Does the spatial arrangement of disturbance within forested watersheds affect loadings of nitrogen to stream waters? A test using Landsat and synoptic stream water data

Travis R. Cowles [a,1], Brenden E. McNeil [a,*], Keith N. Eshleman [b], Lindsay N. Deel [a], Philip A. Townsend [c]

[a] West Virginia University, Department of Geology and Geography, P.O. Box 6300, Morgantown, WV 26506, United States
[b] University of Maryland, Center for Environmental Science, Appalachian Laboratory, 301 Braddock Road, Frostburg, MD 21532, United States
[c] University of Wisconsin-Madison, Department of Forest and Wildlife Ecology, 1630 Linden Drive, Madison, WI 53706, United States

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ABSTRACT

Remotely sensed maps of forest disturbance provide a powerful tool for predicting spatial and temporal variability in the loading of nitrogen to receiving waters, key data needed for effective watershed management of nutrient pollution. We hypothesize that the spatial arrangement of disturbances within small-forested watersheds can affect N loadings. To test this, we developed schemes for spatially weighting maps of yearly disturbance produced through change analysis of the Landsat Tasseled Cap Disturbance Index (DI), and evaluated the ability of each scheme to predict N concentrations, and subsequently estimated N loads, from forty low-order streams within the Savage River drainage of western Maryland, USA during the 2006–2010 water years, a period encompassing extensive defoliations by gypsy moths (*Lymantria dispar*). We generated a base scheme of unweighted, watershed averaged change in DI (ΔDI), and five other schemes that weighted ΔDI by either a pixel's flow accumulation value, the distance to the watershed outlet, or proximity to the stream. Over the five years, the flow accumulation scheme tended to perform better than other weighting schemes, and even explained slightly more variability than the base scheme during years of moderate N loads ($R^2 = 0.15$ vs. 0.03 in 2007 and $R^2 = 0.30$ vs. 0.18 in 2010). However, this best spatial weighting scheme explained comparable or *less* variability during the two post-defoliation years with larger N loads ($R^2 = 0.43$ vs. 0.44 in 2008 and $R^2 = 0.31$ vs. 0.48 in 2009). Thus, for the purposes of utilizing remote sensing information within watershed management of nutrient pollution, these results suggest that coarse-scale, high temporal frequency data such as MODIS could be well suited for characterizing forest disturbance and predicting the resultant episodic N loads.

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1. Introduction

Nitrogen (N) loading to surface waters has multiple negative environmental effects, such as algal blooms, eutrophication, and the resulting impairment of economically valuable water resources across the globe (Driscoll et al., 2003; Galloway et al., 2003; Kim et al., 2011). This is especially true in the densely populated, yet sixty-percent forested, Chesapeake Bay Watershed of the eastern United States, where forests are simultaneously a buffer against N loading and a nonpoint source of N to the Bay (Shulyer, 1995). The forests of eastern North America are typically very effective N "sinks", retaining a greater amount of atmospherically deposited N than they leak to surface waters (Aber et al., 1998; Lovett et al., 2002), but they also can leach elevated levels of N to surface waters following harvest (Likens et al., 1977), insect defoliations (Eshleman et al., 1998), and storm damage (Houlton et al., 2003).

Since being introduced to eastern North America, the gypsy moth (*Lymantria dispar*) has become the primary defoliator of deciduous forests of the eastern USA (Lovett et al., 2002) and these outbreaks have been documented to increase the N exported to surface waters of the Chesapeake Bay by studies using both aerial surveys (Eshleman et al., 2004) and remotely sensed data of defoliations (e.g., Townsend et al., 2004a). Gypsy moths have a typical feeding preference for oak (*Quercus* spp.) and aspen (*Populus* spp.) species in non-outbreak abundances but become less selective, general defoliators during outbreak periods (Lovett et al., 2006), creating a patchwork of defoliation on the landscape.

* Corresponding author. Tel.: +1 304 293 0384.
  E-mail addresses: trcowles1@gmail.com (T.R. Cowles), bemcneil@mail.wvu.edu (B.E. McNeil).
[1] Present address: Department of Geography, University of Idaho, P.O. Box 443021, Moscow, ID 83844-3021, United States.
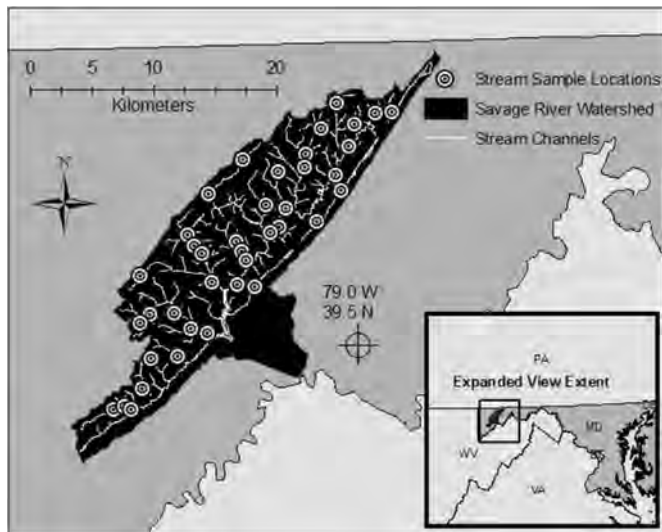
Fig. 1. Map of the Savage River watershed showing the stream reach network and sample locations.

