Rainfall erosivity–intensity relationships for normal rainfall events and a tropical cyclone on the US Southeast Coast

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Abstract

The work done on the intertidal landscape by low tide rainfall events has been shown to augment the cycling of dissolved and particulate nutrients, but low tide rainfall events are not a well-documented component of coastal ecosystem models. Here we develop the relationships between rainfall intensity (I), and median volume raindrop diameter, and three rainfall erosivity indices (kinetic energy, momentum, and momentum multiplied by the drop diameter) using an optical disdrometer deployed in the intertidal zone during summer and fall of 2010 and 2011. These data include the local effects of Hurricane Irene in 2011. Raindrop data measured for 27 days of late summer were analyzed. The best fit between median volume raindrop diameter and I was a combination of the power-law and logarithm equations, and the best fits of three erosivity indices and I were obtained with power-law equations. Kinetic energy was slightly higher than the world average. Observed raindrop velocity was typically lower and more widely distributed than the theoretical raindrop terminal velocity. Hence, erosivity indices based on observed velocity were lower than those based on terminal velocity. The hurricane provided larger raindrops and more widely distributed raindrop velocity than normal events. Overall, results indicate that it is not suitable to assume that background erosivity- I relationships apply to cyclonic events. We derived new erosivity- I relationships to help characterize soil erosion processes in salt marsh areas for normal events. These results will help predict material and nutrient fluxes between intertidal and subtidal landscapes.

Keyword: Disdrometer, Kinetic energy, Raindrop size distribution, Winyah Bay, South Carolina

1. Introduction

Intertidal landscapes, the areas between high and low tide, are susceptible to rainfall-driven material transport in response low tide rain events (e.g., Anderson, 1983). Hence, intertidal rainfall-runoff processes may arrest the incipient long-term estuarine sediment storage (Chalmers et al., 1985), and in the process facilitate the cycling of highly nutritious particulate matter (Torres et al., 2004). For instance, Chen et al. (2015) showed that low tide rainfall events give rise to a narrow range of particulate organic carbon fluxes, regardless of location. Taken together these studies show that low tide rainfall events enhance material cycling at the terrestrial - marine transition, and they augment coastal zone biogeochemical cycling (Chen et al., 2015).

As with terrestrial systems, coastal rainfall events cause erosion through the detachment of soil particles and the subsequent transport of the detached material. Rainfall kinetic energy (KE) is one of the most widely used indicators of rainfall erosivity (e.g., Al-Durrah and Bradford, 1982; Ekern, 1954; Ellison, 1944, 1947; Lal, 1994; Morgan et al., 1998; Morgan, 2009; Nanko et al., 2008; van Dijk et al., 2002). On the other hand, Rose (1960) recognized momentum (M) as a better indicator, and Ghadiri and Payne (1988) showed that KE is not a reliable indicator at all. Later, Salles and Poesen (2000) found that the product of momentum and drop diameter (MD) was more appropriate for describing splash erosion. Regardless of the approach, in order to calculate estimates of these erosivity indices raindrop mass and fall velocity are necessary.

Direct measurements of raindrop impact are rare (Mikoš et al., 2006) because they require inordinate and costly instrumentation (Fornis et al., 2005). Therefore, erosivity is often derived from widely available rainfall intensity (I) data through the implementation of empirical erosivity- I relationships. A number of studies have proposed various expressions for erosivity- I for certain locations with specific climate conditions. The use

of any specific erosivity- I relationship in a climatically different environment should be justified prior to implementation.

Recent studies provided erosivity- I relationships based on raindrop measurements with optical disdrometers (e.g., Salles et al., 2002; Nanko et al., 2008; Petan et al., 2010; Sanchez-Moreno et al., 2012). One of the advantages of optical disdrometers is the independent measurement of raindrop diameter and fall velocity. However, previous studies typically calculated erosivity using observed raindrop size distribution (DSD) with estimated raindrop terminal velocity through well established associations (e.g., Laws, 1941, Gunn and Kinzer, 1949, Atlas et al., 1973; Atlas and Ulbrich, 1977). Stagnant or still wind conditions would give rise to the theoretical terminal velocity; however, actual situations do not always create raindrop terminal velocity, and for windy conditions in particular. In fact, some noise in the velocity distribution relations was reported with the Gunn and Kinzer (1949) curve even under relatively still wind conditions (Krajewski et al., 2006). Moreover, Montero-Martínez (2009) showed all raindrops did not fall at terminal velocity. Although there is uncertainty associated with estimating raindrop velocity with optical disdrometers (Friedrich et al., 2013), estimates of the erosivity- I relationship from such data remain valuable (Nanko et al., 2008 and Petan et al., 2010).

In temperate coastal landscapes of eastern North American, Chen et al. (2015) hypothesized that low tide rainfall events give rise to a characteristic response of carbon and nutrient transport in expansive salt marsh areas. The summer-fall convective storms that they observed have a short duration with high intensity (Torres et al., 2004). Moreover, their particular study location is susceptible to the impacts of tropical cyclone-driven rainfall. Hence, the intertidal landscape is susceptible to sediment redistribution by both high intensity rainfall conditions from summer thunderstorms and from hurricanes.

