Uncertainty Analysis of the InVEST 3.0 Nutrient Model: Case Study of the Cape Fear Catchment, NC

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Summary

There is an increasing demand for assessment of water provisioning ecosystem services. While simple models with low data and expertise requirements are attractive, their use should be justified by adequate uncertainty characterization. In 2013, The Nature Conservancy started a project in the Cape Fear catchment, NC, aiming to characterize non-point source pollution affecting the Cape Fear River and tributaries. It was proposed to use the InVEST nutrient model for the analyses, which prompted a collaboration with the Natural Capital Project to assess the model uncertainties in this decision context.

This report investigates the applicability of the InVEST v3.0 nutrient model to inform decisions on land management in the Cape Fear catchment. The analyses suggested the following:

- In the Cape Fear basin, nutrient exports are highly correlated with subcatchment areas; the model correctly represented this feature, meaning that the **ranking of subcatchments** by nutrient exports (i.e. identification of critical subcatchments) was consistent with observations;
- When nutrient exports were standardized by subcatchment area, the model ranking predictions did not match observations, suggesting that differences in **land use configuration** were not well captured by the model;
- The model was very **sensitive** to the flow accumulation threshold, efficiencies, and loads, but less so to the Z parameter (or any parameter related to the water yield); for the nutrient loads and retention efficiency parameters, the model was more sensitive to land use classes that either cover a large proportion of land or have high load values;
- Two limitations tend to confuse the validation exercise: uncertainties in the magnitude of **subsurface flow and instream processes,** which are poorly captured in the model; and uncertainties in **point source pollution** data, for which reliable estimates are rarely available. These limitations hold for any validation exercise with such simple models.

Given the uncertainties on observed data and the absence of subsurface flow and instream processes in the InVEST model, the analyses do not support the use of InVEST for in-depth assessment of land management scenarios in the Cape Fear catchment. A new model is being developed to improve the conceptual representation of nutrient transport (e.g. ability to represent subsurface flow, improved characterization of retention efficiencies). Analyses are conducted to provide better insights into the applicability of such simple models for assessing land use change scenario in the Cape Fear basin.

1. Introduction

Water quality in the Cape Fear basin has become a major concern for water utilities. Degradation of water quality is mainly attributed to intensive farming (in particular hog farms), and wastewater. The Nature Conservancy is currently conducting a study aimed to i) identify the largest sources of pollution (specifically for nitrogen, N, and phosphorus, P); ii) assess the risk for water utilities to see further water quality degradation in the future; iii) assess the impact of alternative land uses on the water quality of the Cape Fear catchment. The InVEST InVEST nutrient model was initially considered, which provides the Natural Capital Project with an opportunity to test the use of the model in this decision context.

As for many agricultural basins, the study of non-point source pollution in the Cape Fear basin is a complex problem (Harden & Spruill, 2008). The amount of nutrient loads, including various forms of N and P compounds, resulting from different land uses, and their transport via surface or subsurface flow remains challenging to quantify. Complex models have been developed over the past years (see review in Breuer et al., 2008) but their use is limited by the skills and data necessary for adequate calibration. In addition, many of these models are not fully distributed, limiting their use for land use scenario analyses. On the contrary, simple models like InVEST, used in this study, have the advantages of i) being simple to use, with a limited number of parameters, ii) being spatially explicit, iii) being able to be run scenario runs for multi ES assessment and the detection of trends (rather than aiming at predicting accurate values of nutrient export).

Given the simplicity of the InVEST model, specific testing is necessary to understand the model's ability to represent land use change and interpret the outputs correctly. This document reports such analyses for the Cape Fear catchment, including sensitivity analyses, comparison with observed data, and implications for model calibration and interpretation.

2. Model overview

The InVEST nutrient model performs a simple nutrient budget from the spatial representation of N sources, determined by the loading specific to each LULC class, and sinks (or "retention"), representing the processes of denitrification or sediment trapping by a given land use. Complete description of the model can be found in the User's Guide (Tallis et al., 2013) and only the main characteristics are given here.

First, it is noted that the model does not distinguish between surface and subsurface flow paths, implying that the load and retention parameters represent both transport process. Second, the loads are routed along topographically-defined flow paths, with a proportion of the load being removed on each cell between the nutrient load and the stream. This characteristic makes the selection of the retention parameters challenging: the percentage of retention becomes a function of the flow path length, which varies spatially. A new model is being implemented to be able to use more directly the %retention for typical land use found in the literature (see Natural Capital Project website for details).

3. Study area: description and data sources

The Cape Fear catchment is a 23,600 km^2 area in North Carolina. Its major land uses are forest (40%), wetland (15%), grassland (14%), and agriculture (12%), mainly in the lower parts of the catchment and including intensive swine and poultry farms. Agricultural development has generated significant groundwater extraction throughout in the catchment.

Biophysical data

A complete description of the biophysical data sources (precipitation, evapotranspiration) is provided in Appendix I and in a manuscript in preparation[1]. Land use land cover (LULC) maps were obtained from the National Agricultural Statistics Service (NASS, 2013) and reclassified in seven LULCs: Corn, Other Crops, Grass, Forest, Wetland, Urban, and Swine farms. Such reclassification allowed the simplification of the sensitivity analyses by limiting the number of parameters in the model (see Methods).

For agricultural nutrient loads (Appendix I), values were sourced from local studies (Osmond & Neas, 2011). For other land uses, values were sourced from a literature review conducted by Reckhow et al. (1980). Efficiency values, which represent the overland retention of nutrients, are difficult to derive from the literature (see Methods). In this study, values were obtained from local empirical studies that report the maximum nutrient retention expected from vegetated buffers (Osmond et al., 2001). Given the uncertainties on the parameter selection, values for tree and grass buffers were used directly as the efficiencies, and the sensitivity of the model to those was evaluated. The values used for the baseline model run are provided in Appendix I.

