) in the Kung Krabaen Bay, Chanthaburi, Thailand, which covers an area of 5.59 km^2 and has an average depth of 2.5 m in the shallow zone. The classification based on VARI resulted in three classes, namely (i) long-leaved species (*E. acoroides*), (ii) short-leaved species (*H. pinifolia* and *H. uninervis*), and (iii) other objects. Results showed that aerial photographs could clearly differentiate seagrass species having different digital number value ranges with the VARI approach. The overall accuracy of visual interpretation (86.36%) was higher than that of supervised classification (46.97%). This technique could be useful for seagrass species mapping in other areas. The results also showed that *H. pinifolia* and *H. uninervis* were distributed on sandy clay and seashell substrates while *E. acoroides* was distributed only on sandy areas.

Introduction

The seagrass bed is a fertile coastal ecosystem with high biodiversity, and is necessary habitat for many marine creatures (*Paibulkichakul, Jansang & Paibulkichakul, 2016*). It is one of the most productive ecosystems, providing shelter and food for animal communities from tiny invertebrates to large fishes, crabs, turtles, marine mammals, and birds. Seagrasses provide many economically valuable services to people as well, such as commercial and recreational fisheries, nature and wildlife tourism (*Duffy, 2006*).

A study of the distribution of seagrass beds in the Gulf of Thailand found the most seagrass along the coastal zone and islands. The total seagrass area is about 55.2 km^2, which includes the provinces of Trat, Chanthaburi, Rayong, Chon Buri, Phetchaburi, Prachuap Khiri Khan, Chumphon, Surat Thani, Nakhon Si Thammarat, Phatthalung, Songkhla, Pattani, and Narathiwat (*Department of Marine and Coastal Resources, 2016*). Reports on the seagrass situation in Thailand show that the current number of seagrass beds have been continuously decreasing (*Waycott et al., 2009*) because of human activities including anchoring, mining, coastal construction (breakwaters or seawalls), fishing (using illegal gear) and toxic waste release. The seagrass degradation affects growth, spawning, and survival of marine animals in coastal marine ecosystems. Seagrass disappearance may increase the impact of currents and trigger coastal erosion in some areas. The growing concern about seagrass loss and degradation has made government agencies, coastal and marine resources conservation networks, and private organizations work together to perform the conservation and restoration of seagrass areas (*Department of Marine and Coastal Resources, 2016*).

Geo-informatic technology refers to the integration of Geographic Information System (GIS), Remote Sensing (RS), and Global Positioning System (GPS). RS technology has rapidly developed in terms of its abilities, such as very high spatial resolution (*Kushwaha, 2008*). Seagrass exploration using RS technology is based on two data sources, namely satellite imagery and aerial photography. Satellite imagery is suitable for study of a wide area that does not need high spatial resolution. On the other hand, aerial photography is appropriate for smaller areas where very high spatial resolution is required (*Mumby et al., 1997*).

Most vegetation indices combine information contained in two spectral bands, the red and near-infrared (NIR). The Normalized Difference Vegetation Index (NDVI) is one of the common techniques that uses the visible and NIR bands to analyze remote sensing images and assess live green vegetation (*Lebourgeois et al., 2008*). A limitation of NDVI indices is that this technique can't be used to classify objects under water, because NIR light is able to penetrate only a small distance into the water (*Adi, 2015*).

The Visible Atmospherically Resistant Index (VARI) was developed for the regional estimation of crop conditions. The VARI was more sensitive to the vegetation fraction due to the introduction of blue reflectance (*Gitelson et al., 2002a*). This is the reason why VARI technique is more suitable for seagrass classification than NDVI technique. Furthermore, it is suitable with the consumer-grade cameras used on Unmanned Aerial Vehicles.

The objective of this study is to apply the aerial photographs taken by an Unmanned Aerial Vehicle (UAV) for seagrass classification by using VARI. The results of seagrass species classification based on VARI will be used to assess seagrass species bed area. This research is useful for planning and management for seagrass conservation.

Materials and methods

The process of analyzing seagrass classification and status consisted of five steps as shown in Fig.1, namely; (i) aerial photography by using UAV (DJI Mavic Pro) with autonomous flight application on mobile device; (ii) image mosaicking; (iii) data pre-processing, including geometric correction; (iv) detection and classification of seagrass distribution; (v) accuracy assessment by using ground-truth data.

Aerial Photography

Aerial photographs were taken at 10:00 – 15:00 on 4 July 2017 by using DJI Mavic Pro (UAV) with DroneDeploy application software in a free explorer plan which offers unlimited flight, 500 photos/map, and 5 cm/pixel 2D resolution (*DroneDeploy, 2018*). The UAV flies to take each photograph in each flight line or strip so it overlaps the adjacent photographs. The amount of frontlap on each photograph is about 75% and sidelap on each photograph is about 65%. The aerial photos were taken at an altitude of about 500 meters above mean sea level. Four flights were made covering an area of about 7.02 km^2, and a total of 139 images were taken (Fig. 2). The resolution of a mosaicked image was 16.6 cm/pixel and the root-mean-square error (RMSE) was 5.4 meters. The aerial photographs were geometrically corrected by using 1^{st} order polynomial transformation with RMSE of 1.67 meters to maintain the intensity of the pixels.

VARI algorithm

The aerial photograph uses the red, green, and blue channels to make a natural color composite image. The colors are used to calculate VARI scores for the pixel ranging between -1 and +1, based on the following equation:

$$\text{VARI} = (R_{green} - R_{red})/(R_{green} + R_{red} - R_{blue}),$$

where R_x is the reflectance of the canopy for color x. The resulting VARI image is presented in Fig. 3.

