LETTER

Evaluating the effect of data-richness and model complexity in the prediction of coastal sediment loading in Solomon Islands

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Abstract

Global biophysical data are increasingly accessible due to improvements in remote sensing and open datasets. These datasets can be of particular value in remote and data-poor environments to enable estimates of water quality impacts from catchment land clearing. Given the resources required to collect field observations and calibrate detailed process-based models, global datasets are often the only sources available to parameterise simple models however the comparative use of these data sources in process-based models is relatively unexplored. This study compares the widely applied models of Integrated Valuation of Ecosystem Services and Trade-offs and Soil and Water Assessment Tool (SWAT) to a tropical catchment in the Solomon Islands using globally available data. These uncalibrated models are contrasted with a SWAT model calibrated with measured streamflow and turbidity in the catchment and meteorologically forced by data from a nearby weather station. These catchment models were coupled with models of sedimentation to examine deposition rates in the coastal lagoon adjacent to the catchment. Model validation using measured coastal sedimentation rates demonstrated that simpler modelling approaches (one-dimensional basin sedimentation and two-dimensional sediment extent modelling) were marginally better than more complex approaches (three-dimensional Delft3D) in data-poor conditions. However, investment in local catchment observations significantly improved the accuracy of simulation outputs. This insight can guide decisions about model complexity, data-richness and investment in local environmental monitoring in these challenging environments.

1. Introduction

Environmental and ecological questions of a large-scale nature are infamously challenging to answer, even in locally data-rich environments due to the scale and complexity of environmental systems [1]. The challenges in collecting accurate observations across these complex environments to draw system scale conclusions are well known. A common difficulty faced is the trade-off between higher-fidelity datasets collected at small temporal and spatial scales, which often cost a lot to acquire, and broader datasets covering large areas and timescales which are increasingly freely available [2, 3]. Models are often used to make sense of available data by filling the unknown gaps in observed data and estimate past, present, and potential future states through various forms of scenario analysis. For most environmental problems, there are an array of available models of varying complexity based on the range of different processes they attempt to simulate and the approaches taken for this simulation [4]. This range of possible modelling approaches requires an assessment of trade-offs to decide the best approach to use given the available input data and parameterisation requirements. It is often observed that in data-rich environments more complex models are often applied, however this complexity is not always necessary [5]. Policy and management decisions for environments across the world are formed from the pivotal results of investigations.
that began from a range of possible approaches of differing investments [6, 7].

Catchment hydrology is a prime example of a large-scale environmental system that is both challenging to monitor and to model with a high degree of certainty [8–12]. Data collection and modelling approaches used in catchment hydrology are deeply entwined with the management actions of local water authorities and governments for both short- and long-term planning [13]. Furthermore, the quality of water resources is just as important as its quantity, and much of the pathogen, heavy metal, nutrient, and organic loading transport is associated with the export of sediments from these hydrological systems [14, 15].

Whilst the social, ecological, and economic significance of the quality of water within catchments is important in itself, the downstream receiving water environments of these catchments are often highly sensitive to sediment, and are subject to additional complexity of nearshore sediment dynamics [16–19]. Given the interconnectivity of these various processes from the terrestrial catchments to the coastal environments, attempts to model coastal receiving environments are particularly susceptible to cascading errors. To constrain the uncertainty associated with this error propagation, field data across the land-sea continuum is critical [20, 21].

In recent times, there has been a surge in sources of data that provide an alternative to local monitoring from global climatology analysis [22–24] and remote-sensing [25–30], to global-scale models of the oceans and atmosphere [31–34]. The ability to collect high-quality local-scale field data has also improved in this time. However, the technology required to make this information widely available within reasonable timeframes and in a cost-effective way for hydrological analysis is still in a developmental phase, particularly in remote areas [35]. Moreover, there exist data-poor and/or remote regions of the world where local data is sparse at best and difficult to collect. Hydrological assessments in these remote or data-poor environments typically rely on globally available datasets and literature from other systems in order to make predictions and inform policy or management decisions [36, 37]. Hence, data-poor developing nations undergoing rapid transition of catchment land use often rely on uncalibrated models using global data to guide catchment management that could have substantial social, economic, and ecological ramifications [38].