Hydrological observations

Nutrient concentrations at 10 locations were obtained from the Cape Fear River Assembly website (see Figure 1 and details in Appendix II, which reports the data pre-processing and the methodology for conversion from N concentrations to annual N loads). Point sources contributions, resulting from waste water treatment plants or industrial release were obtained from a recent study of nitrogen delivery to southeastern United States streams (Hoos & McMahon, 2009). The authors have calibrated the SPARROW model to determine the nutrient loads from point and non-point sources. We note that the point source loads represent the permitted discharge rather than the observed discharge (Hoos et al., 2008), which may introduce some errors. Based on the results from Hoos & McMahons, we multiplied the loads by a factor 0.8 and again by a factor 0.75 to represent data errors and instream processes (the SPARROW model allows to separate the point source and non-point source contributions, which makes it possible to use their results for the point source data only).

[1] Hamel et al. 2014. Uncertainty analysis of the InVEST Annual water yield model: case study of the Cape Fear catchment, NC. Submitted to PLoS. Please contact the author for details

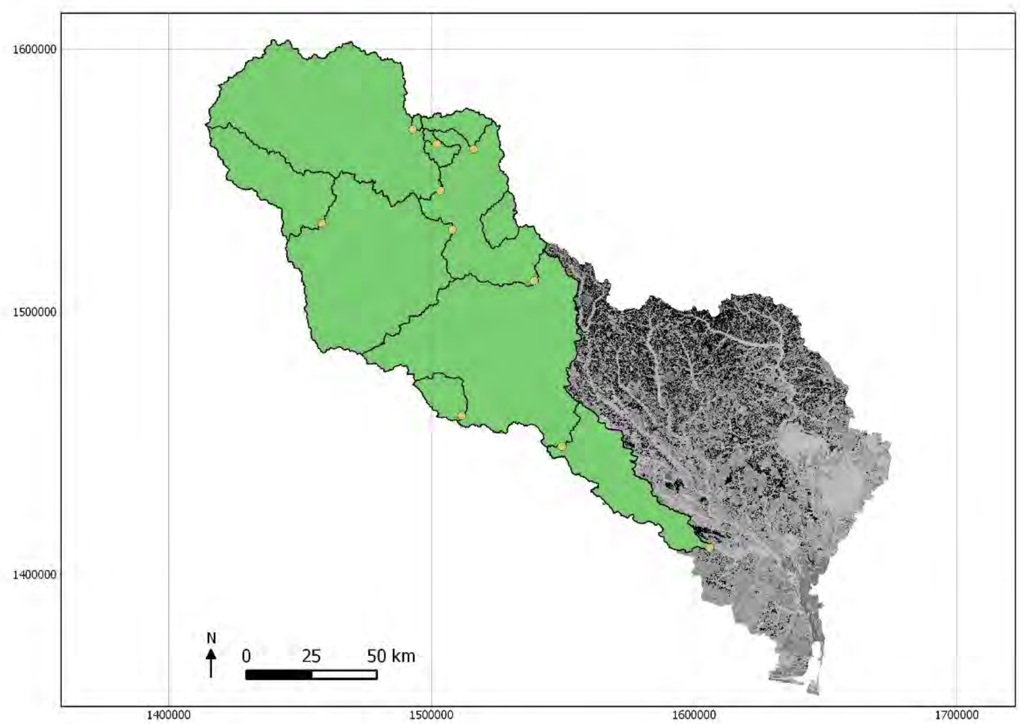


Figure 1. Cape Fear catchment showing locations of the streamgauges and subcatchments used in the study.

4. Methods

4.1 Performance assessment

Model performance was first assessed by comparing the absolute values of export loads to observations. Point source loads were simply added to the non-point source exports modeled by InVEST. However, such model performance measures is typically of limited interest for InVEST applications. Simple models like InVEST are not meant to replace sophisticated tools that represent the finer details of nutrient dynamics. Rather, they are used to understand the effect of land management policies and analyze spatial or temporal trends. It is therefore important to assess alternative indicators of the model's ability to predict land use change.

We compared the ranking of predicted and observed exports for the 10 subcatchments by measuring the Spearman rank coefficient. This performance measure is important to consider for spatial prioritization of restoration activities in a catchment; a low value would result in a misallocation of restoration efforts, decreasing the probability to detect a response to restoration.

Because the time series available are relatively short (12 years), it was not possible to analyze temporal trends, e.g. to compare two time windows with distinct land use/ land cover. We therefore decided to analyze the spatial variability in model performance, assessing the model's ability to represent differences in land use land cover configurations in various sub-catchments. This method, relying on the assumption that in a same region, catchments with similar physiographic characteristics should have similar hydrological responses, is common in hydrology (Hrachowitz et al., 2013). Model bias (relative difference between predicted and observed values) was therefore compared with various spatial characteristics, including %LULC, %LULC in the riparian zone, and catchment area. The riparian zone was defined as the area within 90m (3 pixels) of the stream network.

4.2 Inputs uncertainties and sensitivity analyses

One major source of uncertainty in this study is related to the point source loads, based on the data from Hoos and McMahon (2009). The authors have calibrated the statistical model SPARROW to data from a much larger area than the Cape Fear, which introduce potential errors when using the coefficients for point source contributions. In particular, the attenuation of point sources due to instream processes is represented by a constant value for all points, which may not be realistic since stream length, topography and riparian vegetation may influence this process. Without specific information on the magnitude of this error, we arbitrarily set it to 30% to analyze its effect on results.

