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COUPLING DYNAMIC TOPMODEL AND HEC-RAS TO EVALUATE CATCHMENT-SCALE NATURAL FLOOD MANAGEMENT IN THE UPPER CALDER

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ABSTRACT

In recent years, catchment-scale Natural Flood Management (NFM) interventions have become an increasingly common approach for mitigating flood risk in the UK. Local stakeholder groups now play a strong role in implementing NFM. The significant challenges they face in implementing NFM (tight budgets, limited time frames, an uncertain evidence base etc.) have impacted the role of modelling within catchment-scale design. After reviewing these challenges, this study presents a novel, coupled model methodology (using Dynamic TOPMODEL and HEC-RAS) for evaluating catchment-scale NFM. The benefits of this methodology are demonstrated through a case-study investigation into the impact of hypothetical tree planting on tributary desynchronisation within a Yorkshire catchment. This is shown to enhance the impact of such interventions at a catchment scale.

Keywords: Natural Flood Management, synchronisation, modelling

1 INTRODUCTION

The term 'Natural Flood Management' (NFM) encompasses a wide range of interventions that promote (or restore) natural hydrological processes in the rural uplands of a catchment with the aim of managing sources and pathways of floodwaters (Holstead *et al.*, 2017; Collentine and Futter, 2018). They do this by: (1) promoting infiltration (2) managing overland conveyance and (3) creating lowlands storage (Pitt, 2008; Dadson *et al.*, 2017). Intervention types include: afforestation, moorland restoration, floodplain reconnection and creation of offline ponds (Environment Agency, 2017). The evidence base for the effectiveness of catchment-scale impacts is still developing (Dadson *et al.*, 2017). However, in the UK, NFM approaches have become an increasingly common mechanism for augmenting traditional, hard-engineered solutions.

The implementation of NFM projects in the UK has evolved significantly since the 2008 Pitt Review (Pitt, 2008). Pitt recommended a clearer approach to catchment flood management and a better balancing of hard and soft-engineered interventions. That recommendation resulted in DEFRA's 2011 flood risk strategy, which encouraged decentralised Catchment Based Approaches (CaBA) to flood risk management (DEFRA, 2011). Since 2011, the CaBA philosophy has provided a framework for 'Catchment Management Partnerships' (CMPs). These CMPs are typically the vehicle by which national agencies (the Environment Agency, Natural England, the Rivers Trust, water companies etc.) interact with local stakeholder groups to implement NFM projects. Since 2015 there have been at least 83 CMPs, covering every catchment in the England (Environment Agency, 2015). This collaborative, stakeholder-focused approach is necessitated by the spatially diffuse nature of catchment-scale NFM. Some central funding support (e.g. the £15 million allocated to catchment-scale NFM measures by the UK government in Autumn 2016) has resulted in increased numbers of 'bottom up' community-based projects (Rouillard and Spray, 2017).

The benefits of modelling in the design of these projects has been heavily scrutinised because of the many challenges CMPs face. The primary deliverables for many of these tightly budgeted projects are tangible, physical interventions. Catchment modelling design exercises, which must have sufficient resolution to incorporate the impact of NFM interventions, can therefore be seen (by CMPs) as a superfluous expense, as well as prolonging project lead times (Wingfield *et al.*, 2019) . This problem is magnified by (i) the uncertainty of representing NFM within a hydrological model (ii) the often large data requirements needed to construct models and (iii) the fact that the combinations required to understand optimal sets of interventions across a catchment can be computationally prohibitive (Lane, 2017). As a result, many catchment scale NFM projects base their design philosophies on a 'net positive' justification and assume any intervention must at least have some attenuating impact on downstream peak flows. Such philosophies can be reinforced by the lack of some landowner (and stakeholder) permissions. As a result of all these factors, 'opportunity-led' approaches based on stakeholder engagement have increasingly become the norm in catchment-design of Natural Flood Management.

This provides context for the coupled modelling methodology presented in this study (using Dynamic TOPMODEL and HEC-RAS) for evaluating catchment-scale NFM. Both tools are freely-available and the computational efficiency gives an opportunity to evaluate the potential for using catchment-scale NFM to desynchronise tributary responses. This is an alternative design strategy to the current opportunity-led approaches but it has been suggested it could be beneficial in enhancing catchment-scale impacts (Thomas and Nisbet, 2007; Pattison and Lane, 2011; Lane, 2017). The coupled models are introduced below and then calibrated for a case study catchment. The results section discusses the impact of desynchronising tributaries using afforestation of sub-catchments.

2 COUPLED MODEL

2.1 Dynamic TOPMODEL

Dynamic TOPMODEL is a semi-distributed, semi conceptual hydrological model that has been used in recent years to evaluate NFM interventions (Hankin *et al.*, 2017; Metcalfe *et al.*, 2017, 2018). The model is freely available as an R package in the CRAN repository[1]. The structure of this implementation is discussed in detail in Metcalfe, Beven and Freer (2015).

