Unlocking the potential: The challenge of quantifying the impact of riparian revegetation on sediment load reduction

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Key points

- Utility providers can serve as a significant funding source for river rehabilitation by offsetting nutrient and sediment loads.
- Doing so relies on quantifying the volume of erosion reduction resulting from these efforts.
- This study demonstrated stream reaches with less dense riparian canopy cover contribute more sediment loads during flood events.
- **E**stimating actual sediment load reduction during flood events is complex due to challenges such as insufficient data and computational limitations.

Abstract

Utility providers can serve as a significant funding source for river rehabilitation by offsetting nutrient and sediment loads. However, quantifying erosion reduction associated with these efforts remains a challenge. Historically, hard engineered interventions are favoured due to their immediate and measurable erosion reduction. In contrast, large-scale riparian revegetation's benefits are harder to quantify despite potentially greater benefits.

To address this, a rigorous methodology was developed to demonstrate catchment-scale revegetation benefits in two large catchments in SEQ. This involved analysing historical topography and vegetation canopy data, conducting catchment-wide rain-on-grid modeling and extensive post-processing, and incorporating a large body of scientific literature.

While the study demonstrated that stream reaches with less dense riparian canopy cover contribute more sediment loads during flood events, which is consistent with prior research, many difficulties were encountered. Estimating actual sediment load reduction during flood events, due to increased canopy cover is complex due to challenges such as insufficient data and computational limitations.

While the study strongly suggests riparian revegetation can reduce riverbank erosion, accurately quantifying this reduction requires further work. This paper discusses some of those challenges, such as dealing with large-scale complexity, that were confronted in this project.

Keywords

River Rehabilitation | Environmental Offsets | Erosion Reduction | Mapping | Lockyer | Bremer

Introduction

Utility providers offsetting nutrient and sediment loads represents a potential funding source for river rehabilitation works. For the offset to be approved though, there is a need to quantify the reduction in erosion volume associated with the works. In the past this has meant that hard engineered interventions, such as rock beaching, that provide an immediate and measurable reduction in erosion are favoured. Large-scale riparian revegetation, however, may provide greater long-term reduction in erosion at a lower cost, as well as imparting many co-benefits.

Quantifying the long-term impact of large-scale vegetation-based rehabilitation on stream bank stability and erosion rates is very complex. It requires an intimate understanding of many factors, including but not limited to, catchment hydrology and hydraulics, historical rates and drivers of erosion, the nature of the bed and bank material, and the existing riparian condition. These factors, and the interactions between them, vary both spatially, across the catchment, and temporally, as the catchment evolves. Characterising these factors requires both comprehensive, high quality, multi temporal datasets, and scientifically informed and consistent methods of processing.

In 2022 Water Technology, in partnership with Griffith University, undertook a broad scale project with Urban Utilities in Southeast Queensland (Water Technology, 2022). The investigation focused on the entire Lockyer and Bremer River catchments, over 4,500km^2 in total. Aims of the project included quantifying the benefits of widespread riparian revegetation throughout the catchments of interest as well as guiding how an offset program could work and how sites should be prioritised.

Our study discretised the waterways into polygons. Within each polygon the study used historical erosion rates to define relationships between erosion and hydraulics, in particular, stream power, and erosion and vegetation, in particular foliage projected cover (FPC) of vegetation with a canopy height greater than 5m. The project proved to be more difficult than anticipated with many complexities arising that required collaborative and innovative solutions. The purpose of this paper is to discuss some of those hurdles, how they were overcome, and where they weren't, how they may be in future studies.