The sensitivity analyses focus on the retention efficiencies, loads for the dominant LULC, threshold flow accumulation, and water yield inputs. The following points were considered in designing the analyses:

- Retention efficiencies comprise large uncertainties, since they represent various biochemical processes in a lumped way. We decided to study homogeneous errors in efficiency values, varying all values by +/-20%; and then errors in the efficiency of forest, the dominant land use.
- Loads were varied by +/-50% for forest, Ag-Corn, and urban LULCs. While Ag-corn and urban represent a small LULC, their high loads values justified particular attention.
- The flow accumulation threshold determines the stream network computed by the model. Because overland retention will increase with increasing distance to stream, this parameter is expected to have a large effect on model outputs. Stream network maps are supposed to be used to compare the predicted network with actual streams. However, in the absence of such maps or ground-truthing, there remains uncertainty on this parameter. We varied the flow accumulation threshold by +/-50%.
- The Z coefficient was varied between 1 and 20. As seen in the water yield report[2], the water yield model is very sensitive to the Z coefficient. In turn, the nutrient model relies on the water yield outputs to represent the effect of flow accumulation on the increased loading. This simplistic representation of a physical process introduces a structural error. Varying the Z parameter allows to understand the effect of water yield uncertainties on the nutrient model outputs. Note that non-homogenous differences are not captured here.

[2] Hamel et al. 2014. Uncertainty analysis of the InVEST 3.0 Annual water yield model: case study of the Cape Fear catchment, NC. Submitted to PLoS. Please contact the author for details

Table 1. Inputs and ranges used the sensitivity analysis

	Value for baseline run	Source of uncertainty	Range of variation
Efficiency	All (homogeneous) Forest LULC	Average values from riparian buffers studies	+/-20%
Loads	Forest Urban	Average values from local study; atmospheric deposition not accounted for	+/- 50% +/- 50%
Threshold flow acc.	1000	Stream network map; structural error	[500; 1500]
Z	20	Structural error	[1; 20]

5. Results and discussion

5.1 Comparison with observations

Absolute values

The baseline run showed very large variability in model performance for the 10 subcatchments (Figure 2). In general, the model underestimated the N export, with an average bias of -38%. Although the significant uncertainty on point sources contribution may partially explain these discrepancies (Figure 2), comparison with the data from Hoos and McMahon (2009) suggests that the model underpredicts non-point source pollution. In fact, the results from the SPARROW model indicate that the relative contributions of non-point source and point sources are 92 and 8%, respectively. This ratio is almost inversed in the baseline predictions.

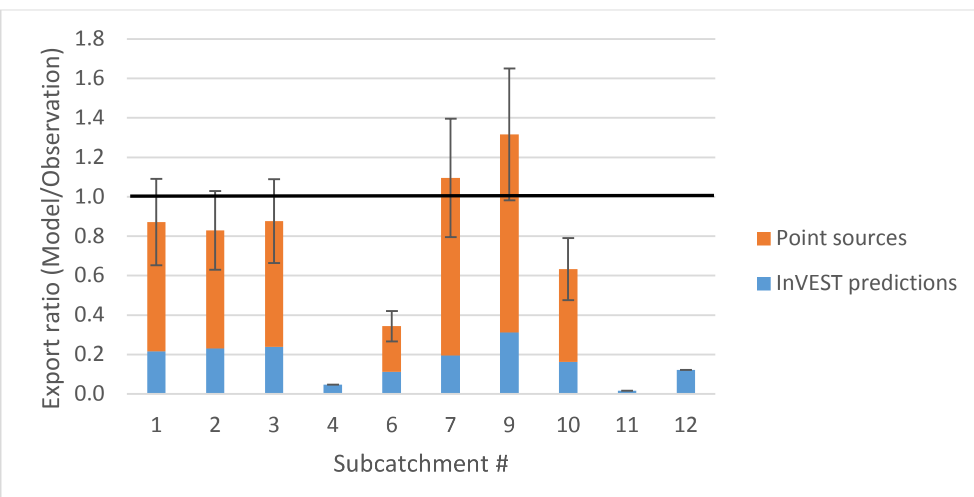


Figure 2. Ratio between model predictions and observations of N exports, for the 10 subcatchments. A value of 1 indicates a match between prediction and observation. Bars show the contribution of point sources and non-point sources (predicted by InVEST), the sum of which represent the total expected N export. Error bars represent the uncertainties on point sources.

Ranks

Figure 3a shows that the model correctly predicted subcatchments ranking by N export. Such predictions are important for prioritization of work. Interestingly, we found that N exports were strongly correlated with subcatchment area (Figure 4a). This characteristic is expected when catchment land use are similar. However, with significant differences in land use cover, one could expect significant differences in N exports. This was not the case in the Cape Fear catchment, and the model represented this characteristic well, resulting in the ranking by N export being very similar to observations.

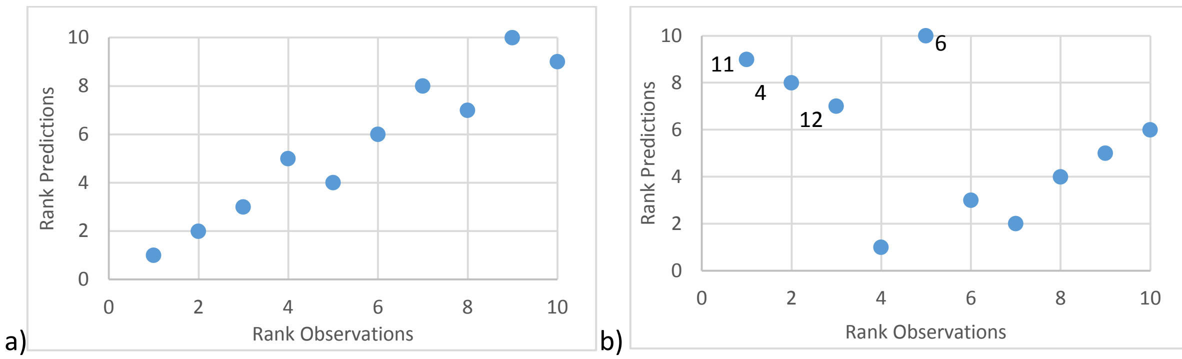


Figure 3. Correlation between subcatchment ranking of observed and modeled N exports (a), and of observed and modeled specific N exports (b), i.e. normalized by subcatchment area (figures on panel b correspond to subcatchment #)

