Monitoring saline intrusion in the Ayeyarwady Delta, Myanmar, using data from the Sentinel-2 satellite mission

Toru Sakai¹ · Keisuke Omori¹ · Aung Naing Oo² · Yan Naung Zaw³

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Abstract

Summer rice cannot be grown near the coast of the Ayeyarwady Delta, Myanmar, because of the high salinity in river water during the dry season. This means that saline intrusion should be monitored to manage the irrigated rice-growing area. The aim of this study therefore is to develop a model to estimate the salinity of river water using satellite imagery. The imagery of Sentinel-2 was suitable for monitoring saline intrusion because of their high spatial (10-m) and temporal (10-day) resolutions. We found that the reflectance of the visible bands was correlated with electrical conductivity, which was influenced by the concentration and composition of dissolved salts. When the river water mixed with the salt water from the sea, suspended particles tended to flocculate and settle, as a result, less turbid water was more saline. The best-fitting model was obtained with the green band (coefficient of determination R^2 of 0.776, root mean square error of 4.896 dSm^{-1} , and mean absolute error of 3.340 dS m^{-1}). The saline intrusion showed considerable spatial and temporal variability during the dry season. The salinity intrusion extended approximately 80 km inland at the end of the dry season in March in the Patheingyi River. The 1 ppt salt concentration line in March marked the boundary between cultivated and non-cultivated areas of paddy field, which indicates that cultivable areas were strongly affected by saline intrusion. The results show that more frequent and higher resolution monitoring than before of the Sentinel-2 can support effective water resource management.

Keywords Ayeyarwady delta · Crop management · Electrical conductivity · Saline intrusion · Sentinel-2 · Turbidity

Introduction

Myanmar has great potential in the agricultural sector, which contributes to most of the national gross domestic product (FAO 2020). Since the government supported the installation of irrigation facilities in 1992, the double cropping system was widely spread in Myanmar (Raitzer et al. 2015). Rice production and the population have both increased in the well-irrigated lowlands of the Ayeyarwady Delta (Matsuda 2009). However, despite the irrigation facilities, rice cropping is impractical near the coast because the irrigation

water is severely affected by salinity during the dry season. Irrigation water with high salinity limits crop growth and renders the soil unsuitable for many crops (Mahmuduzzaman et al. 2014). Therefore, the saline intrusion is one of the biggest limits on crop production in the Ayeyarwady Delta.

Saline intrusion is related to numerous factors including geographical location, tidal amplitude, precipitation, river discharge, and the contribution of ice melt from places like the Himalayas (Mahmuduzzaman et al. 2014). The negative impacts of saline intrusion are also expected to increase because of climate-associated changes, such as sea levels rise, cyclones and storm surges intensify, and the amount and timing of rainfall change (Dasgupta et al. 2015). The landward shift of saline intrusion is related to food security issues. For example, the irrigated crop production could reduce by between 25 and 50% by 2050 in some coastal areas because of increases in salinity (Clarke et al. 2015). Therefore, to support crop management in the delta, the salinity of river water and soil must be monitored.

The government in Myanmar measures salt-related attributes and provides the information to farmers. Traditionally,

✉ Toru Sakai
torus@affrc.go.jp

¹ Japan International Research Center for Agricultural Sciences (JIRCAS), 1-1 Ohwashi, Tsukuba, Ibaraki 305-8686, Japan

² Yezin Agricultural University, Zeyar Thiri Township, Yezin, Nay Pyi Taw 15013, Myanmar

³ Department of Agriculture, Labutta Township Office, Labutta, Ayeyarwady, Myanmar

these attributes have been directly measured in the field. However, this approach is resource intensive because numerous samples are needed to characterize the highly variable spatial and temporal variability in river water salinity. Remote sensing can provide valuable, cost-effective, and frequent information on salinity over large areas, especially in regions such as the Ayeyarwady Delta, where the many rivers hinder the efficiency of direct measurements.

