Evaluating the Accuracy of Stream Power-Based Models for Predicting River Channel Sediment Dynamics.

A Thesis Presented by:

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This study was completed as part of the BSc Geography course at the University of the West of England. The work is my own. Where the work of others is used or drawn on, it is attributed to the relevant source.

Benjamin Zebedee Houghton-Oliver

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Abstract

Evaluating the Accuracy of Stream Power-Based Models for Predicting River Channel Sediment Dynamics, Benjamin Zebedee Houghton-Oliver, BSc Geography, 2024.

River channel adjustment can increase flood risk, harm ecology and negatively impact a river's function. Understanding where, how and why adjustment occurs is therefore vitally important from both an ecological and river management perspective. Adjustment occurs as a result of an imbalance between sediment transport and supply. There is a variety of approaches used to assess channel adjustment, with importance being placed on method cost, reliability and time.

To this end, this report assesses the performance of 30 different stream power balance models that can be applied using remotely sensed data and easily available datasets to predict sediment balance and channel status. Each model is based on stream power calculations made at 50m intervals along a river channel using measurements of channel slope, river discharge and width of flow. The sediment balance of each point is calculated, allowing for sediment balance predictions on either a point or reach-based scale. These predictions of channel status are then compared against observations from the River Habitat Survey to assess their performance.

This report finds that these stream power indices generally correspond well to observed channel status along the River Dee. ST:REAM and $T_{balance}$ based indices have the strongest performance, and $\omega_{balance}$ indices have the weakest performance. This report concludes that limitations within the report's method mean the strong performance displayed by the stream power balance models results should be treated cautiously, with further testing needed before these models are implemented to assist with river management.

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Chapter 1 - Introduction

River sediment dynamics, defined as the movement, transport and deposition of sediment is a highly influential process (Julien, 2010). An imbalance in sediment dynamics can lead to erosion and deposition, otherwise known as channel adjustment (Lea and Legleiter, 2016). Rivers can move away from equilibrium and towards either a state of degradation or aggradation (Soar, Wallerstein and Thorne, 2017). River channels self-adjust to correct this imbalance and restore equilibrium, as Lane (1955) outlines. Channel adjustment can lead to increased flood probability and damage and have negative effects on ecology (Dust and Wohl, 2012; Piégay *et al.* (2000). It is therefore highly beneficial to be able to measure current channel adjustment and also to be able to predict where future adjustment may occur. There are a variety of approaches to achieving this.

Stream power, an expression of the driving forces acting in a channel (Bagnold, 1960), can be used to predict channel status (Bizzi and Lerner, 2013; Vocal Ferencevic and Ashmore, 2011; Biron *et al*., 2012). The main benefits of using stream power over other approaches include the ability to use remotely sensed data instead of having to employ costly and time-consuming field surveys for data collection (Phan, Bertone and Stewart, 2021). This has led to many authors testing the effectiveness of using a stream power-based approach to predict adjustment (Bizzi and Lerner, 2013; Vocal Ferencevic and Ashmore, 2011; Biron *et al*., 2012; Parker, Thorne and Clifford, 2015; Parker and Davey, 2023). If stream power can be used as a reliable indicator of channel status, it would have huge potential benefits for river management.

This report will begin with a literature review which outlines the processes behind channel adjustment, discusses its importance, and reviews methods of assessing it. This provides the basis for the aim of this study: to evaluate the accuracy of stream power-based models for predicting river channel sediment dynamics. The assessed models are: $\omega_{\text{balance1km}}$, $\omega_{\text{balance3km}}$, $\omega_{\text{balance5km}}$, $\omega_{\text{balance10km}}$, $\omega_{\text{balanceAll}}$, $\Omega_{\text{balance1km}}$, $\Omega_{\text{balance3km}}$, $\Omega_{\text{balance5km}}$, $\Omega_{\text{balance10km}}$, $\Omega_{\text{balanceAll}}$, $T_{\text{balance1km}}$, $T_{\text{balance3km}}$, $T_{\text{balance5km}}$, $T_{\text{balance10km}}$, $T_{\text{balanceAll}}$, $\omega_{\text{balance-reach-0.5}}$, $\omega_{\text{balance-reach-0.6}}$, $\omega_{\text{balance-reach-0.7}}$, $\omega_{\text{balance-reach-0.8}}$, $\omega_{\text{balance-reach-0.9}}$, $\Omega_{\text{balance-reach-0.5}}$, $\Omega_{\text{balance-reach-0.6}}$, $\Omega_{\text{balance-reach-0.7}}$, $\Omega_{\text{balance-reach-0.8}}$, $\Omega_{\text{balance-reach-0.9}}$, $T_{\text{balance-reach-0.5}}$, $T_{\text{balance-reach-0.6}}$, $T_{\text{balance-reach-0.7}}$, $T_{\text{balance-reach-0.8}}$, $T_{\text{balance-reach-0.9}}$.

Following the literature review, the research questions will be outlined in Chapter 3. After this, the methodology, covered in Chapter 4, will describe the process of obtaining the necessary values for each model, as well as how they will be assessed against observed channel status. The results will then be displayed in Chapter 5 before being discussed in Chapter 6, with evaluations of model accuracy and performance as well as study limitations. Finally, Chapter 7 covers the report's conclusions.

Chapter 2 - Literature review

This chapter will outline the importance of river channel adjustment and the existing literature surrounding it. Following this, a general overview of the current methods for assessing river channel adjustment will be discussed before specifically exploring stream power model-based approaches in greater depth.

2.1 – River Channel Adjustment

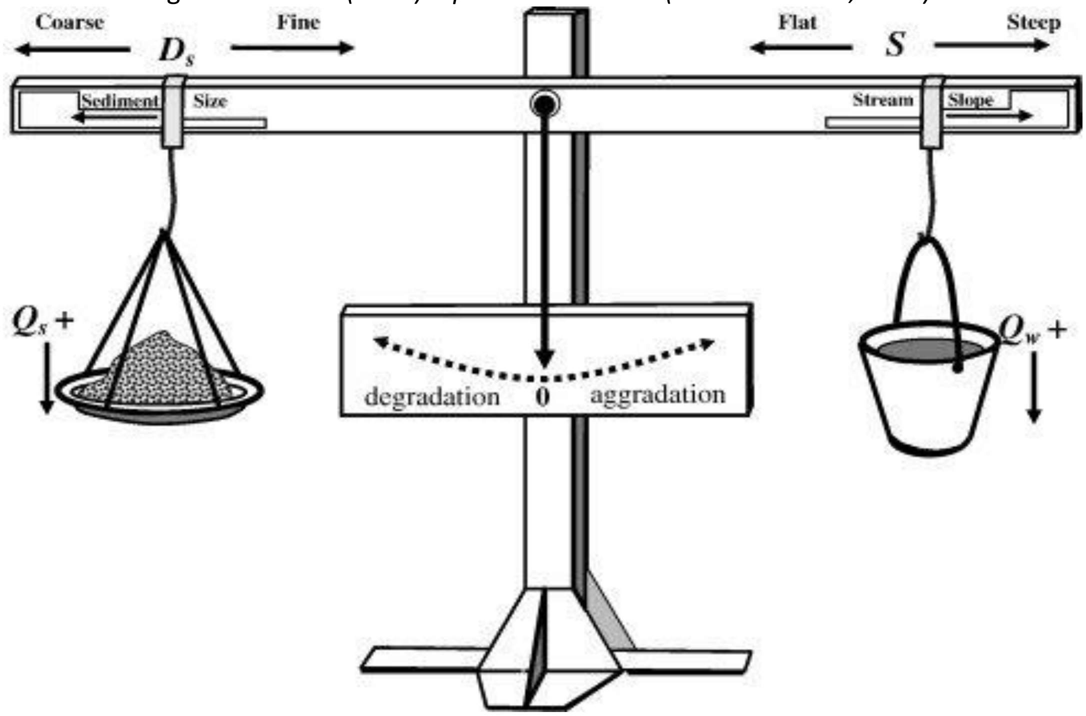
2.1.1 – The Processes Behind Alluvial Channel Adjustment

Geomorphic processes and channel morphology are driven by a balance of driving (e.g. channel gradient and discharge) and resisting (e.g. bed and bank resistance) forces (Bizzi and Lerner, 2013). The ability to perform geomorphic work, commonly expressed as stream power, is a measure of the main driving forces acting in the channel (Bagnold, 1960). River channel adjustment occurs when there is sufficient stream power available to erode, transport and deposit sediment on the channel perimeter, with greater adjustments being more likely to occur where there are greater disparities in available energy between reaches and variations in sediment supply (Soar, Wallerstein and Thorne, 2017; Lea and Legleiter, 2016). Lane's (1955) equation outlines how a channel will adjust to an imbalance in force (Figure 1). The equation states that rivers tend towards a state of balance between sediment transport capacity and sediment supply using this equation:

$$Q_s d \propto Q_w S \tag{1}$$

Where, Q_s is the quantity of sediment, d is the particle diameter of sediment, Q_w is the water discharge and S is the slope of the stream.

Figure 1 - *Lane's (1955) equation visualised (Dust and Wohl, 2012).*



This is an equation of equilibrium, meaning if any of the four variables are altered it indicates the changes which are needed in the other variables to restore equilibrium. It highlights that if sediment supply and capacity are balanced, river channel adjustment will not occur. However, a change in either of these variables with disrupt the equilibrium and shift a channel's sediment dynamics towards either aggradation or degradation, resulting in adjustment (Jha *et al.,* 2022; Soar, Wallerstein and Thorne, 2017). Although a shift away from equilibrium is necessary for adjustment to occur it does not mean it is guaranteed. The mechanics of river channel adjustment are complex and multifaceted, and, as acknowledged in the original paper, Lane's equation is a simplification of these complicated dynamics (Lane, 1955; Eaton and Church, 2011; Dust and Wohl, 2012). Generally, however, adjustment is more likely to occur the larger and more prolonged the shift away from equilibrium is (Su *et al.,* 2021).

Many authors have since expanded upon Lane's (1955) original research to include a great range of measures and factors affecting channel adjustment and dynamics. Influential examples of this include work by Huang and Nanson (2000; 2002) who developed an alternative equilibrium theory based on a channel-shape approach to explain adjustment in river channels. This approach yields a curvilinear equilibrium relationship between channel geometry and bedload transport capacity, revealing an optimum equilibrium condition, termed maximum flow efficiency (MFE), where the imposed bedload within the channel can be moved using the least amount of energy (Su *et al*., 2021). Not all rivers achieve MFE. Importantly however, in all alluvial rivers, MFE acts as an attractor state toward which they will adjust (Su *et al*., 2021; Huang, 2010; Huang and Chang, 2006; Huang and Nanson, 2002). Similarly to Lane's (1955) equation, all rivers are attracted towards a state of equilibrium, in this case, represented by MFE, to which they will self-adjust towards (Huang, 2010).

2.1.2 – The Importance of Understanding River Channel Adjustment

2.1.2.2 – River Channel Adjustment and River Management

A detailed understanding of channel adjustment and the mechanisms behind it are vital for informing river engineering solutions both on a local level as well as more broadly to identify unstable reaches which are adjusting to instability (Bowman *et al*., 2021; Bizzi and Lerner, 2013). Many authors point to the need to account for and consider sediment imbalances when evaluating flood risk (Máčka *et al*., 2022; Pender, 2010; Guo *et al.,* 2018). For example, in a deposition-dominated channel, excessive sediment build up will occur due to insufficient stream power (Papangelakis et al., 2022), this causes a reduced conveyance capacity increasing flood probability and therefore risk (Hooke, 2015). A river's sediment dynamics can also decrease the effectiveness of types of flood defences, research by Tsujimoto and Tsujimoto (2019), which aimed to explore the risk of flooding on rice paddies in Japan. They found that a river being deposition dominated was a contributing factor to increased levee failure causing unintentional flooding and economic damage to farmers. This mirrors research by Mazzoleni *et al.* (2017) where they also found that a river being shifted towards aggradation decreased the effectiveness of levees as a flood defence by decreasing channel depth. A similar effect can be seen in erosion-dominated channels, in a study examining flood risk reduction in the Upper Vistula Basin, Poland, Wyżga *et al.* (2018) found that due to recent decreases in sediment supply caused by accelerated melting of snow and ice the river had become much more erosion dominated. They note this caused increased bank erosion and bed incision which increased flood probability, especially around bridges. They also state that previous flood management efforts, such as attempts to channelise the river and build flood embankments had not decreased flood risk, only accelerated runoff and shifted the flood hazard downstream. Situations like this highlight the importance of fully understanding river sediment dynamics so that effective, long lasting flood management measures can be implemented. Understanding where instability is, or will be, allows for more effective river management schemes and also the more accurate targeting of limited resources. Thus, being able to accurately predict and measure alluvial channel adjustment is highly advantageous (Ward *et al.,* 2017; Bowman *et al*., 2021).

