Spatio-temporal patterns of soil erosion and suspended sediment dynamics in the Mekong River Basin

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Abstract

Understanding of the distribution patterns of sediment erosion, concentration and transport in river basins is critically important as sediment plays a major role in river basin hydrophysical and ecological processes. In this study, we proposed an integrated framework for the assessment of sediment dynamics, including soil erosion (SE), suspended sediment load (SSL) and suspended sediment concentration (SSC), and applied this framework to the Mekong River Basin. The Revised Universal Soil Loss Equation (RUSLE) model was adopted with a geographic information system to assess SE and was coupled with a sediment accumulation and a routing scheme to simulate SSL. This framework also analysed Landsat imagery captured between 1987 and 2000 together with ground observations to interpolate spatio-temporal patterns of SSC. The simulated SSL results from 1987 to 2000 showed the relative root mean square error of 41% and coefficient of determination (R^2) of 0.89. The polynomial relationship of the near infrared exoatmospheric reflectance and the band 4 wavelength (760−900 nm) to the observed SSC at 9 sites demonstrated the good agreement (overall relative RMSE = 5.2%, R^2 = 0.87). The result found that the severe SE occurs in the upper (China and Lao PDR) and lower (western part of Vietnam) regions. The SSC in the

rainy season (June – November) showed increasing and decreasing trends longitudinally in the upper (China and Lao PDR) and lower regions (Cambodia), respectively, while the longitudinal profile of SSL showed a fluctuating trend along the river in the early rainy season. Overall, the results described the unique spatio-temporal patterns of SE, SSL and SSC in the Mekong River Basin. Thus, the proposed integrated framework is useful for elucidating complex process of sediment generation and transport in the land and river systems of large river basins.

Keywords: Integrated framework, RUSLE, sediment erosion, suspended sediment load, suspended sediment concentration, Mekong River Basin

1. Introduction

Soil erosion and sediment dynamics in river basins are determined by a series of complex natural processes, which are strongly related to human activities such as deforestation, agriculture, urbanization and environmental management of basins and river corridors. Such activities often result in increased sediment loads causing many problems, for example a loss of reservoir storage capacity through sedimentation and increased turbidity in water distribution systems (Arnold et al., 1995). Soil erosion can be the major factor to increase the concentration of suspended sediment, which has been recognized as the most important contaminant affecting the Mekong water (Xue et al., 2011). In addition to its direct role in determining water turbidity, bridge scouring and reservoir storage, sediment serves as a carrier for the transport of many binding substances, including nutrients, trace metals, semi-volatile organic compounds and numerous pesticides (EPA, 2000). Therefore, a reliable tool for monitoring and simulating soil erosion and suspended sediment patterns in basin scale is needed for basin development and management.

Soil erosion maps and its conservation planning have been widely developed on the basis of soil erosion models, which can be divided into two categories: empirical and physically-based models (Morgan, 1995). Empirical models are strictly based on the analysis of catchment data using stochastic techniques. The computational and data requirements for empirical models are usually fewer than those for physically-based models, and the output of empirical models is adequately supported by spatially coarse measurements. The Universal Soil Loss Equation (USLE) (Wischmeier and Smith, 1978), one such empirical model, is based on a large amount of data from the United States. The Agricultural Non-Point Source Pollution Model (Young et al., 1989) uses a revised form of the USLE. In contrast, physically-based models are based on fundamental physical equations describing stream flow and sediment generation in a river basin. These models have the potential to represent the physical processes observed in the real world, such as surface runoff, sub-surface flow, ground flow and evapotranspiration. Physically-based models are often used to describe the controlling processes of storm events. The Kinematic Runoff and Erosion model (Smith, 1981), the Water and Energy Simulations and Prediction model (Lopes, 1988) and the European Soil Erosion Model (Morgan et al., 1998) are examples of the physically-based erosion and sediment transport models. In addition, some models integrate both empirical and physically-based components such as the Soil and Water Assessment Tool (Arnold et al., 1998).