Previous studies of defoliation-induced N export to the contributing surface waters of the Chesapeake Bay have successfully used air photos or remotely sensed maps of forest disturbance to predict spatial patterns in the loading of N to surface waters in the water year following a major outbreak (e.g., Eshleman et al., 2009). However, none of these studies has explored either the spatial or temporal characteristics of these relationships. Since research from agricultural systems has shown that the spatial arrangement of N sources (agricultural fields) and N sinks (riparian vegetation) can be very important for predicting N loading (Peterjohn and Correll, 1984; King et al., 2005; Baker et al., 2006; Weller et al., 2011), we ask: do quantitative measures of the spatial arrangement of disturbance within a watershed improve predictions of N loading to forested streams? Relative to the binary of agricultural field (N source) or riparian vegetation (N sink), answering this question in a forested system is more complicated because a pixel in a forested watershed could be an N sink or an N source depending on its disturbance status. Also, does the relationship of disturbance to N export remain static through time? To answer this question we explore the statistical relationships in years prior to and following the peak defoliation event used exclusively in previous studies of this type.

We employ a Landsat based method (Deel et al., 2012) to measure the continuous variation in forest disturbance occurring within low-order watersheds in the Savage River (SR) watershed in the western panhandle of Maryland (Fig. 1) for the five years (2005–2009) surrounding an extensive gypsy moth defoliation outbreak that peaked in 2007. Water quality is evaluated for 2006–2010, since nutrient responses in watersheds are typically lagged one year. We use linear regression analyses to determine whether different spatial-weighting schemes provide additional explanatory power in predicting spatial variation in stream water total dissolved N (TDN) concentration from five years of synoptic ($n = 40$ watersheds) stream survey data.

The serendipitous availability of five years of new synoptic stream survey data bracketing the major defoliation event in 2007 provides the unique opportunity to evaluate the importance of spatial patterns throughout a full cycle of pre- to post-disturbance. These data provide an opportunity to test these relationships outside the availability of the more costly high spatial and temporal resolution monitoring of low order streams

to evaluate the influences forest disturbances have on stream N dynamics.

2. Methods

2.1. Study area

We use data from 40 randomly selected watersheds within the Savage River drainage basin, a fifth order tributary of the Potomac River situated in Garrett County, in the western panhandle of Maryland, USA (Fig. 1). While nearby to the Fifteen Mile Creek basin that has been used for similar investigations (e.g., Townsend et al., 2004b), Savage River is physiographically distinct and has a novel dataset of stream N concentrations not previously described in relationship to forest disturbances. The Savage River basin is located in the Allegheny Plateau region of the Appalachian Highlands on the windward side of the Allegheny Front. Elevations range from 374 to 940 m with an average elevation 745 m. The watershed is composed of fluvially dissected topography with soils derived from the shale and sandstone bedrock. Forests cover an average of 82% of the land within our sampled watersheds and common species present include oaks (*Quercus* spp.), black cherry (*Prunus serotina*), maples (*Acer* spp.), and eastern hemlock (*Tsuga canadensis*), as well as plantations of spruce (*Picea* spp.), pine (*Pinus* spp.), and larch (*Larix* spp.) (Foster and Townsend, 2004). Despite the presence of non-forest lands (typically hay fields) within our study area, correlation analyses of our land cover and stream water data indicate that these non-forest lands have minimal correlation ($r < 0.5$) with the variability in N concentrations within the study area. This is likely due to the small percentage of non-forested land cover, which is typically located on the gently sloping plateaus that divide the watersheds, and the minimal use of fertilizer across all watersheds. Our study watersheds are largely within the Savage River State Forest, which manages the forests on a 100-year rotation for timber harvesting and conservation (Schaefer and Brown, 1991). The SR has experienced extensive gypsy moth defoliation events during our study period with the peak defoliation event occurring in the 2007 growing season and with smaller scale defoliations in 2006 and 2008.

2.2. Stream sampling

We measured changes in stream TDN concentration following the random stream reach sampling technique outlined by Townsend et al. (2004a) and employed as part of earlier work to define the N export from the SR watershed (Hypio, 2000). The design ensures that the probability for stream selection for sampling is directly proportional to the length of the stream reach with respect to the overall length of all streams in the watershed, thus yielding an unbiased selection of stream reaches for the entire watershed. We collected 1.0 L "grab" samples of spring baseflow at least one week after a major precipitation event, from the selected stream reaches at the farthest downstream portion of the reach before its confluence with the next stream reach. The samples were kept on ice while being transported to the lab, and were then filtered and preserved (frozen) within 24 h. The TDN was measured colorimetrically on a Lachat flow injection analyzer following either an in-line or off-line heated persulfate digestion.