Discretisation

Each waterway was divided into lengths along the thalweg to allow for discrete analysis of relationships between variables. Various lengths were trialed ranging from 50m to 1000m; however, due to the variability of data, based on both differing catchment scale characteristics and local influences on channel morphology, vegetation, and hydraulics, larger segments produced better relationship envelopes. 500m length polygons were ultimately adopted as they were considered a practicable length for management. The lateral extent of the polygons was determined by the Top of Bank. Several datasets were used, including the latest available LiDAR data, to manually map the extent of the channel banks to be assessed. Using QGIS software, available datasets (LiDAR, aerial imagery, hydraulic model results) were displayed in several different ways to allow the mapper to observe the alignment of the top of the bank. This included:

- Profiling the data to view the local cross-sectional geometry.
- Producing slope maps from the DEM to help locate breaks in slope.
- Observing water depths from hydraulic model outputs.
- Analysing aerial imagery.

Figure 1 shows an example, for Purga Creek in the Bremer River catchment, of the various data visualisations used to identify the top of bank (ToB). Interpretation was necessary at locations where there was some ambiguity.

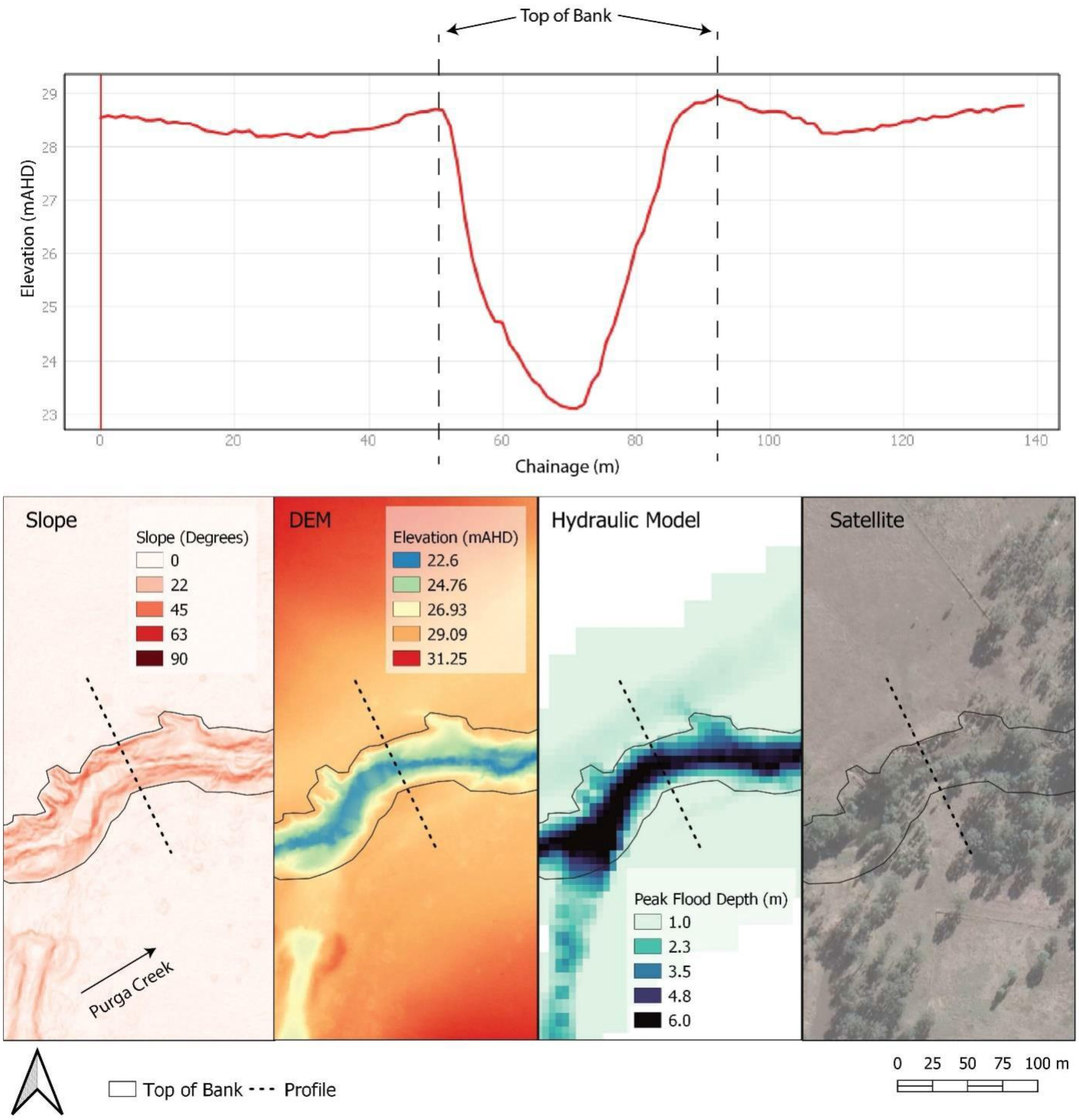

Figure 1. Some of the data visualisations used to map the top of bank

Using the ToB to limit the spatial extent avoided assessing erosion volumes, vegetation data and stream power data from the floodplains. Floodplains within both study catchments are typically unvegetated due to clearing, which biases a relationship between low vegetation and low erosion. Similarly, the stream power is generally significantly lower on the floodplain which would bias a relationship between low stream power and low erosion.
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This method of discretising river reaches introduces several problems that are hard to resolve. Firstly, mapping the ToB by hand, despite the thorough method using multiple visualisations and datasets, will always be, to some degree, subjective. River channels can form and occupy a huge range of vastly different cross-sectional geometries and the point that divides what is in channel from what is not is often ambiguous.