The semi-distributed model is based on Hydrological Response Units (HRUs). These are areas within the catchment that respond in a hydrological uniform manner and are defined through discretisation of spatial input data (e.g. topography, soil conditions or flow distances). The size of HRUs is limited by the individual pixel area in the underlying raster data. The 'efficient-parameterisation' of the model means that the properties of each HRU are defined using only seven parameters (see Table 1), further simplifying the underlying solver and shortening simulation times.

The code solves for three different lumped-storage volumes (root zone, unsaturated and excess) within each HRU in each time step. Horizontal flux (between HRUs) is controlled by a weightings matrix and assuming the hydraulic gradient is equal to the topographic slope (Hankin *et al.*, 2017). These routed fluxes provide input for the river network (a single HRU). In the CRAN implementation, the channel flow is routed to the catchment outlet using a simple 'time-delay histogram' which proportions all flow entering the channel (based on the geographical layout of the river network). This treatment of channel flow has been shown to offer a reasonable approximation in smaller catchments (Beven, 1979) and minimises computational complexity.

However, coupling the overland module of Dynamic TOPMODEL with a distributed hydraulic river solver offers many potential benefits. One of these is an ability to evaluate the potential impact of natural flood management on desynchronising tributary responses. The role of tributary timing and sequencing has been shown to have a significant impact on downstream flows (Pattison *et al.*, 2014). This study will evaluate the impact of NFM on tributary timing in section 5.

It should be noted that, while not a focus of this study, such a coupling would also enable detailed consideration of the hydraulic impact caused by in-channel interventions (e.g. leaky dams, on-line storage etc.) within a catchment-wide implementation strategy.

2.2 HEC-RAS

The Hydrologic Engineering Center's River Analysis System (HEC-RAS) is a freely available, established tool from the US Army Corps of Engineers[2]. It has been applied for various purposes including flood modelling (Kumar *et al.*, 2017), storm surge interaction (Teng *et al.*, 2017) and sediment transport (Haghiabi and Zaredehdasht, 2012). There are solvers for 1D, 2D and coupled 1D-2D scenarios. This study uses the pure 2D solver to characterise channel flow. This solver uses an implicit finite volume method to solve the full shallow equations. There are three reasons why a purely 2D model was used. Firstly – the combination of steep streams and small flows would result in stability problems for a 1D model. Secondly, there is insufficient cross-sectional survey data to inform the geometry of any 1D model. Finally, with the heavily dendritic river network, the ease of construction and coupling of a 2D model (with Dynamic TOPMODEL) outweighed the potential benefits of a cumbersome 1D model (a similar argument is noted in Liu & Merwade (2018)).

To couple the two models together, a spatial buffer (of width $25m$) around each reach was burnt into the Dynamic TOPMODEL discretisation. The upstream inputs for each reach HRU were extracted from each simulation. An Excel Macro was developed (using components of the HEC-DSSVue Excel plugin[3]) to automate the process of converting these TOPMODEL outputs into DSS files (the input structure required by HEC-RAS). In the 2D model, the same spatial buffers were used to define the input boundary lines. The model uses a Digital Elevation Model (DEM) from the Environment Agency (EA) and a sensitivity analysis to calibrate an appropriate roughness – these are the two primary data requirements for a 2D HEC-RAS model (Afshari *et al.*, 2018).

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[1] https://CRAN.R-project.org/package=dynatopmodel

[2] https://www.hec.usace.army.mil/software/hec-ras/downloads.aspx

[3] https://www.hec.usace.army.mil/software/hec-dssvue/

A critical factor in coupling Dynamic TOPMODEL with this model is an associated application programming interface (API) called the 'HECRASController'. The Controller is a toolbox of constituent programming tools which allow automation of HEC-RAS. It is a Component Object Module (COM), meaning it can be called through any program able to read COM DLL (Dynamic-Link Library). There are (limited) examples of its use in Excel VBA (Goodell, 2014), Matlab (Leon and Goodell, 2016) and Python (Dysarz, 2018). The automation of such a software allows (with sufficient computational power) sensitivity analyses in calibration, as well as subsequent scenario testing (critical when evaluating synchronisation of tributaries). The ability to use COMs within the R language (which would have provided a more elegant solution by matching Dynamic TOPMODEL) is very poor, meaning this study accessed the 2D module functions and subroutines using Matlab. Although there is not enough space in this paper to describe all the functions and processes used from the API, the authors are happy to give more details upon request.