Image classification

The processes of image classification applied in this study were supervised classification and visual interpretation. Visual interpretation is a complex process, involving the meaning of the image content in order to classify spatial and landscape patterns (*Albertz, 2007*). Supervised classification based on the maximum likelihood decision rule, depended on the researcher who defined the spectral characteristics of the classes from selected training areas (*Sagawa et al., 2010*) in the VARI image, as shown in Fig. 4. Comparison of VARI images from the selected study areas were compared with the true color images by seagrass leaf type (short-leaved or long-leaved).

Accuracy assessment

Accuracy assessment is a general term for comparing the classified image to reference sites that are considered to be accurate based on ground-truth data. Forty-three sampling points were selected on random raster elements in the classified image and the reference site (Fig. 5). The sampling point and reference data were compared for overall accuracy, producer's accuracy (omission errors), user's accuracy (commission error), and kappa coefficient. The comparison was done by creating an error matrix from which different accuracy measures were calculated (*Dekker, Brando & Anstee, 2005*).

Results

The visual interpretation can be used to identify three classes of seagrass zones: long-leaved species (*E. acoroides*), short-leaved species (*H. pinifolia* and *H. uninervis*) and other objects. The resulting supervised classification image and visual interpretation image are shown in Fig. 6 and Fig.7, respectively. The accuracy assessment results are shown in Table 1. The seagrass identification of each class showed that the long-leaved species could be clearly classified because leaf size was wide, very long length and distributed the cluster. The short-leaved species was difficult to be classified because leaf size was so small, low leaf density and distributed widely.

The classification results show that the overall accuracy of visual interpretation of aerial photographs by using UAV for (i) *E. acoroides*, (ii) *H. pinifolia* and *H. uninervis*, and (iii) other objects was 86.36% and Kappa coefficient of this method was 0.809. The overall accuracy of supervised classification was 46.97% and Kappa coefficient of this method was 0.438.

The results showed that aerial photograph images could clearly be used to classify the seagrass species by having different digital signatures with the VARI approach. The overall accuracy of visual interpretation was higher than that of supervised classification, which could be useful to estimate seagrass species mapping. The results also showed that *H. pinifolia* and *H. uninervis* were distributed on sandy clay and seashell substrates while *E. acoroides* was distributed only on sandy areas.

Discussion

1. Aerial photography using UAV is suitable for seagrass detection in a small area. Aerial photographs taken from a very low altitude (less than 500 meters), result in higher spatial-

resolution than satellite imagery and have no cloud-cover problems (*Dekker et al., 2007*). A UAV, however, has a short flight time of about 20 minutes. Other limitations come from water reflection and surface waves that obscure underwater objects, including seagrass beds.

2. Aerial photographs with VARI can be used to classify only two types of seagrass, namely short-leaved and long-leaved types due to the differences of their morphology (*Marine and Coastal Resources Research and Development Center, The Eastern Gulf of Thailand, 2006*). The stem length of *H. pinifolia* and *H. uninervis* (the short-leaved type) is approximately 5-24 cm and the leaves range in length from approximately 0.6-1.25 cm. However, the stem length of *E. acoroides* (the long-leaved type) is approximately 30-150 cm and the leaf length is approximately 1.25-1.7 cm.

3. The overall accuracy of identifying seagrass by visual interpretation was better than by supervised classification. The results of supervised classification with VARI imagery were poor because some seagrass beds may have been concealed by coastal sediment. Visual interpretation can be more accurate because the eye of a human can detect a pattern and texture better than supervised classification. However, visual interpretation may be problematic for the classifier. The Object-based image analysis (OBIA) is a new classification technique. It is used to create objects by grouping pixels that have the same spectral characteristics together and extracting statistical features from them (*Topouzelis & Papakonstantinou, 2016*). The OBIA may provide better results than both visual interpretation and supervised classification.

4. In the future, UAVs will be used for more mapping purposes. The first advantage of UAVs is that the researcher can plan the observation area for mapping and conduct aerial photography at any time, which is useful for survey frequency and continuity. Aerial photography using UAV costs less than using satellite imagery (*Perez, Aguera & Carvajal,*

2013). In particular, aerial photography using UAV is not affected by cloud cover problems, which means that this technology can increase data availability.

Conclusions

The aerial photograph images taken for this study could clearly be used to classify seagrass species having different digital scores using the VARI approach. The overall accuracy of visual interpretation result (VARI) was higher than that of supervised classification result (VARI). Supervised classification (VARI) was useful for delineating seagrass beds, but not for identifying the seagrass species group. Visual interpretation (VARI) was useful for identifying the long-leaved and short-leaved type group. The supervised classification results were less useful in seagrass zone classification because of limitations of water reflection and surface waves. This problem obscures any underwater objects, including seagrass beds.

Recommendations

1. The problems of surface water reflection in aerial photography may be minimized by applying a polarizing filter to the camera or sensor.

2. The newer drone (UAV) technology may increase image resolution and flight time, which will allow them to cover a larger area per flight and take less time for surveys.

3. In case of windy days, the researcher must reduce the flight time because the UAV needs more energy to return to its home position.

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References

Adi NS. 2015. *Characterisation of the light environment and biophysical parameters of seagrass using remote sensing*. PhD. Thesis, The University of Queensland, Australia. DOI 10.14264/uql.2015.998.

Albertz J. 2007. *Einführung in die Fernerkundung Grundlagen der Interpretation von Luft-und Satellitenbildern*. WBG Darmstadt, Germany.