2.3. Stream loading estimation

Though this study does not have the high temporal frequency N sampling or watershed specific discharge measurements necessary for exact measurements of N loads, we extrapolated the spring baseflow concentrations to annual N loads based on the expected

Table 1

Imagery data. All images were mosaicked together from Landsat Path 17 and Rows 32 and 33. Cloud-free imagery was not available for the summer growing season of 2004. As described in the text, ΔDI was calculated for the 2005–2009 images, while the 2000–2003 images were only used as supplemental years for the calculation of the minimum DI composite image.

Year	Date	Source
2000	2 June	Landsat 5 TM
2001	24 July	Landsat 7 ETM+
2002	24 June	Landsat 5 TM
2003	13 July	Landsat 5 TM
2004	n/a	
2005	25 June	Landsat 5 TM
2006	6 August	Landsat 5 TM
2007	25 August	Landsat 5 TM
2008	19 July	Landsat 5 TM
2009	27 June	Landsat 5 TM

water discharge from each watershed for easy management interpretability. We estimated streamflow for the 40 sub-watersheds from the USGS flow data as the proportion of the sub-watershed area to overall basin area. We did this back of the envelope calculation by multiplying the measured concentrations by streamflow. As such, we assume (1) that the measured spring baseflow TDN concentration represents the mean concentration for the year (i.e., the higher summer stormflow concentrations are buffered by the lower concentrations typical of growing season baseflow) and (2) that flows are proportional to overall discharge by sub-basin area. We compared our estimates of stream loads to direct measurements of annual loads for three nearby gaged watersheds that were not used in this study and found no bias between estimates (K.N. Eshleman unpublished data).

2.4. Disturbance mapping

Annual forest disturbance maps were created for all regions within the SR watershed that were both classified as any forest type by the 2001 National Land Cover Dataset and had cloud free imagery. Then, we measured the change in the tasseled cap forest disturbance index (DI; Healey et al., 2005) to assess spatial variability in the intensity of forest disturbances in each study year. We utilized the method of Deel et al. (2012), which created a synthetic "undisturbed" base image of the minimum DI to compare with each years image. This method calculated the change from the optimal state of 9 years of Landsat images for the region and is more robust to cumulative disturbances than year to year change analysis from the original DI proposed by Healey et al. (2005) for predicting forest canopy changes within this study region (Table 1; Deel et al., 2012).

### 2.5. Spatial weighting of disturbance

We delineated the watershed and stream channel for each sampled stream reach using a flow direction grid based on the USGS National Elevation Dataset (NED) one arc second grids, chosen because the NED most closely matched the pixel size of the Landsat imagery being used for DI data. We defined the sampling location for each watershed at the mouth of the watershed, i.e., one flow accumulation grid pixel upstream from the confluence with the downstream receiving watershed.

Our objective was to test whether the spatial pattern of disturbances could have a disproportionate influence upon measured stream N load. There is no standardized metric for describing the actual or effective position within a watershed, especially with regard to the dentrification of N mobilized by disturbance (e.g., Boyer et al., 2006). We therefore chose to assess the position of each watershed pixel using five metrics, two related to distance

from the watershed outlet and three related to the stream channel position within the watershed (Fig. 2). We compared these weighting schemes to the traditional method of assessing disturbance as the unweighted watershed mean value of all ΔDI pixel values in each of the 40 sub-watersheds. This scheme is the current standard employed in recent studies using remote sensing to evaluate disturbance and its relation to stream-water N export within watersheds of the Chesapeake Bay (Townsend et al., 2004a; McNeil et al., 2007; Eshleman et al., 2009).

The two basic concepts of spatial weighting schemes, distance and stream channel proximity, represent easily computed, first approximations of two opposing hydro-biogeochemical conceptual models of watershed processing of N within flowpaths. Distance based schemes (flow and Euclidean distances) assume that larger distances from the watershed outlet provide increased opportunities for the processing of N in the soil, groundwater, and stream channel. Therefore, regions of increased distance from the outlet of the watershed will have an increased opportunity to be buffered by downslope regions reducing the expected N export relative to nearer distances under the same disturbance regimes. In contrast, stream proximity based schemes (flow accumulation, stream buffer only) assumes that the effective distance from the sample point to the watershed outlet is a function of the pixel's relative degree of connection to a hydrologic flowpath. Use of stream proximity schemes assumes: (1) that near stream zones are the focal points for non-point source N loading to streams (Cirmo and McDonnell, 1997), (2) that the residence time of N in surface waters is minimal relative to the soil and groundwater (Galloway et al., 2003), and (3) that there is minimal in-stream processing of N due to the fact that these are primarily headwater, canopy-shaded watersheds in deeply incised valleys with limited aquatic vegetation (Vannote et al., 1980). Thus, the stream proximity schemes assume that convergent areas, such as streambeds, are the most sensitive to disturbance (Fig. 2). To contrast the sensitivity of stream channel locations we also tested a control of the proximity approach evaluating only the regions outside of the stream buffer region as influential on stream N export (stream buffer excluded), which assumes that only upland areas have an influence on stream N export within these watersheds (Fig. 2).