3 CASE STUDY CATCHMENT

3.1 Catchment Description

The upper reaches of the Calder river drain to the Yorkshire town of Todmorden, forming a catchment area of approximately $18km^2$ (see Figure 1). The catchment is characterised by steep-sided valleys which cut into high moorland (Calderdale Council, 2018). Like much of the UK's uplands, the catchment has a history of overgrazing which has caused the moorland to recede and be replaced with large areas of grassland. The flat-floored valley contains several urban areas as well as major road and rail links that cross the Pennines.

The industrial history of the area means that the lower reaches are heavily engineered, with remnants of river mills and significant culverting. The flashy catchment response has resulted in a significant flood history in Todmorden with at least 16 events in the surrounding area since 2001. Two particularly significant events were in June 2012 and December 2015. The former saw a month's rainfall across 24 hours, flooding 270 properties. There was significant surface and fluvial flooding through November and December 2015, culminating in the 'Boxing Day Floods' which impacted 3500 households (Environment Agency, 2018). There are, however, more frequent events on a smaller scale – in March 2019 flooding was caused by rainfall with an estimated return period of 2 years (it was preceded by two weeks of prolonged rainfall). This impacted 20 properties as well as closing both the rail and road links.

The major events have prompted a significant uptake in Natural Flood Management interventions in the upper Calderdale area. A high profile project in the neighbouring sub catchment aims to plant 200,000 trees across the next 10 years as part of interventions across an area of 100 acres. The lead local flood authority – Calderdale Council – is one of only two LLFAs nationally currently employing an NFM project officer and is currently co-ordinating a £1m grant for local landowners to implement NFM interventions. This scheme has created woody debris dams, runoff attenuation features and afforestation around the local area.