Tropical cyclones have distinct rainstorm characteristics and they occur with relatively strong winds. Previous studies showed various DSD characteristics in cyclonic events. For example, Merceret (1974) reported that the DSD from Hurricane Ginger in 1971 was well represented by the widely-used exponential relation of Marshall-Palmer (1948). Tokay et al. (2008) highlighted a high concentration of small to midsize drops with both the presence and absence of large drops during seven storms. Also, Kumari et al. (2014) showed that DSDs between two cyclones differed in that the precipitation induced by a more stratiform cyclone contained a higher concentration of small drops compared to a more convective cyclone. On the other hand, Friedrich et al. (2013) highlighted the misclassification of particles by an OTT Parsivel disdrometer deployed during Hurricane Ike in 2008 that was characterized by a large concentration of raindrops with large diameters (>5 mm), and unrealistically low fall velocities ($<1\text{--}2$ m s^{-1}). This misclassification was caused by winds in excess of 10 m s^{-1} . Overall, DSD varied with each cyclonic event and the corresponding data were insufficient to determine the corresponding DSD characteristics. Furthermore, the objectives of these previous studies included evaluation of DSDs, but rainfall erosivity in response to these cyclonic events have gone largely unexplored.

The objective of this study is to estimate the three major rainfall erosivity indices (KE , M , and MD) and provide these erosivity- I relationships for the US southeast coast as taken from the OTT Parsivel optical disdrometer measurements. We evaluated the difference between two kinds of erosivity calculated using observed raindrop velocity and estimated raindrop terminal velocity. A second objective is to verify the ability to apply the erosivity- I relationships developed in normal events to hurricane event.

2. Materials and methods

2.1 Site description and measuring equipment

Field measurements were taken in the intertidal area of North Inlet estuary, near Georgetown, SC, an area that is part of the US National Estuarine Research Reserve (Fig. 1). The study site is located in a 32 km² bar-built estuary and is dominated by the smooth cordgrass *Spartina alterniflora*. South Carolina has a humid subtropical climate, with average temperatures ranging between 9 - 27 °C and an average of 1330 mm of rainfall per year (National Climate Data Center <http://www.ncdc.noaa.gov/cdo-web/search>, station GHCND: USC00383470). Mwamba and Torres (2002) report that the low lying coastal plain region of South Carolina extends up to 200km inland and this landscape typically experiences frequent high intensity and low duration convective summer time rainfall events (thunderstorms). For example, for the months of June-August they report regional 30-minute duration storms of 1-yr, 2-yr, 5-yr and 10-yr recurrence intervals have rainfall totals of 35, 42, 52 and 61 mm, respectively.

Rainfall occurs throughout the year but has a distinct seasonal peak for July - September. Late summer and early autumn rainstorms, the focus of this study, are associated with small convective thunderstorms with heavy precipitation over a limited surface area, on the order of 5-10 km². The National Weather Service Hydrometeorological Design Center (<http://www.nws.noaa.gov>) reports that the area can experience 5-min rainfall intensities of 146-171 mm h⁻¹ with a 1-year recurrence interval (Chen et al., 2011).

[Insert Fig. 1]

A weather station was deployed during late summer and early autumn of 2010 and 2011. The weather station consisted of a barometer, a Texas Electronics 525 tipping bucket rain gauge (0.2 mm per tip), a Met One wind sensor set, and an OTT Parsivel disdrometer (Löffler-Mang and Joss, 2000); all run by a Campbell Scientific CR1000

data logger/controller. The station was deployed on a salt marsh island adjacent to the mouth of a tidal creek (Fig. 1) and on a wooden platform about 2 m above the marsh surface and 1 m above high tide. The Parsivel measures the size and velocity of rain drops passing through a laser beam of 5400 mm² (180 mm length × 30 mm width) and it assigns them to one of 32 logarithmically distributed size and velocity bins (Löffler-Mang and Joss, 2000). Measurements by the barometer, the rain gauge, and the wind sensor were recorded every one minute. To conserve battery power, the Parsivel was turned on for 14 seconds and these measurements were recorded when the rain gauge tipped one or more times ($>12 \text{ mm h}^{-1}$) in the previous minute.

2.2 Data filtering and calculation of raindrop data

We used 1-min time unit data with the Parsivel measurements for the analyses. Some data from the Parsivel were removed because they were taken to be unrealistic. For instance, here we assume rain drops have a diameter less than 8 mm, and velocity less than 16 m s^{-1} ; measurements with higher diameter and velocity were believed to be erroneous artifacts of the instrumentation. Also, for drop data with diameter greater than 0.5 mm, the corresponding velocities that were less than 1 m s^{-1} were removed because they were deemed too slow for gravity-fall raindrops, and they could not be distinguished from Parsivel housing splash effects. Further, the data with fewer than 50 drops per time unit were not used. The data on August 26, 2011 was extracted as the data from Hurricane Irene. Subsequent “hurricane” analyses were based on 879 time units of normal events, and 144 time units of a cyclone event.