All weighting schemes were computed in ArcGIS (v. 9.2.1, ESRI, Redlands, CA) and values were transformed to be relevant to each weighting scheme of a standard watershed with a size of 1 unit. The flow distance and flow accumulation schemes were computed from a flow direction grid derived from NED elevations. The flow accumulation data were natural log transformed to reduce the heavy right skew of weights over differentially sized watersheds. The Euclidean distance scheme was calculated simply as the linear distance from the watershed outlet to all points within the watershed. All of the distance and flow accumulation measures were normalized by watershed size and rescaled from zero (0) at the "farthest" distance value plus one unit within each watershed from the sampling point to one (1) at the watershed outlet sampling point to correct for the effects of differentially sized watersheds within each weighting scheme (i.e., larger watersheds did not have a disproportionate weight near the outlet based simply on the increased distances to the headwaters relative to smaller watersheds, and weights ranged from near zero at the maximum distance to one at the watershed outlet). The stream buffer and stream buffer excluded schemes were calculated as the regions within and outside of a 100 m buffer respectively of the stream channels digitized in the original stream sampling process performed by Hypio (2000), and represent "blue line" streams on USGS 7.5 min quadrangle topographic maps (1:24,000 scale). The regions identified by the buffered regions were classified in a binary fashion giving a value of one (1) to any value within the region and zero (0) to any areas outside of the identified region.
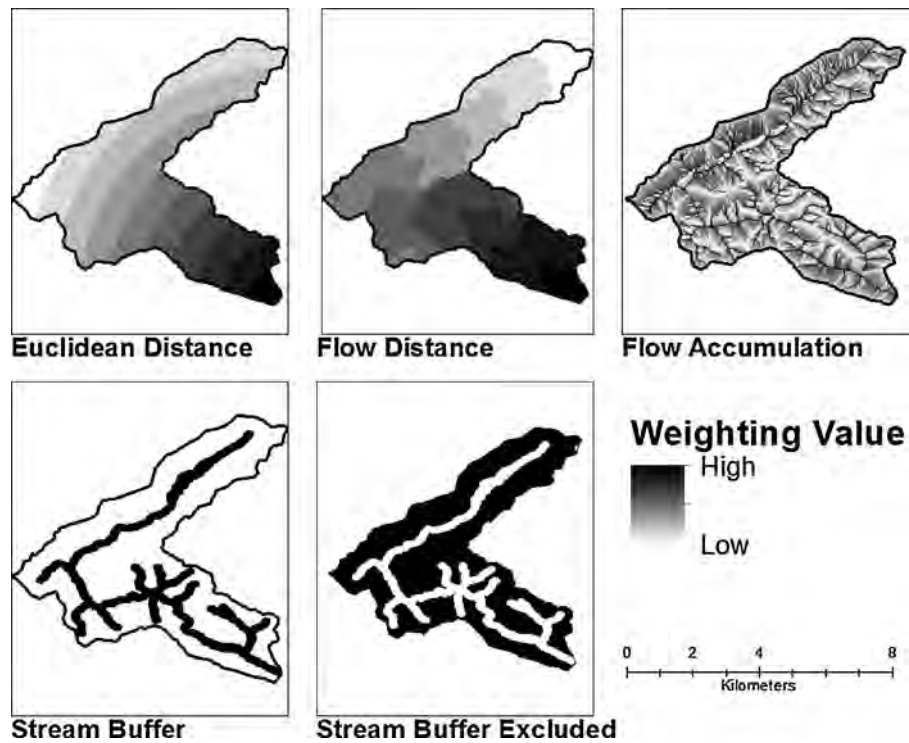
Fig. 2. Visual representation of the spatial-weighting schemes of the ΔDI imagery. For each scheme, darker colors indicate regions that will be weighted more heavily in each analysis.
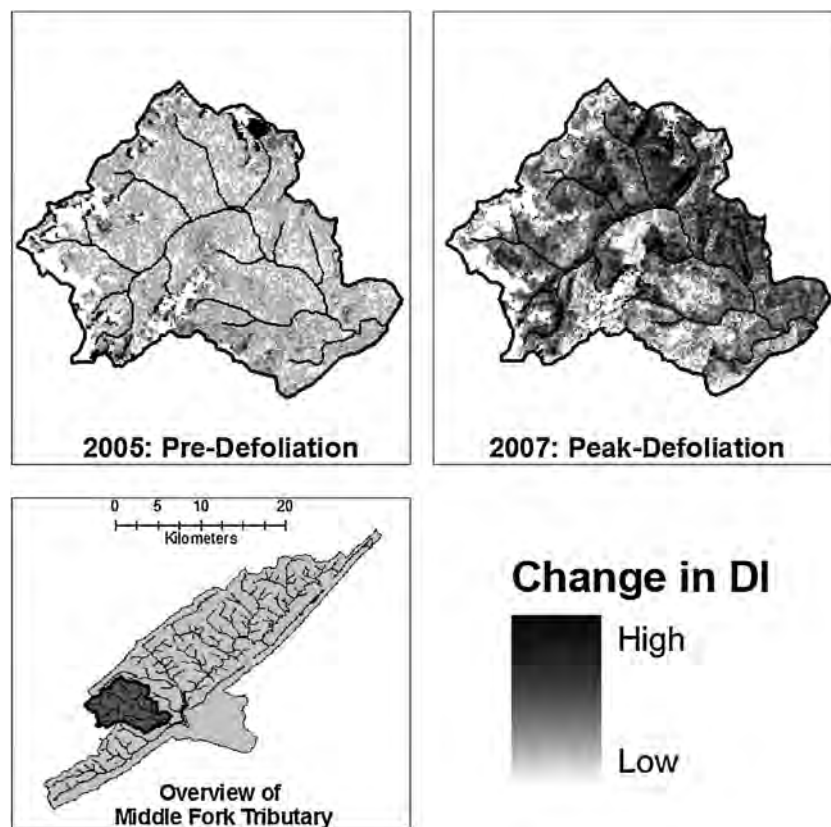
Fig. 3. Landsat ΔDI map showing defoliation in the Middle Fork Creek, a third order tributary in the southwest of the SR watershed. Non-colored areas were masked from the analysis due to cloud or non-forest land cover. Yearly Landsat ΔDI maps covering the entire SR watershed and five-year study period are in the supplemental information.