Meanwhile, the application of remote sensing in the assessment of inland water surfaces has recently escalated because of its capability of scanning wide water bodies within short time periods (Ritchie et al., 2003). Over the past three decades, remotely sensed images have been successfully used in the assessment of suspended sediment (Olmanson et al., 2008; Park et al., 2014; Zhang et al., 2014, Du and Zhang, 2014). Remote sensing technology provides a potentially effective solution for monitoring suspended sediment in turbid rivers (Yang et al.,

2011) because the effect of other optically active substances on the satellite data is negligible in such rivers (Lal, 2005). Consequently, a combination of erosion models with a spatial and temporal coverage afforded by remote sensing has the potential to provide a very useful tool for monitoring sediment dynamics and conducting effective basin management (Julian et al., 2008).

A number of studies have examined both water discharge and sediment behaviour in the Mekong River Basin (Delgado et al., 2012; Lu and Siew, 2006; Walling, 2008; Wang et al., 2011). Although many of these studies have recognized changes in water discharge and sediment load since the operation of dams began in the upper stream of the Mekong River (He et al., 2006; Kummu et al., 2007; Nguyen, 2003; Orr et al., 2012), no systematic analysis or variability estimation of the sediment dynamics (soil erosion, concentration and transport) has been conducted using a consistent framework. Thus, a systematic framework for the assessment of suspended sediment dynamics would significantly benefit the development of a decision support system. Moreover, such a framework can be a tool to assess and mitigate the effects of potential climate and land use changes on sediment dynamics processes, especially in areas with poor monitoring systems for sediment dynamics. Recently, spatial modelling using geographic information systems (GISs) have yielded progressively more suitable tools for the fields of research, such as forestry, agriculture, hydrogeology and soil science (Bocchi et al., 2000; Lu et al., 2004, Chen et al., 2011; Chen et al., 2014), as this technique can analyzes spatially distributed data and thus its useful for understand sediment dynamics.

The aim of this study is to propose an integrated framework for sediment assessment at a basin scale and to apply the framework to estimate the spatio-temporal patterns of sediment dynamics in the Mekong River Basin. We assessed the basin-scale distribution of SSL by coupling the Revised Universal Soil Loss Equation (RUSLE) with a simple scheme for sediment accumulation and routing. Within the framework, we also employed satellite

images for monitoring SSC and estimating its spatio-temporal profile. The proposed framework can be also applied to basins for which there are a limited set of observations (e.g. river discharge) because the proposed framework does not require a hydrological model to the assess sediment dynamic processes.

2. Target river basin

The target of this study is the Mekong River Basin, which is the largest trans-boundary river basin in Asia. The Mekong River originates in Tibet, China, and it flows southward to Southern Vietnam, a distance of more than 4,600 km. The Mekong River Basin covers an area of approximately 795,000 km^2 (Fig. 1) (MRC, 2005) and delivers 475 km^3 of fresh water per year and approximately 160 million tonnes of sediment per year into the South China Sea (Milliman and Meade, 1983). Compared to other major rivers in Asia, the Mekong ranks eighth with respect to average annual runoff (Pantulu, 1986) and is the third largest river in terms of sediment load (Darby et al., 2013). The climate of the lower Mekong (from the China border to the south) is humid and tropical. Mean annual rainfall ranges from 1000 mm in the Thai part to 3200 mm in the mountainous region of Lao PDR (Kite, 2001).

Currently, the Mekong River Basin is experiencing rapid population and economic growth. Increasing demands for hydropower and fresh water has resulted in the construction of a growing number of dams and reservoirs along the river mainstream. For example, the controversial hydropower project on the Mekong River is the Lancang Cascade within China's Yunnan Province in the upstream area. Since the completion of the Manwan Dam in 1993, there has been an ongoing debate about its positive and negative impacts on the Lower Mekong River Basin (Nguyen, 2003). The general consensus is that although there was a sharp decrease in sediment flux at Chiang Sean shortly after completion of the dam, downstream stations did not experience abrupt changes (Lu and Siew, 2006; Kummu and Varis, 2007).