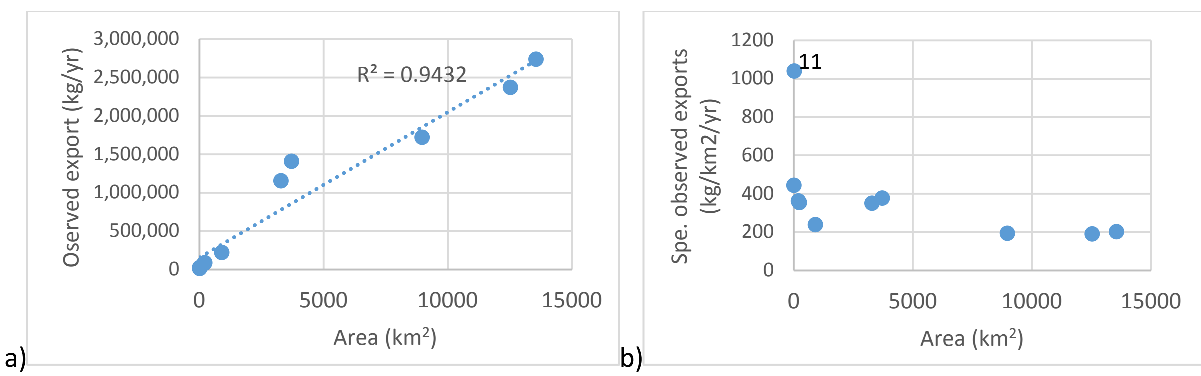


Figure 4. Subcatchment observed N exports (a) and specific N exports (b) as a function of area (subcatchment #11 is identified in panel b).

However, the ranking of specific N exports, i.e. the N exports normalized by subcatchment area show weaker correlation with observations (Figure 3b). In Figure 3b, the largest discrepancies in ranking are for subcatchments #11, #4, #6, and #12; the three latter represent the subcatchments where the model showed a very low performance (i.e. underestimation by >60%), and also happen to have the largest forest cover, as discussed in the next section. The discrepancy in the ranking of subcatchment #11 may be explained by the very high observed specific load (Figure 4b). One reason for this high specific load could be related to point source pollution but the data resolution may not be fine enough to support this hypothesis: while there is no associated load for the reach, there is a load of 137,500 kg/yr for the reach that just downstream from the monitoring station. Adding this point source load would result in an overprediction by 350% but it is likely that only part of this point source load is upstream of the monitoring station. Further investigation would be necessary to assess the validity of this hypothesis.

For the other catchments, the ranking seems relatively consistent between predictions and observations, reflecting the ability of the model to predict relative changes. In other words, the relative difference in loadings from different LULCs seem to be adequately translated into relative differences in export. This finding confirms the results of a study comparing InVEST and the NIRAMS II model in Scotland (Gimona et al., 2014), which showed that the ranking from both models were consistent.

Comparison with %LULC

Analysis of the model performance in relation with LULC shows a strong bias in model performance. As shown in Figure 5, the model slightly overpredicts the exports for catchment with low forest cover, while it dramatically underpredicts the more forested catchments. The only other significant correlation with %LULC was found for the urban land cover (R^2=0.65). The fact that model errors are not random suggests significant structural or parameter errors. Specifically, such observation could indicate that the model parameters associated with the forest or urban land use land cover are not appropriately set. Because the relative value of each LULC class are strongly correlated, it is not a priori possible to determine which LULC coefficient should be corrected, warranting further sensitivity analyses.

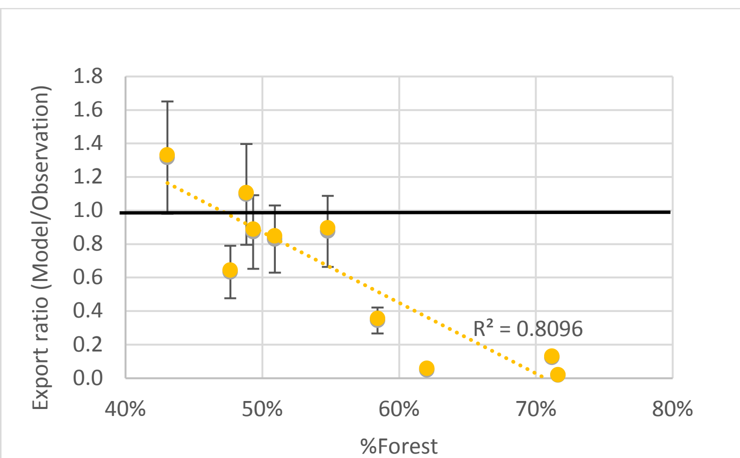


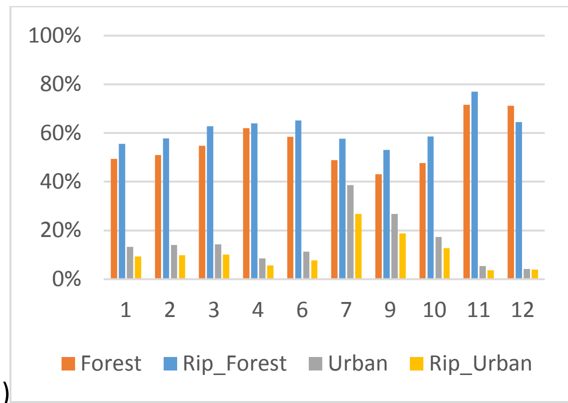
Figure 5. Correlation between model performance (ratio between modeled and observed exports) and Forest LULC proportion. A ratio of 1 correspond to a match between predictions and observations.