Algorithms have been developed so that remotely sensed data from an increasing number of satellite sensors can be used (Kotera et al. 2014). Using recently developed advanced satellite sensors, such as Soil Moisture Active Passive (SMAP) and Soil Moisture and Ocean Salinity (SMOS), the sea surface salinity can be monitored (Font et al. 2010; Meissner et al. 2018; Tang et al. 2017). For example, various researchers have used these sensors to monitor the sea surface salinity at the scale of the Bay of Bengal (Chacko 2018; Subrahmanyam 2018). However, these sensors are too coarse with a spatial resolution of 50 km to identify the salinity of river water. Similarly, Moderate Resolution Imaging Spectroradiometer (MODIS), with a spatial resolution of between 250 and 1000 m, can be used to assess aquatic environments (Liu et al. 2015; Qing et al. 2013; Urquhart et al. 2013), but cannot be used for monitoring narrow rivers. Landsat has a 30-m resolution and can be used to monitor coastal water and rivers, lakes, and reservoirs (Garaba and Zielinski 2015; Wang and Xu 2008; Xie et al. 2013); its temporal resolution (16-day repeat cycle) however, is not enough to detect rapid changes in river water salinity. Choosing a satellite sensor to support accurate, reliable, and timely estimations, therefore means we have to find a balance between the spatial and temporal resolutions. Satellite sensors and algorithms have improved over time; however, the rivers in the study area are small and vary considerably over time, and few satellites provide data at sufficiently high spatial and temporal resolutions for monitoring of saline intrusion. Remarkably, the Sentinel-2 observation mission provides data that meet these requirements, with spatial and temporal resolutions of 10 m and 10 days, respectively; with its twin satellite system, Sentinel-2A and Sentinel-2B, the revisit frequency is just 5 days. There are plans to include 2 more satellites, Sentinel-2C and Sentinel-2D, to this mission in 2021. The Sentinel-2, therefore, enables near real-time monitoring of saline intrusion at a fine spatial resolution. However, the Sentinel-2A and Sentinel-2B were only launched in 2015 and 2017, respectively, so there are few data available to calibrate and validate the algorithms for estimating the salinity of river water (Glukhovets and Goldin 2019).

Previous studies based on Landsat and MODIS have related optical variables of water color, such as salinity, turbidity, suspended sediment concentrations, to single spectral bands, the spectral band ratio, or more complex combinations of spectral bands through regression models (Garaba

and Zielinski 2015; Glukhovets and Goldin 2019; Urquhart et al. 2013). These empirical models are often region- and time-dependent (Cui et al. 2013; Liu et al. 2003; Wu et al. 2015) and thus should be calibrated and validated with data that cover a wide range of field conditions. This means that models need to be developed for specific water bodies or sensors. The aims of this study therefore are to (1) develop empirical models by fitting field measurements from three rivers (i.e., the Patheingyi, Ywé and Pyawbwe Rivers) and two sampling occasions (i.e., beginning and end of the dry season) to Sentinel-2 imagery, (2) monitor the spatial and temporal variability of saline intrusion in the Ayeyarwady Delta during the dry season, and (3) assess the impact of saline intrusion on the distribution patterns of paddy fields.

Materials and methods

Study area

The study area was the Ayeyarwady Delta, which is towards the south of the central plains of Myanmar, between 94.0° and 96.5° E and 15.5° and 18.0° N (Fig. 1). The delta starts from around Nyaung-U, at approximately 30 m above sea level, and spreads to the east and west. The Ayeyarwady River flows into the Andaman Sea through 11 large distributaries, of which the Patheingyi and Yangon Rivers are the furthest west and east, respectively. The dominant type of tide in the Andaman Sea is the lunar semi-diurnal tide (M2-tide). The semi-diurnal tides come from the Indian Ocean and bifurcate towards the strait of Malacca and the coastline of Myanmar, with increasing amplitudes in the shallow continental waters (Rizal et al. 2012). The delta is a flat alluvial floodplain with an area of approximately 35,000 km² and a coastal front of approximately 240 km. Annually, 300 million tons of sediment are transported by the Ayeyarwady River and its tributaries (Bird et al. 2008). These sediments transport high loads of nutrients to the delta area, meaning that a vast part of it is suitable for rice cultivation. A double cropping system has been introduced in certain areas of the delta where there is access to irrigation. Most of the rice is grown during the monsoon season between July and December (i.e., monsoon rice), and the rest is grown during the summer season between January and June (i.e., summer rice). The rice grown in the delta accounts for a large part of the total national production of rice. However, as this coastal region is almost flat and is at a low elevation, the paddy area and rice production are at risk from saline intrusion.