2.1.2.2 – River Channel Adjustment and Ecology

Although not the focus of this report, it is also worth noting the impact of sediment imbalance on river ecology. Piégay *et al.* (2000) discuss the impact of the changing characteristics of the Ain River, France, over the past 100 years. They state that, in recent years, as river stream power has increased due to a change in geometrical characteristics it has resulted in a shift from aggradation to degradation. This has strongly affected the vegetation, especially in the reaches most shifted towards degradation, where helophyte species have been replaced almost entirely by mesophytes. Other authors, such as Gu *et al*. (2023) and Li, Sabokruhie and Lindenschmidt (2023) have found similar effects in other rivers that have undergone a change in sediment dynamics. Gu *et al.* (2023) specifically points to the loss in biodiversity this can cause whilst Li, Sabokruhie and Lindenschmidt (2023) note that degradation in the Saskatchewan River Delta was being caused by the presence of new upstream dams which damaged local fish populations causing them to decline. This highlights the importance of considering ecology when building hydraulic infrastructure or flood defences.

2.2 – Approaches to Measuring Channel Adjustment

There are a variety of approaches to measuring channel adjustment. Su *et al.* (2021) argue that there are purely theoretical, semi-empirical or empirical approaches to identifying significant controlling variables and measuring the adjustments they cause. However, most authors simply divide measurement approaches into two broad categories: an observation of channel form-based approach or a model-based approach which aims to predict the dominant processes and controlling variables (Knighton, 2015; Schneider *et al.,* 2015; Zhou *et al.,* 2021; Chin and Gregory, 2009). This section will provide a broad explanation of these two approaches as well as more closely evaluating specific techniques used to measure channel adjustment.

2.2.1 - Channel Status Observation Methods

Field observations have often been used to determine the dominant processes within a river channel (Furbish *et al*., 1998; Angermann *et al.,* 2017). Channels in a state of either aggradation or degradation will present different geomorphic features and characteristics (Bizzi and Lerner, 2013). For example, the presence of small, vegetated islands and gravel bars is usually associated with low stream power channels undergoing aggradation (Ferguson and Church, 2009; Rice *et al*., 2009). Whereas, the presence of rills and ephemeral gullies are usually associated with higher stream power channels undergoing degradation (Sofia *et al*., 2017). Using these observations, the dominant processes within a channel can be deduced (Bizzi and Lerner, 2012).

2.2.1.1 – Traditional Field Surveys

Typical observational approaches use field surveys to gather information about a channel (Bizzi and Lerner, 2013). Many field survey methods are organised around Rosgen's (1984) Stream Classification System, a four-tier, hierarchical approach which organises streams based on a morphological arrangement of their characteristics. Examples of this include the work of Moghaddas, Jalilvand and Soloki (2013) who examined the morphology of the Sistan River using Classification Levels I and II, and the work of Roper *et al.* (2008), who evaluated the effectiveness of using field surveys when determining Rosgen stream types in the John Day Basin, Oregon. Their findings highlight a key flaw of field observations, as only 4/12 of the surveyed streams yielded the correct stream type. The authors determine that this was the fault of discrepancies in determining maximum bankfull depth among different monitoring groups. In some cases, this led to large differences in determining other values such as flood-prone width, leading to incorrect river classification. Field data collection error is a serious problem with purely observational based approaches, especially when attempting to collect large amounts of data and many different variables (Bangen *et al*., 2014; MacVicar *et al*., 2009). Generally, field surveys are an intensive approach, being both time consuming and costly, especially in cases where data needs to be frequently updated to observe change (Rinaldi, Simoncini and Piégay, 2009; Wilkinson *et al*., 1998).

2.3.1.1 – Field Survey Advancements

There have recently been several innovations in the way field surveys can be conducted. Rusnák *et al*. (2018) monitored channel evolution and morphology in the Ondava River, Slovakia, using images taken by unmanned aerial vehicles (UAVs). They found that the data gathered by the UAVs could correctly identify river sediment size over 60% of the time when compared to observations from a 2012 field survey.

The authors state that most of the inaccurate results were caused by areas of dense vegetation. Sediment size can be indicative of channel evolution and status and is therefore a useful metric for observing adjustment (Wu *et al*., 2017; Julien, 2012; Lepesqueur *et al*., 2019). Singh *et al*. (2022) used a UAV swarm semi-autonomous system to map the river bed and width of the Solani River, India. This approach utilises many drones which cooperate together, allowing a greater area to be covered in a much shorter amount of time. High resolution imagery collected in this way can be used to determine channel dynamics, with the benefit of much quicker data collection (Cassel *et al*., 2020). However, Singh *et al*. (2022) note in their study that the cost of using drones in this way is still much higher than traditional field surveys which is a significant drawback of this approach currently. These studies highlight that in the future UAVs could play an important role in gathering field data which could be used to determine channel status, however, in their current state they are still flawed, being expensive and often giving inaccurate results (Singh *et al*., 2022; Cassel *et al*., 2020).

2.3.1.3 – Field Survey Conclusion

Based on the discussed literature in this section, the need for easier to implement, lower cost and less intensive methods for measuring channel adjustment is obvious. Especially when considering the previously discussed literature by Ward *et al.* (2017), who stress the importance of low-cost solutions to identify flood risk and applying river management schemes due to the often-limited resources available.

2.3.2 - Modelled Channel Status Methods

A model-based approach can be used to predict the balance between erosional and depositional processes within a channel. Models attempt to take a more holistic approach to channel adjustment, where the causes of channel adjustment are considered more thoroughly compared with observational methods (Chen *et al*., 2020). A key advantage of models is that they not only show the current status of a river channel but, can also be used to predict future channel adjustments, which is incredibly useful and important when designing river management strategies (Gomes, Ralph and Humphries, 2023; Mould and Fryirs, 2018). Models typically rely on remotely sensed data, which removes the need for much of the data collected in field surveys, requiring fewer resources and lowering costs (Phan, Bertone and Stewart, 2021). Despite these compelling benefits, there remains uncertainty regarding the accuracy of various model types (Soar, Wallerstein and Thorne, 2017; Ziliani *et al*., 2013), data availability (Young, Brandis and Kingsford, 2006), and whether the complexity of river catchment dynamics is fully considered (Ziliani and Surian, 2016). The following section will evaluate various model types and their effectiveness at predicting current and future channel adjustment.

2.3.2.1 – Reduced Complexity Models (Cellular Modelling)

Cellular models are a type of reduced complexity model, representations of physical processes which simplify underlying mechanisms without compromising the phenomenological nature of predictive outcomes (Coulthard, Hicks and Van De Wiel, 2007; Vušanović and Voller, 2021). In general geomorphology, cellular models work by simulating geomorphic forms and processes using a series of gridded cells (Shroder, 2013). By using relaxed interpretations of equations that determine flow, cellular models can quickly produce water depth and velocity which can then be used to calculate sediment transport and determine the dominant channel process (Coulthard, Hicks and Van De Wiel, 2007). Examples of cellular models that attempt to predict river channel adjustment include CAESAR (Cellular Automaton Evolutionary Slope And River) and HEC-RAS (Hydrological Engineering Centre River Analysis System) (Coulthard, Macklin and Kirkby, 2002). Ziliani *et al*. (2013) found that the CAESAR model accurately predicted bed load yield in the Tagliamento River, Italy when compared with observations of the Tagliamento and other large gravel-bed rivers. However, concerns remain around several aspects of cellular modelling. Nicholas (2005) writes that it is challenging to apply numerical models such as CAESAR or other cellular models to braided channels due to their complicated dynamics. Coulthard, Hicks and Van De Wiel (2007) state that while cellular models can be helpful, they compromise accuracy for speed and eventually, as computing power and algorithms develop, more complex models will likely supersede them.

2.3.2.2 – Machine-Learning Models

Machine learning can be used to predict a variety of river characteristics. Hosseiny *et al.* (2023) used an artificial neural network (ANN) model to predict bed load transport rates across 134 rivers. River discharge, flow width, bed slope and sediment sizes were inputted into the ANN model. Once trained, the model was able to accurately predict mean observed flux per unit width and river discharge. Using publicly available geospatial data, Guillion *et al*. (2020) used machine learning to predict reach-scale geomorphic channel types. They tested their machine learning model on the Sacramento River basin, US. They found that, when compared with 290 different field surveys, the model correctly predicted channel type with a 61% median cross-validation accuracy. Generally, machine-learning based models are still in their infancy, and very few authors have looked at using machine learning to measure channel adjustment specifically; however, they have measured many variables that are linked to or can be used to measure adjustment. In the future, machine learning could develop into the most effective type of channel status model (Olusola *et al*., 2022).

2.3.2.3 – Stream Power Models

Total stream power (Ω, W/m^1) and unit width stream power (ω, W/m^2) are measures of the energy used to drive geomorphic change within a river channel (Bagnold, 1960; Knighton, 1999)

$$\Omega = \gamma.Q.S \tag{2}$$

$$\omega = \gamma.Q.S/w \tag{3}$$

Where y is unit weight of water (9810 N/m^3), Q is river discharge (m^3/s), S is energy or bed slope (m/m) and w is width of flow (m), often approximated by bankfull width (Soar, Wallerstein and Thorne, 2017).

Bagnold (1960; 1966) described stream power as a significant important factor within river sediment dynamics and adjustment. More recent studies have also come to the same conclusion, highlighting the strong relationship between stream power and adjustment (Chen *et al.,* 2012; Conesa-García *et al*., 2022; Jha *et al*., 2022; Yochum *et al.,* 2017). The dominant process within a channel on any given scale is determined by both local and upstream stream power (Bizzi and Lerner, 2013; Tetford, Desloges and Nakassis, 2017). Multiple authors have stated that a catchment-wide application of stream power-based modelling can be applied with only a small amount of in-field collected data (Soar, Wallerstein and Thorne, 2017; Bizzi and Lerner, 2013; Tetford, Desloges and Nakassis, 2017). This is primarily due to the higher resolution of modern digital elevation models (DEMs), which allow for accurate slope calculations along an entire river channel (Soar, Wallerstein and Throne, 2017; Marcinkowski, Kiczko and Kardel, 2022). As with all modelling approaches, stream power modelling relies on several assumptions and simplifications of complex systems (Barker et al., 2009). They do not comprehensively factor in bed material transport or fully represent sediment supply (Parker and Davey, 2023). They are also limited the resolution, accuracy availability of remotely sensed data available at a catchment-wide level (Soar, Wallerstein and Thorne, 2017). Despite this, there is huge potential for stream power modelling to predict adjustment accurately and as such it is necessary to further research the effectiveness of different stream power modelled approaches (Lague, 2013).

2.4 Stream Power Balance Models

This section will discuss and evaluate various stream power models and indices used to predict channel adjustment. The models are categorised into either point-based or reach-based. Point-based models calculate balance using the ratio between a specified upstream distance, representing sediment supply, and a points stream power, representing transport capacity (Bizzi and Lerner, 2013). This same logic applies to reach-based models however, points are replaced with much larger reaches (Parker, Thorne and Clifford, 2015).