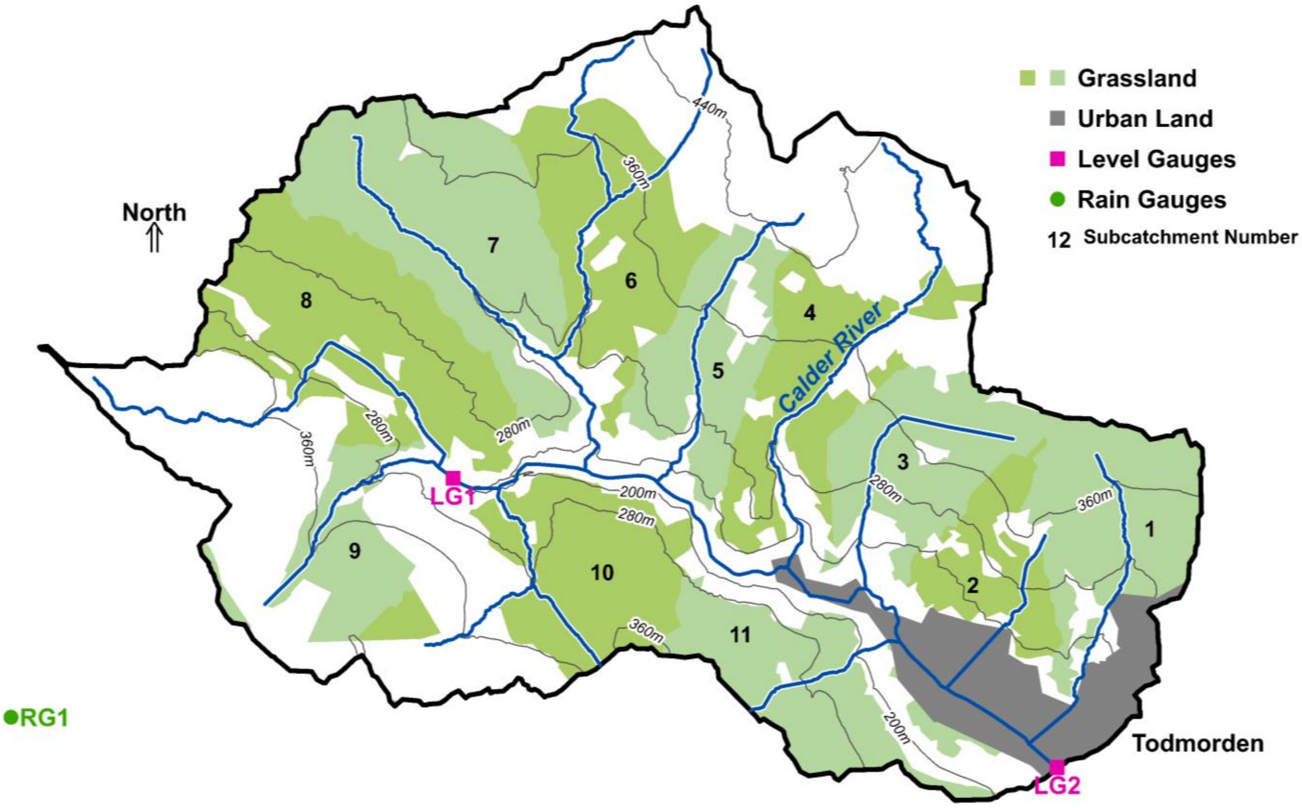

Figure 1. The Calder River catchment above Todmorden

3.2 Data Availability

The spatial data used in this study are extracted from national datasets, meaning a similar methodology could be applied in other UK catchments. A digital terrain model (DEM), needed for both Dynamic TOPMODEL and HEC-RAS, was built from elevation data the OS Terrain 5 map[4]. This has a spatial resolution of $5m$ which was deemed suitable as it minimises both the probability of sinks and computation times. Catchment watersheds were derived from this data. The river network was extracted from the OS MasterMap Water Network[5]. The Centre for Ecology and Hydrology's CHESS database was used to extract the potential evapotranspiration (with interception correction) data (Robinson *et al.*, 2016). This is available at daily intervals with a $1km$ resolution. The land use came from the 2012 CORINE Land Cover inventory[6]. This dataset classifies regions with area greater than 25 hectares and width greater than $100m$.

The temporal data (for the level and rain gauges shown in Figure 1) were obtained through Freedom of Information (FoI) requests to the Environment Agency. It should be noted that the LG2 (the primary gauge used for calibration) is within Todmorden and therefore subject to contribution from the urban area. All of the gauging data has a record period of over 10 years and a measurement time interval of 15 minutes. The primary function of the level gauges is to monitor and inform flood warning systems, meaning there are no associated control structures, spot flow records or rating curves. Therefore, a rating curve for LG2 was constructed using the Manning's formula. The hydraulic radius and slope for the pertinent river section was informed by (1) local LIDAR data (spatial resolution $25cm$) (2) data from an existing EA river model and (3) visual inspection.

An initial Manning's roughness value of 0.03, informed by the EA river model, was subject to a sensitivity analysis. Figure 2 illustrates the impact of different roughness values on the resultant rating curve. As a result, it was decided to adopt a 'fuzzy approach' to the rating curve by applying 30% error bounds (also shown in Figure 2) and use a Limits of Acceptability approach to calibration.

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[4] https://www.ordnancesurvey.co.uk/business-and-government/products/os-terrain-5.html

[5] https://www.ordnancesurvey.co.uk/business-and-government/products/os-mastermap-water-network.html

[6] https://catalogue.ceh.ac.uk/documents/32533dd6-7c1b-43e1-b892-e80d61a5ea1d

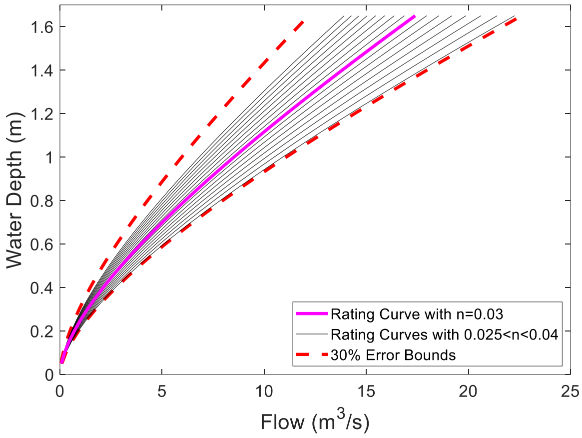

Figure 2. Impact of roughness change on the subsequent rating curve

The error associated with the constructed rating curve can be considered a 'Relevant Dominant Uncertainty' (RDU) (Smith and Petersen, 2014; O'Donnell, Thorne and Yeakley, 2018; Thorne *et al.*, 2018) in that it is "the most likely known unknown limiting [the] ability to make more informative [...] scientific probability distribution on some outcome of interest." There are other, significant sources of uncertainty (e.g. in the input data or the parameterisation and numerical structure of the models) which should be evaluated in any further work (through field measurements or ensemble modelling etc.).

4 CALIBRATION

The calibration procedure for the hydrological model was based on the Generalised Likelihood Uncertainty Estimation (GLUE) approach (Beven, 2006; Beven and Binley, 2014). The calibration period runs from midnight on the 27th November 2015 to midnight on the 19th December 2015 with a 15 minute time step (mirroring the EA gauge data). This was a period of extended rainfall (16% of the annual average rainfall in two weeks) followed by a 1 in 10 year event on the 12th December. Uniform rainfall across the catchment was assumed (the only available local gauging station is shown in Figure 1). An initial Monte Carlo procedure began by creating five thousand input parameter sets using a uniform sampling distribution between the bounds given in Table 1. These bounds were informed by the other Dynamic TOPMODEL calibrations in the literature (Freer *et al.*, 2004; Page *et al.*, 2007; Younger, Freer and Beven, 2009; Metcalfe *et al.*, 2017, 2018) and an evaluation of catchment characteristics. One parameter, sd_{max} (the maximum effective deficit of saturated zone) was fixed at 0.5 (this was also done in Metcalfe et al. (2018)) as it only becomes influential during dry periods.