Field measurements of river water

We measured the salinity, turbidity, and suspended sediment concentration (SSC) of the river water in three distributaries

Fig. 1 Study area in the Ayeyarwady Delta in Myanmar. The four rectangles indicate the tiles of the Sentinel-2 (T46QFD, T46QGD, T46PFC, and T46PGC)

in the western part of the Ayeyarwady Delta, namely the Patheingyi, Ywe, and Pyawbwe Rivers (Fig. 1). River water salinity is expressed as electrical conductivity (EC) in decisiemens per meter (dS m^{-1}). From a ship, we collected samples of river water from between the surface (0 cm) and 50 cm depth, at 3–4 km intervals from each estuary to the upstream. We then measured the EC and turbidity onboard the ship using a portable EC meter (D-74; Horiba, Ltd., Kyoto, Japan) and Lacom tester turbidity meter (TN100IR; As One Corporation, Osaka, Japan). The SSC was measured gravimetrically by filtering the water sample on glass fiber paper (GFP) filters with a pore diameter of 1 μm in the laboratory. The water sampling points and the path taken by our ship were recorded using a global positioning system (GPSMAP64; Garmin, Ltd., Olathe, KS, USA). To reduce the effect of the tides, we surveyed at the time of last quarter moon, namely, neap-tide and took the first field measurements in the estuaries to coincide with the time of the low tide whenever possible. Table 1 shows the tide times (low and high tides) and tidal ranges in the Ayeyarwady Delta corresponding to field measurement time. We started field measurements from between 09:13 and 10:35. The ship traveled at a speed of between 6.5 and 10.0 knots. Between 12 and 20 water samples were collected from each river

over a period of between 5 and 6 h, and all the measurements in one river were carried out on the same day. The tidal range was from 0.60 m to 1.27 m. The EC was measured twice, namely at the beginning (November–December 2018) and end (March 2018) of the dry season. The sampling dates were 10 March 2018 ($n = 17$) and 30 November 2018 ($n = 12$) in the Patheingyi River, 9 March 2018 ($n = 20$) and 2 December 2018 ($n = 13$) in the Ywe River, and 11 March 2018 ($n = 16$) and 29 November 2018 ($n = 13$) in the Pyawbwe River, making a total of 91 samples from the three rivers.

Sentinel-2 imagery

The satellite data used in this study were from the Sentinel-2 Level-1C. These data are orthorectified top-of-atmosphere reflectance with 13 spectral bands that span from blue to shortwave infrared at spatial resolutions of 10, 20, and 60 m. The reflectance values are multiplied by 10,000. The product is available free from the Copernicus Open Access Hub (<https://scihub.copernicus.eu>) and is distributed as tiles of 110×110 km in the UTM/WGS84 projection. We downloaded four tiles, namely T46QFD, T46QGD, T46PFC, and T46PGC, that covered seven estuaries in the western part

Table 1 Date, tide times (low and high tides) and tidal ranges in the Ayeyarwady Delta corresponding to field measurement time

Date	Low tide time	High tide time	Tidal range (m)	Field measurement time
2018/03/09	08:20	14:29	0.98	10:20–16:31
2018/03/10	09:20	15:39	0.70	10:35–15:16
2018/03/11	11:01	17:48	0.60	09:26–15:00
2018/11/29	08:09	14:35	1.11	09:13–14:07
2018/11/30	09:24	16:04	0.99	09:20–15:17
2018/12/02	12:04	18:44	1.27	09:35–15:52

of the Ayeyarwady Delta (Fig. 1) and included large distributaries such as the Patheingyi, Ywe, and Pyawbwe Rivers. The Sentinel-2 passed over the tiles at around 10:30 with a 10-day revisit cycle (5-day revisit cycle for the Sentinel-2A and Sentinel-2B twin system). The top-of-atmosphere of the Level-1C product was converted into the bottom-of-atmosphere corrected reflectance using the Sen2Cor version 2.8 implemented in the Platform (SNAP) Tool version 6.0 (Vuolo et al. 2016).

Regression analysis for EC

Regression analysis is generally used for modeling the relationship between two variables, where one is usually difficult or costly to measure (e.g., EC from field measurements), and the other is relatively easy to obtain (e.g., spectral band from Sentinel-2). In this study, we evaluated whether data from the Sentinel-2 could be used to estimate the EC in the Ayeyarwady Delta of Myanmar.