Despite the challenges with modelling complex hydrological processes in data-poor regions there has been limited reporting of investigations into the value of increasing model complexity and data-richness in these systems. This study addresses this research gap by comparing commonly applied models to assess sediment export from an undisturbed tropical catchment in a remote and data-poor region that faces pressures for natural resource extraction [39–42]. The model development approaches considered in this study explore the two dimensions of process-based model complexity and input data-richness. We used a regionally unique in-stream water quality dataset and measured coastal sedimentation rates to assess the performance of different modelling approaches across the land–sea continuum.

2. Methods

2.1. Overview of methods

This study applied two catchment sediment export models, using input sources of varying data-richness, to explore seven sediment export scenarios. Catchment sediment export estimations and the frequency of total suspended solids (TSS) exceedance were compared using in situ stream observations and water quality guideline thresholds. Simulation results from the catchment models were used as inputs to three coastal sedimentation models. Outputs from the sedimentation models were evaluated using coastal sedimentation measurements under both data-poor and data-rich catchment sediment export scenarios.

2.2. Study characterisation

The study site is the approximately 75 km² Jejevo catchment (−8.1° S, 159.12° E) located on the windward side of Isabel Island in Isabel Province, Solomon Islands (figure 1). Solomon Islands is a country formed by over 900 islands, where six of the largest islands form the majority of the approximately 650 000 population [43]. Annual rainfall total averages measured in coastal areas of Solomon Islands have mostly been in the range between 3 000 mm and 5 000 mm. Although no long-term rainfall stations exist at higher elevations relative to the coast, it is thought that local topographies may increase the average annual rainfall total to the order of 9 000 mm in some places [44]. While nearby catchments have been disturbed by logging operations, the study area remains a predominantly undisturbed from human interference (a small gardening settlement exists near the mouth of the river) with prevailing steep tropical rainforest (where erosion processes are not well-known). A rare high-quality dataset was collected in the study area, providing a unique opportunity to investigate the value of increased investment in data-richness over a range of model complexities. Hourly in situ stream monitoring and flood event sampling (rising stage samplers and ISCO automated samplers) collected over the duration of 2013, and coastal sedimentation observations over this same period were used from the downstream monitoring site (due to continuous data availability and quality considerations). There were also hourly recorded local weather (rainfall, wind, relative humidity, air temperature, solar radiation, and barometric pressure) observations (Nuha Camp Weather Station) available during this time (figure S1 (available online at stacks.iop.org/ERL/15/124044/mmedia)).
Event sampling and analysis were combined with in situ turbidity from data loggers (YSI 6820 V2) deployed in the Jejevo stream to determine the approximate relationship with the TSS measured in the corresponding samples (figure S2). The best fit was found at approximately one NTU for every $2 \text{ mg l}^{-1}$ of suspended sediment in the stream ($R^2$ of 0.77 with events measured up to 227 NTU and 420 mg l$^{-1}$ using 40 samples; figure S3 and S4).

TSS frequency of exceedance was calculated for the observations and higher complexity catchment model development scenarios, drawing comparison to turbidity guidelines for thresholds in drinking and environmental water quality [45, 46]. Further evaluation was also able to be undertaken in the receiving waters by using a combination of settling tube deployments and sediment core dating. A sediment core taken from the nearshore site was found to show a sedimentation rate of 1.07 cm yr$^{-1}$ over the previous 40 year period [47]. This is equivalent to a sedimentation rate of 7.77 mg cm$^{-2}$ d$^{-1}$ adjacent to the Jejevo river mouth (assuming a sediment density of 2650 kg m$^{-3}$).