2.4.1 – Point-based models

Bizzi and Lerner (2013) explored using a stream power point-based approach to predict channel stability on the River Lune and the River Wye, England. In their study they used two stream power indices, ω and Ω. Point ω and Ω values were taken and compared to the averaged ω values over a specified upstream length of the channel. In their study, they used 3km ($\omega_{balance3km}$), 5km ($\omega_{balance5km}$), and 10km ($\omega_{balance10km}$) upstream distances respectively and they found that confined channels are more strongly defined by stream power at $\omega_{balance3km,}$ and unconfined channels are better defined by stream power at $\omega_{balance5km}$. They found a strong link between stream power and channel stability. Although not utilised in their study, a new $\omega_{balanceAll}$ model is noted by Bizzi and Lerner (2013), with this new model using the average of all points upstream to represent sediment supply. However, Soar, Wallerstein and Thorne (2017) critique the study by Bizzi and Lerner (2013), stating that the coarse 50m DEM used to provide slope information is too inaccurate for this type of modelling and further criticising the approximation of channel width used. Other authors who have conducted point-based stream power models include Vocal Ferencevic and Ashmore (2011) and Biron *et al*. (2012). Both Vocal Ferencevic and Ashmore (2011) and Biron *et al*. (2012) found point-based stream power modelling to be an effective tool for understanding river status. However, uncertainty remains around its effectiveness and ability to accurately predict channel adjustment (Soar, Wallerstein and Thorne, 2017).

2.4.2 – Reach-based models

As well as using point-based models to assess a channels dominant process, a reach-based approach can also be used. Parker, Thorne and Clifford (2015) have developed a model named Sediment Transport: Reach Equilibrium Assessment Method (ST:REAM). ST:REAM applies a zonation algorithm to stream power values which are spaced 50m along a catchment network and then divides the network into relatively homogenous reaches. Then ST:REAM compares each reach's stream power value with its upstream neighbour's stream power in order to predict whether or not the reach is likely to be either erosion-dominated or deposition-dominated. Parker, Thorne and Clifford (2015) found that ST:REAM correctly predicted the status of 87.5% of sites within the River Taff, Wales, when compared to River Habitat Survey (RHS) observations. Additionally, Marcinkowski, Kiczko and Kardel (2022) found that an approach derived from ST:REAM correctly predicted channel status in a majority of rivers across Poland. However, Bowman *et al*. (2021) found ST:REAM to have a variable performance, with it more accurately predicting high energy rivers. Parker and Davey (2023) also failed to accurately predict channel status using the ST:REAM model across five different catchment networks in the UK.

2.4.3 – Stream Power Balance Modelling Limitations and Conclusions

Stream power-based methods of predicting river channel adjustment have great potential and the previously discussed studies and models in sections 2.4.1 and 2.4.2 highlight the high accuracy ratings these models can achieve in some river catchments. However, there is also evidence of the limitations of using a catchment-scale stream power-based approach to predict river channel adjustment. Newson *et al*. (1998) attempted to use ω values to predict channel stability in England and Wales. However, they found a weak relationship between predicted channel status and RHS observations across 484 different reaches. Parker and Davey (2023) studied the ability of 33 different stream power indices to predict channel status across six river catchments in the UK, finding that all assessed indices corresponded poorly between observations of alluvial channel adjustment. In their study they used ω and Ω based approaches as well *T,* a representation of total sediment transport capacity across channel width, accounting for the non-linear relationship between ω and transport capacity calculated with:

$$T = \omega^{3/2}.w \tag{4}$$

Where ω is unit width stream power (W/m²) and w is bankfull flow width (m).

The contrasting literature discussed in this section highlights the need for additional testing of all stream power-based method of predicting river channel adjustment. If stream power balance modelling can be used to accurately predict channel status and adjustment it would be hugely beneficial to the field of river management (Brierley and Fryirs, 2016). This report will therefore evaluate the performance of a range of stream power balance models. The method and processes behind this are outlined in the next chapter.

Chapter 3 - Research Questions

After a review of the surrounding literature in Chapter 2, the need for effective and resource-light approaches to river channel adjustment assessment is evident. Stream power balance modelling has the potential to fulfil this need, however the consensus surrounding its effectiveness is unclear. Therefore, this report will attempt to evaluate the performance of a variety of stream power indices in an effort to ascertain their potential application as tools for determining channel status. This leads to the reports two research questions:

1. **What is the *performance* of a variety of *stream power-based* models for predicting river sediment dynamics.**
2. **How does the *performance* of different *stream power-based* models compare.**

The 30 stream power indices which will be used to model and predict channel status are list below:

$\omega_{balance1km}$, $\omega_{balance3km}$, $\omega_{balance5km}$, $\omega_{balance10km}$, $\omega_{balanceAll}$, $\Omega_{balance1km}$, $\Omega_{balance3km}$, $\Omega_{balance5km}$, $\Omega_{balance10km}$, $\Omega_{balanceAll}$, $T_{balance1km}$, $T_{balance3km}$, $T_{balance5km}$, $T_{balance10km}$, $T_{balanceAll}$, $\omega_{balance-reach-0.5}$, $\omega_{balance-reach-0.6}$, $\omega_{balance-reach-0.7}$, $\omega_{balance-reach-0.8}$, $\omega_{balance-reach-0.9}$, $\Omega_{balance-reach-0.5}$, $\Omega_{balance-reach-0.6}$, $\Omega_{balance-reach-0.7}$, $\Omega_{balance-reach-0.8}$, $\Omega_{balance-reach-0.9}$, $T_{balance-reach-0.5}$, $T_{balance-reach-0.6}$, $T_{balance-reach-0.7}$, $T_{balance-reach-0.8}$, $T_{balance-reach-0.9}$.

Performance will be evaluated in two ways, accuracy and Matthew's Correlation Coefficient (MCC). The reasoning for this and the equations used to assess performance are discussed in Section 4.2.6. Although the literature surrounding stream power balance modelling is uncertain, as the method used in this study is very similar to that of Parker and Davey (2023) the hypothesis for RQ1 will be that stream power-based models will perform poorly at predicting river sediment dynamics, and the hypothesis for RQ2 is that there won't be a noticeable difference in model performance.

Chapter 4 - Methodology

The literature examined in Chapter 2 has highlighted the need for efficient, resource effective approaches to predicting current and future channel adjustment to aid in river management schemes. A variety of approaches and models were discussed, however, the focus of this report as stated in Chapter 3 is to evaluate the accuracy of a variety of stream power balance-based approaches to predicting adjustment. Therefore, a variety of stream power balance models and indices, shown below, will be tested and their accuracy evaluated for assessing channel adjustment.

- A point-based balance of ω, Ω and T, following an approach similar to Bizzi and Lerner (2013) and Parker and Davey (2023) with a range of five different lengths used for the upstream average ($\omega_{balanceAll}$, $\omega_{balance1km}$, $\omega_{balancekm3}$, $\omega_{balance5km}$, $\omega_{balance10km}$).
- A reach-based balance of ω, Ω and T, using the ST:REAM model (Parker, Thorne and Clifford, 2015) with a range of give different reach resolutions (R = 0.5-0.9).

4.1 – Sampling Strategy

4.1.1 - Data sources

As previously discussed, catchment wide field surveys are out of the scope of this report as they are expensive and time-consuming. Nevertheless, observations of actual channel status are needed in order to assess the accuracy of the models tested. A method similar to that of Bizzi and Lerner (2012; 2013) and Newson *et al*. (1998) will therefore be implemented, with data from the RHS being used to provide observed channel status. Other data sources used in this report include the Environment Agency (1m/2m LiDAR DTM), the Ordnance Survey (OS) (5m DTM, OS OpenRivers, OS Mastermap Water) and the Centre for Ecology and Hydrology (CEH) (Gauging station Q_{med} values).

4.1.2 – Introduction to the River Dee

The river chosen for this study is the River Dee, located in Eastern Scotland (Figure 2). The catchment has a drainage area exceeding 1844km^2 (CEH, 2023). The Dee is a mostly unconfined, single-thread channel, the relevance of this will be discussed in Section 4.2.1. The main stem rises on the Braeriach plateau in the Cairngorm Mountains at an elevation of 658m ASL (3.7786°W, 56.9301°N) before flowing downstream to an elevation of 24m ASL at the end of the catchment boundary used in this report (2.3343°W, 57.0753°N) (Figure 4). Outside of the catchment boundary used in this report the river continues to flow downstream through Aberdeen before exiting into the North Sea. The Dee and significant tributaries which contributed towards the stream power value calculation (>1% of total drainage area) are shown in Figure 3. The catchment is mostly comprised of granite, mud & silt stone (pelite) and sandstone (psammite) (Figure 5). The River Dee was selected due to its large number of RHS sites (417) as well as it's depositional nature.