To obtain the relationship between the Sentinel-2 data and EC, we first extracted pixels where river water was sampled from two Sentinel-2 images on 12 March 2018 (tidal range: 0.38 m) and 2 December 2018 (1.27 m). Then, data from different rivers and sampling occasions were merged to examine whether the regression model was robust. Four spectral bands commonly used in many previous studies, namely, blue (central wavelength of 490 nm), green (560 nm), red (665 nm), and infrared (842 nm), and the band ratios generated by four-band combinations (C_2) were considered as explanatory variables. Linear, quadratic, exponential, and power models were evaluated to estimate the EC from the Sentinel-2 imagery. The accuracy of the calibrated models was assessed using leave-one-out cross-validation (Craven

and Wahba 1978; Roberts et al. 2017). This type of cross-validation guarantees that the training and validation datasets are spatially independent. We used the data from the 91 samples to calibrate and validate the regression models. Of the 91 samples, one sample was used for validation, and the remaining 90 samples were used as training data to fit the regression model using the least-squares method. The resulting regression models were then used to estimate the EC of the validation datum. We repeated the process 91 times to estimate the EC of all the samples. Then, we compared the coefficient of determination (R^2), root mean square error (RMSE), and mean absolute error (MAE) of all the calibrated models to determine the best-fitting model. Finally, the best-fitting model was used to estimate the spatial and temporal distributions of EC in the delta from the Sentinel-2 images during the dry season from November to April.

Results

Seasonal changes in precipitation and river discharge

Figure 2 shows seasonal changes in precipitation at Labutta (16.15° N, 94.76° E) and river discharge at Nyaung-U (18.04° N, 95.44° E, Fig. 1). In 2017, the annual precipitation was approximately 3255 mm and varied seasonally, with a dry season from November to May and a rainy season from June to October. Almost all (95.8%) of the annual precipitation fell during the rainy season. The climate in the area is dominated by the monsoon, which brings heavy rainfall during the rainy season. The river discharge showed the same seasonal pattern as the precipitation, with 72.2% of the

Fig. 2 Precipitation at Labutta and river discharge at Nyaung-U

annual discharge ($298 \text{ km}^3 \text{ year}^{-1}$) during the rainy season. The river discharge was approximately $20,000 \text{ m}^3 \text{ s}^{-1}$ during the rainy season and gradually decreased from October to May.

EC regression model

Figure 3a, b shows the relationships between turbidity and EC, and between turbidity and SSC, respectively. There was the cumulative relationship between turbidity and EC ($R^2=0.451$) and the linear relationship between turbidity and EC ($R^2=0.953$). EC, turbidity, and SSC were related to each other.

We used either single spectral bands or the ratios between two bands from the Sentinel-2 imagery to determine which regression models could be used to estimate the EC. We chose the best-fitting model for each explanatory variable from linear, quadratic, exponential, and power regression models, as detailed in Table 2. The accuracy for all the explanatory variables was best with the green band, with cross-validated R^2 , RMSE, and MAE values of 0.776, 4.896 dS m^{-1} , and 3.340 dS m^{-1} , respectively. The results from the leave-one-out cross-validation for the green band best-fitting model are summarized in Table 3. By repeating the calculations 91 times to validate the statistical parameters, we found they were relatively stable with low standard

Fig. 3 **a** Relationships between turbidity and EC, and **b** turbidity and suspended sediment concentration

Table 2 Best-fitting models between EC and either single spectral bands or ratios between two bands from Sentinel-2 data. Leave-one-out cross-validated R^2 , RMSE, and MAE are shown

Regression model	Explanatory variable (X)	R^2	RMSE (dS m^{-1})	MAE (dS m^{-1})
$EC = -0.0682 X + 99.054$	Blue (490 nm)	0.460	7.597	5.779
$EC = 0.0000921 X^2 - 0.285 X + 220.991$	Green (560 nm)	0.776	4.896	3.340
$EC = 383.7 \exp(-0.00420 X)$	Red (665 nm)	0.613	6.431	4.528
$EC = -0.0171 X + 19.327$	NIR (842 nm)	0.051	10.084	7.936
$EC = 0.00000314 X^2 - 0.0540 X + 11.800$	Blue/Green	0.744	5.239	4.054
$EC = 0.0843 \exp(3.194)$	Blue/Red	0.593	6.600	5.135
$EC = 34.571 X - 36.546$	Green/Red	0.270	8.840	6.857
$EC = -13.098 X + 15.999$	NIR/Blue	0.011	10.468	8.443
$EC = -49.381 X + 20.288$	NIR/Green	0.068	9.996	8.068
$EC = -23.277 X + 17.044$	NIR/Red	0.007	10.442	8.478