2.3. Catchment model development scenarios
Two commonly used catchment models for sediment export estimations were selected to represent the lower and upper ranges of model complexity. The Integrated Valuation of Ecosystem Services Sediment Delivery Ratio Model (InVEST SDR version 3.2) [48] was selected as a low complexity model. InVEST is often applied where local data availability has been considered poor or non-existent [49, 50]. This modelling approach uses a digital elevation model (DEM) to estimate the yield of sediment from the revised universal soil loss equation with a ratio determining the proportion of soil loss exported from a respective stream [48]. Beyond the 30 m resolution DEM provided by the shuttle radar topography mission (SRTM) [51], spatial data is required to delineate the catchment (figure S5) and represent the distribution of soil types (from surveying [52]) and land use (derived from satellite analysis of tree coverage [53] with a 10% tree canopy cover threshold for deforestation [54] determining 99.98% of the catchment to be covered by rainforest). Furthermore, two rainfall erosivity (MJ mm ha$^{-1}$ hr$^{-1}$) equations using rainfall in mm were compared as a current constraint is that most studies in soil erosion have been done in agricultural landscapes of the United States of America [55, 56]. The Roose equation

$$R = \text{MEAN ANNUAL RAINFALL} \times \text{MULTIPLIER}$$

is recommended for InVEST with a multiplier of 0.2–0.6 expected for mountainous tropical areas near the ocean [57]. As with a previous study in the region
The settling rate is a key parameter representing the particle class size of sediment to be modelled, and was selected at 0.00005 m s\(^{-1}\) based on coastal environment fine sediments in the concentration range observed [65]. This revised settling rate compensates for near-shore processes such as wave turbulence which may hinder or reduce the effective settling rate of a particle in suspension. Thereafter, a path distance algorithm is applied using a horizontal relative moving angle and the predefined ‘forward’ horizontal factors using a cost dataset comprised of the calculated seconds needed to traverse a single element of the grid using the surface velocities [36]. Sediment extent areas were calculated for each month’s mean surface currents [33] using a surveyed bathymetry dataset (figure S6) and uniformly loaded from the source catchment, with aggregation of these monthly plume areas over the year. The bathymetry survey dataset applied to the SEM in this study was of higher resolution (sampled to 50 m from a higher resolution survey) to those applied in previous studies using global-scale coarse resolution sources on the order of 1 km with simulations carried out at 90 m resolution [36].

A Delft3D model [66] with a 50 m horizontal grid resolution of the receiving waters was developed as the highest model complexity scenario considered in this study. This scenario represents the development of a resource-intensive three-dimensional hydrodynamic, cohesive sediment transport [67], and ocean heat flux model [68] typical of the highest degree of complexity employed to model a coastal receiving water environment [69]. Eleven sigma-coordinate vertical layers were used in the model with higher resolution at the top of the water column reaching 0.17% of the total depth and down to one-third of the total depth at the bottom of the water column. Sedimentation was simulated over the full 2013 study period using the catchment sediment
export loading from scenario 3 and 7. The tidal forcing signal was developed using astronomical constituents [70], while Mannings bed roughness was specified at 0.025 in the receiving waters, enhanced to 0.1 in reef regions [71], and 0.05 used in the lower Jejevo stream to the river mouth [72]. The bathymetry of the model was smoothed towards the open ocean boundary for numerical stability in the regions where steep bed slopes were present.

An averaged NRMSLE was calculated between the measured sedimentation rates during the 2013 study period, and the simulated sedimentation rates estimated by each of the coastal models. This performance measure was selected to fairly represent the relative error in the model domain over the larger scales of variation across the study domain and simulation results.

### 3. Results

#### 3.1. Catchment sediment export

In all metrics ($R^2$, NSE, and PBIAS) the SWAT model calibration in scenario 7 demonstrated a ‘very good’ performance for streamflow and ‘not satisfactory’ performance for TSS [73], highlighting a much larger challenge in calibrating sediment export processes at a daily timescale (table S2). The observed mean TSS for the 2013 study period was 110 mg l$^{-1}$ (20 mg l$^{-1}$ geometric mean) with a standard deviation of 370 mg l$^{-1}$, whilst the calibrated SWAT model in scenario 7 achieved a mean TSS of 98 mg l$^{-1}$ (0.5 mg l$^{-1}$ geometric mean) with a standard deviation of 312 mg l$^{-1}$ over the same period. Minimums between the observed and simulated datasets were more similar with 0 mg l$^{-1}$ for scenario 7 and 2 mg l$^{-1}$ for the field measurements. In the maximum observations recorded during the 2013 study period, the peak range of the turbidity logger was reached for between 1 day and 1 week. The corresponding potential magnitude of sediment loading to events larger than the measurement range of the turbidity sensor were subsequently unavailable, and hence the maximum observed TSS was 2593 mg l$^{-1}$, whilst scenario 7 produced an estimated unrestricted maximum of 3305 mg l$^{-1}$ based on the available measurements.