We note that correlation analyses performed here assume that subcatchments are independent, when some subcatchments are actually nested (see Figure 1). However, as detailed in the water yield analyses[3], the subcatchments each have unique LULC configurations, which justifies their use in

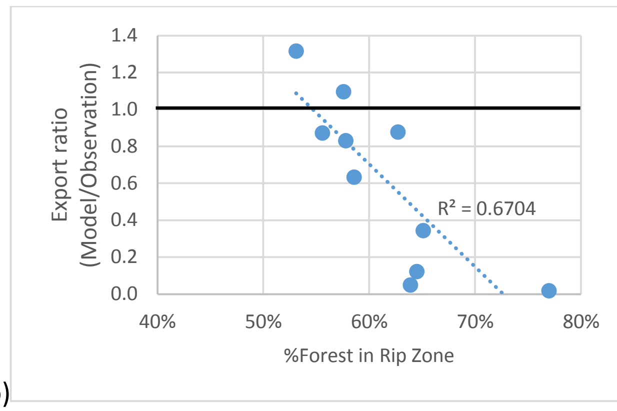
[3] Hamel et al. 2014. Uncertainty analysis of the InVEST 3.0 Annual water yield model: case study of the Cape Fear catchment, NC. Submitted to PLoS. Please contact the author for details

correlation analyses. This was also verified by the calculation of correlation coefficients on the 5 spatially independent subcatchments: although the sample size was smaller, the trends and correlation coefficients were similar to the results obtained with the 10 subcatchments.

One way to investigate model structural errors is to analyze the land use land cover in the riparian zone. Indeed, the model routing is such that retention overland will increase exponentially along the flow path, meaning that most of the N exports will come from the riparian zone. This characteristic is a simplification of nutrient dynamics, as discussed in subsequent sections. However, the relative proportion of forest and urban land cover were very similar in the riparian zone and in the whole subcatchments (Figure 6a). Therefore, the correlation between the riparian zone LULC and model performance was also high (although slightly lower, see Figure 6b) and the hypothesis could not be verified.



a)



b)

Figure 6. a) Forest and Urban LULC proportions in the 10 subcatchments, and in their riparian zones only; b) Correlation between model performance (ratio between modeled and observed exports) and forest LULC proportion in the riparian zone. A ratio of 1 correspond to a match between predictions and observations.

5.2 Sensitivity analyses

The results from the sensitivity analyses, illustrated in Figure 7, can be summarized as follows:

- Variations in the efficiencies had an asymmetrical response for the investigated range (Figure 7a): a 20% increase in efficiencies resulted in a 13% decrease in N export, while a 20% decrease in efficiencies resulted in a 18% increase in N export. Analysis of the model structure confirms that this response should be exponential. However, because most of the N exports are contributed by riparian cells (due to this exponential retention), the effect of the reduction in efficiency is mostly felt for these cells.
- Sensitivity to forest efficiency is consistent with the above results and the relative cover of forest (~50%): the decrease by ~25% of this parameter translated into ~10% reduction (Figure 7b).
- As expected from analysis of the model structure, the Z parameter has a very limited influence on the N exports (Figure 7c).

- Conversely, the threshold flow accumulation has a large influence on the N exports (Figure 7d): because it affects directly the river length, and thus the area of riparian zone, the model is very sensitive to this parameter.
- The sensitivity of the model to loads varied significantly with the LULC (Figure 7e): the elasticity was higher for the urban class, despite the fact that it represents a very low proportion of the land cover (13% vs. 49% for the forest LULC). This suggests that the absolute value of load (10 kg/ha/yr for urban, vs. 2.8 kg/ha/yr for forest) may indeed influence the model sensitivity to this parameter.