Table 3 Summary of the 91 leave-one-out cross-validations for the best-fitting model to estimate EC using the green band from Sentinel-2 data ($EC = a \cdot X^2 + b \cdot X + c$)

	a	b	c	R^2	RMSE (dS m^{-1})	MAE (dS m^{-1})
Maximum	0.0001017	-0.275	237.723	0.814	4.768	3.278
Minimum	0.0000884	-0.311	214.088	0.777	4.288	3.048
Mean	0.0000921	-0.285	220.991	0.790	4.737	3.230
Standard deviation	0.0000017	0.005	2.973	0.005	0.063	0.038

deviations. The fitting accuracy was also acceptable with the blue to green band ratio, with cross-validated R^2 , RMSE, and MAE values of 0.744, 5.239 dS m⁻¹, and 4.054 dS m⁻¹, respectively. The accuracies for the regression based on the infrared bands were low.

The EC and green band reflectance were strongly correlated regardless of the river and sampling occasion (Fig. 4a), which shows that the regression model could be used to estimate the spatial and temporal variations in EC in the Ayeyarwady Delta. The cross-validation results for the best-fitting model (green band in Table 3) are shown in Fig. 4b. There was good agreement between the measured and estimated EC, and the trends using the blue and red bands were similar.

The photographs in Fig. 5 show that the downstream, midstream, and upstream reaches of the Ywe River on 9 March 2018. The turbidity of the river water varied spatially and was high in the upstream area, where the reflectance of the green, blue, and red bands was also high. In contrast,

the reflectance was low close to the estuary, indicating very low turbidity.

EC from the estuary to the upstream reaches

The variation in EC from the estuary to the upstream reaches at the end of the dry season (12 March 2018) is shown in Fig. 6. The river water sampling points and ship pathway are shown in Fig. 6a. The dots indicate where the EC was measured, at intervals of approximately 3–4 km, and the solid lines represent the EC that was estimated at 10 m intervals from Sentinel-2 imagery (Fig. 6b). The measured and estimated EC mostly followed a similar pattern, but the estimated EC was low where small tributaries joined the main channel and where two channels rejoined downstream of river islands. The satellite-derived EC was underestimated at places where the river water tended to become turbid because of flow.

Fig. 4 **a** Relationship between EC and green band reflectance retrieved from the Sentinel-2 and **b** leave-one-out cross-validation results for the best-fitting model (green band). The dashed line represents the regression curve

Fig. 5 Photographs of river water conditions in the **a** downstream, **b** midstream, and **c** upstream reaches of the Ywe River on 9 March 2018

Fig. 6 **a** Sampling points and ship trajectory overlaid on the true color composite image of Sentinel-2 on 12 March 2018, and **b** changes in EC from the estuary to upstream area

The EC values varied among the rivers, but generally reached a maximum at the estuary facing the sea, with values of 40.9, 32.6, and 14.4 dS m^{-1} , at the estuaries of the Pathein, Ywe, and Pyamalow, respectively. The EC values then gradually decreased in an upstream direction. The distances upstream at which the EC approached zero also varied among the rivers. A concentration of 1 ppt (part-per-thousand = 1000 ppm) is deemed suitable for irrigation water (Driel and Nauta 2015). We used a simple relationship to convert the EC to TDS (total dissolved solids) using $\text{EC} (\text{dS m}^{-1}) = \text{TDS} (\text{ppm})/640$ (Richards 1954), i.e., $1 \text{ ppt} \approx 1.56 \text{ dS m}^{-1}$. The EC values in the Pyamalow and Ywe Rivers remained below 1.56 dS m^{-1} at 39.7 and 61.2 km upstream, respectively. During the time-limited survey in the Pathein River, the EC did not fall below 1.56 dS m^{-1} , which shows that the effects of salinity are felt for a long distance upstream.