The total estimated sediment export for the 2013 study period out of the Jejevo estuary was summed for each catchment model scenario and compared with the sediment export distribution observed from field monitoring in the lower Jejevo river (figure 2(A)). Between the two simpler InVEST modelling scenarios, the Roose rainfall erosivity equation was found to be an order of magnitude closer to the observed range compared to the Bols rainfall erosivity variant. In contrast, the SWAT model scenario using global data (scenario 3) was on the same order of magnitude as the Roose rainfall erosivity approach (scenario 1) with an error between the two InVEST scenarios. This result suggests that increasing model complexity without any investment in increased data-richness was of no increased value for predicting sediment export from this catchment in the study period.

Increasing the rainfall data-richness from a global coarse resolution monthly source to global coarse resolution daily sources both improved the estimation of total sediment export to within one order of magnitude at 87.2% NRMSLE (scenario 4) and slightly worsened the estimation of total sediment export at 99.7% NRMSLE (scenario 5). Noting that both the CFSv2 global forecast model rainfall predictions and TRMM satellite remotely sensed rainfall estimations resulted in under predictions. Figure 2(B) presents the cumulative rainfall for each of the rainfall datasets used across the seven catchment scenarios. Whilst the rainfall total for the global monthly WorldClimv2 is higher than those for both the CFSv2 forecast model and remote TRMM satellite-based rainfall estimations, the sediment export predictions from the catchment under the CFSv2 rainfall dataset is increased and approaches the observed range. Results highlight the significance of capturing local rainfall events on a daily scale compared to monthly
timescales when estimating sediment export from this catchment. Scenario 6 using local rainfall measurements with a much higher cumulative rainfall total, was the only scenario to overpredict the observed range with a 72.1% NRMSLE, however it was very close to the observed range. Again, this reinforces the importance of capturing the local rainfall events. As expected, the results of scenario 7 provided the only estimate in this study that matched the observed range, however the calibration of the more complex model comes with the introduction of parameter identifiability challenges [74]. This is especially concerning where differences in rainfall data have been found to have a significant impact on the resulting sediment export. In an environment where local measurement location bias can be very large within the spatial heterogeneity characteristic of local rainfall patterns at the catchment scale, significant recalibration effort is required [9].

3.2. Catchment TSS exceedance frequency
The TSS exceedance time-frequency distribution revealed strong differences in the data-richness dimension across the SWAT model development scenarios 3–7 (figure 3). The ungauged scenarios (3–6) performed particularly poorly in the estimation of TSS exceedance for both drinking [45] and tropical estuarine environmental turbidity guidelines [46]. Whilst the data-poor scenario (scenario 3) predicted guidelines would not be exceeded at all in the study period, investing further in data-richness was able to predict that the guidelines would be exceeded. However, this revealed that exceedances were not predicted to occur with the same frequency as was
observed in the catchment. Specifically, observed exceedance of environmental and drinking water guidelines occurring 23% and 60% of the time, respectively. Scenario 4 revealed a 7% frequency of drinking water guideline exceedance, whilst the environmental guideline was rarely exceeded at <1% frequency. The environmental guideline was not exceeded at all in scenario 5, with the drinking water guideline exceeded at a frequency of just 2%. The addition of local rainfall data in scenario 6 improved this estimate to 20% frequency for exceeding the drinking water guideline (40% underestimated), and 9% for the environmental guideline (14% underestimated). Scenario 7 provided a much-improved estimate of the TSS exceedance frequency for the environmental guideline threshold virtually matching the observed frequency of exceedance. However, there still remained more than a 20% underestimation in frequency of exceeding the drinking water guideline. In particular, the results from scenario 7 suggest there are still substantial challenges in simulating low-flow, low-turbidity patterns.