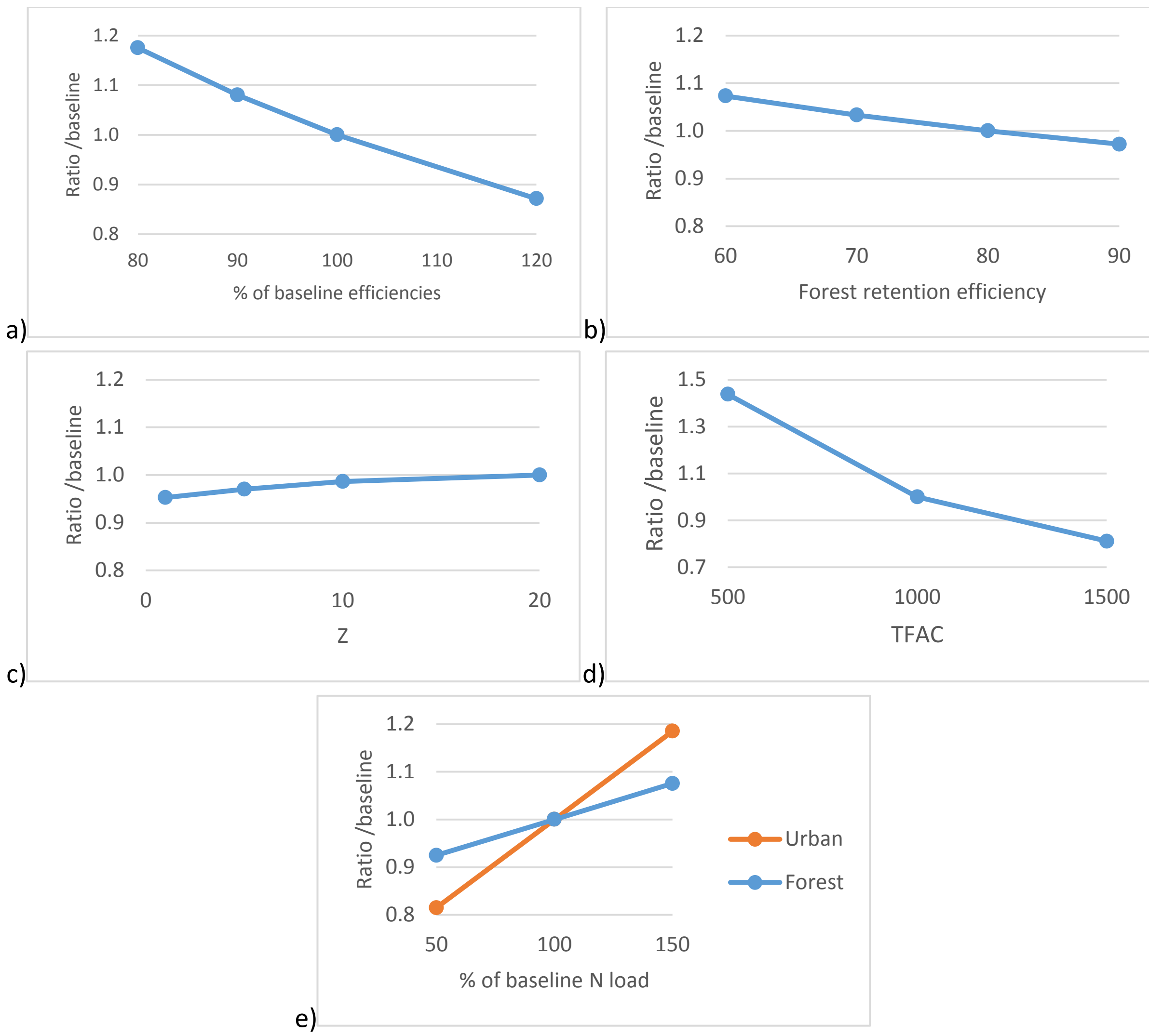


Figure 7. One-at-a-time sensitivity analysis for key model parameters: a) retention efficiencies (baseline values for each LULC were multiplied by [80; 120]%); b) retention efficiency of forest LULC; c) Z parameter; d) Threshold Flow Accumulation (TFAC); e) N loads for forest and urban LULC (baseline values for each LULC were multiplied by [50; 150]%). Ratio between the baseline N export ond the model prediction for each parameter increment are presented.

Analysis of spatial variability

As observed before, analysis of the model performance as a function of LULC configuration helps understand the model response to sensitive parameters. Figure 8 complements the information obtained from the analysis of sensitivity to load values and illustrates the response of each subcatchment to a 50% increase in the load value for forest or urban LULC. Plotting this response against the percentage of urban LULC in the riparian zone confirms that the sensitivity analyses presented above are catchment specific: the sensitivity of the modeled exports to a change in loads is a function of the extent and spatial distribution of the corresponding LULC in the catchment.

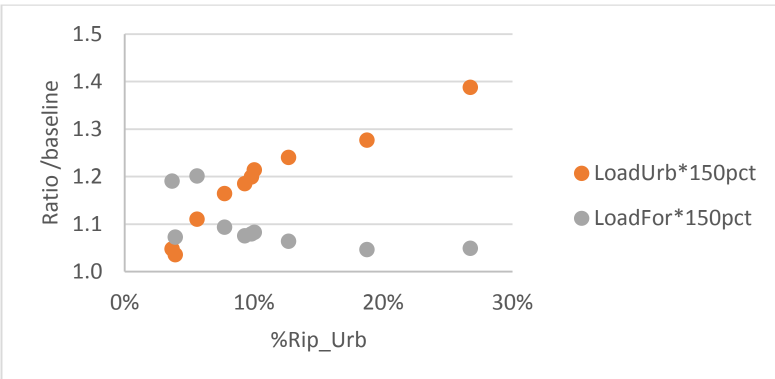


Figure 8. Sensitivity of the subcatchment N exports to a 50% increase in forest and urban loads

6. Practical implications

This study allowed to reach the following conclusions concerning the use of the InVEST model v3.0.

- In the Cape Fear catchment, the nutrient export is highly correlated with catchment area; the model was able to represent this feature, meaning that the ranking of subcatchments by total N exports is consistent with observations.
- When standardized by area, the rankings based on observed and modeled values show more inconsistencies. This result contrasts with the results for Gimona et al. (in review), who found that despite the significant underestimation of nutrient export by the model, relative ranking of subcatchments was well predicted.
- The threshold flow accumulation is a critical parameter to the model, which is difficult to select without the comparison with actual stream maps or ground-truthing of the “beginning of the stream”. One way to interpret the model conceptual representation of nutrient transport is to assume that streams are ephemeral: during rain events, these ephemeral reaches will be flowing, which is consistent with the fact that most overland transport of nutrient will happen at that time.
- For the sensitivity analyses, focusing on the dominant LULC (either in the whole catchment or in the riparian zone) is not sufficient: as expected, the model is also very sensitive to LULCs that

have the highest loads, so both %LULC and loads should be targeted when designing the analyses.

- Both point sources and instream processes introduce large uncertainties in modeled exports, which confuses the validation exercise. As illustrated in this study, reliable point source data may be hard to obtain, with the annual allowed discharge being only a proxy for actual released concentration. Instream processes could also reduce the observed loads by 25%, according to the regional study conducted by Hoos and McMahon (2009). This suggests that they should be represented by the model. For example, they could explain that the model performance decreased with subcatchment area in our study (Figure 3b) since the nutrient travel longer distance instream.

Implications

The analyses performed with multiple sampling points in the Cape Fear catchment proved useful for model interpretation, highlighting the following points:

- **Reclassifying** the LULC map is strongly recommended to simplify the sensitivity analyses. In this study, we reduced the initial table obtained from NASS to seven LULC. While there is no general rules regarding the number of classes that should be retained, the main two criteria are the relative cover and the particular high loads. As mentioned above, one possible criteria to identify parameters to use in the sensitivity analyses could be the relative area times the loads. In our study, urban and forest LULC had the highest values for this variable, which seems consistent with the fact that the model was very sensitive to the parameters related to these classes.
- **Minimizing bias** with LULC cover (correlation between model performance and percentage cover of key LULCs) is a necessary, although not sufficient, condition to ensure model robustness.

Next steps

Together with the sensitivity analyses, observation of spatial variability in model performance allowed us to better understand model behavior and guide model calibration. The strong bias observed in Figure 5 is indicative of a structural or parameter error, which means that model results with the baseline parameterization should be interpreted with care. It is suggested to reduce this bias by modifying the corresponding parameters (urban and forest loads). As mentioned above, uncertainties related to instream processes and point source discharge should also be taken into account when comparing model's predictions with observations.

A new model is being developed to improve the conceptual representation of nutrient transport. In particular, the model has the ability to represent subsurface flow, which should be useful in the Cape Fear basin. The new model structure also facilitates the parameter selection (e.g. retention efficiencies). Analyses are in progress to compare the new model's performance with InVEST 3.0, and assess its applicability for assessing land use change scenario in the Cape Fear basin.