Apodaca JJ, Rissler LJ, Godwin JC. 2012. Population structure and gene flow in a heavily disturbed habitat: implications for the management of the imperiled Red Hills salamander (*Phaeognathus hubrichti*). *Conservation Genetic Resources* **13(4):**913-923 DOI 10.1007/s10592-012-0340-3.

Dekker AG, Brando VE, Anstee JM. 2005. Retrospective seagrass change detection in a shallow coastal tidal Australian lake. *Remote Sensing Environment* **97(4):**415-433 DOI 10.1016/j.rse.2005.02.017.

Dekker A, Brando V, Anstee J, Fyfe S, Malthus T, Karpouzli E. 2007. Remote sensing of seagrass ecosystems: use of spaceborne and airborne sensors. Seagrasses: *biology, ecology and conservation*, 347-359 DOI 10.1007/978-1-4020-2983-7_15.

Department of marine and coastal resources. 2016. *Conservation and restoration of seagrass by transplanting*. Department of marine and coastal resources, Thailand.

DroneDeploy. 2018. How to select the right DroneDeploy Plan for your drone program. *Available at https://prismic-io.s3.amazonaws.com/dronedeploy-www%2F0fac4d0d-769c-4faa-8e45-7a3c96b50f78_dronedeploy_pricing-11_2018.pdf* (accessed 15 November 2018).

Duffy J. 2006. Biodiversity and functioning of seagrass ecosystems. *Marine ecology-progress series* **311:**233-250 DOI 10.3354/meps311233.

Gitelson AA, Stark R, Grits U, Rundquist D, Kaufman Y, Derry D. 2002a. Vegetation and Soil Lines in Visible Spectral Space: A Concept and Technique for Remote Estimation of Vegetation Fraction. *International Journal of Remote Sensing* **23(13):**2537-2562 DOI 10.1080/01431160110107806.

Gitelson AA, Kaufman YJ, Stark R, Rundquist D. 2002b. Novel algorithms for remote estimation of vegetation fraction. Remote sensing of environment **80(1):**76-87 DOI: 10.1016/S0034-4257(01)00289-9.

Kushwaha S. 2008. Geoinformatics-technology and applications. *ENVIS newsletter* **14 (1&2):**2-13.

Lebourgeois V, Begue A, Labbe S, Mallavan B, Prevot L, Roux B. 2008. Can commercial digital cameras be used as multispectral sensors? A crop monitoring test. *Sensors* **8(11):**7300-7322 DOI 10.3390/s8117300.

Marine and Coastal Resources Research and Development Center, The Eastern Gulf of Thailand. 2006. *Seagrasses in Thai waters*. Department of marine and coastal resources, Thailand.

Mumby PJ, Green EP, Edwards AJ, Clark CD. 1997. Measurement of seagrass standing crop using satellite and digital airborne remote sensing. *Marine ecology progress series* **159:**51-60 DOI 10.3354/meps159051.

Paibulkichakul B, Jansang P, Paibulkichakul C. 2016. Distribution of seagrass (Enhalus acoroides) and relationship with environmental factors at Kung Krabaen Bay, Chanthaburi province. *KKU science journal* **44(1):**201-211.

Perez M, Aguera F, Carvajal F. 2013. *Low cost surveying using an unmanned aerial vehicle. International archives of the photogrammetry, remote sensing and spatial information sciences* **XL-1/W2:**311-315 DOI 10.5194/isprsarchives-XL-1-W2-311-2013.

Sagawa T, Boisnier E, Komatsu T, Mustapha KB, Hattour A, Kosaka N, Miyazaki S. 2010. Using bottom surface reflectance to map coastal marine areas: A new application method for Lyzenga's model. *International journal of remote sensing* **31(12):**3051-3064 DOI 10.1080/01431160903154341.

Topouzelis K, Papakonstantinou A. 2016. *The use of unmanned aerial systems for seagrass mapping. In: ISISA islands of the world XIV conference 2016 Niss(i)ology and Utopia: back to the roots of island studies*. Greece, 1671-1692.

Waycott M, Duarte CM, Carruthers TJB, Orth RJ, Dennison WC, Olyarnik S, Calladine A, Fourqurean JW, Heck KL, Hughes AR, Kendrick GA, Kenworthy WJ, Short FT, Williams SL. 2009. Accelerating loss of seagrasses across the globe threatens coastal ecosystems. *Proceeding of the national academy of sciences of the United States of America* **106(30):**12377-12381 DOI 10.1073/pnas.0905620106.

Figure 1

Workflow of aerial photograph analysis for seagrass species classification.