3.3. Coastal receiving waters sedimentation rate

Simulated estimates of coastal sedimentation rates were highly variable depending on data-richness and model complexity. Plume centerline sedimentation rate estimations from the BSM were plotted over the distance from the mouth of the Jejevo river (figures 4(E) and (F)). The nature of the method predicts a radial pattern of potential sedimentation impact, underpredicting the observed rates by a mean NRMSLE of 88.8% in the data-poor catchment export (scenario 3) and overpredicting with a mean NRMSLE of 421.9% in the data-rich catchment export (scenario 7). It is important to note that whilst the data-poor scenario has resulted in a lower error, correct interpretation of the results of the BSM would likely find the data-rich scenario to be the preferable result representing the maximum expected sedimentation from the plume centerline. Although when compared to the highest investment model development scenario (figure 4(B)), the sedimentation patterns and radial rates of the data-rich BSM depict a very different representation of sedimentation in the receiving waters.

Increasing model complexity to the SEM saw an increase in error compared to the BSM whilst using the scenario 3 catchment sediment export (figure 4(C)). However, when the catchment sediment export from scenario 7 was used the mean NRMSLE was reduced by 46.2% (figure 4(D)). Sedimentation patterns from the SEM over the study domain allow the influence of the local geometry of the receiving waters environment to be examined, however results show no resemblance to the patterns predicted by the more detailed scenario (figure 4(B)).

Increasing the model complexity further (D3D model) without any added investment in data-richness (figure 4(A)) was found to further increase the NRMSLE of the resulting sedimentation rate predictions. This result indicated a negative return on investment of model complexity resourcing without any investment to improve data-richness. The D3D scenario representing the most investment in model complexity and data-richness in this study (figure 4(B)) has the lowest error of all the scenarios considered. Estimation of the potential impact from sediment loading into the nearshore was therefore found to highly benefit from the collection of in situ data.

4. Discussion

The results reported here have indicated the possible magnitudes of error involved in the estimation of sediment loading in remote data-poor regions, and the significant benefits of investment in local measurements.

Sediment export results from this study compare favourably with the same scales of magnitude and variation found across similar tropical volcanic catchment environments, such as the Hawaiian Islands ranging from 0.11 t ha$^{-1}$ yr$^{-1}$ to 2.97 t ha$^{-1}$ yr$^{-1}$ [60]. Estimations of sediment export in Indonesia have been found to range from 0 t ha$^{-1}$ yr$^{-1}$ to 100 t ha$^{-1}$ yr$^{-1}$ [36], and similarly for estimates elsewhere assessing the InVEST modelling approach [75]. Furthermore, the observed sediment export found at the study site over the period of measurement was found to be well within the range of sediment export observed globally in previous studies [76]. A previous study in the Solomon Islands region has explored concentration–frequency distributions of TSS using an InVEST and SWAT hybrid approach under locally
data-poor conditions (with distant weather observations 50 km away) finding similar TSS ranges for the baseline management scenario [49]. Similarly, the range of sedimentation rates from this study are in line with sedimentation rates observed and estimated in other studies with nearshore coral reef environments [36, 77].

Here, the SEM was limited to the extent of the lagoon study domain, where normally the model plume extents could extend to larger areas than available in this study. SEM has been previously applied in much larger study areas at a regional scale, noting that it is expected to be limited in relevance towards nearshore environments [36]. However, these nearshore environments, which are not covered sufficiently by global datasets, have been shown to be some of the most important areas to understand [78]. The consequence of this is the SEM scenarios

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**Figure 4.** Sedimentation rates for the 2013 case study period compared against observations using mean normalised root mean square logarithmic error for (A) data-poor catchment loading scenario 3 with D3D model, (B) data-rich catchment loading scenario 7 with D3D model, (C) data-poor catchment loading scenario 3 with SEM, (D) data-rich catchment loading scenario 7 with SEM, (E) data-poor catchment loading scenario 3 with BSM, and (F) data-rich catchment loading scenario 7 with BSM.
distributing the catchment sediment loading over a smaller area than would ordinarily occur for this approach, resulting in artificially higher sedimentation than would otherwise be expected.