3. Methods

In this study, we developed an integrated framework based on a soil erosion model and satellite-based SSC estimations for the spatial interpolation of sediment dynamics in a large river basin (Fig. 2). This study relies on historical data published by the Mekong River Commission (MRC) (MRC, 2005). We used hydrological and rainfall observations from 1987 to 2000 obtained from 65 rainfall stations located along the Mekong River Basin and its tributaries to represent the hydrological effects from sediment dynamics. In addition, we obtained the annual river discharge and SSC records from 1987 to 2000 from nine gauging stations located along the Mekong River (MRC, 2005) (Fig. 1).

3.1. Soil erosion

The RUSLE (Wischmeier et al., 1978) was applied in a distributed manner using a 3.6-km resolution GIS. This equation assesses soil erosion using feasible estimations of spatial resolution with reasonable accuracy over large areas (Lu et al., 2004). The RUSLE model is generally represented as follows:

$$A = R\ K\ LS\ C\ P \tag{1}$$

where A is the average soil erosion per unit area during a unit period of time, (typically one year) (tonnes/ha/year), R is the average rainfall-runoff factor (the erosion potential of rainstorms) (MJ.mm/ha^2), K is the soil erodibility factor (tonnes M/J h/mm), L is the slope length factor, S is the slope gradient factor, C is the crop and management factor and P is the support practice factor. C, LS and P are unitless. The modified RUSLE model is operated on annual time scales and covers the entire Mekong River Basin area (795,000 km^2). At this spatial scale, erosion processes are predominantly controlled by soil type, land use and climate patterns in relation to the topography (Auzet et al., 2002). The RUSLE model emphasises rill and inter-rill erosion and does not describe the sediment transport and sedimentation in the rivers.

The average rainfall-runoff factor (R) is calculated by a threshold-type equation by Loureiro and Coutinho (2001) as follows:

$$R = \sum_{i=1}^{N} \sum_{j=1}^{12} (7.05 rain_{10} - 88.92 days_{10})_{i,j} \quad (2)$$

where N is the number of observation years, $rain_{10}$ is the monthly rainfall ≥ 10 mm, which is otherwise set to zero, and day_{10} is the monthly number of days with rainfall ≥10 mm. Eq. (2) shows higher erosion potential for higher monthly rainfall, $rain_{10}$. It also accounts to the fact that for a given rainfall amount, a lower number of day_{10} rainy days results in both higher rainfall intensity and erosion potential. Then, using the inverse distance weighted interpolation method from the ArcGIS Spatial Analyst tool, we interpolated the resulting average annual R factor to make the resolution (grid cell size) consistent with that from maps of the other factors.

The soil erodibility factor (K) is a function of soil texture, organic matter content and permeability. To estimate the K factor, we used the soil erodibility nomograph that Wischmeier based on measurable properties (Wischmeier and Smith, 1978). The soil erodibility nomograph comprises five soil profile parameters: percent of silt (0.002–0.1 mm), percent of sand (0.1–2.0 mm), percent of organic matter (OM), class of soil structure (s) and permeability (p). For this study, we obtained a global digital soil map of the Mekong River Basin from the Food and Agriculture Organization of the United Nations (FAO, 2003).

The crop and management factor (C) represents the effect of vegetation and management on the soil erosion rates. The C factor ranges from 0 to 1. The land cover of the Mekong River Basin is classified into six categories: water, urban, wetland, forest, crop field and grassland. We adopted the C factor values for individual land cover of the Mekong from literature data for the Vietnam river basin (Ranzi et al., 2012).

The term LS represents the effect of slope length and slope gradient. A higher slope results in a higher velocity of the overland flow, thus increasing shear stresses on the soil

particles. Slope steepness (%) was directly derived from a digital elevation model (DEM), which represents the surface terrain of the catchment and permits the retrieval of geographical information. In this study, the DEM of the Mekong River Basin was built from the Global 30 Arc-Second Elevation model (http://lta.cr.usgs.gov/GTOPO30) with a spatial resolution of approximately 20 km^2 (grid area: 2×2 min).