Spatial and temporal changes in EC

Maps of the monthly natural color composite and EC using Sentinel-2 during the dry season from November 2017 to April 2018 are shown in Figs. 7, 8, respectively. We selected one cloud-free image for each month from the archives of the Sentinel-2. To estimate spatial and temporal changes in EC, we applied the best-fitting model using the green band to six Sentinel-2 images on 17 November (tidal range: 0.86 m) and 17 December in 2017 (1.46 m), and on 11 January (0.83 m), 25 February (0.84 m), 12 March (0.46 m), and 16 April in 2018 (2.12 m).

In November 2017, at the beginning of the dry season, the river water was severely turbid (Fig. 7a) and the EC in the rivers, apart from around the estuaries, was below 1.56 dS m^{-1} (Fig. 8a). Then, clear water flowed from the estuaries to the upstream (Fig. 7b, c, d, e), and the water was clearest in March 2018 (Fig. 7e). Water with high EC values also showed similar patterns (Fig. 8b, c, d, e). The speed at which this water flowed to the upstream varied among rivers and

was fastest in the Pathein River and slowest in the Pyamalow River. In April 2018, at the end of the dry season, all the river water was turbid again (Fig. 7f) because of inflow of soil erosion products by precipitation and snowmelt from upstream, and the EC within the rivers was below 1.56 dS m^{-1} (Fig. 8f). The saline water penetrated and retreated during the dry season.

The 1 ppt salt concentration lines during the dry season are shown in Fig. 9. The lines connect the locations where EC was 1.56 dS m^{-1} in Fig. 8 and indicate whether river water could be used as irrigation water. The green area at the center of natural color composite map (Fig. 9) represents paddy fields of summer rice and mainly locates at the northern side of the 1 ppt salt concentration line in March. In other words, the 1 ppt salt concentration line in March can be regarded the boundary line between cultivated and non-cultivated paddy fields during the dry season. During the rainy season, the paddy fields reach the coastline because the heavy rain is used to irrigate the rice (Fig. 2). In Fig. 7a, the green area along the coastline represents paddy fields of monsoon rice before harvest, except for evergreen mangrove forests.

Discussion

Spatial and temporal resolutions of Sentinel-2 data

Water color remote sensing has evolved as a research tool, facilitated by a wide variety of operational sensors, and algorithms (Zhang et al. 2017). To date, however, it has been used infrequently to determine the salinity in narrow riparian areas because of a lack of information at appropriate resolutions. In this study, we evaluated whether the Sentinel-2 data could be used to monitor the extent of saline intrusion at the Ayeyarwady Delta during the dry season, from November to April.

Fig. 7 Monthly true color composite images of Sentinel-2 during the dry season

Fig. 8 Spatial and temporal changes in EC during the dry season

Fig. 9 The 1 ppt salt concentration lines during the dry season. The lines connect locations where EC is 1.56 dS m^{-1} (i.e., 1 ppt) in Fig. 8

We found that the spatial resolution of the Sentinel-2 data, at 10 m, could be used to monitor the main rivers in the Ayeyarwady Delta, which were generally wider than 10 m at the places where the EC became 1 ppt. We could not however monitor small tributaries (Fig. 8). Additionally, we achieved a revisit cycle of 5 days when we used the data from the twinned satellites and thus were able to calibrate with the field measurements to within ± 3 days (Fig. 4). Ideally, the field measurements should be calibrated with an image from the same day. We had field measurements from 1 day for each river. Fortunately, there were no large or rapid fluctuations in the few days between the image and the field measurements during the low-flow season (Fig. 2). One should exercise caution therefore if using images with longer revisit cycles, such as Landsat images with a revisit cycle of 16 days, as the EC shows considerable seasonal variation (Figs. 7, 8). It is difficult to obtain cloud-free images, even in the dry season. If an image that coincides with the date of the field measurement that is obscured with clouds, it cannot be used; instead, a cloud-free image from the closest date from the field measurement must be used. This practice, while necessary, can undermine the accuracy of the modeling, and the accuracy will diminish as the length of time between the image acquisition and field measurements increases. Moreover, EC estimation may be affected by halation which makes the sea surface brighter due to the strong reflection of sunlight (see in Fig. 7f). In the Ayeyarwady Delta area, it started to rain in April, but the amount was not yet large (Fig. 2). The decrease in EC was largely affected by halation. The scene number of Sentinel-2A and 2B that

could be used for EC monitoring was not large. When the Sentinel-2C and Sentinel-2D are launched, the EC will be allowed to monitor more frequently. Indeed, frequent revisit cycles are needed to capture the dynamics between coastal and inland waters.