Estimation of loading rates into these remote or data-poor environments is expected to be increasingly crucial for catchment and coastal environmental management into the future. This is especially pertinent with continuing pressures for natural resource extraction from these tropical islands and a need to predict, assess, and plan for the impact of climate change in these environments [53, 79–81].

This study demonstrated the importance of collecting in situ data for estimating catchment sediment loading for water quality and sedimentation in the receiving waters. Estimation of the frequency of water quality threshold exceedance is critical for prediction of potential impacts for ecological resources [82], however this study demonstrated significant deviations in estimated frequencies of exceedance of TSS with different, readily available choices of rainfall input data-richness and catchment gauging for calibration datasets.

It is recognised that field measurements relating to sediment transport and loading are highly uncertain on the scale of at least an order of magnitude [83]. However, this study has demonstrated that this range of uncertainty is dwarfed by the range produced by different combinations of modelling approach and input datasets. Therefore, investment in field monitoring is a highly valuable contribution to making predictions or furthering understanding of sediment movement in these environments. At the very least, recording local rainfall measurements improved annual loading estimations. However, to obtain a reasonable estimation of water quality exceedance frequencies of higher relevance to the health of these ecosystems [84], you need to gauge the catchment with streamflow and turbidity monitoring. The local data used in this study cost on the order of US$ 250,000 in human resources and equipment for this remote region of the world, and novel lower cost monitoring techniques such as camera-based particle image velocimetry/space-time image velocimetry (PIV/STIV) [85–89] would be recommended for further development in deploying to these environments in addition to lower cost sediment monitoring equipment [83] which should be developed to minimise maintenance requirements.

The calibration of these field datasets to models of increasing complexity is not without significant challenges in itself [90]. However, it is clear in this study that increasing model complexity investment in either catchment or coastal receiving water prediction has not returned any positive value to the estimations in the absence of in situ data collection. This study saw increasing model complexity without additional investment in local data resulted in a further divergence in results away from the observations, potentially resulting in a poorer set of information from which environmental management decisions are made.

Data availability statement

The data that support the findings of this study are available upon reasonable request from the authors.