The support practice factor (P) reflects the effects of practices that reduce the amount and rate of the water runoff, thus reduces erosion. It is the ratio of soil loss with a specific support practice for croplands to the corresponding loss with upslope and downslope tillage. In this study, a P value was applied in non-agriculture areas or in areas with natural erosion, assuming the presence of no supporting practice in the agricultural areas. The P factor value ranges from 0.5 to 1.0, as adopted by Ranzi et al. (2007), and the highest value is assigned to areas with no supporting practice. Subsequently, the R, K, LS, C and P factors were multiplied using the Raster calculator function tool of ArcGIS to calculate A.

3.2. Sediment transport

The transport model by Ranzi et al., (2012) in their study in Red River is the one implement in this study. Soil erosion was estimated on a monthly basis from 1988 to 2000, and then these values were accumulated across the channel network, as extracted from a 3.6-km resolution DEM using the standard D8 flow direction method (O'Callaghan and Mark, 1984; Orlandini and Moretti, 2009). We used the ArcGIS interface to estimate the spatially distributed soil erosion in each of the 39 sub-basins, SE_k (k = 1–39), based on estimates from the RUSLE model. Then, SE_k was routed through the channel network with a conceptually lumped scheme to reproduce the dominant behavioural mode of the sediment transport processes (Moore, 1984; Ranzi et al., 2012). With this scheme, we estimated the mean travel time of sediment, θ_k (days), in each sub-basin as the ratio of the length scale, L_k, to the velocity scale, V:

$$\theta_k = {L_k}/{V} \tag{3}$$

The length scale was assumed to follow the power law function in each basin area, A_k, according to Hack's law (Hack, 1957; Rigon et al., 1996):

$$L_k = 1.4A_k^{0.6} \tag{4}$$

where L_k is the mainstream length expressed in kilometres and A_k is the area of each sub-basin in km^2. Assuming each sub-basin serves as a storage area, is fed by sediments detached from its hillslopes and releases a sediment discharge at its outlet $SSL_k(t)$ in each month ($SE_k(t)$). The sediment stored in the sub-basin $W_k(t)$ is proportional to $SSL_k(t)$ following a linear reservoir concept:

$$W_k(t) = \theta_k SSL_k(t) \tag{5}$$

The mass conservation for sediments at the basin scale can be described as the differential equation of Eq. (4) with respect to time (t):

$$\frac{dW_k(t)}{dt} = \frac{\theta_k dSSL_k(t)}{dt} = S_k - SSL_k(t) \tag{6}$$

In this conceptual and lumped modelling framework, the monthly SSL_k (tonnes/month) in each k_{th} basin and each i_{th} month (T days) yields (Ranzi et al., 2012):

$$SSL_{i,k} = SSL_{i,k-1}e^{{-T}/{\theta_{k-1}}} + S_{k,i}e^{{-T}/{\theta_k}} \tag{7}$$

and the monthly SSL yield is:

$$SSL_{i,k} = SSL_{i,k}\theta_k(1 - e^{{-T}/{\theta_k}}) + S_k\theta_k\left(e^{{-T}/{\theta_k}} - 1\right) \text{ (tonnes)} \tag{8}$$

Because of a lack of input data, we assumed the mean sediment transport velocity (V) to be constant (V = 0.5 m/s) for the entire Mekong River Basin, which is the mean value obtained from the Hjulstrom curve (Hjulström, 1935).

In the target period of this study, there was a dam in the mainstream (Manwan Dam), but we didn't quantitatively estimate its effect on sediment dynamics because of the limited availability of dam-related sediment data. Nevertheless, the Manwan dam storage volume is

relatively small (total storage volume: 0.92 km^3) among dams in Mekong River Basin and gives a minor contribution on sediment dynamics in the Mekong River Basin (Plinston and Daming, 2000; Fu et al., 2008). Thus, we assumed that the Manwan dam caused little change in both the magnitude and the seasonal pattern of SSL and SSC in the mainstream.