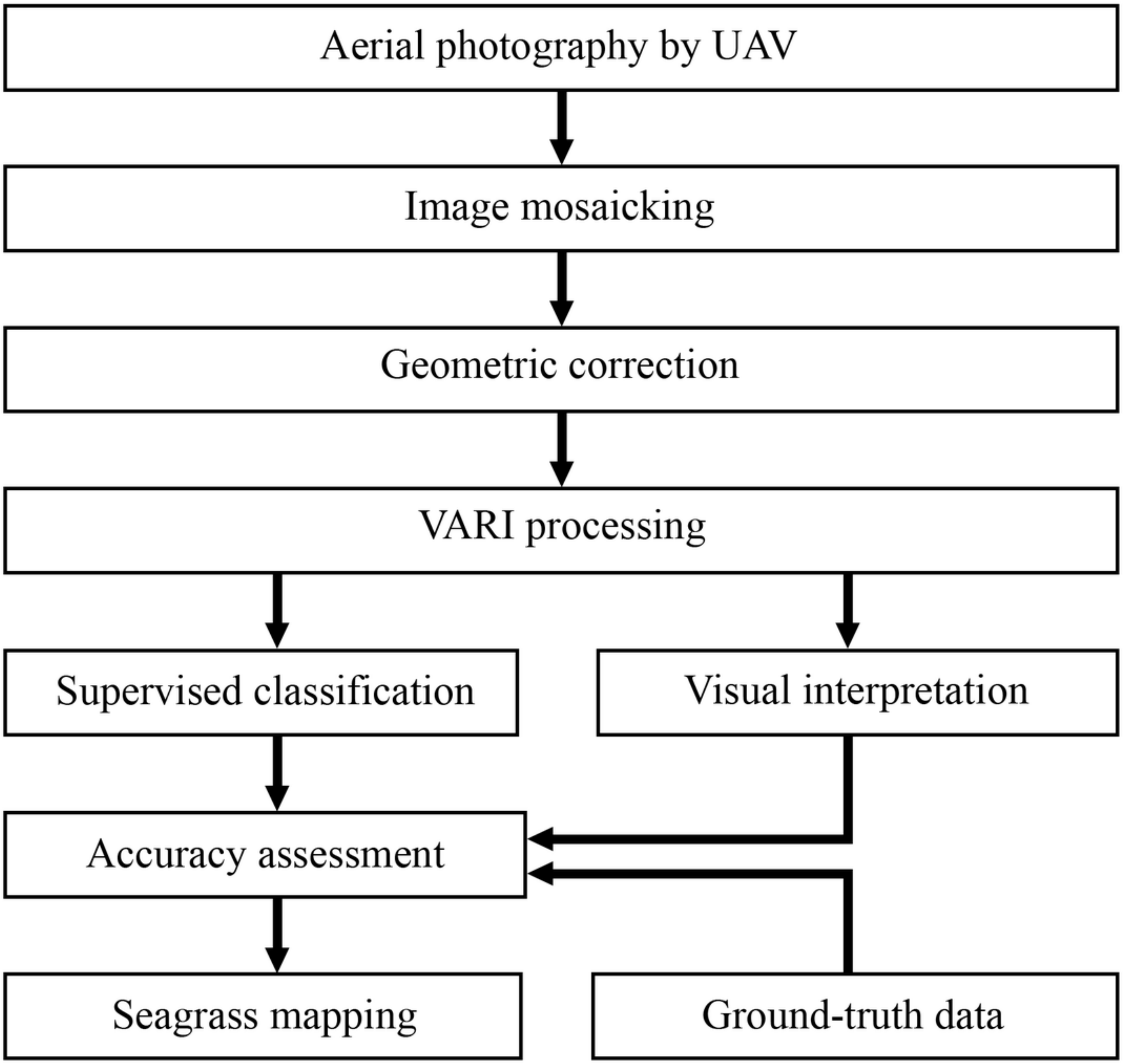
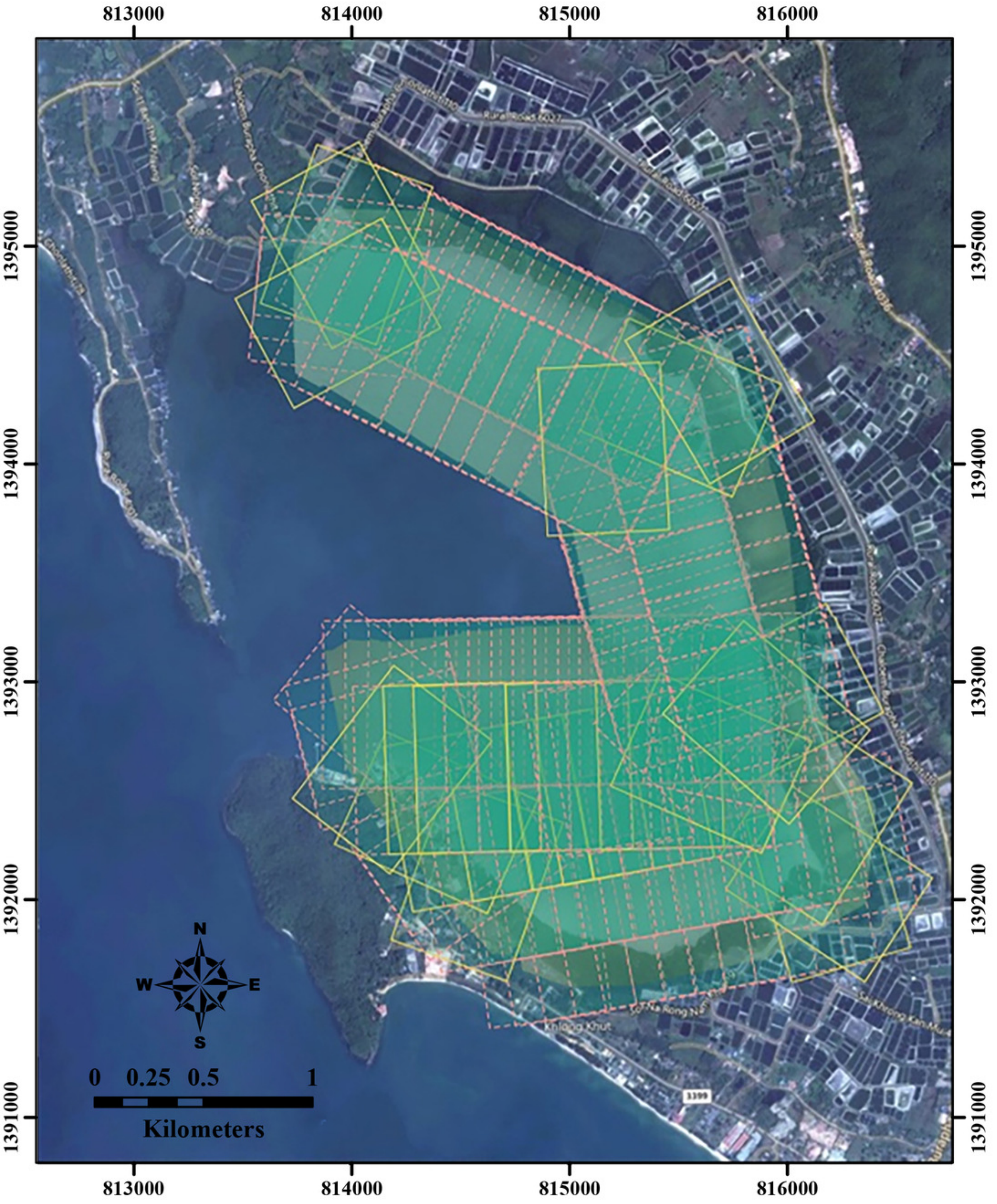