EC estimation using Sentinel-2

A number of study has reported good relationships among EC, turbidity and SSC in the estuaries. Although the sea surface salinity has no direct color signal, turbidity and SSC have often been observed to be strongly inversely correlated with salinity (Azhikodan and Yokoyama 2015; Oliver et al. 2010). The similar results were also obtained in this study (Fig. 3). Salinity increases the cohesion of clay minerals and the flocculation of fine-grained sediments in suspension (Portela et al. 2013). Therefore, suspended sediment is mainly removed from turbid water in estuaries by flocculation and settling (Wang and Andutta 2013). Studies of sediment dynamics in estuaries have frequently discussed the physical and chemical behavior of fine sediment particles (Thill et al. 2001; Mietta et al. 2009; Mikeš 2011). The basic mechanisms for flocculation and settling are briefly outlined below.

Individual sediment particles are negatively charged around the perimeter and positively charged in the center, such that they repel each other in fresh water. However, the sodium and chloride ions act to neutralize the repulsion in saline water, and thus particles in close proximity come together. These flocs (i.e. aggregates of particles) that form in saline water settle faster than individual particles in fresh water. Further, these flocs, as they fall, sweep up smaller particles and flocs in the water column. Using this positive feedback, the SSC decreases rapidly when the salinity is high. From these mechanisms, we can gain useful insights into saline intrusion through indicators, such as SSC and turbidity, from various satellite ocean color sensors.

The Ayeyarwady River is ranked as having the fifth-largest suspended sediment load of the world (Bird et al. 2008), and thus the main channel and its tributaries are usually extremely turbid (Fig. 7). The water around the estuaries was generally less turbid than that further upstream during the dry season (Fig. 5), and the reflectance of the Sentinel-2 was also lower in less turbid areas. This suggests that it may be possible to estimate salinity from satellite imagery. We compared the relationships between EC and satellite-driven indices with data collected from three rivers in the Ayeyarwady Delta at the beginning and end of the dry season. The correlation was best for the quadratic regression model with a single green band ($R^2 = 0.776$, Fig. 4, Table 2). To estimate SSC, Islam et al. (2002) used the single green band of Landsat-5 TM in the same coastal sea in the Bay of Bengal, Wong et al. (2007) used the single green band of MODIS in Hong

Kong. Similarly, at the Vietnamese Mekong Delta, the use of a green band of Landsat-8 OLI presented the highest correlation with salinity in the single-band selection (Nguyen et al. 2018). However, Nguyen et al. (2018) recommended multi-band combinations to enhance the sensitivity of surface water. The blue-to-green band ratio is a more popular index to estimate salinity and other water-related variables (Ahn et al. 2008; Son et al. 2012). Our research results also showed a good relationship between the blue-to-green band ratio and EC ($R^2=0.744$, Table 2). Satellite imagery has already been used to observe the distribution of EC and SSC in estuarine and coastal waters for many years (Stumpf 1988; Walker 1996). The algorithm is easy to understand and simple to implement and can be applied to data from past and current satellite sensors. However, there is no robust theoretical basis for selecting the green band. Empirical models to estimate salinity from satellite imagery are often chosen on a case-by-case basis because of unique features, such as the type of particles, river discharge, geology, and relief (Cui et al. 2013; Liu et al. 2003; Wu et al. 2015). While the processes of sedimentation are already reasonably well explained, we would need more detailed measurements to determine whether the proposed model can be applied widely.