Table 1. Parameters in calibration and representation of NFM interventions

	Description	Units	Sampling Range	Calibrated Value (2 s.f.)	NFM Scale Factor
$\ln T_0$	Lateral saturated transmissivity	m^2h^{-1}	$[5, 10]$	8.2	1.5 (to T_0)
m	Exponential decline in conductivity	m	$[0.001, 0.01]$	0.0092	1.2
srz_0	Initial root zone storage	$\%$	$[80, 100]$	0.94	0.95
srz_{max}	Maximum root zone storage	m	$[0.03, 0.2]$	0.077	$-$
t_d	Unsaturated zone time delay	h^{-1}	$[10, 30]$	20	$-$
v_{of}	Overland flow routing velocity	mh^{-1}	$[50, 100]$	58	0.75
v_{chan}	Channel routing velocity	mh^{-1}	$[1000, 2000]$	1800	$-$

The initial 5000 variations were each compared against the acceptability bounds for the observed flow (created using rating curves shown in Figure 2). It was predefined that 'behavioural simulations' were those between the acceptability bounds for 90% of the calibration period. The Monte Carlo procedure yielded 224 such simulations. While the subjective nature of such thresholds within the GLUE procedure have been extensively discussed (Montanari, 2005; Stedinger *et al.*, 2008; Jin *et al.*, 2010; Beven and Binley, 2014; Mirzaei *et al.*, 2015), there is precedent for such limits (Blazkova and Beven, 2009; Liu *et al.*, 2009; Westerberg *et al.*, 2011). Each of the behavioural simulations was then ranked using a simple triangular weighting scheme between 0 and 1 (Blazkova and Beven, 2009; Liu *et al.*, 2009; Metcalfe *et al.*, 2018). The weighting scheme was based on each simulation's replication of the observed peak flow ($n = 0.03$).

The larger computational requirement for HEC-RAS prevents every behavioural simulation providing input for the hydraulic model calibration. Therefore, the simulation with the highest likelihood function was carried forward as input for the 2D model. The channel culverting had to be replicated in the DEM by burning in a channel (of equivalent width and depth). Therefore, any throttling impacts of the culverts are not represented.

The model was calibrated using a sensitivity analysis of a global Manning's n value (between 0.02 and 0.04). The final roughness used was 0.025; the Nash Sutcliffe Estimation (NSE) of the output from the coupled model was 0.89 – see Figure 3 for a comparison with the observed flow. The baseflow and the flashy response is reflected well in the simulation. However, the coupled model does tend to underpredict some of the smaller peak magnitudes.