Rainfall intensity, I (mm h^{-1}), was calculated as the sum of raindrop volumes in all drop classes c , assuming spherical drops had passed through the detection area A ($= 5400 \text{ mm}^2$) of the monitoring duration Δt ($= 14 \text{ s}$):

$$V_i = \frac{\pi}{6} D_i^3 \quad (1)$$

$$I = \frac{3600}{A\Delta t} \sum_i^c n_i V_i \quad (2)$$

where n_i , D_i , and V_i are the number of detected raindrops, the raindrop class diameter, and the raindrop class volume in the size class i , respectively. Cumulative raindrop class volumes were calculated in ascending order of size classes for estimating median volume raindrop diameter (D_{50} , mm) for every time unit (Fig. 2). The m_1 value was determined as the maximum raindrop size class with cumulative raindrop class volume less than half of total raindrop volumes, and m_2 was determined as the minimum raindrop size class with cumulative raindrop volume exceeding 50% of total raindrop volumes. D_{50} was calculated from the following equation:

$$D_{50} = D_{m_1} + \frac{\frac{1}{2} \sum_i^c n_i V_i - \sum_i^{m_1} n_i V_i}{\sum_i^{m_2} n_i V_i - \sum_i^{m_1} n_i V_i} (D_{m_2} - D_{m_1}) \quad (3)$$

where D_{m_1} and D_{m_2} are raindrop class diameters in size class m_1 and m_2 .

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176 [Insert Fig. 2]

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Three rainfall erosivity indices were calculated with these data, the kinetic energy (KE , $J m^{-2} h^{-1}$), the momentum (M , $kg m s^{-1} m^{-2} s^{-1}$, i.e., $N m^{-2}$), and the product of momentum and drop diameter (MD , $N m^{-2} mm$). Each erosivity value was calculated from the following equations:

$$KE = 3.6 \times \frac{\pi \rho}{12 A \Delta t} \sum_{i,j} n_{i,j} D_i^3 v_j^2 \quad (4)$$

$$M = \frac{\pi\rho}{6A\Delta t} \sum_{i,j} n_{i,j} D_{i,j}^3 v_j \quad (5)$$

$$MD = \frac{\pi\rho}{6A\Delta t} \sum_{i,j} n_{i,j} D_{i,j}^4 v_j \quad (6)$$

where ρ is raindrop density ($= 1000 \text{ kg m}^{-3}$), $n_{i,j}$ is the number of detected raindrops in the size class i with velocity class j and v_j is the raindrop class velocity. Two types of each of the three erosivity indices were calculated using observed raindrop velocity (v_{obs}) and estimated raindrop terminal velocity (v_{term}). v_{term} was estimated by the expression from Atlas et al. (1973) based on Gunn and Kinzer (1949) for the calculation of fall velocity:

$$v_{\text{term}} = 9.65 - 10.3 \exp(-0.6D_i). \quad (7)$$

Therefore, the three erosivity indices were indicated as KE_{obs} , M_{obs} , and MD_{obs} in using v_{obs} , and KE_{term} , M_{term} , and MD_{term} in using v_{term} , respectively.

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194 2.3 Development of erosivity-I relationship

Erosivity-I relationships were expressed with regression equations including linear, logarithmic, power function and the three-parameter exponential type. The regressions were developed using the Levenberg–Marquardt non-linear least squares method available in the minpack.lm R package (version 1.1-7) (Elzhov et al., 2013). The cross-validation was repeated 1000 times for each regression equation. For the cross-validation, the whole dataset was divided into two parts by random sampling without replacement. The training dataset contained 80% of the samples and was used to determine the regression equations. The validation set contained 20% of the samples and was used to validate the regression equations. To compare predictive capabilities of the regression models mean prediction error (MPE), root mean square error (RMSE), normalized RMSE (NRMSE), and R^2 were used:

$$MPE = \frac{1}{n} \sum_{i=1}^n (\hat{y}_i - y_i) \quad (8)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (\hat{y}_i - y_i)^2} \quad (9)$$

$$NRMSE = \frac{RMSE}{y_{\max} - y_{\min}} \quad (10)$$

$$R^2 = \frac{[\text{cov}(\hat{y}_i, y_i)]^2}{\text{var}(\hat{y}_i) \text{var}(y_i)} \quad (11)$$

where $\hat{y}_i$ and y_i are the predicted and observed values, respectively, n is the total number of observations, and $y_{\max}$ and $y_{\min}$ are the maximum and minimum observed values, respectively. Indices of MPE, RMSE, NRMSE, and R^2 were computed from the validation dataset. The median values of the cross-validation replicates will be referred to as $\langle \rangle$ (e.g., $\langle \text{MPE} \rangle$), similar to the notations used by Nanko et al. (2014).