Application of satellite remote sensing monitors the reflectance of surface water, and thus superficial EC is estimated from satellite imagery. However, according to Attema and Hendriks (2014), water in the Ayeyarwady Delta is well-mixed over the vertical because the tidal range is quite large when compared to the river depth, i.e. the concentration of salinity barely varies over the vertical. Therefore, monitoring of saline intrusion is possible because the superficial EC represents the entire EC in vertically well-mixed flows, and the EC varies from the estuary toward the upstream horizontally. However, one thing needs to be addressed in satellite-based EC estimation. The mechanism of EC estimation is based on the sedimentation of suspended material. However, SSC in river water is affected by various factors, such as tide, wind, precipitation, flow velocity, and discharge. Resuspension of bottom sediments and inflow of suspended material from upstream can lead to underestimation of EC. Therefore, it is also important to investigate the meteorological environment during satellite observations. In particular, the Ayeyarwady Delta appears to have a mean tidal range between 2 and 4 m (Ramaswamy et al., 2004). As a subject of future work, the tidal excursion in the semidiurnal cycle (and other effects, such as the spring-neap cycle) should be considered while determining saline intrusion.

Saline intrusion in the Ayeyarwady Delta

The Ayeyarwady Delta has a distinct wet–dry monsoon climate, with only 4.2% of the annual precipitation during the

dry season (Fig. 2). When the precipitation is low, the river discharge is also low. Saline intrusion occurs because of the extremely low precipitation and river discharge during the dry season (Islam et al. 2002). The saline intrusion gradually progressed through the dry season and peaked in March, the end of dry season. Following this, the saline water was pushed toward the coast as the river flow increased dramatically in the rainy season (Fig. 2). However, the distance of saline intrusion and EC values varied depending on the river (Fig. 6). Large area monitoring by sentinel-2 is useful for evaluating the progress of saline intrusion.

Saline intrusion varies not only between seasons but also between years. The patterns of the 1 ppt salt concentration lines in the Ayeyarwady Delta found by Driel and Nauta (2015) were similar to what we found (Fig. 9) but showed considerable spatial variability, reaching tens of kilometers, over their measurement period from 2009 to 2013. The distance penetrated by saline water might be affected by precipitation and river discharge of a given year. Because river water is used for irrigation, agriculture in this area is very sensitive to shifts in saline intrusion. As the salinity in the irrigation water increases, the amount of salt that accumulates in soil also increases, meaning that the land is less suitable for agriculture and crop production decreases (Clarke et al. 2015; Dasgupta et al. 2015; Mahmuduzzaman et al. 2014). We found that the 1 ppt salt concentration line in March was closely related to the summer rice cropping area (Fig. 9). Basically, there was no cropping in the areas to the south of the 1 ppt salt concentration line during the dry season. Saline intrusion and loss of crop production during the dry season may be unavoidable at some areas in the delta, but saltwater management is important for paddy fields. To prevent further deterioration, systems that can detect early damage by salt should be developed. Although salt damage is not generally obvious until after the vegetation is damaged, the EC of river water should be used to monitor saline accumulation in soil. Remote sensing systems, such as the Sentinel-2, can provide fundamental information about EC at appropriate times. These measurements of EC across large areas can then be used to develop water resource management strategies to protect agricultural land from salt damage.

Conclusion

We examined whether Sentinel-2 imagery could be used to estimate the river salinity (EC) in the Ayeyarwady Delta and also assessed the impact of saline intrusion on the distribution patterns of paddy fields. The salinity was measured twice, at the beginning (November–December) and end (March) of the dry season, in three rivers: the Patheingyi, Yw, and Pyawbwe. The sampling times were chosen to cover the range of possible measurement conditions. The spatial and

temporal resolutions of the Sentinel-2 were suitable for monitoring river salinity over large areas. The reflectance from visible bands of the Sentinel-2 was strongly correlated with river water salinity. When flowing freshwater mixes with sea water, flocculation and settling of suspended particles are induced, resulting in less turbidity as the salinity increases. The best-fitting model using the green band showed high accuracy and gave R^2 , RMSE, and MAE values of 0.776, 4.896 dS m⁻¹, and 3.340 dS m⁻¹, respectively. While empirical models often limit the estimation range, our model could be used to estimate salinity over large areas. We also found that the river salinity varied considerably over space and time. The main factors that controlled the salinity in the river water in the delta were the precipitation and river discharge. The salt water mostly penetrated in March, at the end of the dry season when the discharge was low. Moreover, monitoring river water salinity can be profitable for paddy field management. In fact, we found that the 1 ppt salt concentration line in March marked the boundary between cultivated and non-cultivated paddy fields of summer rice. The frequent data from the Sentinel-2 can be combined with river water salinity measurements to provide information that can help to support the management of agricultural areas in this delta.

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