Figure 2 - *The River Dee and surrounding catchment shown within the wider UK.*

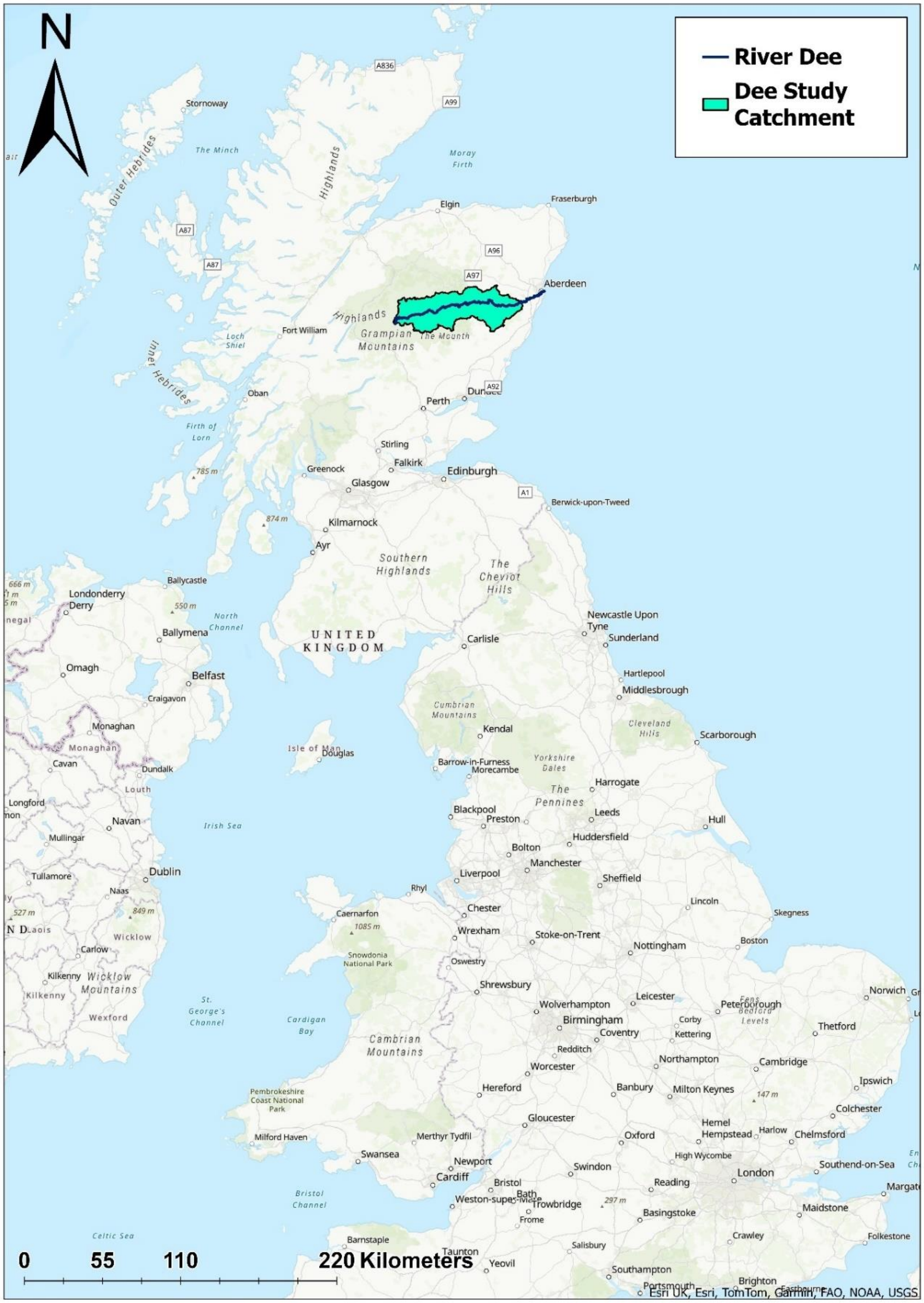


Figure 3 - *The River Dee and Significant Tributaries.*

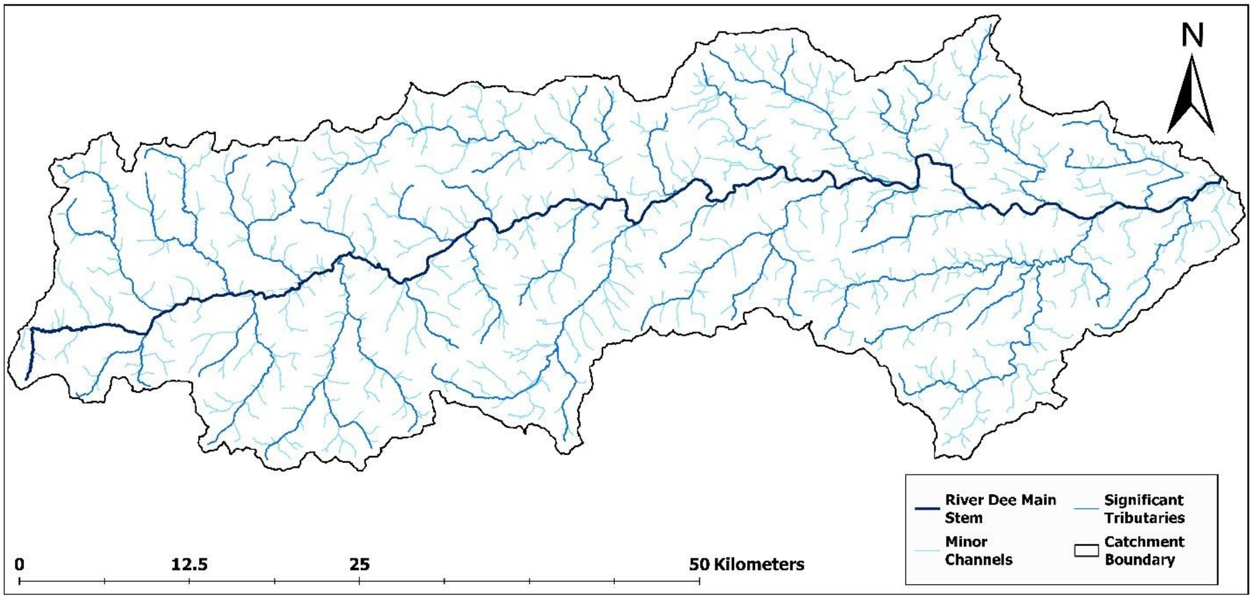


Figure 4 - *Topographic map of the River Dee catchment.*

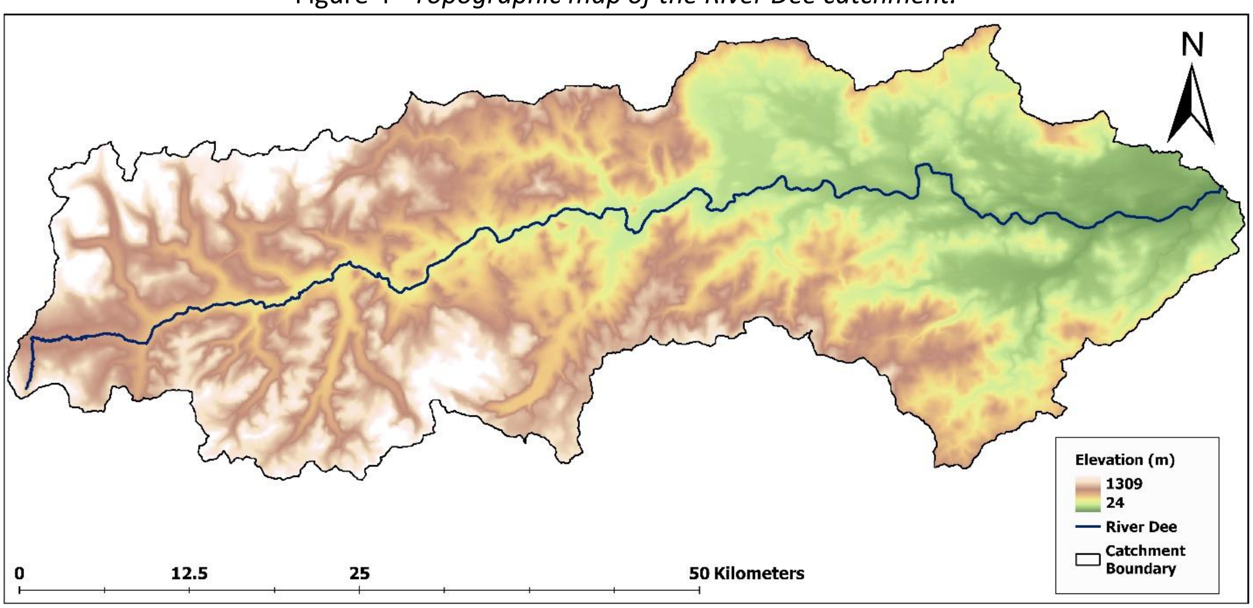
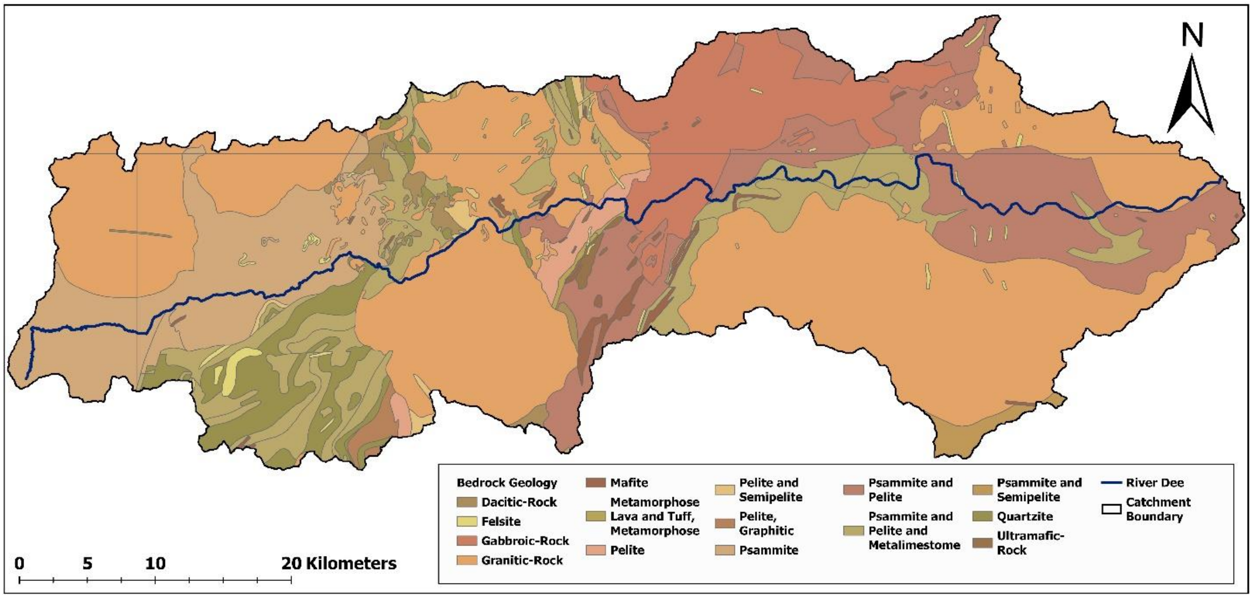


Figure 5 - *Bedrock Geology of the River Dee catchment.*



4.2 – Measurement Techniques

This section will outline measurement techniques used to answer the research questions set out in Chapter 3.

4.2.1 – Channel Status Classification

As previously stated, this report will use a method derived from Bizzi and Lerner (2012; 2013), with observations from the RHS being implemented to assess the dominant processes within the River Dee. The observations used from the RHS are those concerning features found within the river channel. As discussed in Section 2.3.1, the presence of different types of features within a channel can indicate the dominant processes of a river. However, when interpreting dominant processes using river features, river type needs to be considered (Schumm, 1985; Nanson and Croke, 1992). Bizzi and Lerner (2013), based on research by Newson *et al*. (1998) and Bizzi, Harrison and Lerner (2009), define criteria for determining dominant channel processes for both confined and unconfined channels using RHS observations of bed and bank material as well as valley setting and floodplain extent (Table 1&2). As the Dee is a predominantly unconfined channel it will likely be characterised by earth, gravels and sand as bank material and unstable beds characterised by gravels, cobbles and sand (Bizzi and Lerner, 2013, Scammardo *et al*., 2023). Unconfined channels also have a higher lateral mobility, supporting the creation of a meandering river (Reid and Brierley, 2015). Bizzi and Lerner (2013) state that in an unconfined channel, the presence of unvegetated bars indicates deposition as it requires a large upstream sediment supply, whereas the presence of eroding cliffs and vertical or undercut banks indicates erosional processes. Table 1 below presents Bizzi and Lerner's (2013) approach to using RHS observations for determining dominant channel processes. Table 2 then presents the criteria used to classify channel status based on the dominant channel processes determined in Table 1. Bizzi and Lerner (2013) looked at predicting erosion, deposition and equilibrium within their study. In this report only erosion or deposition will be predicted, following a method derived from Parker and Davey (2023). Therefore, sites that are classified as stable or unstable equilibrium will be omitted. This classification will then be applied to the 417 RHS sites within the Dee catchment.

Table 1 - *Criteria used for determining dominant channel processes for confined and unconfined channels using RHS observations (rows relevant to this report are highlighted in green)* (Bizzi and Lerner, 2013).

Feature	Criteria
Confined Channel	
Deposition	*Extended* if the sum of all the types[(a)] of unvegetated bas is <2[(b)] and the occurrence of exposed bedrock and boulders is not extended, *limited* otherwise
Erosion	*Extended* if eroding earth cliff >2[(b)] and vertical/undercut bank profile is extended[(c)] and the occurrence of bedrock as bank material is <3[(b)], *limited* otherwise
Unconfined Channel	
Deposition	*Extended* if the sum of all the types[(a)] of unvegetated bars is >3[(b)], *limited* otherwise
Erosion	*Extended* if eroding earth cliff >4[(b)] or eroding earth cliff >2[(b)] and vertical/undercut bank profile is extended(c), *limited* otherwise

[a]Points, side or mid-channel bars as recorder in the RHS 10-spot checks form.

[b]Refers to presence/absence within the RHS 10 spot-checks

[c]Refers to RHS sweep-up section, it is considered extended if present over >33% of the 500m reach surveyed

Table 2 - *Classification criteria for confined and unconfined channels with dominant sediment process (rows used for classification in this report are highlighted in green)* (Bizzi and Lerner, 2013).

Status	Criteria	Sediment Process
Confined Channel		
Stable Equilibrium	Limited deposition and erosion and features	Transport/potential source
Deposition Dominated	Extended deposition features and limited erosion ones	Sink
Unconfined Channel		
Stable Equilibrium	Limited deposition features and limited erosion ones	Transport
Deposition Equilibrium	Extended deposition features and limited erosion ones	Sink
Erosion Dominated	Extended erosion features and limited deposition ones	Source
Unstable Equilibrium	Extended deposition and erosion features	Transport

4.2.2 – Stream Power Values Calculations

Unit width stream power (ω, W/m^2), Total stream power (Ω, W/m^1) and T will be calculated with the follow formulas:

$$\omega = y.Q.S/w \tag{5}$$

$$\Omega = y.Q.S \tag{6}$$

$$T = \omega^{3/2}.w \tag{7}$$

Where y is unit weight of water (9810 N/m^3), Q is river discharge (m^3/s), S is energy or bed slope (m/m) and w is bankfull flow width (m).