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References

[1] Elliott K C, Cheruvell K S, Montgomery G M and Sornam P A 2016 Conceptions of good science in our data-rich world BioScience 66 1–10
[2] Pan S, Tian H, Dangal S R S, Ouyang Z, Tao B, Ren W, Lu C and Running S 2014 Modeling and monitoring terrestrial primary production in a changing global environment: toward a multiscale synthesis of observation and simulation Adv. Meteorol. 2014 1–17
[3] Behmel S, Damour M, Ludwig R and Rodriguez M J 2016 Water quality monitoring strategies—a review and future perspectives Sci. Total Environ. 571 1312–29
[4] Clark. M F, Bierkens M F P, Samaniego L, Woods R A, Uijlenhoet R, Bennett K E, Pauwels V R N, Cai X, Wood A W and Peters-Lidard C D 2017 The evolution of process-based hydrologic models: historical challenges and the collective quest for physical realism Hydrol. Earth Syst. Sci. 21 3427–40
[5] Haraldsson H V and Sverdrup H 2013 Finding simplicity in complexity in biogeochemical modelling Environmental Modelling: Finding Simplicity in Complexity 2nd edn (Chichester: Wiley) pp 277–89
[6] Oenema O, Kros H and De Vries W 2003 Approaches and uncertainties in nutrient budgets: implications for nutrient management and environmental policies Eur. J. Agron. 20 3–16
[7] Robson B J 2014 When do aquatic systems models provide useful predictions, what is changing, and what is next? Environ. Model Softw. 61 287–96
[8] Reichert P and Mielke Jr 2009 Analyzing input and structural uncertainty of nonlinear dynamic models with stochastic, time-dependent parameters Water Resour. Res. 45 W10402
[9] Villarini G, Mandapaka P V, Krajewski W F and Moore R J 2008 Rainfall and sampling uncertainties: a rain gauge perspective J. Geophys. Res. Atmos. 113 D11102
[10] Horner I, Renard B, Le Coz J, Branger F, McMillan H K and Pierrefeu G 2018 Impact of stage measurement errors on streamflow uncertainty Water Resour. Res. 54 1952–76
[11] McMillan H, Freer J, Pappenberger F, Krueger T and Clark M 2010 Impacts of uncertain river flow data on
[53] Hansen M C et al 2013 High-resolution global maps of 21st-century forest cover change Science 342 850–3
[54] FAO 2018 Terms and definition FRA 2020 global forest resources assessment report 2020 Rome (Forest Resources Assessment Working Paper). Report No: 188. (available at: www.fao.org/3/I8661EN/I8661en.pdf)
[55] Nearing M A 2000 Measurements and models of soil loss rates Science 290 1306–01
[56] Rapp J F, Lopes V L and Renard K G 2013 Comparing soil erosion estimates from RUSLE and USLE on natural runoff plots Soil Erosion (St. Joseph, MI: American Society of Agricultural and Biological Engineers) p 24
[57] Wischmeier H, Dwight D and Smith D 1978 Predicting rainfall erosion losses: a guide to conservation planning United States Department of Agriculture. Department of Agriculture, Science and Education Administration pp 1–48
[58] Bols P L 1978 The Iso-erodent map of Java and Madura. Rep Belgian Tech Assist Proj ATA 105 (Soil Research Institute) pp 39
[59] Razad A Z A et al 2020 Sediment yield modeling as sediment management strategies towards sustainability of hydropower reservoirs in Malaysia Water Resources Development and Management (Singapore: Springer) pp 26–37
[60] Falinski K 2016 Predicting sediment export into tropical coastal ecosystems to support ridge to reef management (Honolulu, HI: University of Hawaii at Manoa)
[61] Arnold J G et al 2012 SWAT: model use, calibration, and validation Trans. ASABE 55 1491–508
[62] Gassman P W, Reyes M R, Green C H and Arnold J G 2007 The soil and water assessment tool: historical development, applications, and future research directions Trans. ASABE 50 1211–50
[63] Abbaspour C K 2012 User manual for SWAT-CUP, SWAT calibration, and uncertainty analysis programs. Swiss Fed Inst Aquat Sci Technol Eawag, Duebendorf, Switz 93
[64] Syvitski J P M, Smith J N, Calabrese E A and Boudreau B P 1988 Basin sedimentation and the growth of prograding deltas J. Geophys. Res. 93 6895–908
[65] Thorn M F C 1982 Physical processes of silation in tidal channels. In: Hydraulic modelling in marine engineering Proc conference ICE, London, October 1981 (Thomas Telford, for Institution of Civil Engineers), Thomas Telford Publishing, pp 65–78
[66] Lesser G R, Roelvink J A, Jatm V K and Stelling G S 2004 Development and validation of a three-dimensional morphological model Coast Eng. 51 883–915