We multiplied the normalized weighting grids by the ΔDI imagery in each year to generate the pattern-adjusted estimates of ΔDI. The weighted ΔDI measures of flow distance, Euclidean distance, and flow accumulation reduce the ΔDI values of areas assumed to be hydro-biogeochemically "farther" from the sampling point, as defined by each weighting scheme. The stream buffer and buffer excluded ΔDI measures evaluated only the mean from the regions of interest and did not take other areas into account in their mean. Statistical analysis employed the watershed mean of the unweighted and weighted ΔDI maps.

2.6. Regression analyses

The effect of forest disturbance on stream N usually lags the year following the disturbance (Vitousek et al., 1979; Cirmo and McDonnell, 1997; Eshleman et al., 2004). We performed linear regression analyses to test the hypotheses that increases in ΔDI measures of forest disturbance for one year would be predictive of increases in stream water TDN concentration for the year prior to analysis and that the spatially-weighted ΔDI schemes would be more predictive of N concentrations (i.e. higher R^2) than the unweighted base scheme. The hypotheses were then applied to examine the temporal effects of these relationships prior to and following the peak defoliation year of 2007. The distributions of both concentration and ΔDI data were examined for outliers, which were removed, and were found to have a unimodal distribution with minimal skew. As cloud cover was variable among each year, watersheds were selected only if there was greater than 50% image coverage of the watershed in that year with cloud masked areas not included in the weighting scheme analyses. These data exclusions caused our sample size to vary between 36 and 39 watersheds per year as cloud cover varied.

3. Results

3.1. Disturbance mapping

The forest disturbance maps (Fig. 3 and Supplemental Information) exhibit spatial variability in disturbance intensity across the entire SR watershed and within our forty sub-watersheds. Defoliation was distributed randomly across the landscape and we detected no bias toward disturbance in riparian versus upland forested areas. Consistent with our field observations (Townsend et al., 2004b), related remote sensing analyses (Deel et al., 2012 and Townsend et al., 2004b), and digitized aerial sketch maps provided by the Maryland Department of Natural Resources, our disturbance maps illustrate (1) minimal forest disturbances in 2005, (2) a spatially scattered, moderate defoliation event in 2006, (3) a severe, widespread defoliation event in 2007, and (4) continuing, but moderate defoliation and forest harvest events in 2008 and 2009 (Fig. 3 and Supplemental Information).

### 3.2. Variability in N concentration and potential loading

Relative to the baseflow concentrations in the other water years, the TDN concentrations in the 2008 water year displayed an increased mean and overall variability following the extensive defoliation event recorded in the growing season of 2007 (Table 2). Following the increase in concentration variability in the 2008 water year the variability slowly returned toward pre-outbreak levels in the 2009 and 2010 water years.