Figure 2

Aerial photographs of the area, which were taken on 4 July 2017


813000
814000
815000
816000
1395000
1394000
1393000
1392000
1391000
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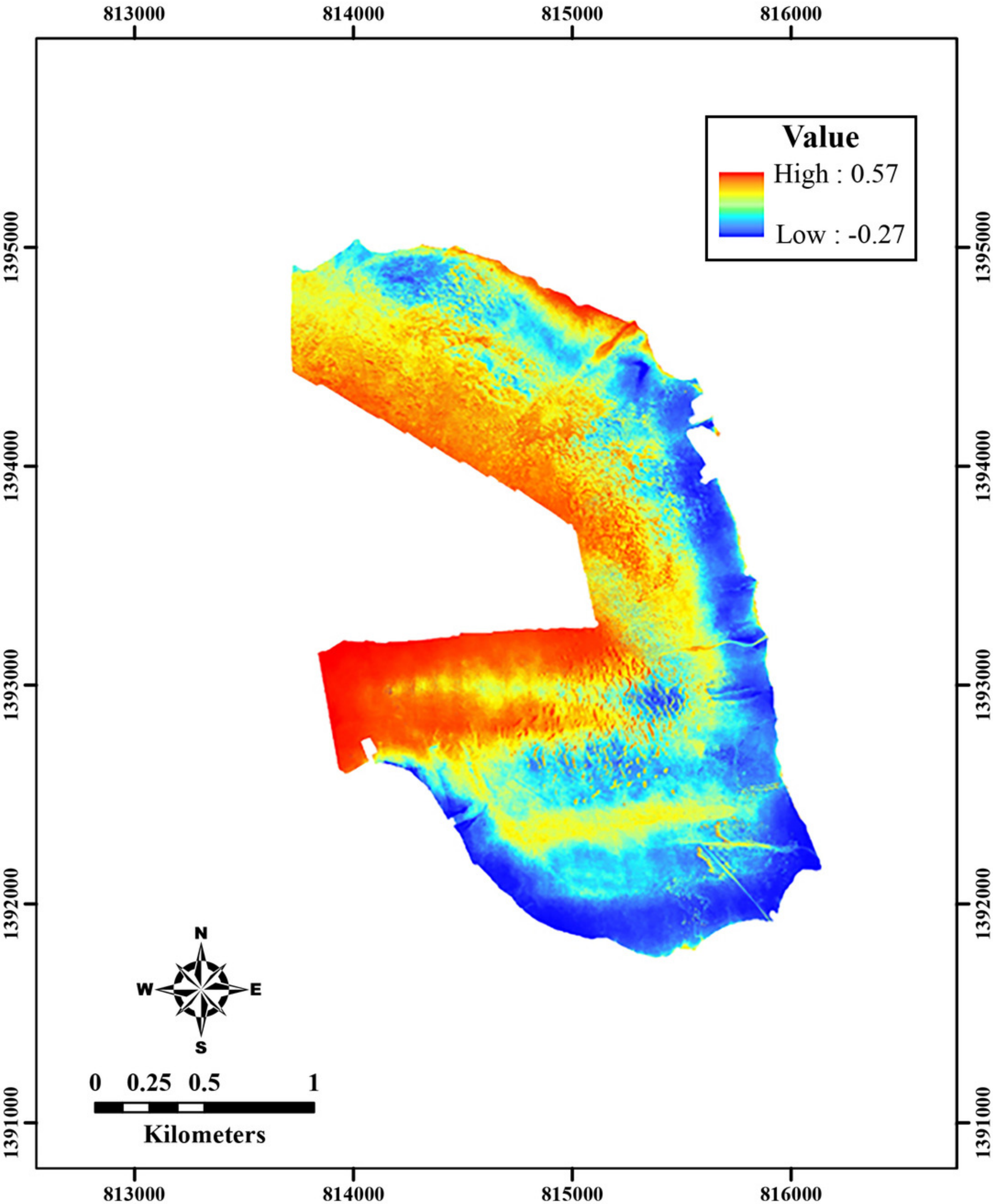
W
E
S
0 0.25 0.5 1
Kilometers

Figure 3

A VARI image was calculated using aerial photographs.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1391000
Value
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Low : -0.27
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E
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0 0.25 0.5 1
Kilometers

Figure 4

Comparison of VARI images from the selected study areas were compared with the true color images by seagrass leaf type.

(A) short leaves were shown in the natural color composite image. (B) short leaves were shown in the VARI image. (C) long leaves were shown in the natural color composite image. (D) long leaves were shown in the VARI image.