4.2.3 – ST:REAM Model

ST:REAM, as discussed in Chapter 2, is a reach-based approach for measuring channel balance. It uses Gill's (1970) global zonation algorithm to statistically search for functional reach boundaries. (Parker, Thorne and Clifford, 2015). The ST:REAM algorithm uses an iterative analysis of variance approach, meaning a data sequence begins as a single, long zone and is then temporarily divided into two zones, with a provisional partition falling between the first and second points in the sequence. The sum of squares within the two temporary zones (SS_w) is calculated using the following equation:

$$SS_W = \sum_{j=1}^{m} \sum_{i=1}^{n_j} \left(x_{ij} - \bar{x}_{*j}\right)^2 / \sum_{j=1}^{m} n_j - m \tag{8}$$

where x_{ij} = the i-th point within zone j, $\bar{x}*_j$ = mean of the j-th zone, n_j = number of points in the j-th zone, and m = number of zones.

The partition between the two zones is then moved along the sequence to successive positions and SS_w is calculated for every possible position of the partition. The partition which results in the lowest SS_w is selected as the first zonal boundary, forming two zones. The procedure is then repeated, with the SS_w calculated for every possible position of the second partition, the minimum of which is used to divide the sequence into three zones. The zonation procedure continues to insert new reach boundaries until the proportion of total variance (*R*) reaches the specified level. A higher R value will result in a greater number of reaches (Parker, Thorne and Clifford, 2015; Gill 1970).

$$R = SS_w/SS_I \tag{9}$$

In this report Gill's global zonation algorithm has been applied to the 50m spaced ω, Ω and T values at R values of 0.5-0.9.

4.2.4 – Balance Calculations

Once point ω, Ω and T calculations have been carried out for the catchment balance calculations are possible for each point. These are listed below:

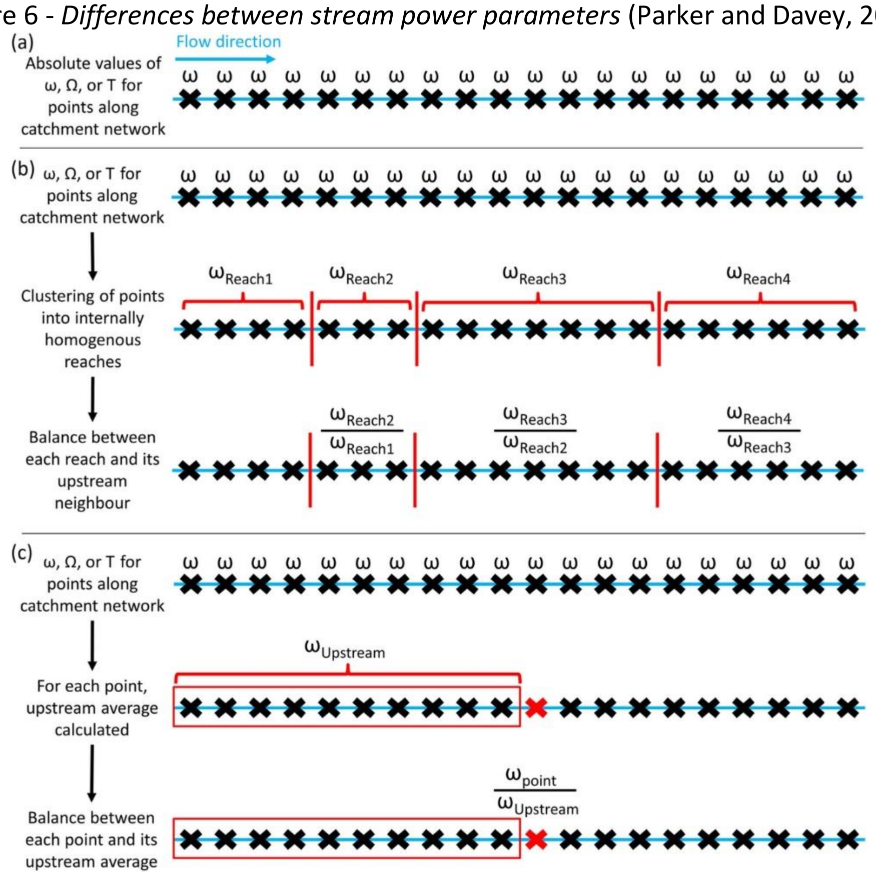
$$SPI_{BalanceType} = Point\ SPI/Upstream\ average\ SPI \tag{10}$$

$$ST{:}REAM = Reach\ SPI/Upstream\ reach\ SPI \tag{11}$$

Where SPI is desired stream power index (ω, Ω or T) and $_{BalanceType}$ is desired balance index (e.g. $_{Balance3km}$).

A stream power balance value of >1 will be considered erosion dominated and a value of <1 will be considered deposition dominated. Figure 6 displays a representation of these different stream power parameters based on a method applied by Parker and Davey (2023), in their study absolute values (a) were also used as a parameter however these have been omitted from this report so only the point (b) and reach (c) based sections are relevant.

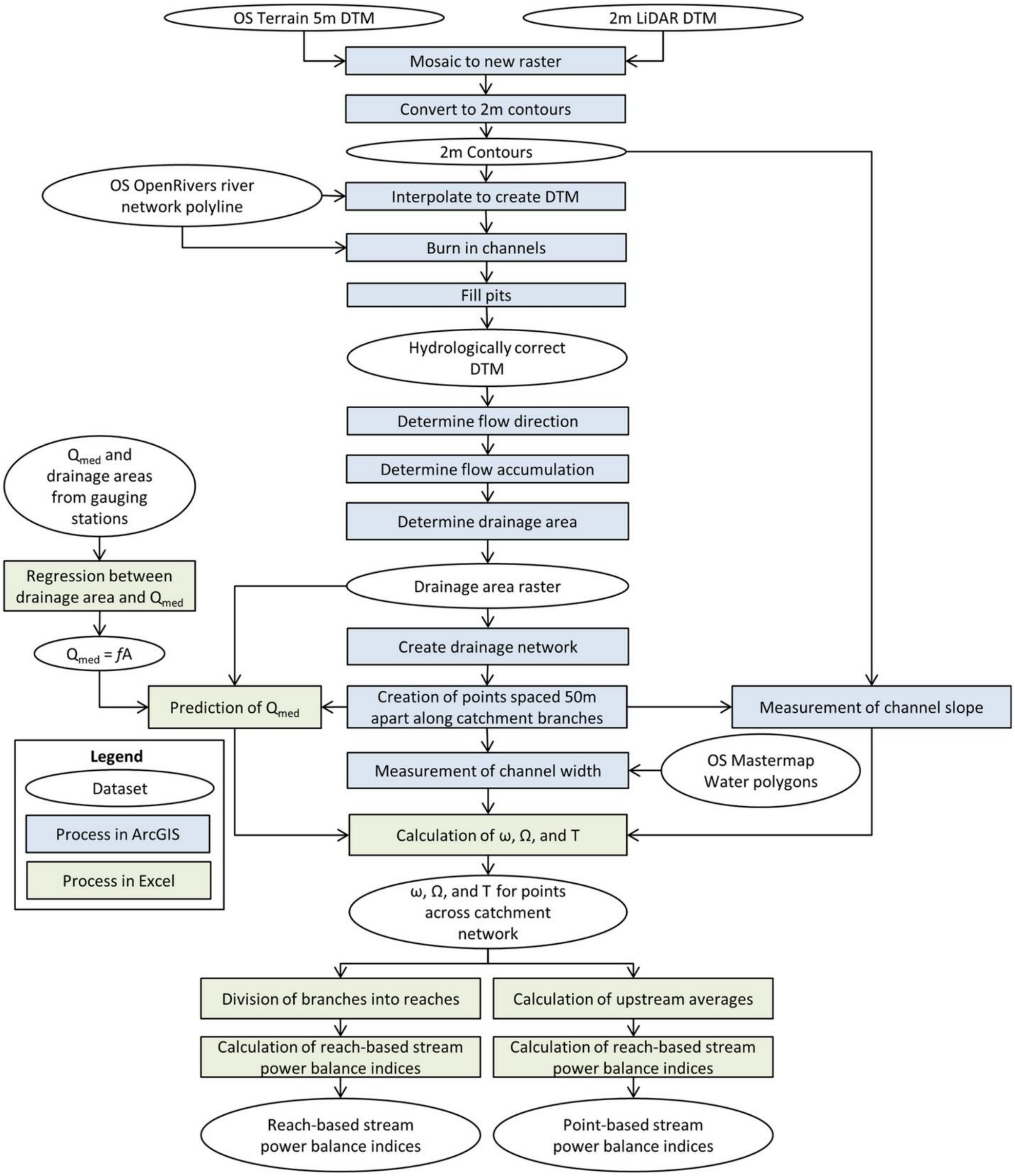
Figure 6 - *Differences between stream power parameters* (Parker and Davey, 2023).



4.2.5 – Method Process Outline

In this report ω, Ω and T will be calculated at points spaced 50m apart along the length of the Dee. The overall process of obtaining these stream power parameters is shown below in Figure 7. This method is taken from research by Parker, Thorne and Clifford (2015) and Parker and Davey (2023).

Figure 7 - *Representation of method used to obtain ω, Ω and T balance values* (Parker and Davey , 2023)



4.2.5.1 – Overview of Stream Power Indices Calculation

Figure 7 displays the general process used to obtain the stream power indices used in this report. Below is a more detailed list of the steps used to obtain reach and pointed-based stream power balance indices. This list is a modified version of a list taken from Parker and Davey (2023). The data processing was done in Microsoft Excel and ESRI's ArcGIS Pro software. All steps referring to tools are undertaken in ArcGIS.

1. The OS 5m DTM and 1m/2m LiDAR DTM combined using the 'Mosaic' tool. The 5m DTM provides coverage to areas where there is not 1m/2m data available, allowing coverage of the whole catchment area whilst maintaining the highest accuracy level possible.

2. A 2m contour layer was created from the two DTM rasters using the 'Contour' tool.

3. A 10m DTM was interpolated using the 'Topo to Raster' tool from the 2m contour layer and OS OpenRivers polyline.

4. The 'Minus' tool was used to burn the location of the river channel onto the 10m DTM to ensure the river channel location accurately matches its known location.

5. The 'Fill' tool was used to fill in 'pits' within the DTM layer to prevent them from obstructing the modelled progress of water flowing downslope.

6. Flow direction was determined using the 'Flow Direction' tool (D8 algorithm) to identify the outgoing flow direction for each raster cell.

7. The 'Flow Accumulation' tool was used to identify the total number of upstream cells that contribute flow into each cell.

8. Using the 'Times' tool to calculate the drainage area of each cell by multiplying each cell's flow accumulation value by the area of a 10m cell.

9. Using the 'Greater Than Equal' and 'Stream to Feature' tools to create a polyline representation of all cells with a drainage area of >0.5km^2.

10. Using the 'Generate Points Along Lines' tool to create points spaced 50m apart along all branches (significant tributaries) that contribute at least 1% of the total catchment drainage area.

11. Using the median annual flood (Q_{med}) and drainage areas (A, km^2) for flow gauges across the catchment to create a power regression relationship, shown below. This approach is consistently used by studies that represent stream power at a catchment scale (Vocal Ferencevic and Ashmore, 2011; Knighton, 1999; Parker, Thorne and Clifford, 2015; Parker and Davey, 2023).

$$Q_{med} = \alpha . A^{\beta} \tag{12}$$

Where α and β are constants derived for each catchment.

It was determined that the relationship between the River Dee's flow gauges was $Q_{med} = 1.8747.A^{0.7639}$, $R^2 = 0.8828$. Based on this, the Q_{med} for each point was predicted along with the drainage raster.

12. Using the elevation difference between the contours up and downstream of each point and the along-stream distance between those contours to calculate the channel slope (S) for each point. This is used as a substitute for energy slope in Bagnold's (1966) original equation.

13. Channel width (w) is measured using MasterMap Water polygons at each point across the catchment network.

14. Using the calculated values of Q_{med}, S and w to calculate absolute values of ω, Ω and T at each of the points across the river catchment network.

15. Using the ST:REAM model, as shown in Section 4.2.5, to calculate reach-based balances of ω, Ω and T based on the previously calculated point values. This is done at five different reach resolutions (R = 0.5-0.9).

16. Using the values of ω, Ω and T, as shown in Section 4.2.5, to calculate point-based balances of each, with a range of five different lengths used for upstream average (1km, 3km, 5km, 10km and all upstream points).