Assuming our estimation of N loading scheme provides general annual values, the N loads increased significantly in the 2008 water year and then decreased slowly toward pre-outbreak levels in the 2009 and 2010 water years (Fig. 4). These increasing N loads are logical and expected results following the defoliation event and

Table 2
Measured total dissolve nitrogen concentration statistics from stream sampling analysis.

Year	2006	2007	2008	2009	2010
Mean	0.765	0.666	0.900	0.771	0.612
Median	0.742	0.620	0.742	0.703	0.550
Std dev	0.271	0.262	0.545	0.383	0.275
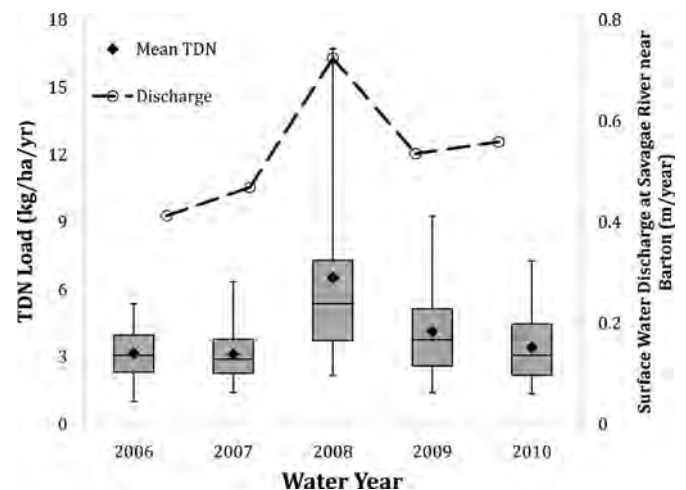
Fig. 4. Estimated TDN loads for the sampled watersheds within the Savage River watershed. Line represents the measured discharge at the USGS gauge of Savage River at Barton for each water year 2006 through 2010. Boxes represent the median, first, and third quartiles of the loading estimates, and whiskers represent the range of estimates.

agree with the combination of increased baseflow N concentrations in conjunction with the increased annual discharge.

3.3. Prediction of N concentrations

The unweighted and spatially weighted schemes for ΔDI ranged in predictive ability of TDN concentration from nearly zero to forty-seven percent explained variance during the five years of our study (Table 3). In 2005, the first year of our study, there was minimal forest disturbance within the SR watershed (Fig. 2 and supplemental information). As a consequence, we found that neither the unweighted nor the spatially weighted ΔDI schemes from 2005 were predictive of the variability in TDN concentration for the 2006 water year (Table 3). A limited amount of defoliation was recorded

Table 3
Results of linear regression analyses predicting the water year's total dissolved nitrogen as a function of the previous year's ΔDI weighting scheme.

Water year	ΔDI (no weighting) R^2	p-Value	Flow accumulation R^2	p-value	Flow length R^2	p-Value
2006	0.02	0.373	0.03	0.298	0.05	0.172
2007	0.02	0.337	0.15	0.016	0.01	0.537
2008	0.44	0.000	0.43	0.000	0.32	0.000
2009	0.48	0.000	0.31	0.000	0.24	0.002
2010	0.18	0.008	0.30	0.000	0.00	0.857

Water year	Euclidean distance R^2	p-Value	Stream buffer R^2	p-Value	Stream buffer excluded R^2	p-Value
2006	0.02	0.374	0.00	0.841	0.01	0.603
2007	0.00	0.995	0.00	0.589	0.05	0.169
2008	0.38	0.000	0.44	0.000	0.41	0.000
2009	0.27	0.001	0.23	0.003	0.44	0.000
2010	0.04	0.208	0.00	0.733	0.25	0.002

in 2006 and the flow accumulation weighted ΔDI was the only scheme to yield a statistically significant model to predict spatial variability in TDN concentration in the subsequent water year of 2007 (Table 3).

After the heavy defoliation of 2007, all ΔDI schemes showed relationships with TDN concentration during the subsequent 2008 water year (Table 3), with ΔDI positively correlated with TDN concentration (see Supplemental Materials). The unweighted and stream buffer only ΔDI performed identically, with the flow accumulation weighting demonstrating slightly less predictive power ($R^2 = 0.444$ vs. 0.426) for the 2008 water year concentration response. In the year following the expected peak of TDN concentration, the unweighted ΔDI scheme had the highest explained variance of all schemes tests ($R^2 = 0.475$) and the stream buffer excluded weighting performed nearly as well ($R^2 = 0.440$), which ran counter to our expectations. In the final year (2010), the flow accumulation spatial weighting scheme ($R^2 = 0.295$) explained the most variability in TDN concentrations with the stream buffer excluded scheme a close second ($R^2 = 0.248$).