Secondly, manually mapping hundreds, if not thousands, of kilometres of riverbank, and capturing the necessary detail, is on the verge of being too time consuming to be financially viable. At the same, however, we found that mapping of the ToB alone was not detailed enough to capture the full level of complexity required of the analysis. Ideally, discretisation would account for more geomorphic features than just what is ‘in channel’. The ToB method will, for many polygons, include large areas where neither erosion nor vegetation are expected to occur, such as where there is standing water. Ideally this area would be excluded from the analysis, however, doing so introduces more time and more ambiguity. The dynamic nature of these features would be very hard to capture. After prolonged dry periods vegetation may establish where it couldn’t during wet periods. This is particularly evident in Lockyer Creek which, despite the capacity to convey substantial flood flows (>1000m^3/s), can cease to flow and dry out for long periods of time.

It becomes very hard to compare features, across time, when the spatial extent of those features is not fixed. Even comparing discrete polygons over time is problematic as waterways can completely shift course, as occurred at multiple locations during the time period that was the focus of this study.

Ultimately, the problems mentioned above arise due to limited capacity and the subjective experience of the scientists carrying out the work. Much work is currently being done to advance the use of machine learning to map landscape features such as riverbanks (Gerber et al. 2024, van der Meij, et al.2022). Machine learning and artificial intelligence will, in time, likely offer a solution to both the limited capacity, and the subjectivity, of human users. Another way to manage these problems would be to focus on a smaller spatial extent by restricting the study area to smaller sub-catchments with more manageable stream lengths.

Hydrology and hydraulics

A key aim of this project was to identify areas of high erosion risk within the stream network, with stream power (SP) being recognised as one of several factors that contribute to erosion risk (Nanson and Hickin, 1986; Larsen et al., 2006). Of particular interest is the cumulative energy associated with available stream power to contribute to erosion during a flow event. This is, in effect, the total work done by flowing water against the strength related resistance offered by the substrate (the bed and banks of the river) during a flow event.

The analysis aimed to quantify and map SP throughout the channel network and, subsequently, the spatial distribution of the work done by water, on the bed and banks of the river, over the course of each storm event analysed. As this study was framed around time intervals between LiDAR capture dates and those time intervals sometimes included multiple events it was necessary to understand the cumulative hydraulic forces acting on the channel within those dates. This would allow for comparison of hydraulic forces against the volume of erosion and changes to vegetation coverage (and density) indicated by the LiDAR data.