3.3. Suspended sediment concentration

To estimate the suspended sediment patterns in the Mekong, we used Landsat imagery captured between 1988 and 2000, including 110 Thematic Mapper (TM) images and 21 Enhanced Thematic Mapper Plus (ETM+) images. The spatial resolution of the TM and ETM+ data is 30 m, except for band 6 of the thermal infrared channel (120 m). The images were acquired for different seasons of the year from the Landsat archive of the United States Geological Survey (http://glovis.usgs.gov). Three visible and near infrared (NIR) bands were included in the analysis. These data were combined with the in situ measurements to determine the statistical relationships between the reflectance of the different TM and ETM+ bands and the SSCs. Cases from December 1995 to November 1996 were used to illustrate the longitudinal profile of the suspended sediment of the Mekong River Basin. All available cases from 1987 to 2000 were used to investigate the temporal variation in SSC between the dry and rainy seasons. In situ measurements of SSC from January 1987 to December 2000 were also used in this study to establish the empirical relation between the satellite images and the observed SSC data.

Suspended sediments increase the radiance emergent from surface waters in the visible and NIR portion of the electromagnetic spectrum (Ritchie et al., 1976). The Landsat TM and ETM+ visible and NIR bands 1–4 are optical bands that record electromagnetic radiations of 0.45–0.52, 0.52–0.60, 0.63–0.69 and 0.76–0.90 μm, respectively. To estimate SSC, we used cloud-free pixels in the middle of the river’s width using information only from the water surface and not from the land. Because analyses were made for individual images with quite

small angular ranges, there was little effect from the atmospheric correction on the correlation analysis (Zhang et al., 2003). Thus, we ignored atmospheric correction.

In the analysis, the raw Landsat TM and ETM+ digital numbers (DNs) were transformed into the physical values of radiance using in-flight sensor calibration parameters (Markham and Barker, 1987). These parameters are supplied with the imagery and are determined by comparing the in-flight calibration sources with pre-flight absolute radiance values. Then, the exact radiometric response function for each band were determined (Jensen, 1996) as follows:

$$L_\lambda = \left(\frac{L_{max} - L_{min}}{255}\right) DN + L_{min} \quad (9)$$

where L_λ is the spectral radiance measured over the bandwidth λ (m W/cm^2/sr/μm), DN is the digital number value recorded, L_{max} is the radiance measured at detector saturation (m W/cm^2/sr/μm) and L_{min} is the lowest radiance measured by a detector (m W/cm^2/sr/μm). Then, the exoatmospheric reflectance for each bandwidth were computed (Jensen, 1996) as follows:

$$\rho_\lambda = \frac{\pi d^2 L_\lambda}{E_{o\lambda} \cos\theta_s} \quad (10)$$

where ρ_λ is reflectance as a function of bandwidth λ, d is the Earth–Sun distance correction, $E_{o\lambda}$ is exoatmospheric spectral irradiance and θ_s is the solar zenith angle. Some of the conversion parameters are available in the image header files, whereas the TM exoatmospheric irradiance values are available from Markham and Barker (1987), and those from the ETM+ area are available from NASA's (National Aeronautics and Space Administration) Landsat 7 Science Data Users Handbook (NASA, 2008).

Traditionally, statistical techniques are used to establish relationships between satellite reflectance or their ratios and water quality parameters (Allee and Johnson, 1999). A few studies have used non-linear power models to address the curvilinear behaviour of this relationship (Lathrop, 1992). In this study, we examined regression methods, including linear, exponential, polynomial and log formulations, to establish the relationships between SSCs

monitored on the ground and remote sensing reflectance values in the TM and ETM+ bands 1–4.

4. Results and discussion

4.1. Spatio-temporal patterns of soil erosion (SE)

The mean annual soil erosion (SE) was evaluated using the RUSLE model and ranged from 0.0 to 32.2 t/ha/yr in the Mekong River Basin (Fig. 3). The *R* factor increases gradually from north (upper region) to south (lower region) (Fig. 4a). The lower range of SE (0.0–4.4 t/ha/yr) was scattered all over the Mekong River Basin, occupying 60% of the study area and corresponding with gentle slope areas ranging from 0% to 5.98%. The clay in these areas has a greater permeability and highly resistant to the impact of runoff (FAO, 2003; Morgan, 1995), making it difficult for soil to detach. The medium range of SE (4.4–13.0 t/ha/yr) occupied 35% of the study area and was scattered around the middle region in Vietnam (some areas near Myanmar and Lao PDR). This SE range is attributable to cropland cover and relatively high average annual rainfall. The highest value range of the *R* factor, between 7,986–12,599 MJ.mm/ha^2, occurred in the middle region in Vietnam and Lao PDR (Fig. 4a). Furthermore, the dominant soil type is clay (area from Vietnam to Lao PDR) (Kyuma, 1976), which are difficult to detach by rain.