This method will result in 30 stream power balance indices (listed in Chapter 3) at points spaced 50m across the River Dee catchment. These will be used to answer the research questions set out in Chapter 3. Once the 30 stream power balance indices have been calculated they will be matched with RHS observed channel status. This will be done in the same way as Parker and Davey (2023), where every RHS observation site will be matched with its closest 50m point.

4.2.6 – Channel Status and Model Performance

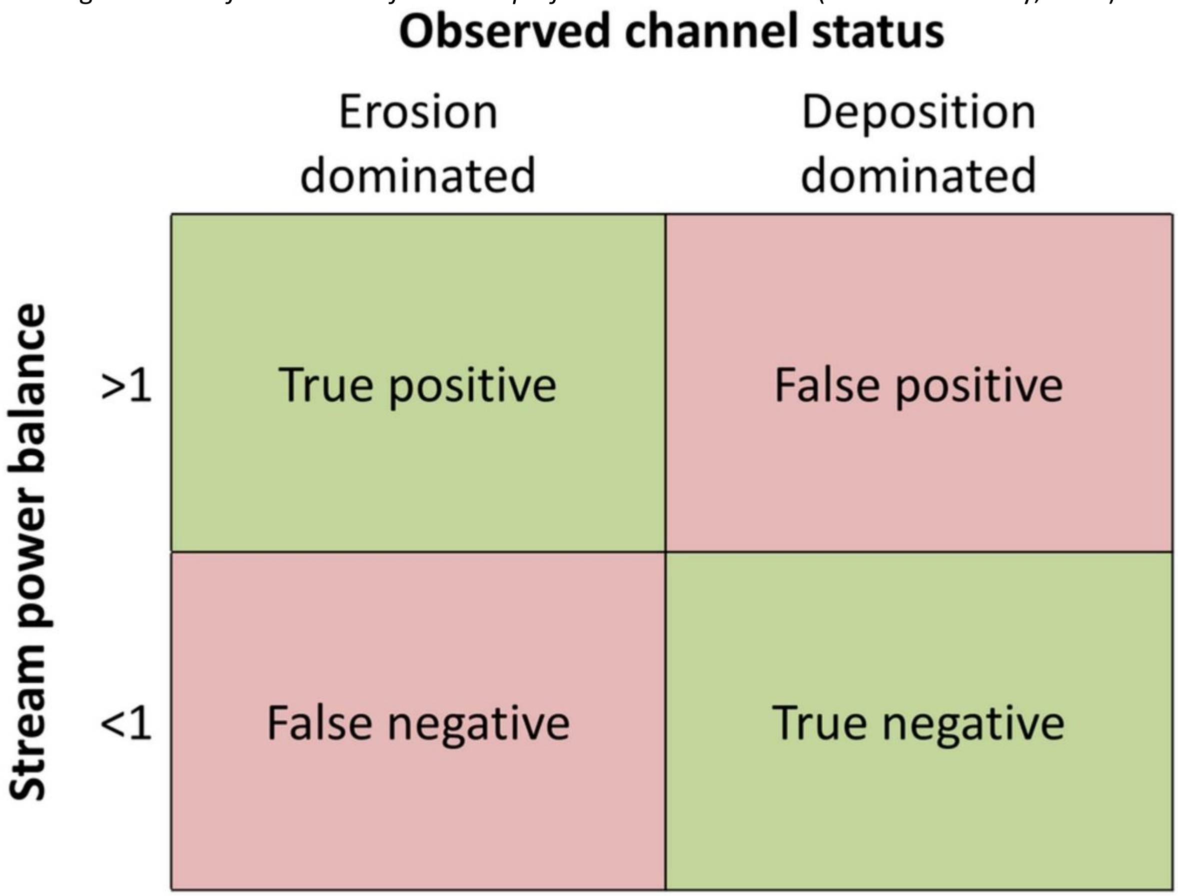
As stated in Chapter 3, model performance will be calculated in two ways. Performance Method 1 will use accuracy as a measure of performance, with accuracy defined as the proportion of total observations correctly predicted. Performance Method 2 will utilise Matthew's Correlation Coefficient (MCC). This follows an approach similar to that of Parker and Davey (2023), who used accuracy, MCC and area under the receiver operating curve (AUC), although this final performance assessment has been excluded from this report. The confusion matrix used to assess performance of the balance indices is shown in Figure 8. Accuracy values range from 0 to 1, with 0.5 being equivalent to a random allocator, MCC values range from -1 to 1, with 0 being equivalent to a random allocator.

$$Accuracy = (TP + TN)/(TP + TN + FP + FN) \tag{13}$$

$$MCC = \frac{(TP.TN) - (FP.FN)}{\sqrt{(TP + FP).(TP + FN).(TN + FP).(TN + FN)}} \tag{14}$$

Where TP refers to true positive, TN to true negative, FP to false positive and FN to false negative.

Figure 8 – *Confusion matrix for model performance assessment* (Parker and Davey, 2023).



MCC is used in addition to accuracy as accuracy does not provide a reliable representation of predictive ability because it is affected by observed value distribution (Huang and Ling, 2005; Chicco, Tötsch and Jurman, 2021). This means a model with a bias towards predicting erosion or deposition would achieve high accuracy in a catchment which is observed to be erosion or deposition-dominated respectively. This is especially relevant for the Dee as observations of depositional channel dominance are far greater than erosional. MCC equally accounts for all four elements of the confusion matrix, only generating a high score if most of the positive data instances and most of the negative data instances, and if most of its positive predictions and most of its negative predictions are correct (Chicco, Tötsch and Jurman, 2021).

4.2.7 – Results Comparison

The RHS site observations along the Dee and tributaries will be displayed on a map, highlighting the location of depositional and erosional observations along the river. To assess the performance of the 30 stream power balance indices, they will be plotted on a graph against both accuracy and MCC. Accuracy and MCC calculations for the 30 stream power balance indices, as well as the mean accuracy and MCC value for each group ($\omega_{balance}$, $T_{balance}$ and $\Omega_{balance}$), will then be displayed in a table using Microsoft Excel conditional formatting colour scale to compare the performance of the indices to each other and across groups.

Chapter 5 - Results

This chapter will describe and outline the model output results in relation to the two report research questions

5.1 – Observed Channel Status

Figure 9 shows the RHS based channel status observations along the River Dee and significant tributaries. Channel status was derived from the information shown in Tables 1&2, with only sites being classed as either depositional or erosional being displayed. Overall there was 37 sites classified as deposition dominated, with 23 being along the main Dee channel. There is only 1 site classified as erosion dominated and it is not on the main Dee channel.

Figure 9 – *RHS site locations showing site classification along the Dee and significant tributaries*.

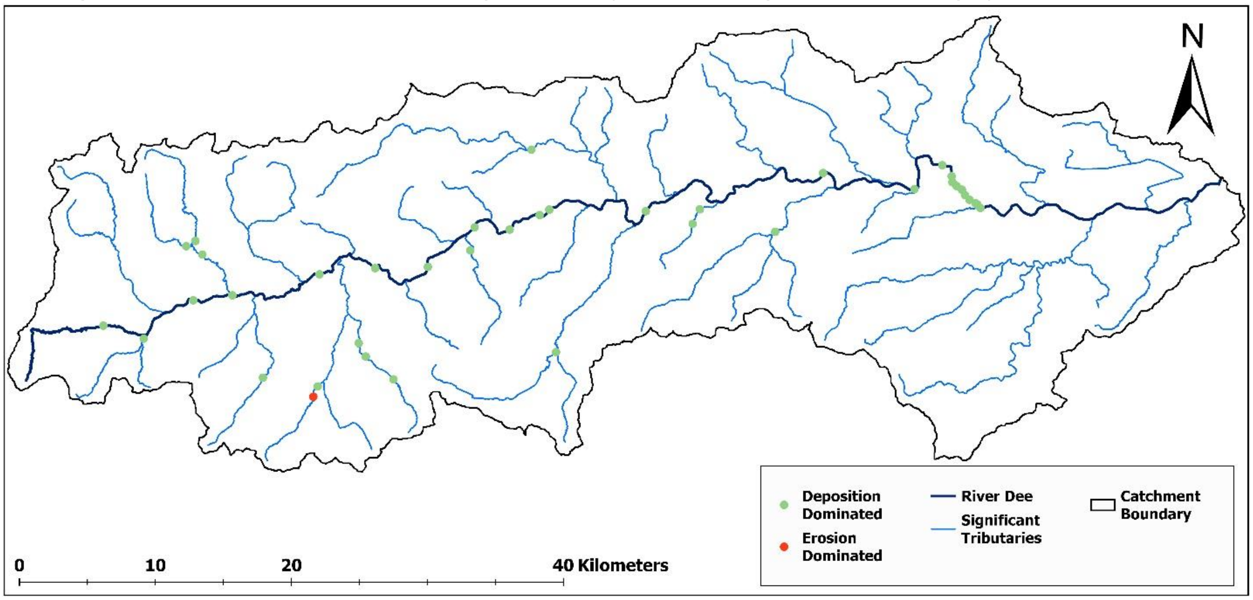
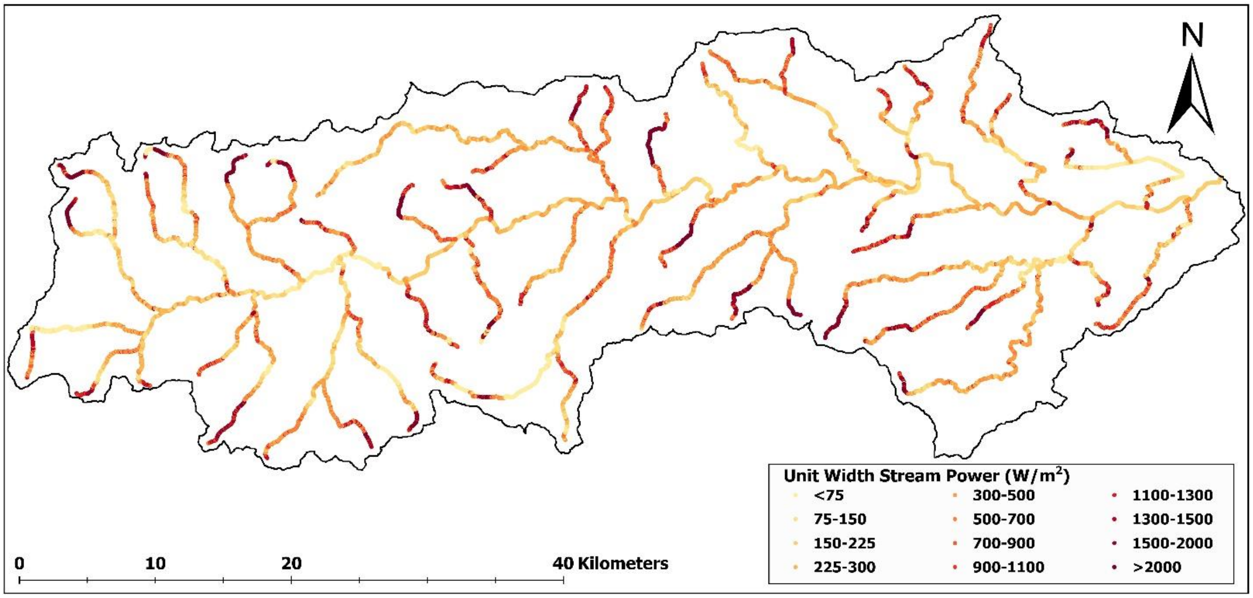


Figure 10 shows the calculated ω values for points spaced every 50m across the catchment network of the Dee. This is provided give an overview and illustrate the variation in stream power across the catchment network.

Figure 10 - *Unit width stream power (ω) values for points spaced 50m across the Dee catchment*.