Acknowledgments

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Appendix I – Data summary

Table A2. Sources and values of model inputs. Ranges for the raster data represent the spatial minima and maxima. Values dependent on LULC classes are not given.

Data	Type	Value (Mean and range)	Source
Precipitation	Raster	1180 mm [1030; 1450] mm	PRISM* (Gilliland, 2003) USGS (USGS, 2014)
Reference evapotranspiration	Raster	1240 mm [1160; 1310] mm	FAO* MODIS (Mu et al., 2012) Climate Office (NCSU, 2014)
DEM	Raster	90 m [0; 250] m	(USGS, 2013a)
Land Use Land Cover (LULC)	Raster	Cf. Appendix	(NASS, 2013)
Soil depth	Raster	1710 mm [0; 2110] mm	(USGS, 2013b)
PAWC	Raster	0.18 [0.07; 0.52]	(USGS, 2013b)
Root depth	Per LULC class	n.a.	(Allen et al., 1998)
K_c	Per LULC class	n.a.	(Allen et al., 1998)
Z	Constant	20** [1;20]	(Tallis et al., 2013)

* Indicates the data source used for the baseline run (see Section 3.2 on inputs uncertainties)

** Value of 20 was used for the baseline (see text for details).

Table A2 - Biophysical table used for the baseline nutrient analyses

LULC_desc	root_depth (mm)	Kc	LULC_veg	load_n (kg/ha)	eff_n
Ag-Corn	2100	0.65	1	100	0.5
Ag-other	1760	0.7	1	10	0.5
Grass	1000	0.65	1	8	0.75
Forest	5000	1	1	2.8	0.8
Wetland	1	1.1	0	2.8	0.8
Urban	1	0.5	0	10	0.05
Swine Farm	2100	0.65	1	100	0.5

Appendix II – Report on the hydrological data collection and processing

By Chris Cook

Summary of flow and land use characteristics of the ten subwatersheds selected for this study

ID	Name	Area (km²)	Flow mean (2002-2012) (m^3/s)	Flow mean (2002-2012) (Mm^3/y)	%Agriculture	%Grassland/ fallow	%Pasture	%Forest	%Wetland	%Open water	%Urban
2105769	CapeFear @Kelly	13,567	120	3,780	9	13	6	49	6	2	13
2105500	CapeFear @Tarheel	12,535	105	3,320	9	13	6	51	3	2	14
2102500	CapeFear @Lillington	8973	67	2,120	9	10	8	55	1	2	14
2104220	RockfishCR @Raeford	237	3	87.1	1	18	0	62	7	1	8
2102000	DeepRiver @Moncure	3727	30	932	7	9	11	58	0	1	11
2097314	NewHopeCR @Blands	197	2	70.4	2	5	2	49	3	0	39
2100500	DeepRiver @Ramseur	913	8	264	9	9	10	43	0	1	27
2096960	HawRiver @Bynum	3294	29	917	14	10	9	48	0	1	17
2097464	MorganCR @WhiteCross	22	0.1	3.82	10	7	5	72	0	0	5
2096846	CaneCR @OrangeCR	20	0.1	3.93	11	6	6	71	0	0	4

Note: LULC Shrubland, Swine, and Barren were <2% are not reported here

Precipitation Data

The available precipitation data consisted in the PRISM dataset (http://www.prism.oregonstate.edu/) (Gilliland, 2003)(Gilliland, 2003)and a network of eight rain gages maintained by the USGS (http://nc.water.usgs.gov/realtime/real_time_cape_fear.html). Data missing at stations was infilled with data taken from nearby stations when those stations experienced similar magnitudes of rainfall on a daily timescale. Daily data was then averaged by month and year in Microsoft Excel using pivot tables. The use of pivot tables allowed for the calculation of total monthly and annual rainfall at each site. The use of pivot table also allowed for the calculation of the total number of days of data missing at each individual rain gauge. Years missing more than 25% of their daily data (~90 days) were removed from analysis.

Precipitation Interpolation and PRISM Rainfall data

Rain data was then summarized by station and by year. This data was then imported into Arcgis as a shapefile for each individual year and was projected in a geographic coordinate system. Data was then interpolated using the default settings of a spline interpolation, and inverse-distance weighted (IDW) interpolation for each year. Kriging was not used because it requires the creation of a semivariogram to explain how a phenomenon (rainfall) varies with distance from a given location (or cell in a raster), which is then used to approximate the variability of the phenomenon in space and is then used in calculating values. The creation of a semivariogram requires many points, ususally many more than 8 points (which was used for most years of the interpolation), typically at least 30, but upwards of 100 is recommended.

PRISM rainfall data was downloaded for each year and clipped to the boundaries of the Cape Fear catchment to act as a rough spatial and numeric comparison for the interpolated rainfall rasters.

IDW and spline both predicted a similar maximum and minimum rainfall (2002-2012 rainfall average by year), although the surfaces appeared differently. The IDW and spline interpolation both predicted lower rainfall values when compared with the PRISM rainfall dataset. The PRISM rainfall dataset, however, returned similar values and appeared spatially similar to the dataset provided by the TNC. This can be attributed to the following reasons: 1) The interpolations underestimate the amount of rainfall occurring in NC, or 2) The PRISM dataset is overestimating the maximum and 3) minimum amount of rainfall occurring within the state.