To address the potential for the nested watersheds within our sampling scheme to inflate the explained variance within the regression analysis, we resampled our data to explore the relationships in only the non-overlapping lower order watersheds of the study extent ($n = 22$). This process reduced our sample size by approximately one-third each year, however the generally higher R^2 values in the sub-sample data analysis suggested that our nested scheme did not inflate our correlations and resultant explained variance in the larger sample (see Supplemental Materials).

4. Discussion

4.1. Disturbance and stream N loading

The simple loading extrapolations explained above suggest annual N loads increased by 2.25 kg ha^{-1} yr^{-1} for each 0.5 unweighted ΔDI mean increase in the year following peak defoliation (2008) (see Supplemental Materials). This confirms that ΔDI can be used to effectively characterize the influence of disturbance on water quality following major disturbances. DI is a z-score based index (Healey et al., 2005), so our results indicate that an overall change in image statistics from an undisturbed year for forests of 0.5 standard deviations may have important implications for water quality in Appalachian watersheds. The fact that ΔDI did not predict N concentrations well, and therefore N loads, in non-disturbance years reinforces our conclusions, especially insofar as variation in N loads was minimal in years that did not follow a disturbance.

4.2. Variability in N loading

The synoptic stream water data underscore the importance of characterizing spatial and inter-annual variability of stream N loads. Because N loads from forests are not constant from year-to-year, watershed models seeking to understand N in large hydrological systems such as the Chesapeake basin must incorporate sensitivity to annual variations in the capacity of forests to retain N. In particular, the N loads, suggested by moderately elevated concentrations in conjunction with increased annual discharge, in the two post-disturbance years represent significant departures from baseline N loads contributed by forests during years of minimal or even moderate forest disturbance (Fig. 4). This departure is reflected in both the estimated average N loads from this set of 40 watersheds, but also particularly within several of the most intensively disturbed watersheds, which we observed to contribute N loads up to three times higher than years of minimal disturbance (Fig. 4). Though these load increases still lag far

behind higher nutrient impact systems, such as agriculture, the overwhelming influence of forests in the Chesapeake Drainage, approximately 60% of the total land area, suggest that forest disturbances could have a large influence on the total nutrient load to the feeding waters of the Bay if disturbance events were widespread.

We used discharge data from nearby gauged watersheds to estimate loads in our ungauged watersheds, so our linkage of forest disturbance to N loading is inferential rather than mechanistic. However, the declining N loads during periods of elevated discharge in the 2009 and 2010 water years provides further evidence that N loading in this system is likely to be controlled more strongly by ephemeral forest disturbances than by hydrologic flushing (Townsend et al., 2004a; Eshleman et al., 2009). While ephemeral forest disturbances are likely to be a principal driver of N loading in this and other forested systems, the magnitude and inter-annual pattern of N loading observed in our study may not be necessarily representative of other regions, or even representative of other large sub-watersheds in the Chesapeake Bay watershed. Indeed, a study within the nearby (~60 km), but physiographically distinct, Fifteen Mile Creek (FMC) watershed found much lower loads of N, even in years following extensive disturbance (Eshleman et al., 2009). In particular, following the large 2001 defoliation event at FMC, using the same loading estimation methods as our study, demonstrated loads that averaged no greater than 2.1 kg ha^{-1} yr^{-1} following disturbance periods (compared to 6.5 kg ha^{-1} yr^{-1}; Fig. 4), with non-disturbance periods averaging less than 1.0 kg ha^{-1} yr^{-1} (compared to 3 kg ha^{-1} yr^{-1}; Fig. 4). Thus, the comparison of our results with this nearby catchment suggests that, in addition to spatial information on forest disturbances, other factors (e.g., geologic substrate, physiography, species composition) can play important roles in driving spatial variability in N loading.

4.3. Spatial arrangement of forest disturbance

Our results do not lend strong support to the hypothesis that N loadings are affected by the spatial arrangement of disturbance within small forested watersheds. This suggests that disturbances to all watershed areas may be equally important to the N export regime for forested catchments in this region. Nevertheless, our data do suggest that disturbances near hydrological flowpaths could have an disproportionate influence upon stream N loadings under moderate levels of forest disturbance. The flow accumulation and both stream buffer weighting schemes performed better than the other models in mild to moderate disturbance years. This suggests that disturbances near the stream channel may play an influence in moderate disturbance regimes based on the results of the flow accumulation and stream buffer only schemes. However, the stream buffer excluded model's performance was unexpected and runs counter to the influence suggested by the flow accumulation and buffer only schemes. Despite the slight improvements in predictive ability during years of moderate disturbance and due to the conflicting evidence of the stream buffer schemes, we conclude that spatial weighting of ΔDI based on watershed position only minimally impacts our ability to predict N loads from this heavily forested basin. It is likely that the effects of heavy disturbances overwhelm the ability of near-channel forests to buffer streams from increased N loads so that spatial location is largely irrelevant during basin-wide disturbance events in this forested system.