[67] Partheniades E 1965 Erosion and deposition of cohesive soils Lane A 1989 The heat balance of the North Sea vol 8, proudman oceanographic laboratory report (Birkenhead: Proudman Oceanographic Laboratory ) (available at: http://nora.nerc.ac.uk/id/eprint/3872)
[68] Boudet L, Sabatier F and Radakovitch O 2017 Modelling of sediment transport pattern in the mouth of the Rhone delta: role of storm and flood events Estuar. Coast Shelf Sci. 198 568–82
[69] Taguchi E, Stammer D and Zahl W 2014 Inferring deep ocean tidal energy dissipation from the global high-resolution data-assimilative HAMTIDE model J. Geophys. Res. Ocean 119 4573–92
[70] Rosman J H and Hench J L 2011 A framework for understanding drag parameterizations for coral reefs J. Geophys. Res. Ocean 116 C08025
[71] Marcus W A, Roberts K, Harvey L and Tackman G 1992 An evaluation of methods for estimating Manning's n in small mountain streams Mt Res Dev 12 227–39
[72] Moriasi D N, Gitau M W, Pai N and Dagupatii P 2015 Hydrologic and water quality models: performance measures and evaluation criteria Trans. ASABE 58 1763–85
[73] Her Y and Chaubeay J 2015 Impact of the numbers of observations and calibration parameters on equifinality, model performance, and output and parameter uncertainty Hydrol. Process. 29 4220–37
[74] Hamel P, Falinski K, Sharp R, Auerbach D A, Sánchez-Canales M and Dennehy-Frank P J 2017 Sediment delivery modeling in practice: comparing the effects of watershed characteristics and data resolution across hydroclimatic regions Sci. Total Environ. 580 1381–8
[75] Milliman J D and Meade R H 1983 World-wide delivery of river sediment to the oceans J. Geol. 91 1–21
[76] DeMartini E, Jokiel P, Beets J, Stender Y, Storlazzi C, Minton D and Conklin E 2013 Terrigenous sediment impact on coral recruitment and growth affects the use of coral habitat by recruit parrotfishes (F. Scaridae) J. Coast. Conserv. 17 417–29
[77] Breddon-Hermann A, Brown C J, Albert S, Klein C I, Mangubhai S, Nelson J L, Tenea L, Wenger A, Gaines S D and Halpern B S 2016 Where does river runoff matter for coastal marine conservation? Front. Mar. Sci. 3 273
[78] Connell J 2018 Islands: balancing development and sustainability! Environ. Conserv. 45 111–21
[79] Connell J, Lovett K, Saint Ville A and Hickey G M 2020 Food security and sovereignty in small island developing states: contemporary crises and challenges Food Security in Small Island States (Singapore: Springer) pp 1–23
[80] van der Velde M, Green S R, Vanclooster M and Clothier B E 2007 Sustainable development in small island developing states: agricultural intensification, economic development, and freshwater resources management on the coral atoll of Tongatapu Ecol. Econ. 64 456–68
[81] Wenger A S et al 2018 Management strategies to minimize the dredging impacts of coastal development on fish and fisheries Conserv. Letters. 11 e12572
[82] Grinnah A, Deering N, Fisher P, Gibbes B, Cossu R, Linde M and Albert S 2018 Near-bed monitoring of suspended sediment during a major flood event highlights deficiencies in existing event-loading estimates Water 10 34
[83] Erfemeijer P A L, Riegl B, Hoeksema B W and Todd P A 2012 Environmental impacts of dredging and other sediment disturbances on corals: a review Mar. Pollut. Bull. 64 1737–65
[84] Tsukuba R, Fujita I and Tsutsumi S 2011 Measurement of the flood discharge of a small-sized river using an existing digital video recording system J. Hydro-Environ. Res. 5 313–21
[85] Fujita I et al 2017 Accuracy of KU-STIV for discharge measurement in Ghana, Africa J. Japan Soc. Civ. Eng. Ser. B1 (Hydraulic Eng.) 73 J 499–L 504
[86] Fujita I, Watanabe H and Tsukuba R 2007 Development of a non-intrusive and efficient flow monitoring technique: the space-time image velocimetry (STIV) Int J River Basin Manag 5 105–14
[87] Lee M C, Leu J M, Chan H C and Huang W C 2010 The measurement of discharge using a commercial digital video camera in irrigation canals Flow Meas. Instrum. 21 150–4
[88] Bradley A A, Kruger A, Meselhe E A and Mcke M V I 2002 Flow measurement in streams using video imagery Water Resour. Res. 38 51–1–51–8
[89] Renard B, Kavetski D, Kuczera G, Thyer M and Franks S W 2010 Understanding predictive uncertainty in hydrologic modeling: the challenge of identifying input and structural errors Water Resour. Res. 46 W05521