Stream power(Ω), expressed in Watts, refers to the amount of energy the water in a river or stream exerts on the substrate in a given instant (Bagnold, 1966). Stream power is calculated according to Equation 1:

(1) $$\Omega=\rho g Q S$$

Where:

ρ = the density of water (kg/m3)
g = acceleration due to gravity (m/s/s)
Q = flow (m3/s)
S = water surface slope (m/m)

The potential for work to be done (Wp) on the substrate during a flow event is equal to the instantaneous stream power integrated with respect to time, over the duration of the event (expressed in Joules) as shown in Equation 2.

(2) $$W_p=\int\Omega\ (dt)$$

Where:

Ω = Stream Power (W)
dt = change in time (s)

The hydrology and hydraulics for this study were informed by a 2D, Rain on Grid (RoG) modelling approach using TUFLOW. While a 1D hydraulic model, where cross sections are defined along the stream length, is well suited to calculating stream power as defined by Equation 1, a 2D model grid is not. To output stream power for each 2D cell within the model extent, TUFLOW calculates stream power as a function of velocity and bed shear stress (TUFLOW, 2018) as shown in Equation 3:

(3) $SP = |V|\ \tau_{bed}$

Where:

$|V|$ is the absolute value of the velocity (m/s)

τ_{bed} is the Bed shear stress (N/m2) as defined by Equation 4 below:

(4) $\tau_{bed} = \frac{\rho g V^2 n^2}{y^{\frac{1}{3}}}$

Where:

ρ = the density of water (kg/m3)
g = acceleration due to gravity (m/s/s)
V = velocity (m/s)
n = Manning's n
y = depth (m)

A key difference between Equations 1 and 3 is that the Manning's n value of the underlying material is not a direct input into Equation 1 (though it will indirectly influence the flow and water surface slope), whereas it is in Equation 3. This proved to be problematic when investigating stream power results output from TUFLOW. Stream power results varied greatly with changes to the underlying materials layer and outputs were more representative of the underlying materials than the stream hydraulics and were not deemed suitable for subsequent analysis.

A considerably more labour-intensive method for measuring Wp was developed by setting up an extensive network of approximately 600 plot output (PO) points and lines to track flow (Q) and water surface elevation (WSE) throughout the stream network. Ensuring that each point and line was labelled with a stream ID, and a number to identify its sequence along the stream chainage, allowed change in water surface elevation (S) to be tracked throughout the stream network over the duration of the model simulation. The water surface slope (S) was calculated by subtracting the WSE at the downstream point from the WSE at the upstream point and dividing by the length. Figure 2 shows an example of the PO setup on the Bremer River. A series of excel worksheets was then set up for post processing of the plot output results. First, the instantaneous SP was calculated for each length of stream (between reporting points) for every reporting timestep (15 minutes). SP values were then integrated with respect to time to produce a single Wp value per length of stream, per event analysed. Labels previously assigned to the POs were then able to be used to reintegrate the results of the post processing back into GIS.