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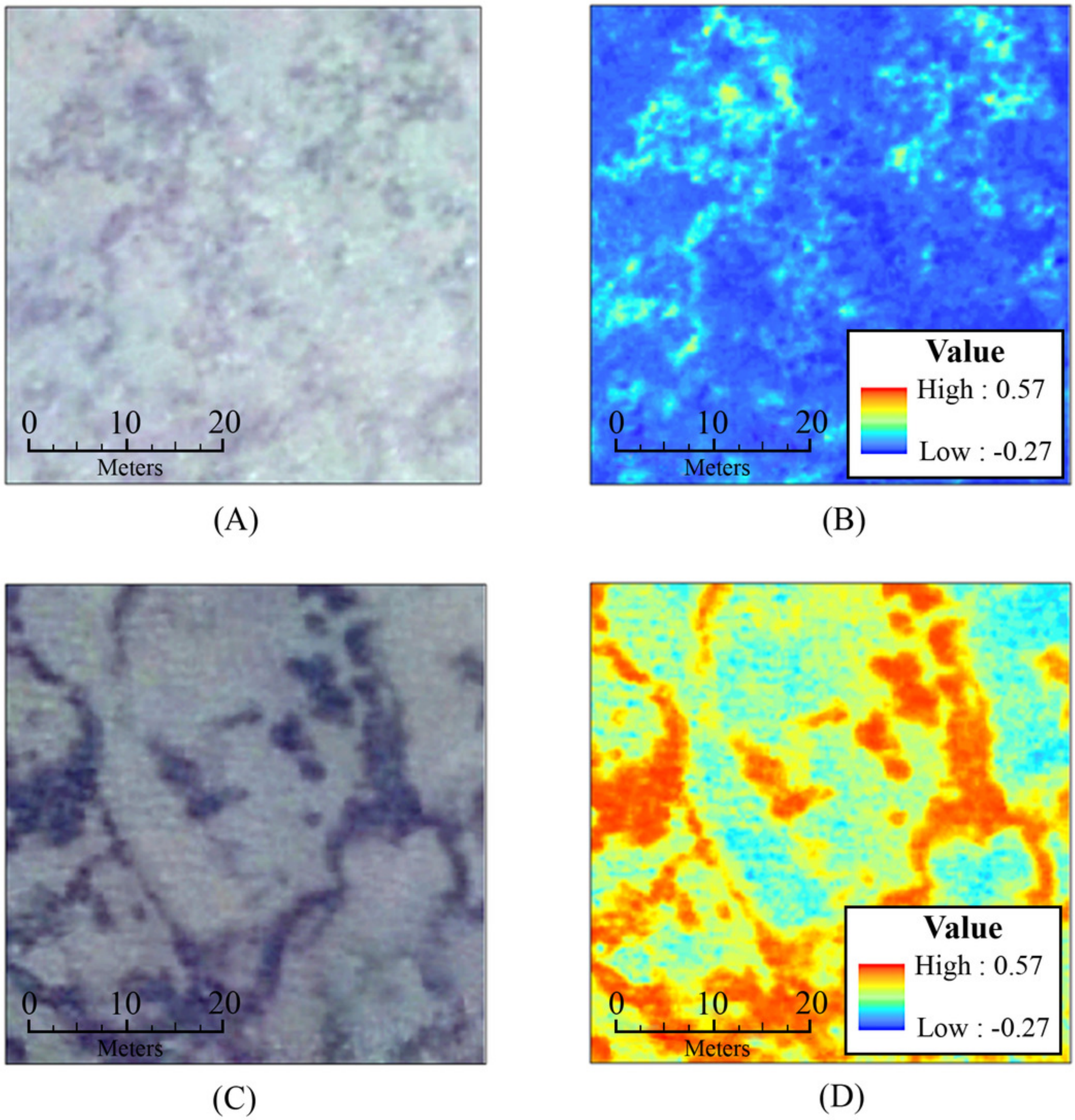
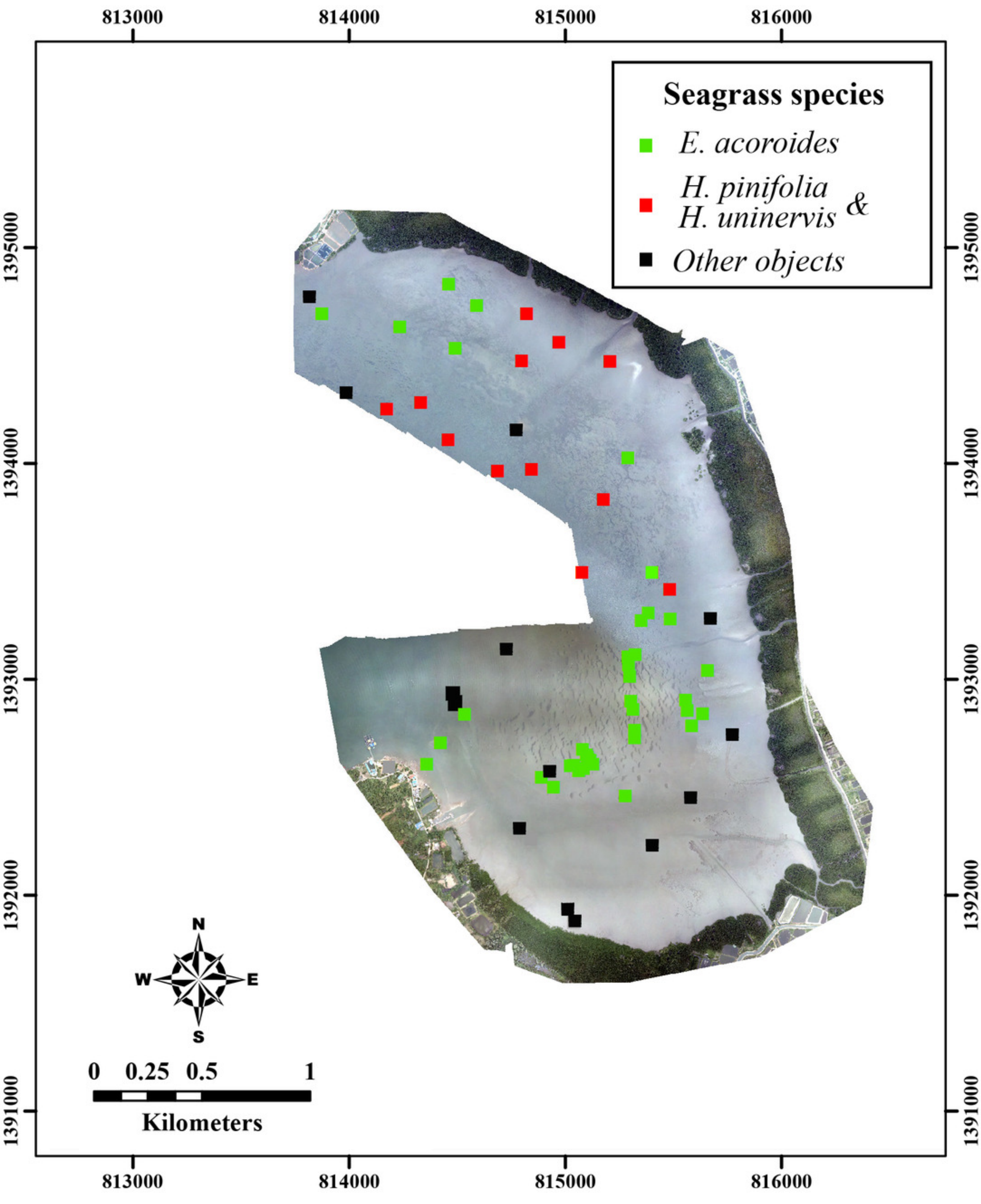