3. Results and discussion

We acquired six days of rainfall data in 2010, and 21 days in 2011 (Table 1). The sum of time units was 1023. Total precipitation estimated by the Parsivel raindrop data was 518 mm, with 402 mm from normal events and 116 mm from the cyclone. Daily precipitation estimated by the Parsivel raindrop data was generally higher than that by tipping bucket. Rainstorms with long duration were uncommon; in fact, the maximum duration was 64 minutes on September 24, 2011 (Table 1). On the other hand, intermittent and short events occurred most frequently. Rainfall intensity I in each time unit ranged from 0.2 to 190.3 mm h⁻¹ in normal rainfall events, and from 0.8 to 328.5 mm h⁻¹ for the Hurricane Irene. Median I was 15.0 and 24.3 mm h⁻¹ for the normal cyclone events, respectively. From the intensity-duration-frequency curves in the study area (Georgetown, SC) by the South Carolina Department of Transportation, 5-minute rainfall

intensity of 147 mm h^{-1} can be expected in a 2-year recurrence interval, 184 mm h^{-1} in 10-year recurrence interval, and 250 mm h^{-1} in 100-year recurrence interval. Measured normal events were normal in this area and the measured cyclone event was extremely rare in this area. The 1-min wind speed in each time unit ranged 0.0 to 21.3 m s^{-1} in normal events, and from 4.5 to 18.0 m s^{-1} for the Hurricane Irene. Median 1-min wind speed was 5.2 and 11.6 m s^{-1} in normal events and with the cyclone event, respectively.

[Insert Table 1]

3.1 Velocity-diameter of raindrop relationship

Most raindrops were close to terminal velocity, but raindrop velocity distribution deviated from terminal velocity (Fig. 3). Relationships between diameter and observed drop velocity (v_{obs}) differed between normal events and the cyclone event (Fig. 3). For example, for the hurricane conditions more raindrops had a greater departure from the terminal velocity line. Also, in most cases drops $<2 \text{ mm}$ had a $v_{\text{obs}} < 1 \text{ m s}^{-1}$ most likely associated with strong turbulence around the laser sheet causing highly variable acceleration. For instance, Friedrich et al. (2013) reported that the Parsivel gave unrealistically low fall velocities ($<1\text{-}2 \text{ m s}^{-1}$) under the strong wind ($>10 \text{ m s}^{-1}$) of a passing cyclone. Hence, windy conditions gave rise to spurious velocity readings and an uncharacteristically wide velocity distribution.

[Insert Fig. 3]

3.2 D_{50} - I relationship for normal events

The median volume raindrop diameter (D_{50}) was positively correlated with I (Fig. 4). Pearson's product-moment correlation coefficient was 0.671 in normal events. The

variation of D_{50} was negatively correlated with I (Fig. 4). This was due to the uncertainty in estimating D_{50} derived from sample size of raindrops. Salles et al. (1999) reported that smaller sizes of raindrops generated higher uncertainty in the estimate of D_{50} , for example a D_{50} of 100 or 1000 raindrops had 0.3 or 0.1 of the coefficient of variation, respectively. Lower I was computed for smaller size of raindrops (Eq. 2).

[Insert Fig. 4]

The logarithm equation and power-law equation for the D_{50} - I associations for normal events are (Fig. 4):

$$D_{50} = 0.981(\pm 0.012)\log_{10} I + 0.874(\pm 0.012) \quad (<R^2> = 0.621) \quad (12)$$

$$D_{50} = 1.07(\pm 0.009)I^{0.221(\pm 0.003)} \quad (<R^2> = 0.622). \quad (13)$$

where parameters in parentheses refer to one standard deviation. All of the estimated coefficients were significant ($p < 0.001$) in 1000 times iteration.

These results indicate that each equation has robust predictive capabilities (Table 2). Our findings are consistent with previous studies that highlight the power-law equation for the D_{50} - I relationship (e.g., Laws and Parsons, 1943; Zanchi and Torri, 1980; Atlas, 1953; Brandt, 1988; Uijlenhoet and Stricker, 1999). The coefficients of Eq. (13) were similar to Uijlenhoet and Stricker (1999) using 1.08 and 0.210, respectively. However, when $I < 20 \text{ mm h}^{-1}$, the logarithm equation tended to underestimate D_{50} , whereas, when $I > 100 \text{ mm h}^{-1}$, the power-law equation tended to overestimate D_{50} . For the intersection points between Eqs. (12 and 13) gained by 1000 time replicates the median was 48.9 mm h^{-1} and two-sided 95% confidence interval ranged from 46.4 and 51.1 mm h^{-1} . When we applied Eq. (13) in case of I was lower than the intersection point and Eq. (12) in case of I was higher than the intersection point, the $<R^2>$ increased to 0.627. Consequently, we

propose that conditions of highly variable rainfall intensity may require the use of two D_{50} - I relationships, one for high and for low I .