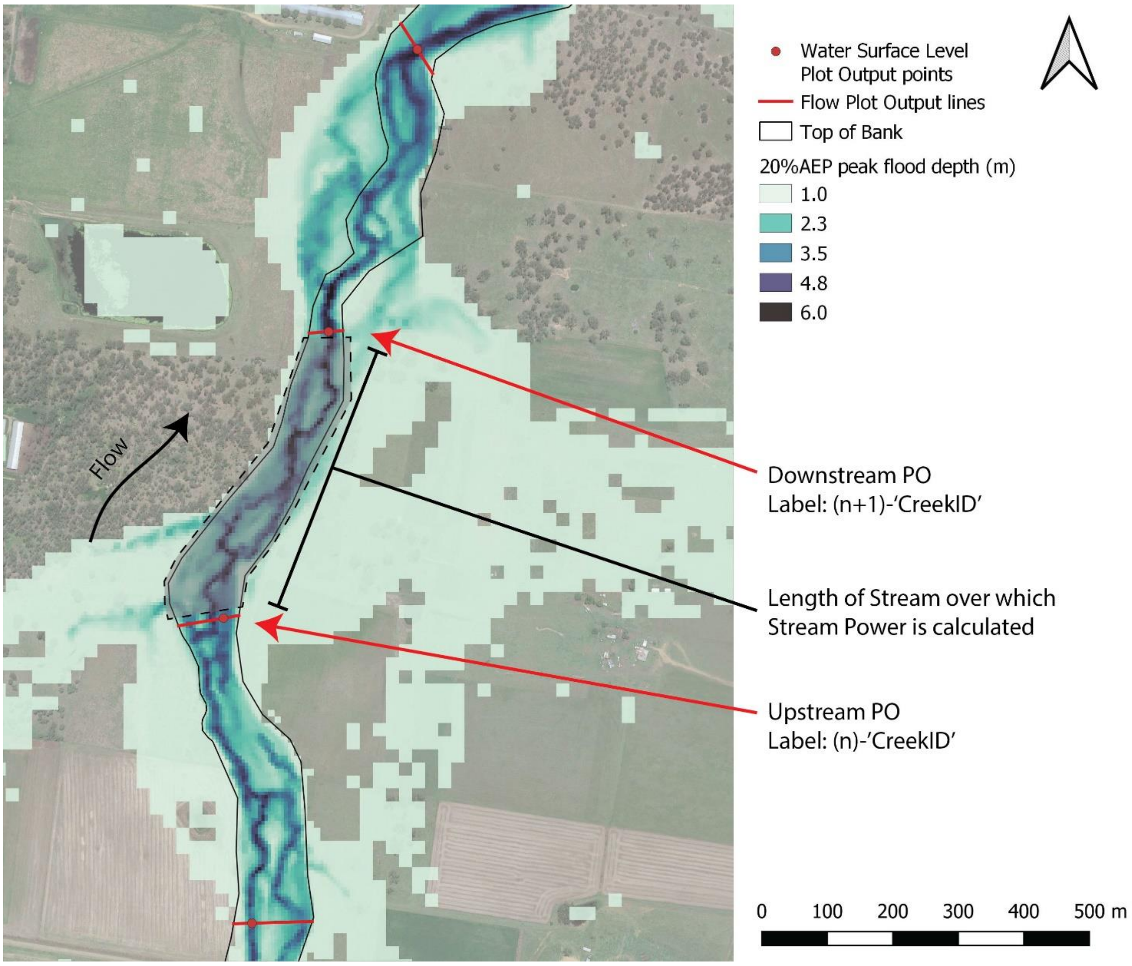

Figure 2. Example of PO setup on the Bremer River

DEMs of difference

Rates of historical erosion were estimated in this study using DEMs of Difference (DoDs). Creating and analysing the DoDs over such a large spatial extent proved problematic in many ways, largely due to underlying problems with the data, principally, that there was not enough of it. For both the Bremer and Lockyer catchments analysed we were forced to work with a patchwork of spatially and temporally segmented datasets. While LiDAR was available for nearly all of both catchments, there was no single LiDAR dataset that covered all of either catchment. In the wake of the severe flooding in southeast Queensland in 2021and 2022 it seems there is an increased demand for more LiDAR capture. This increased demand, coupled with continual developments in remote sensing technology and data processing capacity, is likely to result in the availability of more comprehensive LiDAR datasets being produced in the future.

Another problem faced with producing DoDs at such a large scale is that LiDAR is generally good for representing larger waterways but unreliable in smaller waterways, especially with dense vegetation. Lower stream order creeks in the study catchments are generally (though not always) narrower and more densely vegetated than the higher stream order creeks. Due to the way that LiDAR data is captured and processed, the resultant DEM is less accurate in areas of denser vegetation. There is less opportunity for LiDAR to penetrate to the ground, increasing the incidence of nonground returns and decreasing the capture of points on the riverbed and banks. This can result in substantial discrepancies, particularly along riverbanks where vegetation is likely to be overlying abrupt topographic variability. Previous studies show a tendency for surface elevations to be overestimated in densely vegetated areas (Su and Bork, 2006; Leitão et al. 2016). This means that the DEM produced from the LiDAR data will be less reliable in lower stream order creeks compared to higher stream order creeks. This is demonstrated in Figure 3 which shows an example cross section from Laidley Creek within one of the polygons that measured unusually high erosion given the high vegetation. In this instance, the creek bed has been misrepresented in the 2015 LiDAR, likely due to the above-mentioned issues with LiDAR data capture along heavily vegetated riverbanks.