The high range of SE (13.0–32.2 t/ha/yr) occupied 0.2%–0.6% of the Mekong River Basin, located particularly in valleys with steep slopes of more than 25° and a high rainfall-runoff factor of 7,986–12,599 MJ.mm/ha^2 in the upper, middle and lower regions. Puustjarvi (2000) reported that some of the sediment within in the Lower Mekong system sourced from its Chinese reach and 28% of this basin area has been classified as ‘erosion prone’ (Figs. 3, 5). Highly erosive areas also dominate in the middle (Lao PDR) and lower (Cambodia and Vietnam) regions (Figs. 3, 5). This distribution of highly erosive areas is due to cropland cover, especially in valleys with steep slopes and high annual rainfall. Furthermore, the

typical soil type in these areas is mainly a mixture of silt and sand, which is prone to detach as surface runoff (FAO, 2003), as indicated in Fig. 4b.

Dry seasons (December to May) produced lower SE levels than rainy seasons (June to November), obviously because of the low precipitation in dry seasons (Figs. 5a, 5b). The average SE in dry seasons is 0.34×10^7 t/month, whereas the average SE in rainy seasons is 1.05×10^7 t/month. Generally, areas exhibiting low SE levels (< 0.83 t/ha/month) in summer (June, July and August) are scattered around the Mekong River Basin, occupying 80.0–84.8% of the study area that corresponds to areas of gentle slope (i.e. 0–5.98%). The type of soil that predominates in such areas is sand (i.e. high permeability) and produces less runoff and less erosion (FAO, 2003). The low erosion levels also reflect the protective role of forest and natural vegetation cover, as indicated by the *P* factor ranging from 1.0 to 0.5 (Fig. 4e).

4.2. Spatio-temporal patterns of suspended sediment load (SSL)

The average relative root mean square error (RMSE) between the simulated and observed SSL was 1.00×10^7, 0.42×10^7 and 0.25×10^7 t/month in the upper, middle and lower stations, respectively, in the period 1987–2000 (Figs. 6a–c). The mean Nash–Sutcliffe efficiency (NSE) was 0.50, 0.67 and 0.65 in the upper, middle and lower stations, respectively. Table 1 show the summary of model performance indicators for monthly SSL in the 9 stations. Although the model simulation underestimated SSL by 41% on an average, the seasonal SSL pattern was fairly well simulated at the nine stations. Both in observations and simulations, SSL was the highest in autumn at Kratie and Phnom Penh in the lower region (Fig. 6). The lowest SSL was estimated to occur in either winter or spring in the three regions. The SSL at Pakse in the middle region was estimated to be 3.61×10^7 t/month in summer, which was the highest monthly SSL value among the studied stations. The *C* factor around Pakse indicated that SE increased by 85%, resulting in the high SSL (Fig. 4c).

Fig. 7 shows the longitudinal SSL profile at each of the 30 sections along the mainstream of the Mekong River. This longitudinal SSL profile showed no consistent SE trend from the upstream to the downstream along the Mekong River. The results illustrate that the fluctuation in SSL is weaker in the upper and middle regions than in the lower region around year except in winter (Fig. 7). The results show local reductions of SSL in all seasons possibly due to changing topography and drainage areas in the Mekong River Basin. Moreover, in the upper part of the middle region (near Vientiane) and the lower region (near Pakse), SSL increased as maximum precipitation in the Mekong River Basin was observed at Nakhon Phanom (middle region), and the average *R* factor ranged from 7,986 to 12,599 MJ.mm/ha^2 (Fig. 4a).