[Insert Table 2]

3.3 Erosivity- I relationship for normal events

KE was positively correlated with I (Fig. 5). Pearson's product-moment correlation coefficient was 0.970 for KE_{obs} and 0.989 for KE_{term} . KE - I relationships were developed as linear, power-law, and three-parameter exponential equations by 1000 times cross-validation replicates (Table 2 and Fig. 5). All of the estimated coefficients were significant ($p < 0.001$) in the 1000 times iterations.

[Insert Fig. 5]

M was also positively correlated with I (Fig. 6). Pearson's product-moment correlation coefficient was 0.989 for M_{obs} and 0.997 for M_{term} . M - I relationships were developed as linear, power-law, and three-parameter exponential equations by 1000 times cross-validation replicates (Table 2 and Fig. 6). All of the estimated coefficients were significant ($p < 0.001$).

[Insert Fig. 6]

Lastly, MD was positively correlated with I (Fig. 7). Pearson's product-moment correlation coefficient was 0.963 for MD_{obs} and 0.961 for MD_{term} . MD - I relationships were developed as linear, power-law, and three-parameter exponential equations by 1000 times

cross-validation replicates (Table 2 and Fig. 7). All of the estimated coefficients were significant ($p < 0.001$).

[Insert Fig. 7]

All of the linear equations had lower predictive capabilities than the other relationships (Table 2). The linear equations tended to overestimate erosivity on lower I and underestimated it on higher I (Figs. 5-7). The power-law or the three-parameter exponential equations were adequate. The power-law and the three-parameter exponential equations had close predictive capabilities but the power-law types had slightly higher predictive capability (Table 2). Therefore, the most suitable equation to link each erosivity (KE , M , and MD) and I was power-law relationship. This finding is consistent with that of Salles et al. (2002). Finally, the developed erosivity- I relationships are:

$$KE_{obs} = 11.2(\pm 0.52)I^{1.18(\pm 0.011)} \quad (14)$$

$$KE_{term} = 14.9(\pm 0.29)I^{1.14(\pm 0.005)} \quad (15)$$

$$M_{obs} = 1.22(\pm 0.030)I^{1.10(\pm 0.006)} \quad (16)$$

$$M_{term} = 1.45(\pm 0.014)I^{1.08(\pm 0.002)} \quad (17)$$

$$MD_{obs} = 1.75(\pm 0.092)I^{1.27(\pm 0.012)} \quad (18)$$

$$MD_{term} = 2.28(\pm 0.110)I^{1.23(\pm 0.011)} \quad (19)$$

where parameters in parentheses refer to one standard deviation.

Each erosivity obtained from v_{term} ($Erosivity_{term}$) was usually higher than that from v_{obs} ($Erosivity_{obs}$). All of the regression lines estimated higher erosivity in $Erosivity_{term}$ than $Erosivity_{obs}$. $Erosivity_{term}$ had lower variability than $Erosivity_{obs}$ (Figs. 4-6). These differences were due to the widely distributed v_{obs} (Fig. 3a). Estimated $Erosivity_{term}$ from

observed I in this study were higher than estimated $Erosivity_{obs}$. KE_{term} was 1.13 times higher than KE_{obs} , M_{term} was 1.10 times higher than M_{obs} , and MD_{term} was 1.11 times higher than MD_{obs} . Applying erosivity- I relationships based on v_{term} likely overestimate erosivity. The verification of raindrop fall velocity is a necessary component of future work.

The widely used KE - I relationship underestimated the observed KE at the site location. In the USLE/RUSLE (Wischmeier and Smith, 1978; Renard et al., 1997), KE was estimated by a following equation:

$$KE = I(11.9 + 8.73 \log_{10} I) \quad (20)$$

Both KE_{obs} and KE_{term} were higher than the USLE KE estimation (Fig. 4). We should apply new KE - I relationships (Eqs. 14 or 15) for calculating KE to characterize soil erosion processes in salt marsh areas for normal events.

Median of principal coefficients in the three-parameter exponential equation for KE (Table 2) were 28.9 and 30.6 for KE_{obs} and KE_{term} , respectively. These values indicate that rainfall conditions attained maximum kinetic energy content expressed as $J m^{-2} mm^{-1}$ (van Dijk et al., 2002). These values are consistent with world-wide average maximum kinetic energy content reported as $28.3 \pm 2.9 J m^{-2} mm^{-1}$ as reported by van Dijk et al. (2002). In particular, our results were within this range but the values were typically higher than the average. Hence, rainfall conditions at the monitoring site had higher kinetic energy than the typical.

Among three erosivity indices, M had narrower scatter about the regression line (Fig. 6), whereas KE and MD was wider (Fig. 5 and 7). M , KE , and MD were proportional to D^3v , D^3v^2 , and D^4v , respectively (Eqs. 4-6). Thus KE was proportional to the product of M and v , and MD was proportional to M multiplied by D . These caused wider scattering in KE and MD than with M . Therefore, it is difficult to accurately estimate KE and MD

from I alone because both DSD and raindrop velocity vary substantially, even with the same I .