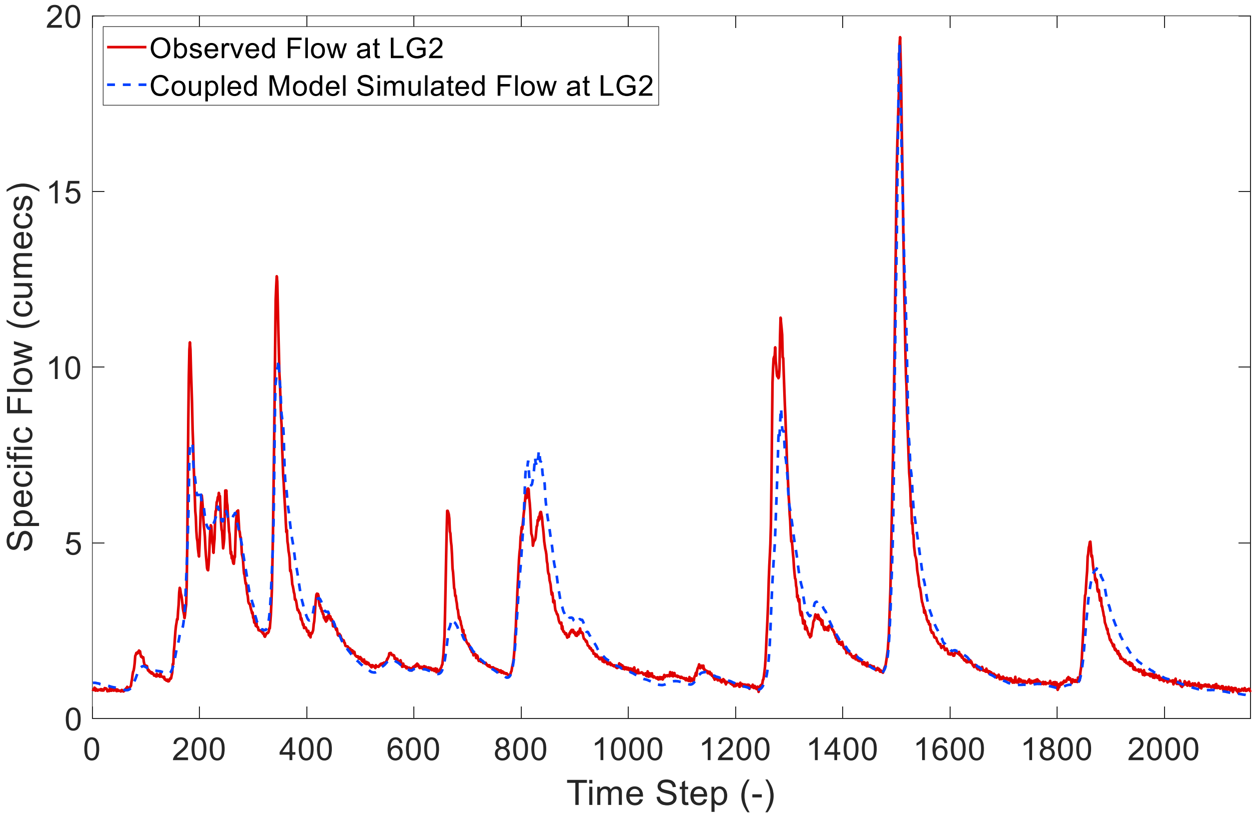

Figure 3. Comparison of Observed and simulated flows

5 RESULTS

Having obtained a calibrated model for the upper Calder, the impact of afforestation in different sub catchments will be evaluated. Figure 1 shows the areas assumed to be available for tree planting within each. These are areas of open, rough grassland (similar to those being forested in the neighbouring catchment). The impact of tree planting is represented in Dynamic TOPMODEL using parametric scaling. These scalars (given in Table 1) reflect the drier antecedent conditions and the slight increases in shallow soil permeability and evapotranspiration that would be caused by fully matured trees. There are limited examples in the literature to determine the magnitude of the these scalars – those used in this paper are based on: (1) a joint report from the Lancaster Environment Centre and Jeremy Benn Associates (Hankin *et al.*, 2016) and (2) consideration of catchment characteristics.

To understand the impact of sub catchment tree planting on synchronisation (through the HEC-RAS model), different combinations of intervention were considered. Two sub catchments (numbers 2 and 9 in Figure 1) were not part of this analysis – they had the smallest area available for planting (and therefore likely to have the smallest impact). This significantly reduces the number of permutations needed to be considered (and therefore the computational time). With nine separate sub catchments there are 511 combinations (9 with a single sub catchment afforested, 36 with two afforested, 84 with three etc.). These took approximately 80 hours to run through HEC-RAS using a 2.9GHz processor. Figure 4 illustrates the impact of each on the peak flow seen during the calibration period.

Figure 4 demonstrates the general trend from the model – the more afforestation within the catchment as a whole, the lower the peak flow. Interventions across all nine sub catchments (56% of the total catchment area) result in a peak reduction of approximately 13.8%. The figure also illustrates that *all* permutations have a mitigating effect on the downstream hydrograph. This supports the approach used by CMPs in that every intervention, no matter the location, will have a positive impact. However, the results also show that by careful targeting of interventions, one could enhance the impact seen at a catchment-scale.

For example, individually there is a large range of potential impact – sub catchments 4, 5 and 7 (see Figure 1 for locations) each reduce the peak by over 4%. This is despite the fact that these are not the sub catchments with the three largest areas currently designated for tree planting. In fact, the model suggests that these three individual areas can each have more impact than certain combinations where six sub catchments are planted. It is also interesting to note the large improvement in overall peak reductions when increasing the intervention from two to three sub catchments. Finally, there are two combinations where planting in eight sub catchments produces a greater impact than that seen when all are – again suggesting that synchronisation can be used to enhance downstream impact. Although the scale of such an intervention is hypothetical, it demonstrates that careful targeting of sub catchments might produce a greater impact from a smaller intervention and hence the benefit of this modelling approach.