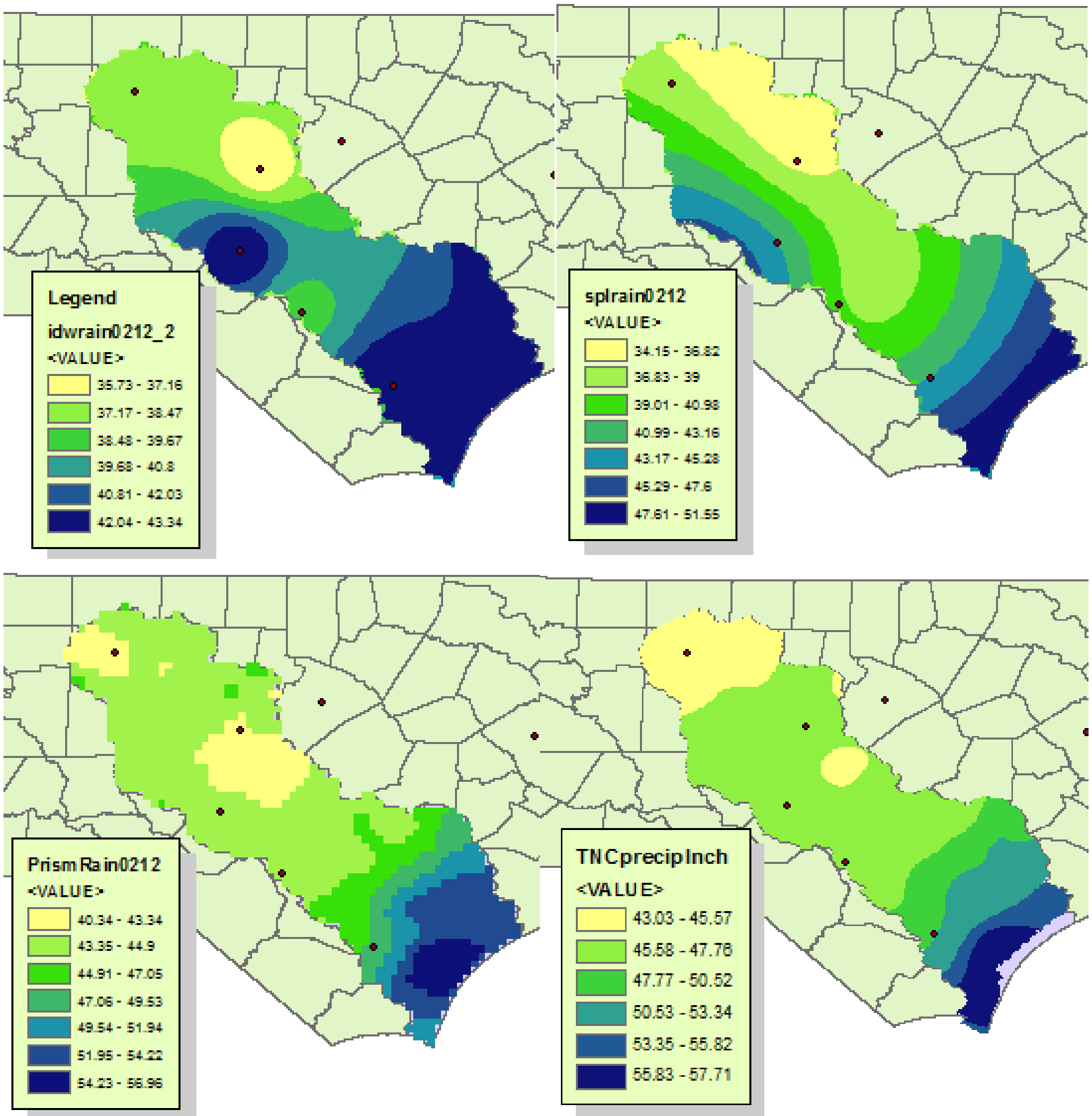

Figure 1. Significant differences in precipitation inputs may occur due to differences in the data source (IDW, Spline, PRISM, or long-term values obtained from TNC)

Streamflow Data

Streamgauging data downloaded for the majority of Cape Fear Watershed from USGS water websites (http://nc.water.usgs.gov/realtime/real_time_cape_fear.html). Data and site selection focused on selecting those sites that lie on major rivers within the catchment (the Cape Fear River, the Deep River, the Haw River) that eventually feed into the Cape Fear River. Sites were, however, chosen based on the availability of data and the amount of data logged/ available at individual sites.

Nutrient / Water Sample Data

Nutrient data was retrieved for sites within the Cape Fear River Basin Monitoring Coalition and also from the USGS website. Data downloaded from the Coastal Ocean Research and Monitoring Project (CORMP; http://www.cormp.org/CFP/) comprised all samples at all sites within the Cape Fear area that were taken for both total nitrogen and total phosphorous.

After downloading data and projecting in ArcMap it was apparent that there was poor overlap between USGS stream gaging sites and nutrient data from CORMP and the USGS. The USGS lacked desired site numbers, but typically had longer datasets at a given site (typically monthly measurements), while CORMP had many sites that were typically on the Cape Fear River itself.

To compute the annual nutrient loads from the grab samples, USACE program “Flux32” was downloaded (from a mirrored webpage as it is no longer available on the USACE website ftp://simpletools.dyndns.org/Flux_Install/).

FLUX32 was successfully used after reading through all of the associated help files included with the program. A very specific excel layout is needed for both the daily discharge value file and the individual samples collected.

After finding that the temporal resolution of the majority of USGS nutrient sampling data at relevant stream gages was insufficient, data from CORMP monitoring was appended to the USGS data. This was only possible for those CORMP stations/samples taken that were on the same river reach as a USGS stream gage. These samples were chosen by location as carefully as possible. In a number of cases the CORMP was taken directly at USGS stream gage sites. However, there are also cases where CORMP sample data falls on the same reach as the USGS discharge measurement sites. These sites were cross examined with google satellite imagery to insure that these upstream nutrient measurements would be apt to translate to the downstream (or upstream) to USGS sites. For instance, one USGS discharge site on the Cape Fear River is just above a dam, so the CORMP data taken just above the USGS station was chosen to represent the gage, while the CORMP data from below the dam was discarded because of the potential impacts of the dam on sediment suspension and nutrient concentration.

Data was then put into the format deliverable to Flux32, as mentioned above. Data input requires a daily discharge file (one column date, one column discharge (slightly more complicated)), and a nutrient consistent file (one date column, one nutrient concentration, one instantaneous discharge).