3.4 Comparison of erosivity indices between normal events and cyclone event

For the cyclonic event, D_{50} , KE , M , and MD were positively correlated with I (Fig. 8). Pearson's product-moment correlation coefficient was 0.483 for D_{50} , 0.913 for KE_{obs} , 0.957 for M_{obs} , and 0.960 for MD_{obs} . However, the data of each index were more widely distributed than with non-cyclonic, or normal events. D_{50} in cyclones was higher than in normal events with the same I (Fig. 8a). The regression power-law Eq. (13) underestimated D_{50} for the cyclone event. The predictive performance of Eqs. (12 and 13) for D_{50} in the cyclone event was worse (Table 3). In this case, cyclone conditions provided larger raindrops thereby causing the normal predictive equation to underestimate D_{50} (Table 3).

[Insert Fig. 8]

[Insert Table 3]

For erosivity indices, the cyclone data were more widely distributed than in normal events, in particular for $I > 80 \text{ mm h}^{-1}$ (Fig. 8b-d), and the predictive performance of erosivity- I relationships of power-law equations was worse (Table 3). The regression equations underestimated KE and MD , and overestimated M . MD was usually higher than the estimates from the regression equation for normal events (Fig 8d). Therefore, the difference between normal and cyclone events for raindrops was significantly higher DSD than fall velocity. Hence, estimated accumulative daily erosivities were well fitted in normal events, but KE and MD were underestimated in cyclone event (Fig. 9). Cyclone

events gave rise to more erosive rainfall, and not only higher rainfall intensity but also more erosive raindrops.

[Insert Fig. 9]

For the cyclone raindrop diameter and velocity both varied with wind speed. For instance, the 1-min wind speed ranged from 4.5 to 18.0 m s⁻¹ with a mean of 11.6 ± 2.8 m s⁻¹ and scattering of v_{obs} was more substantial under windy conditions (Fig. 10). In this case, when wind speed was more than 10 m s⁻¹, the threshold of Friedrich et al. (2013), resulted in a high concentration of raindrops with large diameters and unrealistically low fall velocities. Also, some raindrops were classified with lower velocity. Hence, the lower v_{obs} were likely caused by the Parsivel's misclassification under these especially problematic conditions for the deployment of a laser disdrometer system.

[Insert Fig. 10]

In summary, the application of the regression equations established from normal conditions were not suitable for cyclone conditions. Establishing erosivity-*I* relationships that may arise with a cyclone are complicated because the relationships vary substantially, even with the same cyclonic event. Nevertheless, the translation of rain power to material cycling in estuarine landscapes remains largely unexplored and these *erosivity-I* relationships will add deeper insight into the associated nutrient and organic carbon fluxes to the subtidal zone, and the overall estuarine turbidity response to coastal rainfall events.

4. Conclusions

A laser disdrometer was installed in a salt marsh on the US east coast to estimate rain erosivity in the context of estuarine material cycling. We measured raindrops during late summer and early autumn in 2010 and 2011, and include the effects of a hurricane. Median volume raindrop diameter (D_{50}) and three rainfall erosivity indices, kinetic energy (KE), momentum (M), and the product of momentum - drop diameter (MD) were calculated and their relativity to rainfall intensity (I) were estimated. We compared the erosivity from raindrop velocity (v_{obs}) and that calculated by estimates of terminal velocity (v_{term}) in normal events. The main conclusions are:

- For normal events, the best fit D_{50} - I relationship was obtained with the combination of power-law and logarithm equations, and the best fitted erosivity- I were obtained with power-law equations. Observed KE was higher than previous USLE KE estimates.
- Erosivity indices calculated by v_{obs} were lower but more variable than those calculated by v_{term} . This was due to the variation of v_{obs} from v_{term} line, and all raindrops did not reach v_{term} . The measured v_{obs} was usually lower than v_{term} . Applying v_{term} to calculate erosivity may overestimate the actual erosivity.
- Compared with normal events, the cyclone event had higher rainfall intensity, larger raindrops, and higher v_{obs} variation. Erosivity- I relationships were more widely scattered and erosivity tended to be higher in the cyclone event. The application of the regression equations established from normal event data were not suitable for cyclone conditions.

Together these results can facilitate prediction of material fluxes between the intertidal and subtidal zones during low tide rainfall events.