While Figure 4 indicates the potential benefits of such an implementation strategy, it does not detail the constituent sub catchments within each combination. This might be of interest to a CMP wishing to identify within which sub catchment to target interventions. Figure 5 gives the cumulative frequency of individual sub catchments within the most effective 10% of combinations (i.e. the lowest 50 points in Figure 4). The figure shows that within these top 50 permutations, the most common pairing is sub catchments 7 and 8. It is interesting to note that these are both in the uplands – one might have expected the attenuation to be lost through the dampening hydrodynamic dispersion). It is possible desynchronization is playing a role, but also

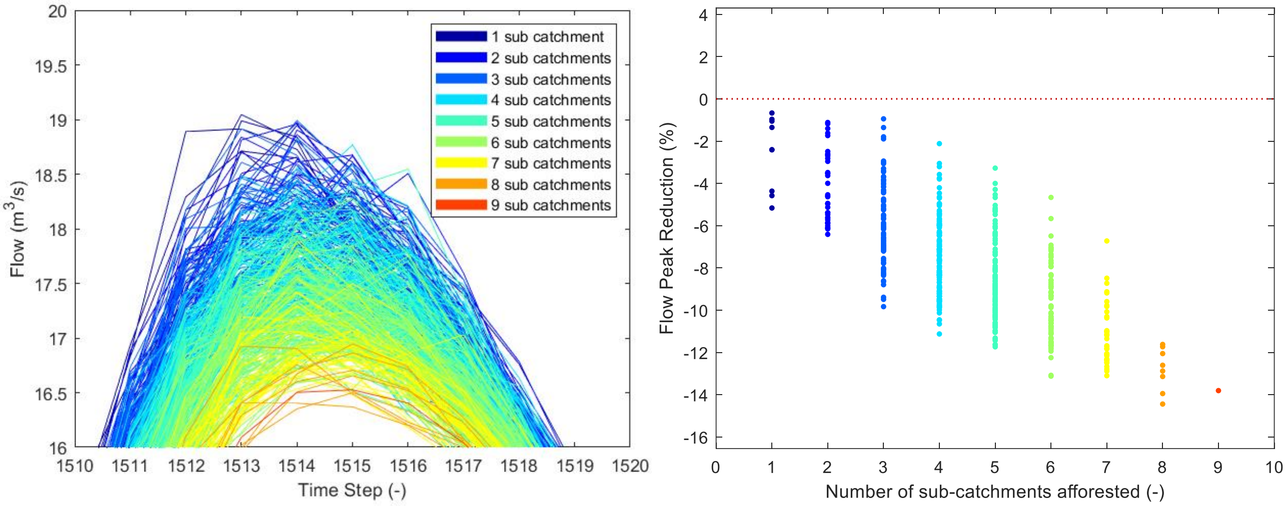

Figure 4. (a) Peak flows resulting from afforestation combinations and (b) the associated peak reduction

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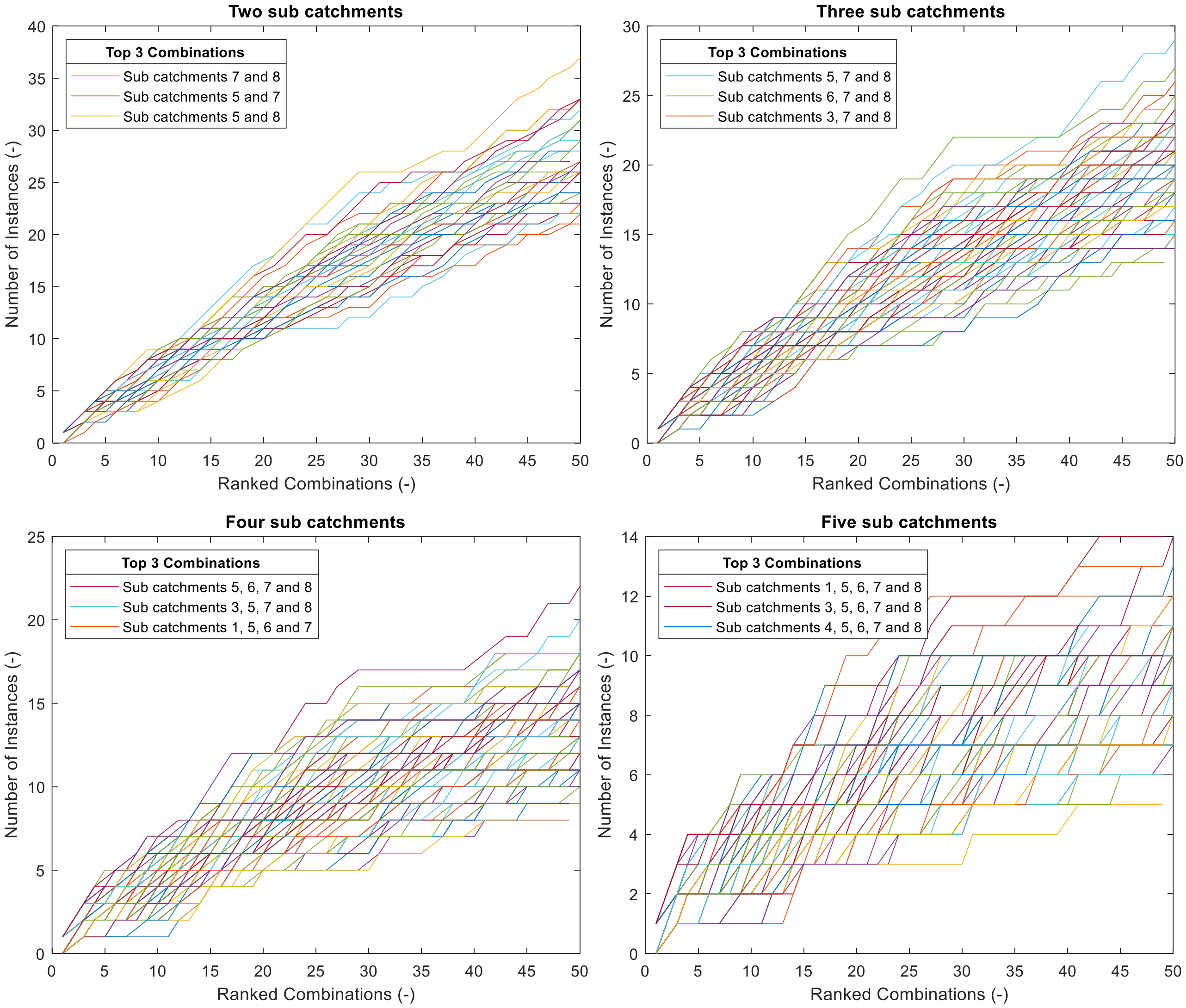