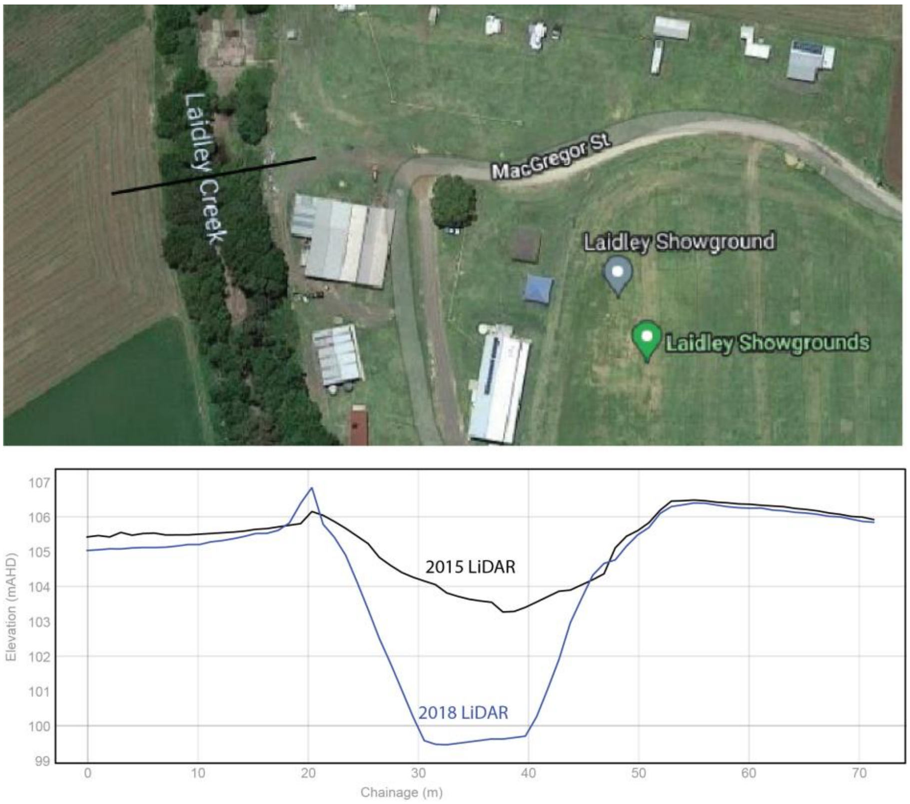

Figure 3. Example cross section from Laidley Creek

Analysis

A method was developed to estimate the potential for erosion reduction through revegetation of identified sites. This involved attempting to define a relationship between existing vegetation cover and the observed unit erosion rate. Looking for an overall trend in the data, a least squares regression analysis was carried out. Given the spread of y-values (unit erosion) for a given x-value (FPC) was found to be large and non-uniform, the results of this analysis were not useful in defining a trend. This is likely due to the presence of many additional explanatory variables that influence the unit erosion rate (flow, slope, bank angle, bank material, bank height etc.).

A subsequent step involved looking to find a distinct visual upper limit, defined by a marked reduction in the maximum y-values as the x-value increases. In such cases, defining a 'limit line', with no points (excluding outliers) lying above it, can be an appropriate method for identifying a trend in the data (Carling, et al, 2022). In statistics, a 'limit line' is a line, or a threshold value, used to determine whether a set of data falls within expected limits. Using a limit line approach allows the user to find a trend, not by identifying the central trend in the data, but by finding the maximum values of erosion to occur for given states of vegetation. Having defined a limit line, observed data can be contained within the x- and y-axes and the limit line as shown in Figure 4.