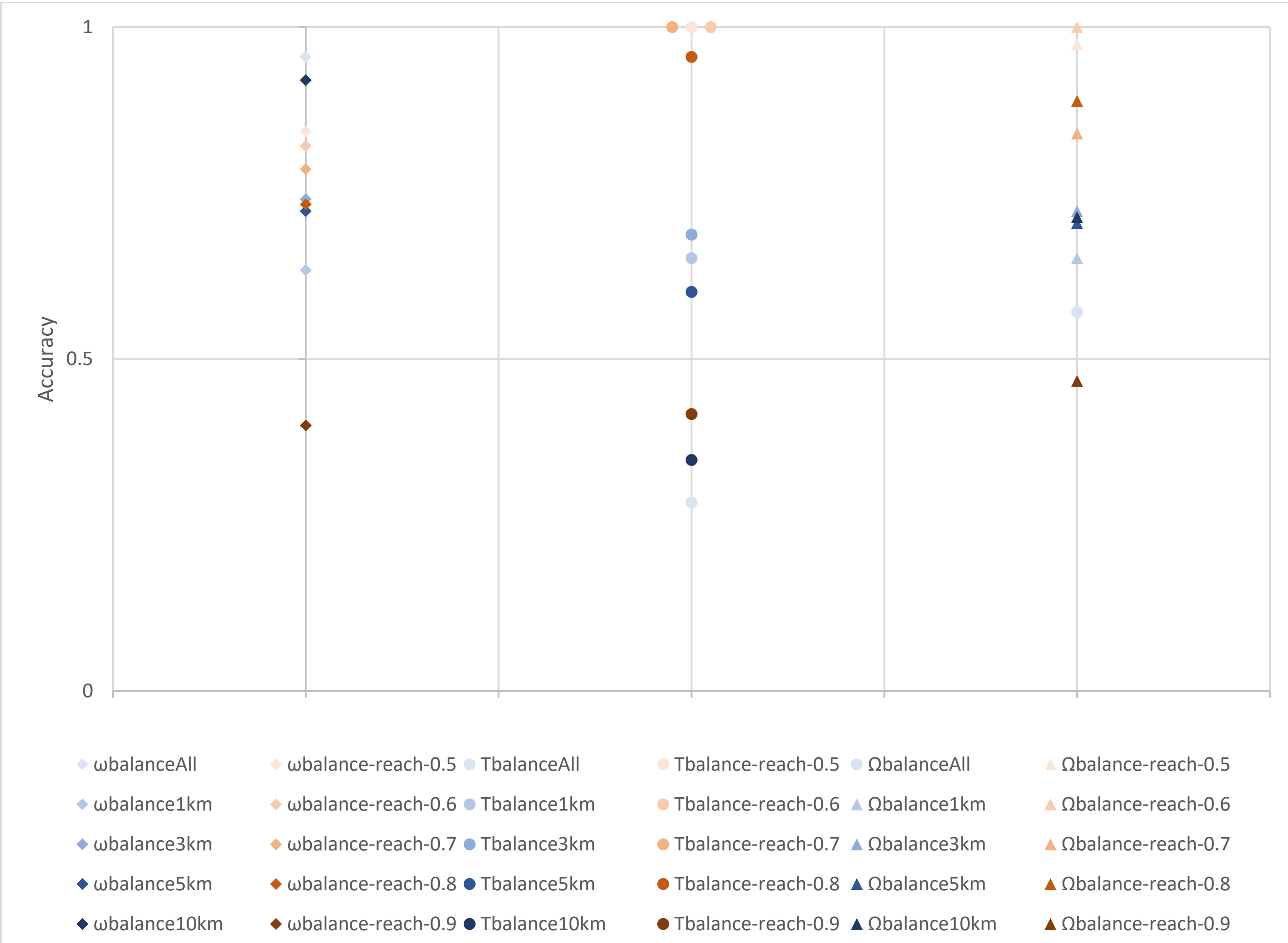


Lower ω should in theory indicate deposition dominance, this is mostly reflected in the observed channel status of the RHS points shown in Figure 10 with points observed to be deposition dominated generally having lower ω values. However, there is a lack of erosion dominated points to compare this against so conclusion based on this visual assessment should be limited.

5.2 – Model Performance

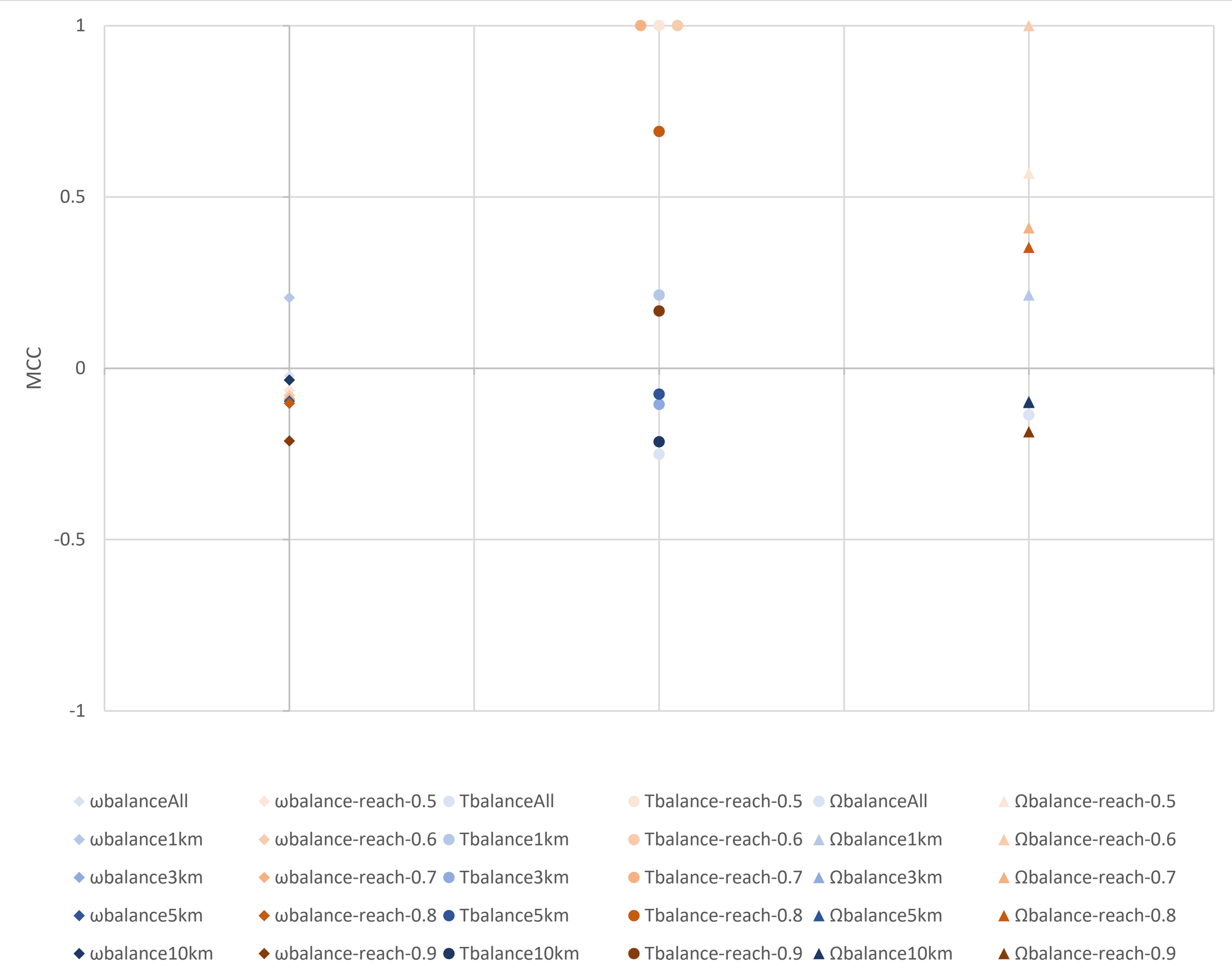
Figures 11&12 display the calculated accuracy and MCC scores for the 30 *ω, Ω* and *T* balance indices. Table 3 displays these results, highlighting specific indices which performed well, as well as comparing the overall performance of the three (*ω, Ω* and *T*) balance groups.

Figure 11 – *Accuracy performance for the 30 stream power balance indices. Accuracy ranges from 0 to 1, with a value of 0.5 being equivalent to a random allocator.*



Accuracy scores are generally high, with only 5 indices scoring below a 0.5 accuracy score. This means most of the indices performed far better than a random allocation, managing to consistently predict channel status compared to observations. $T_{balance\text{-}reach\text{-}0.5}$, $T_{balance\text{-}reach\text{-}0.6}$, $T_{balance\text{-}reach\text{-}0.7}$ and $\Omega_{balance\text{-}reach\text{-}0.6}$ achieved accuracy scores of 1, meaning that they correctly predicted observed channel status at every point. The exception to the strong accuracy scores are all of the $_{balance\text{-}reach\text{-}0.9}$ indices, which perform poorly ($\omega_{balance\text{-}reach\text{-}0.9} = 0.4$, $T_{balance\text{-}reach\text{-}0.9} = 0.417$ and $\Omega_{balance\text{-}reach\text{-}0.9} = 0.467$).

Figure 12 - *MCC performance for the 30 stream power balance indices. MCC score ranges from -1 to 1, with a value of 0 being equivalent to a random allocator.*



MCC scores are much more mixed than accuracy ratings, with most of the indices failing to score significantly better than a random allocator. The exception to this is the 4 indices ($T_{balance\text{-}reach\text{-}0.5}$, $T_{balance\text{-}reach\text{-}0.6}$, $T_{balance\text{-}reach\text{-}0.7}$ and $\Omega_{balance\text{-}reach\text{-}0.6}$) which correctly predicted observed channel status 100% of the time, meaning they achieved an MCC score of 1. $\omega_{balance}$ perform especially poorly in comparison to $T_{balance}$ and $\Omega_{balance}$ indices. Within the $T_{balance}$ and $\Omega_{balance}$ groups the ST:REAM based indices ($_{balance\text{-}reach\text{-}0.5\text{-}0.9}$) generally perform better than the point-based balances ($\omega_{balanceAll,}$ $\omega_{balance1\text{-}10km}$

Table 3 - *Colour scaled formatting showing the performance of all 30 balance indices as well as the mean value for the ω, Ω and T parameter groups. Values which are green performed the best, whereas values which are red performed the worst, with orange/yellow indicating values which were closer to random allocator equivalent.*

Balance Index	Accuracy	MCC
$\omega_{balanceAll}$	0.955	-0.022
$\omega_{balance1km}$	0.634	0.206
$\omega_{balance3km}$	0.741	-0.091
$\omega_{balance5km}$	0.723	-0.096
$\omega_{balance10km}$	0.92	-0.034
$\omega_{balance\text{-}reach\text{-}0.5}$	0.843	-0.065
$\omega_{balance\text{-}reach\text{-}0.6}$	0.821	-0.079
$\omega_{balance\text{-}reach\text{-}0.7}$	0.786	-0.089
$\omega_{balance\text{-}reach\text{-}0.8}$	0.733	-0.102
$\omega_{balance\text{-}reach\text{-}0.9}$	0.4	-0.212
$T_{balanceAll}$	0.284	-0.251
$T_{balance1km}$	0.652	0.214
$T_{balance3km}$	0.6875	-0.105
$T_{balance5km}$	0.601	-0.075
$T_{balance10km}$	0.348	-0.214
$T_{balance\text{-}reach\text{-}0.5}$	1	1
$T_{balance\text{-}reach\text{-}0.6}$	1	1
$T_{balance\text{-}reach\text{-}0.7}$	1	1
$T_{balance\text{-}reach\text{-}0.8}$	0.955	0.691
$T_{balance\text{-}reach\text{-}0.9}$	0.417	0.167
$\Omega_{balanceAll}$	0.571	-0.136
$\Omega_{balance1km}$	0.652	0.214
$\Omega_{balance3km}$	0.723	-0.096
$\Omega_{balance5km}$	0.705	-0.1
$\Omega_{balance10km}$	0.714	-0.098
$\Omega_{balance\text{-}reach\text{-}0.5}$	0.974	0.57
$\Omega_{balance\text{-}reach\text{-}0.6}$	1	1
$\Omega_{balance\text{-}reach\text{-}0.7}$	0.84	0.41
$\Omega_{balance\text{-}reach\text{-}0.8}$	0.889	0.353
$\Omega_{balance\text{-}reach\text{-}0.9}$	0.467	-0.185
Balance Indices Group Mean	Accuracy	MCC
$\omega_{balance}$	**0.7556**	**-0.0584**
$T_{balance}$	**0.6945**	**0.3427**
$\Omega_{balance}$	**0.7535**	**0.1932**

Table 3 supports the assessments made about Figures 12&13. The mean values support the idea that all groups generally perform well when accuracy is used as a measurement of performance. However, when MCC is used as a measure of performance, only $T_{balance}$ and $\Omega_{balance}$ balance achieve a value over 0, with $T_{balance}$ indices corresponding with observed channel status most strongly (mean = 0.3427). The strong performance of the reach-based balances, with the exception of $_{balance\text{-}reach\text{-}0.9}$, in comparison to point-based balances, is also visually highlighted. Table 4 shows additional calculated mean values for a variety of different stream power parameters, again highlighting the strength of the $T_{balanceReach}$ and $\Omega_{balanceReach}$ indices.