Figure 5. Distributions of combinations for top 50

both these sub catchments have a large area being 'planted' and so the attenuation impact will be larger. In fact sub catchments 5 (which has a smaller area of grassland), 7, and 8 make up all three most successful pairings. When evaluating the most common three sub catchments seen together within the top 50 combinations, it is unsurprising the most successful is all of these together.

6 CONCLUSIONS

The coupling Dynamic TOPMODEL and a HEC-RAS 2D model has created a numerical replication for the different domains within the hydrological system in the upper Calder valley. Both solvers are freely available and their computational efficiency provides benefit in calibration or when considering multiple scenarios.

There is huge scope for further investigation into synchronisation using the presented methodology beyond this initial, demonstrative study. Firstly, by considering the difference in times to concentration at confluences, one could potentially rule out particular combinations of intervention. This would further reduce the computational requirement and allow better demonstration of interventions' attenuation on relative tributary timings. Secondly, the research presented in this paper assumes a uniform rainfall across the catchment. The computational efficiency of the model may enable an evaluation of how the response from different storm tracks might be desynchronised using catchment-scale NFM.

However, there are also significant improvements that could be made to the methodology. Quantification of uncertainty (within both models) is necessary, particularly if such a model was to inform a catchment-wide implementation strategy. Despite the benefits of the 2D model used here, a 1D (or coupled 1D/2D) model could reduce computation times further and would enable better capturing of culverted reaches. There is also further work required to understand the error in the coupling method between the models. It is a loose coupling (i.e. no feedback from the hydraulic model) and therefore channel inflows are not impacted by the receiving water level (i.e. any backwatering effects are not replicated). There is also no distinguishing between sub-surface and overland contributions to the channel network, potentially preventing the hydraulic model from capturing the flashiness of the response. These channel inflows have also been averaged across entire river reaches – such lumping may not reflect the local hydrology.

There is also potential with the methodology to evaluate the combined impact of many different forms of intervention. The minimum area of interventions in the hydrological model is constrained only by the resolution of the underlying DEM data. For example, Metcalfe et al. (2018) evaluated the impact of distributed runoff attenuation features but the scope for representing interventions is wide and other potential examples include moorland restoration or improved farming practices. The primary constraint is parameterising the impact of interventions. The patchy evidence base (Lane, 2017) and the semi-conceptual nature of Dynamic TOPMODEL creates significant uncertainty and requires careful treatment. Interventions in the hydraulic model could be represented using structures with defined depth-flow relationships or by roughness alterations. This would allow evaluation of interventions such as large woody debris (Metcalfe *et al.*, 2017), floodplain reconnection or large bunded storage. Although the purpose of this study has been to use a modelling methodology to provide a conceptual evaluation of catchment-scale impact, a full design exercise would need to consider landowner permissions. While conceptual, these conclusions can still be of value in helping CMPs to identify sub catchments within which to target interventions, or the most efficient ways to build on existing interventions.

The many challenges faced by Catchment Management Partnerships in implementing NFM have led to justified scepticism of the benefits of modelling in the design process. The results from applying the coupled model to this single case study catchment suggest that the 'net-positive' approach often adopted by CMPs is justified, but greater attenuation can be achieved through targeted interventions which this kind of modelling can inform.

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