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References

- Anderson, F.E., 1972. Resuspension of Estuarine Sediments by Small Amplitude Waves. *J. Sediment. Petrol.* 42, 602-609.
- Al-Durrah, M.M., Bradford, J.M., 1982. Parameters for describing soil detachment due to single waterdrop impact. *Soil Sci. Soc. Am. J.* 46, 836-840.
- Atlas, D., 1953. Optical extinction by rainfall. *J. Meteorol.* 10, 486-488.
- Atlas, D., Srivastava, R.C., Sekhon, R.S., 1973. Doppler radar characteristics of precipitation at vertical incidence. *Rev. Geophys. Sp. Phys.* 11, 1-35.
- Atlas, D., Ulbrich, C.W., 1977. Path- and area-integrated rainfall measurement by microwave attenuation in the 13 cm band. *J. Appl. Meteorol.* 16, 1322-1331.
- Brandt, C.J., 1988. The transformation of rainfall energy by a tropical rain forest canopy in relation to soil erosion. *J. Biogeogr.* 15, 41-48.
- Chalmers, A.G., Wiegert, R.G., Wolf, P.L., 1985. Carbon Balance in a Salt Marsh: Interactions of Diffusive Export, Tidal Deposition and Rainfall-caused Erosion. *Estuar. Coast. Shelf Sci.* 21, 757-771.
- Chen S., Torres R., Bizimis M., Wirth E.F., 2012. Salt marsh sediment and metal fluxes in response to rainfall, *Limnol. Oceanogr. Fluid. Environ.* 2, 54-66.
- Chen S., Torres R., Goni M., 2015. Intertidal zone particulate organic carbon redistribution by low-tide rainfall, *Limnol. Oceanogr.* 60, 1088-1101.
- Ekern, P.C., 1954. Rainfall intensity as a measure of storm erosivity. *Soil Sci. Soc. Am. J.* 18, 212-216.
- Ellison, W.D., 1944. Studies of raindrop erosion. *Agricultural Engineering* 25, 131-136.
- Ellison, W.D., 1947. Soil erosion studies - Part I. *Agric. Eng.* 28, 145-146.
- Elzhov, T.V., Mullen, K.M., Spiess, A.-N., Bolker, B., 2013. minpack.lm: R Interface to the Levenberg–Marquardt Nonlinear Least-squares Algorithm Found in MINPACK,

460 Plus Support for Bounds. R Package Version 1.1-7. [http://CRAN.R-](http://CRAN.R-project.org/package=minpack.lm)
461 [project.org/package=minpack.lm](http://CRAN.R-project.org/package=minpack.lm).

462 Fornis, R.L., Vermeulen, H.R., Nieuwenhuis, J.D., 2005. Kinetic energy–rainfall
463 intensity relationship for Central Cebu, Philippines for soil erosion studies. *J. Hydrol.*
464 300, 20-32.

465 Friedrich, K., Higgins, S., Masters, F.J., Lopez, C.R., 2013. Articulating and Stationary
466 PARSIVEL Disdrometer Measurements in Conditions with Strong Winds and Heavy
467 Rainfall. *J. Atmos. Ocean. Technol.* 30, 2063-2080.

468 Ghadiri, H., Payne, D., 1988. The formation and characteristics of splash following
469 raindrop impact on soil. *J. Soil Sci.* 39, 563-575.

470 Gunn, R., Kinzer, G.D., 1949. The terminal velocity of fall for water droplets in stagnant
471 air. *J. Meteorol.* 6, 243-248.

472 Krajewski, W.F., Kruger, A., Caracciolo, C., Golé, P., Barthes, L., Creutin, J.-D.,
473 Delahaye, J.-Y., Nikolopoulos, E.I., Ogden, F., Vinson, J.-P., 2006. DEVEX-
474 disdrometer evaluation experiment: basic results and implications for hydrologic
475 studies. *Adv. Water Resour.* 29, 311-325.

476 Kumari, N., Kumar, S., Jayalakshmi, J., Reddy, K., 2014. Raindrop size distribution
477 variations in JAL and NILAM cyclones induced precipitation observed over Kadapa
478 (14.47°N, 78.82°E), a tropical semi-arid region of India. *Indian J. Radio Sp. Phys.*
479 43, 57-66.

480 Lal, R., 1994. *Soil Erosion Research Methods*. Second Edition. Soil and Water
481 Conservation Society, St. Lucie Press, Ankey, Iowa, USA.

482 Laws, J.O., 1941. Measurements of the fall-velocity of water-drops and raindrops. *Trans.*
483 *Am. Geophys. Union* 22, 709-721.

484 Laws, J.O., Parsons, D.A., 1943. The relation of raindrop-size to intensity. *Trans. Am.*
485 *Geophys. Union* 24, 452-460.