Table 4 - *Colour scaled formatting showing the performance of a variety of stream power parameter group means. Values which are green performed the best, whereas values which are red performed the worst, with orange/yellow indicating values which were closer to random allocator equivalent.*

Balance Index Group Mean	Accuracy	MCC
$\omega_{balancePoint}$	0.7946	-0.0074
$T_{balancePoint}$	0.5145	-0.0862
$\Omega_{balancePoint}$	0.673	-0.0432
All $_{balancePoint}$	**0.6607**	**-0.0456**
$\omega_{balanceReach}$	0.7166	-0.1094
$T_{balanceReach}$	0.8744	0.7716
$\Omega_{balanceReach}$	0.834	0.4296
All $_{balanceReach}$	**0.8083**	**0.3639**

Chapter 6 - Discussion

This chapter will discuss the results displayed in Chapter 5, determining the answer to the report research questions, explaining the model outputs and evaluating performance, before finally outlining the report limitations and the implication of the report findings on future work.

6.1 – Explanation of Findings

6.1.1 (RQ1) - What is the performance of a variety of stream power-based models for predicting river sediment dynamics?

The results displayed in Chapter 5 demonstrate an overall strong performance for most of the stream power models tested. This was unexpected based on the results of Parker and Davey (2023), who found that the 30 stream power balance indices tested in this report corresponded poorly with observations of alluvial river channel adjustment. However, other studies do support the findings of this report. ST:REAM performed very well, with a mean grouped accuracy of 0.8083 and a mean MCC score of 0.3639. This supports the findings of Parker, Thorne and Clifford (2015), who found ST:REAM to be 87.5 accurate when applied to the River Taff. It is worth noting that reach-based models which used an R-value of 0.9, performed extremely poorly compared to the other reach-based indices, with the best, $\Omega_{balance\text{-}reach\text{-}0.9}$ only achieving an accuracy rating of 0.467 and an MCC score of -0.185, much worse than a random allocator. A likely reason for this is that lower R values are more appropriate for the River Dee, as reach-based performance is strongest at lower R values. The high accuracy rating of most of the point-based indices again contradicts the findings of Parker and Davey (2023) but is supported by other studies such as Bizzi and Lerner (2013), Vocal Ferencevic and Ashmore (2011) and Biron *et al*. (2012) who found that point based stream power balance values corresponded well with observations alluvial river channel adjustment. An additional finding of this report is the inconsistent outcomes that the two different measures of performance produce. Generally all models performed less well when MCC was used as a measure of performance, with the exception of the models which only achieved TP AND TN results ($T_{balance\text{-}reach\text{-}0.5}$, $T_{balance\text{-}reach\text{-}0.6}$, $T_{balance\text{-}reach\text{-}0.7}$ and $\Omega_{balance\text{-}reach\text{-}0.6}$). This supports the findings of Parker and Davey (2023) and the arguments made by Huang and Ling (2005) that accuracy does not provide a reliable representation of a model's predictive ability. An example of this is the $\omega_{balancePoint}$ group, which achieved a mean accuracy of 0.7946, suggesting a strong correspondence to channel adjustment; however, the group only achieved a mean MCC of -0.0074, meaning it performed no better than a random allocator. This is likely due to accuracy being affected by the imbalanced distribution of observed values in the Dee (Chicco et al., 2021; Huang & Ling, 2005).

6.1.2 (RQ2) – How does the performance of different stream power-based models compare?

Table 4 highlights that reach-based models perform most strongly, achieving a mean accuracy rating of 0.8083 and a mean MCC score of 0.3639, whereas point-based models only achieve a mean accuracy rating of 0.6607 and an MCC score of -0.0456. This means they performed a little better than, or similar to, a random allocator depending on which performance metric is used. This contradicts the hypothesis and the findings of Parker and Davey (2023), who found that the tested stream power models performed poorly across the board with no outlying variables, which had a strong performance when tested with both accuracy and MCC. The best performing point-based approach was $\omega_{balanceAll}$, which achieved an accuracy rating of 0.955, but a poor scoring MCC value of -0.022. $T_{balance}$ based models performed most strongly, with a mean accuracy of 0.6945 and an MCC score of 0.3427 which suggests a correlation between them and observed channel status. $\Omega_{balance}$ and $\omega_{balance}$ did achieve slightly higher mean accuracy than this (0.7556 and 0.7535, respectively); however, their worse MCC scores (-0.0584 and 0.1932) infers that when both performance measures are considered, they performed worse. Overall, the findings indicate that a reach-based approach using the $T_{balance}$ indices can most effectively be used to predict river sediment dynamics.

6.2 – Finding Implications

This report contradicts the findings of Parker and Davey (2023) and many other authors (Newson *et al.,* 1998; Soar Wallerstein and Thorne, 2017), who have found poor correspondence when attempting to use stream power to predict channel adjustment. This is not entirely surprising as many other authors have found it to be effective (Parker, Thorne and Clifford, 2015; Bizzi and Lerner 2013; Vocal Ferencevic and Ashmore 2011; and Biron *et al*. 2012). This highlights general the general need for continued research into the effectiveness of using stream power to measure alluvial channel adjustment. Moreover, it specifically highlights the need to use additional measures of performance other than accuracy, which may not provide a reliable measure of representation of a model's predictive ability, as stated by Huang and Ling (2005). Additionally, due to the strong performance of *T* as a variable, further research is needed to evaluate its performance on a variety of different rivers and catchment types.

6.3 – Report Limitations And Recommendations for Future Work

6.1 – Limitations of Using Stream Power to Measure Channel Adjustment

There are several limitations to using stream power indices to predict channel adjustment. Using a simple stream power value to predict channel adjustment is a great simplification of complex, non-linear and dynamic systems (Parker and Davey, 2023). In the tested models, stream power is used as a representation of sediment transport rate so that sediment output can be determined. However, factors such as bed material size and sorting can influence sediment transport rate so variations in bed material will change sediment output in a way that cannot be predicted using stream power (Su *et al*., 2021; Huang and Nanson, 2002). Additionally, sediment can be supplied from hillslopes, altering local stream morphology, and increasing sediment supply and transport (Hovius *et al*., 2000; Benda and Dunne, 1997). The effectiveness of stream power indices can also be limited by the resolution, accuracy and availability of remotely sensed data, especially at a catchment-wide scale (Soar, Wallerstein and Thorne, 2017; Persiano *et al.,* 2022). Using stream power indices at a catchment wide scale requires using techniques to measure discharge, slope and width, which make assumptions and may not be accurate (Parker and Davey, 2023; Kidová *et al*., 2021). Discharge measurements assumed a consistent relationship between calculated Q_{med} and drainage area across the catchment. Slope measurements are limited by the 2m contours used which do not capture variations in slope between each other. Width measurements are based on OS Mastermap polygons, which do not consistently represent the width of the flow at Q_{med} (Parker and Davey, 2023).

6.2 – Limitations of RHS data for defining observation

Using the RHS database to provide observations of channel status has several limitations. Firstly, the survey's primary purpose is to assess physical habitats rather than geomorphic characteristics (Newson *et al*., 1998). Thus, its ability to accurately identify depositional and erosional processes is inherently limited. Secondly, as stated in Chapter 2, observational methods are limited by the subjectivity among different assessors (Bangen *et al*., 2014; MacVicar *et al*., 2009; Roper *et al.*, 2008). Additionally, the low number of RHS observed erosion-dominated sites along the Dee was problematic, as it could mean that strong model performance is due to a large bias for predicting deposition. More observation points along the tributary rivers with high total ω (Figure 10) values would have been benefitted this report. To expand the total number of available observations, data was taken from as far back as 1994. Using survey data closer to the other data sets used in the report would be beneficial (Bizzi and Lerner, 2013). Finally, the simple classification schemes set out in Table 1&2 can easily be confused by channel adjustments. Erosional features can be found in deposition-dominated channels and vice versa (Parker and Davey, 2023). Based on these limitations, it is potentially worth exploring alternative sources of observed morphological status. An example of an alternative approach is using databases of applied management activities, where stream power indices can be evaluated against locations where either erosion or deposition management has been used. This approach was applied by Marcinkowski, Kiczko and Kardel (2022) in a study of the spatial variability in stream power distribution in Polish rivers. They used a database of restoration works conducted in river streams, with restoration type being used to determine processes. Dredging indicates deposition domination where backfilling eroded river banks indicates erosion. They note a key advantage of this approach is it allows for large-scale assessments across entire regions or countries, where performing field surveys is not feasible.

6.3 – Limitations of Performance Measurements

As previously discussed, accuracy is a flawed measurement of performance (Huang and Ling, 2005). Therefore, MCC was utilised in this report. However, using it as one of the two measures of model performance in this report has somewhat decreased the validity of the discussion around result performance. Other additional measures of performance could be utilised in future reports, with accuracy as a performance measure potentially being discarded. Parker and Davey (2023) used the area under the receiver operating curve (AUC) as an additional, more robust measure of performance. This also allowed for the absolute values of ω, Ω and T to be included in the modelled indices. The default threshold of 1 used in this report cannot be applied to these indices as they require bespoke calibration, and therefore, their performance could not be evaluated. However, AUC does not require a set threshold value; thus, these values could have been included in the study (Huang and Ling, 2005).

6.4 – Sample Size Limitations

Finally, only testing the 30 stream power balance indices on one highly deposition-dominated catchment, does not give a good representation of model performance. As mentioned previously, the strong performance of the indices found in this report could simply be down to a strong bias for predicting deposition, which would inherently cause strong performance. Even in cases where MCC was utilised in an attempt to prevent this bias, it may not be sufficient. The indices which correctly predicted channel status correctly 100% of the time ($T_{balance\text{-}reach\text{-}0.5}$, $T_{balance\text{-}reach\text{-}0.6}$, $T_{balance\text{-}reach\text{-}0.7}$ and $\Omega_{balance\text{-}reach\text{-}0.6}$) each only tested against one observed erosion-dominated RHS site. Testing the method applied in this report on multiple river catchments with a greater variation in observed channel status would provide more significant results.

Chapter 7 - Conclusions

Overall, the key findings of this study are that the 30 assessed stream power balance-based models generally predicted alluvial channel adjustment well when compared to RHS observations of channel form. Particular attention should be given to the strong performance of the ST:REAM model as well as the $T_{balance}$ indices. These results suggest the need to further evaluate the performance of these models specifically, as they could be reliably used to measure channel adjustment. This report also strengthens the findings of Parker and Davey (2023), in relation to accuracy being a poor measure of model performance.

However, the limitations of this report also must be considered. There are many simplifications and assumptions made when calculating each model. The RHS database may also provide a flawed method of testing observed channel status. It is also difficult to make statements about model performance when this study only tested each model on one river catchment. The conclusions and findings of this study should be carefully considered alongside these limitations.

Generally, it is recommended, based on the discussed literature and findings within this report, that further testing is needed before these stream power balance models can be applied to river management. It is suggested that future stream power balance studies aimed at assessing channel adjustment, incorporate different sources of observed morphological status and performance measurement techniques. These studies should attempt to remove simplifications around sediment supply and catchment characteristics, as well as test models on multiple catchments with varying characteristics.

The variation in the findings of this report and Parker and Davey (2023) is difficult to explain as a highly similar method was used. Mirroring the conclusion of Parker and Davey (2023), this difference again highlights the need to understand the underlying reasons as to why stream power indices perform better in some circumstances than others.

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