Future changes in the SSL due to dam construction will have serious implications for sediment management planning. It is estimated that the annual sedimentation in the Manwan dam is 2.28% of the storage capacity as 10 year average (Plinston and He, 2000; Fu et al., 2008). In general, the SSL at Chiang Sean decreased from 7.1×10^7 t/yr in 1962–1992 to 3.1×10^7 t/yr in 1993–2002 in average according to the water quality database of MRC (Kummu, 2007). Yet, Fu et al. (2008) indicates that there was no evident casuality between the sediment series at Yunjinghong and Chiang Sean. Cross-verified estimates of the impact of sedimentation are difficult due to the different measurement methodologies adopted in each research.

The result also provides clear evidence of the trend of seasonal cumulative SE to increase from upstream (0 km) to downstream (4000 km, Phnom Penh station) (Appendix A). Furthermore, seasonal SSL shows a significantly high SSL at points where SE shows an increasing change from upstream to downstream especially for all seasons. A cumulative plot of SE indicates that the impact of SE changes was apparent in distance 1544 km from upstream (0 km). Firstly, SE was stable (from distance 0 to 1544 km), then gradually

increased within distance 1544 to 2366 km and then rapidly increased after the distance 2366 km (middle region). This rapidly increasing trend was closely related with the high annual rainfall and the resultant land clearance and intensification of agricultural production, caused by rapidly increasing population (You, 1999).

4.3. Spatio-temporal patterns of suspended sediment concentration (SSC)

Based on coefficient of determination (R^2), we chose the polynomial regression method to relate SSC to the exoatmospheric reflectance of visible bands 1–3 and the NIR band 4 because of the nonlinear properties of reflectance. Overall, the best relationship was obtained from the Landsat TM and ETM+ band 4:

$$SSC = 24016.1\rho_4^2 - 930.35\rho_4 + 4.955 \quad (11)$$

where *SSC* is the suspended sediment concentration (mg/l) and ρ_4 is the exoatmospheric reflectance of band 4. The best wavelengths for the satellite assessment of SSC are found in the NIR, which is consistent with the previous research (Ritchie et al., 2003). In addition, we also obtained the multiple linear regression for the exoatmospheric reflectance in bands 1, 2 and 3 using the SSC equation as follows:

$$SSC = -332.1 + 9871.9\rho_1 - 14625.4\rho_2 + 8416.4\rho_3 \quad (12)$$

where ρ_1, ρ_2, and ρ_3 are the exoatmospheric reflectances of bands 1, 2 and 3, respectively.

The correlation coefficients of the predicted and measured SSC values were 0.87 for Eq. (11) (Fig. 8) and 0.74 for Eq. (12), respectively. Although both models show reasonable agreement with the observed values, these correlation coefficients show that the polynomial relationship based on the NIR data (Eq. 11) was better for predicting SSC along the Mekong River. Park et al. (2014) reported SSC patterns in the Amazon River that showed a statistically significant relationship in the regression model in an R^2 range from 0.83 to 0.93, which is similar to R^2 in the present study. With respect to the SSC observed at the nine gauging stations, the RMSE between the observed and estimated SSC values was 50.2, 68.0,

94.5 and 109.7 mg/l for winter, spring, summer and autumn, respectively, with an average relative RMSE of 41% (Fig. 9).

Generally in observation, the SSC was higher in the rainy season than in the dry season. The decrease in SSC estimation along the mainstream was also clearly shown (Fig. 9). The average SSC in summer was 634.8 mg/l and 377.5 mg/l in the upper and middle regions, respectively, which were the highest values, compared to those in the other seasons (Fig. 9). Moreover, the average SSC estimation was the highest (181.1 mg/l) in autumn in the lower region at Kampong Cham. Conversely, the lowest estimation SSCs occurred in winter in the three regions. The average SSC estimation in winter was 112.4, 63.8 and 32.5 mg/l for the upper, middle and lower regions, respectively. These results were reasonably supported by the seasonal SE distributions (Fig. 5) that also showed higher SE in the rainy season than in the dry season.