0 10 20
Meters
(A)
Value
High : 0.57
Low : -0.27
0 10 20
Meters
(B)
0 10 20
Meters
(C)
Value
High : 0.57
Low : -0.27
0 10 20
Meters
(D)

Figure 5

Location and sampling points map of the study area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1395000
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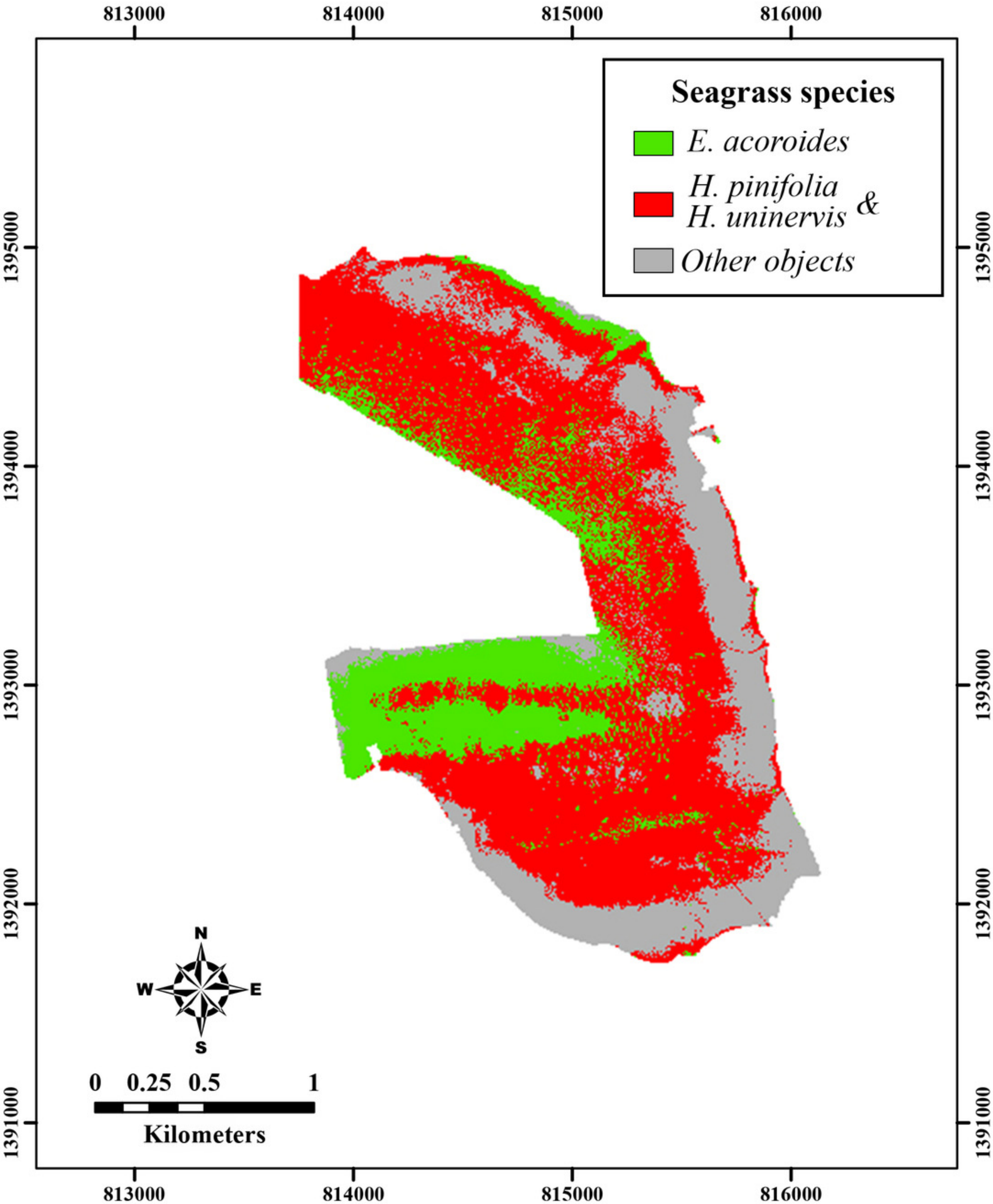
1391000
Seagrass species
E. acoroides
H. pinifolia & H. uninervis
Other objects
N
S
W
E
0 0.25 0.5 1
Kilometers