486 Löffler-Mang, M., Joss, J., 2000. An optical disdrometer for measuring size and velocity
 487 of hydrometeors. *J. Atmos. Ocean. Technol.* 17, 130-139.
 488 Marshall, J.S., Palmer, W.M., 1948. The distribution of raindrops with size. *J. Meteorol.*
 489 5, 165-166.
 490 Merceret, F.J., 1974. On the Size Distribution of Raindrops in Hurricane Ginger. *Mon.*
 491 *Weather Rev.* 102, 714-716.
 492 Mikoš, M., Jošt, D., Petkovšek, G., 2006. Rainfall and runoff erosivity in the alpine
 493 climate of north Slovenia: a comparison of different estimation methods. *Hydrol. Sci.*
 494 *J.* 51, 115-126.
 495 Montero-Martínez, G., Kostinski, A.B., Shaw, R. a., García-García, F., 2009. Do all
 496 raindrops fall at terminal speed? *Geophys. Res. Lett.* 36, L11818.
 497 Morgan, R.P.C., Quinton, J.N., Smith, R.E., Govers, G., Poesen, J.W.A., Auerswald, K.,
 498 Chisci, G., Torri, D., Styczen, M.E., 1998. The European Soil Erosion Model
 499 (EUROSEM): a dynamic approach for predicting sediment transport from fields and
 500 small catchments. *Earth Surf. Process. Landforms* 23, 527-544.
 501 Morgan, R.P.C., 2009. Soil erosion and conservation. Wiley-Blackwell.
 502 Mwamba, M.J., Torres, R., 2002. Rainfall effects on marsh sediment redistribution, North
 503 Inlet, South Carolina, USA. *Mar. Geol.* 189, 267-287.
 504 Nanko, K., Mizugaki, S., Onda, Y., 2008. Estimation of soil splash detachment rates on
 505 the forest floor of an unmanaged Japanese cypress plantation based on field
 506 measurements of throughfall drop sizes. *Catena* 72, 348-361.
 507 Nanko, K., Ugawa, S., Hashimoto, S., Imaya, A., Kobayashi, M., Sakai, H., Ishizuka, S.,
 508 Miura, S., Tanaka, N., Takahashi, M., Kaneko, S., 2014. A pedotransfer function for
 509 estimating bulk density of forest soil in Japan affected by volcanic ash. *Geoderma*
 510 213, 36-45.

511 Petan, S., Rusjan, S., Vidmar, A., Mikoš, M., 2010. The rainfall kinetic energy–intensity
 512 relationship for rainfall erosivity estimation in the mediterranean part of Slovenia. *J.*
 513 *Hydrol.* 391, 314–321.

514 Renard, K.G., Foster, G.R., Weesies, G.A., McCool, D.K., Yoder, D.C., 1997. Predicting
 515 soil erosion by water: a guide to conservation planning with the revised universal soil
 516 loss equation (RUSLE)., *Agriculture Handbook*. United States Department of
 517 Agriculture, Washington, DC.

518 Rose, C., 1960. Soil detachment caused by rainfall. *Soil Sci.* 89, 28-35.

519 Salles, C., Poesen, J., 2000. Rain properties controlling soil splash detachment. *Hydrol.*
 520 *Process.* 14, 271-282.

521 Salles, C., Poesen, J., Borselli, L., 1999. Measurement of simulated drop size distribution
 522 with an optical spectro pluviometer: Sample size considerations. *Earth Surf. Proc.*
 523 *Landforms* 24, 545–556.

524 Salles, C., Poesen, J., Sempere-Torres, D., 2002. Kinetic energy of rain and its functional
 525 relationship with intensity. *J. Hydrol.* 257, 256-270.

526 Sanchez-Moreno, J.F., Mannaerts, C.M., Jetten, V., Löffler-Mang, M., 2012. Rainfall
 527 kinetic energy–intensity and rainfall momentum–intensity relationships for Cape
 528 Verde. *J. Hydrol.* 454-455, 131-140.

529 Tokay, A., Bashor, P.G., Habib, E., Kasparis, T., 2008. Raindrop Size Distribution
 530 Measurements in Tropical Cyclones. *Mon. Weather Rev.* 136, 1669-1685.

531 Torres, R., Goni, M.A., Voulgaris, G.V., Lovell, C.R., Morris, J.T., 2004. Effects of Low
 532 Tide Rainfall on Intertidal Material Cycling, in: Fagherrazi, S., Marani, M., Blum,
 533 L.K. (Eds.), *The Ecogeomorphology of Tidal Marshes*, American Geophysical Union,
 534 Washington, D.C., pp. 93-114.

535 Uijlenhoet, R., Stricker, J.N.M., 1999. A consistent rainfall parameterization based on the
 536 exponential raindrop size distribution. *J. Hydrol.* 218, 101-127.

537 Van Dijk, A.I.J.M., Bruijnzeel, L.A., Rosewell, C.J., 2002. Rainfall intensity–kinetic
538 energy relationships: a critical literature appraisal. *J. Hydrol.* 261, 1-23.

539 Wischmeier, W.H., Smith, D.D., 1978. Predicting rainfall erosion losses. A Guide to
540 Conservation Planning. *Agricultural Handbook*, vol. 537. US Department of
541 Agriculture, Washington, DC.

542 Zanchi, C., Torri, D., 1980. Evaluation of rainfall energy in Central Italy, in: De Boodt,
543 M., Gabriels, D. (Eds.), *Assessment of Erosion*. Wiley, Chichester, pp. 133-142.

544

Figure

Fig. 1. Site map

Fig. 2. How to calculate D50

Fig. 3. Diameter vs velocity as a contour plan (log scale).

Fig. 4. Intensity vs D50

Fig. 5. Intensity vs KE

Fig. 6. Intensity vs M

Fig. 7. Intensity vs MD

Fig. 8. Normal vs Cyclone