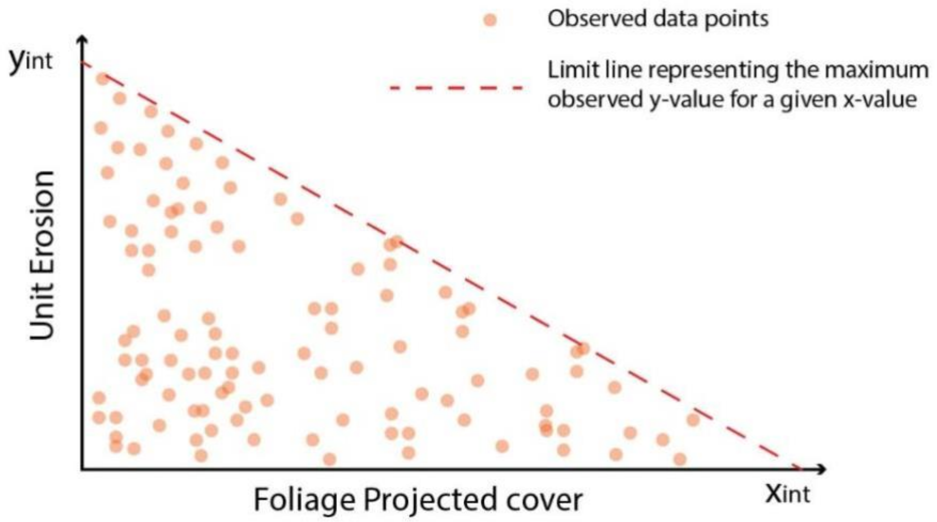

Figure 4. Idealised figure demonstrating the limit line relating erosion to vegetation.

Limit lines are commonly used to examine relationships between processes in natural systems. However, it is important to note that limit lines are only a statistical tool. They cannot be used to predict the exact amount of erosion that will occur, in a given area, under any given vegetation coverage. Additionally, limit lines can be affected by several factors, such as climate, soil type, and slope. Therefore, it is important to use limit lines in conjunction with other methods of assessing erosion, such as field surveys and soil samples.

Conclusions

Tapping into funding for river rehabilitation that utility providers can offer, by offsetting nutrient and sediment loads, hinges on quantifying the volume of erosion reduction resulting from these efforts. Through this project, the authors found that, while it is highly likely this goal can be realised, there remain many obstacles that must be overcome.

The approach of discretising waterways is problematic over temporal scales where features within the waterway shift and change and even more so when the waterway is realigned. Using the top of bank to discretise the waterway is problematic because it is, at once too time consuming, and not detailed enough to account for geomorphic units within the polygons.

Using DoDs is problematic because there is rarely enough data. In Southeast Queensland at least, there is currently a paucity of overlapping multi temporal datasets. Furthermore, when relying on data captured by LiDAR, densely vegetated areas, which are specifically of interest to such studies are, inherently, the most poorly represented areas within the dataset.

Relationships between variables are not linear and are best described by envelopes. While the envelopes help support the hypotheses that vegetation is linked to erosion rates the relationship cannot be used to predict the actual effect of change (increase in cover of riparian vegetation), only to predict the maximum possible effect of the change.

Opportunities to overcome some of these problems include analysing smaller areas or subcatchments. This would allow for greater effort to be concentrated on mapping features and manually checking all analysis outputs. The use of artificial intelligence and machine learning algorithms will likely help overcome human limitations in the near future, assisted further by a general increase in computational capacity.
Another key opportunity will come with the availability of more data. Increased demand, coupled with continual developments in remote sensing technology and data processing capacity, is likely to result in the availability of more comprehensive LiDAR datasets being produced in the future.

Acknowledgments

Cameron Jackson and Tony Constantini at Urban Utilities

Jon Olley at Griffith University

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