Figure 6

Supervised classification map of the study area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Seagrass species
E. acoroides
H. pinifolia &
H. uninervis
Other objects
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Figure 7

Visual interpretation map of the study area

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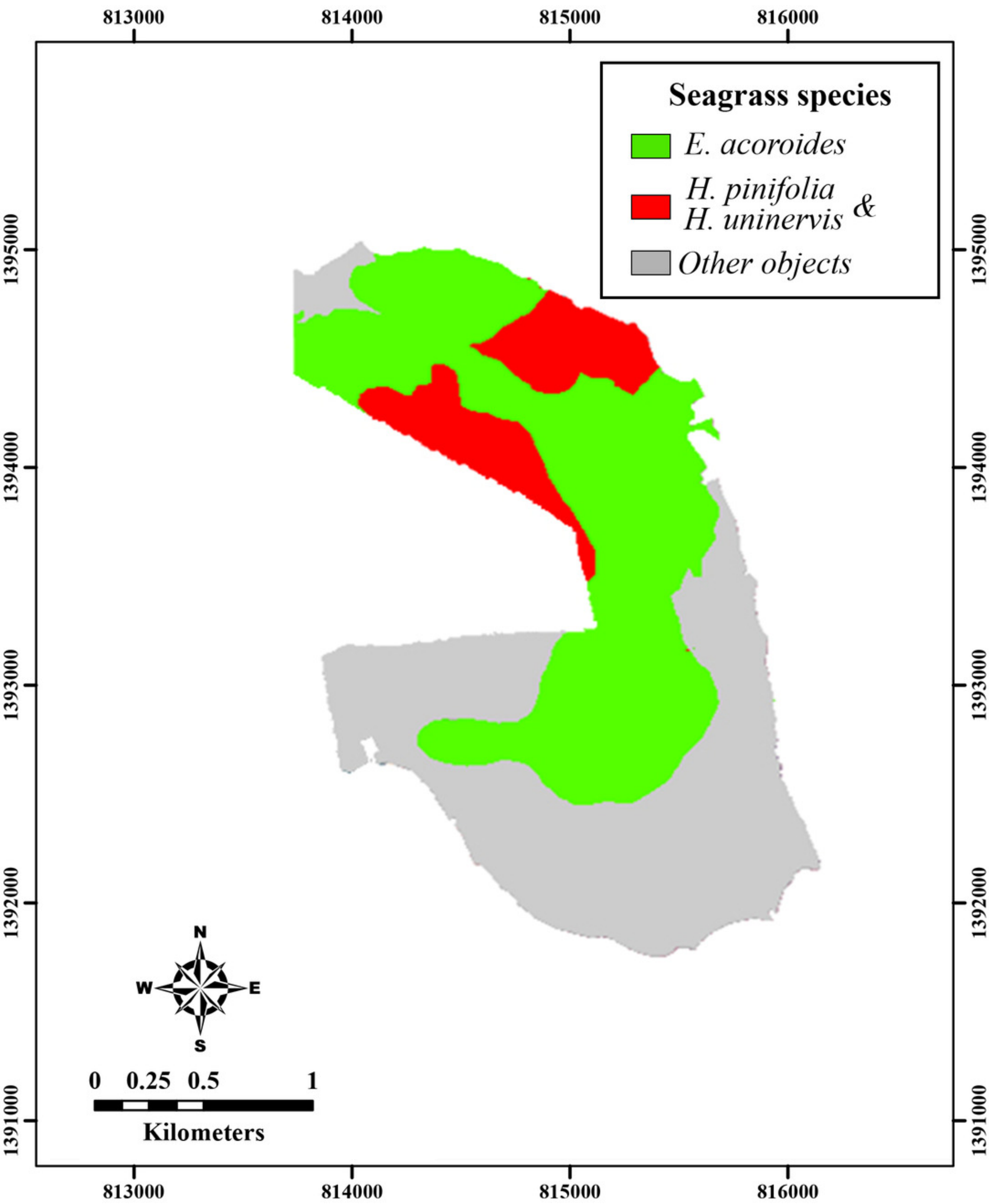
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1391000
Seagrass species
E. acoroides
H. pinifolia &
H. uninervis
Other objects
N
W
E
S
0 0.25 0.5 1
Kilometers

Table 1 (on next page)

Comparison of overall accuracy and kappa coefficient using different classification

Classification method	User's accuracy (%)			Producer's accuracy (%)			Overall accuracy (%)	Kappa Coefficient
	Long leaves	Short leaves	other	Long leaves	Short leaves	other		
Supervised Classification	41.03	83.33	33.33	80.00	26.32	62.50	46.97	0.438
Visual interpretation	89.74	83.33	80	92.11	90.91	70.59	86.36	0.809

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