Despite the mild support for our hypothesis during the moderate defoliations an subsequent water years, the base case of the unweighted ΔDI outperformed the flow accumulation weighted ΔDI for the elevated N loads of 2008 and 2009 following the peak defoliation. As noted earlier, we suggest that the magnitude (i.e., the geographic scope and intensity) of the 2007 defoliation was sufficient to overwhelm any disproportionate influence of disturbances

to riparian environments. Many watersheds were almost completely defoliated, in which case the flow-accumulation weighting scheme discounted many defoliated upland pixels that could have mobilized N to hydrological flowpaths. Given the likelihood of a concomitant decrease in the ability of the defoliated forest to take up all the N mobilized farther up the flowpath (i.e., decreased buffering ability, sensu Baker et al., 2006), much of the N mobilized within the upland forests likely moved through shallow and deep throughflow pathways, and contributed to the N load without much modification or uptake during the 2008 and 2009 water years. Thus, our results qualitatively agree with the methods of studies conducted in other similar nearby environments, where fluvially-dissected, steep, Appalachian Plateau basins characterized by V-shaped valleys and narrow floodplains may geomorphologically minimize the role of riparian sinks for mobilized N (Weller et al., 2011).

Our finding of support for the null hypothesis under high N loads has important potential implications for future remote sensing studies. In particular, spatial-weighting of ΔDI may provide little added benefit in the prediction of N loading in the years immediately following major disturbances while the major pulse of N is being released. Thus, for detecting the landscape patterns in N loading responses to major disturbance events, calculating an unweighted watershed mean value of ΔDI from Landsat or even coarser spatial resolution sensors such as 500 m MODIS may be equally powerful (McNeil et al., 2007; de Beurs and Townsend, 2008), or even preferred due to increased revisit times and higher probability of obtaining the combination of anniversary date images that are cloud free. The potential improvement of cloud free image availability offered by MODIS may have improved our regression model results as our peak defoliation years had the latest collected images (25 August 2007) of any growing season within our study period that may have reduced our information for analysis as forest canopies may have reflushed in the time between the defoliation and image collection.

4.4. Potential drivers of residual spatial variation in N loading

Our maps describing variability in forest disturbance explained a maximum of 47% of the variation in TDN load among the SR watersheds. Previous studies of N loading to surface waters following disturbances have cited spatial variability in species composition, land cover, geology, or disturbance history as potential explanatory variables for the residual variation in stream TDN following disturbance events (Vitousek et al., 1979; Eshleman et al., 1998; Lovett et al., 2004; Townsend et al., 2004a). Within our study area, we found that spatial data describing variability in land cover, geology, or historic forest disturbances provided little predictive power for describing residual N loads. Nevertheless, the interactive effects of factors such as forest disturbance history, geology, and topographic setting are likely responsible for the marked spatial variation in forest species composition amongst sub-watersheds in the SR.

As a post hoc analysis, we estimated species composition on a sub-watershed basis using a forest composition map derived from AVIRIS imaging spectrometer data that was created by Foster and Townsend using the same methods as in nearby watersheds (Foster and Townsend, 2004). We found that the residual N loads could be partially explained by species composition and/or forest successional status. In particular, our analysis indicated significant effects of two species. Increased watershed abundance of the early successional species *Prunus serontina* was related to increased retention of N (i.e., negative relation to residual N loading). Alternately, increased abundance of the late successional species *Tilia americana* was related to decreased retention of N. When we combined the watershed-averaged values of % Prunus, and % Tilia in a stepwise linear regression model with our base case scheme of

unweighted ΔDI, the explained variance in N loading increased by approximately 20% during the 2008 (R^2 adj = 0.65; $p < 0.0001$) water year and by approximately 13% in the 2009 water year (R^2 adj = 0.61; $p < 0.0001$). This result supports the idea that the species composition or successional status of the forest can strongly impact the magnitude of the N load exported from a system following a disturbance event. Moreover, it indicates further potential for enhancing the remote prediction of N loading via mapping forest species composition in addition to forest disturbances in future analyses.

5. Conclusions

While additional studies should test our spatial weighting methods in river basins that are geomorphologically better suited to higher rates of riparian processing, we found minimal support for our hypothesis that the spatial arrangement of disturbance can improve the prediction of stream N concentrations in our study area. Since spatial weighting only provided small improvements in predictive ability, and only during moderately elevated N loads, we suggest that coarser sensors such as MODIS could be equally suited or even preferable for predicting the important large N loads occurring following extensive forest disturbances. Moreover, our ancillary analysis suggests that the combination of forest disturbance and species composition datasets can lead to further improvements in the prediction of N loading from forested watersheds. We suggest that further refining the use of these geospatial datasets can help reduce the uncertainty of N loads from forested areas, and enable more effective management of nutrient pollution in large drainage basins.

Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.jag.2013.05.012.

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