The longitudinal gradient of SSC was not linear and showed no steady trend along the fluvial continuum of the Mekong River Basin (Fig. 10). This is because of the heterogeneous SE distribution from the upstream to the downstream of the basin. Walling (2008) explained this phenomenon as convergent boundary losses associated with sediment storage in the river starting from approximately 50 km upstream of Chiang Sean. Middle-high SE levels were scattered in the upper region (Myanmar and Lao PDR) in the summer profile (Fig. 5c), which corresponded to a high SSC in the upper region (Fig. 10c). Moreover, the range of the C factor analysis in the upper region was 0.00 to 0.15, indicating a reduction only by 15% in soil erosion (85% potential erosion). High SSC variations were observed in the section from Vientiane to Nakhon Phanom in all seasons (Fig. 10). The SSC generally increased along this section in spring and summer because the precipitation around Nakhon Phanom was at a maximum in the Mekong River Basin and this area is mainly a cropland. The R factor

showed a high range of the average rainfall-runoff factor of between 7,986−12,599 MJ.mm/ha^2.

Both simulated SSL and SSC values significantly correlated with the estimated SE distribution in autumn, as 40% of the area in the lower region (from Kratie to Phnom Penh) shows a middle-high SE level (539–2770 t/ha/month). This result is clearly significant, as shown in Appendix A and B. Moreover, the both of the simulated results were also consistent with the SE distribution in winter, as 80% of the basin area shows a low SE level (0−70 t/ha/month).

5. Conclusion

In this study, we proposed an integrated framework for sediment assessment and applied this framework to the Mekong River Basin. The main findings were as follows.

5.1. Integrated framework

The conceptual modelling framework was based on land use, a DEM, soil maps, precipitation data and satellite images to estimate surface erosion and sediment transport. This approach provided a simple and reasonable means to model SE and SSL in the Mekong River Basin and allowed us to take land use management practices into consideration. In addition, we used an effective combination of Landsat TM and ETM+ images with conventional in situ measurements in this framework to monitor SSCs along the Mekong River Basin. The results indicate that the best wavelengths for satellite assessment of SSC were in the NIR range, band 4. Overall, we successfully applied this framework to describe the distributions of SE, SSC and SSL in this river basin. Our results helped us to identify severe SE areas and high SSL sections, which deserve priority attention in basin management efforts toward soil and water conservation. The proposed framework can also be applied to basins for which there are limited observations (e.g. river discharge). For example, in this study, we did not use a hydrological model to assess the dynamics of the sediment process.

Furthermore, this framework allows the assessment of sediment not only in rivers but also in the interaction between sediment yield, transport and sedimentation. It may be applied not only to the Mekong but also to other large basins that have a similar climate and hydrogeology.

5.2. Suspended sediment in the Mekong

Our results indicate that the overall range of SE in the Mekong was from 0.0 to 32.2 t/ha/yr. While, the range of SSL and SSC in its mainstream were from 1.39×10^5 to 3.35×10^7 t/month and from 181.1 to 397.8 mg/L, respectively. As a result of the application of the proposed framework, we found that severe SE occurs in the upper (Lao PDR and China) and lower (Vietnam) regions mainly because of the presence of steep slopes. The SSC in the Mekong River Basin showed fluctuating patterns along the Mekong river, especially during the rainy season (Autumn) because of high annual precipitation and its distinctive spatial distribution, whereas the SSL decreased in the lower region (Kampong Cham to Phnom Penh) probably because of the high deposition processes in the lower region. Furthermore, in the longitudinal profiles of spring and summer season, SSCs showed an increasing trend (between Vientiane and Nakhon Phanom) because of high rainfall observed in this region. In addition, the highest SSC variation was identified in the section from Vientiane to Nakhon Phanom, which was caused by heavy precipitation and subsequent intense soil erosion. Moreover, the longitudinal profiles of SSC show a decreasing trend from Kratie to Phnom Penh in summer and autumn because of the decreasing in the main stream water velocity, which increases the sediment deposition and decreases SSC.

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