

# **Approaches for investigating wildfire impacts on catchment hydrology**

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## **Declaration**

This is to certify that to the best of my knowledge, the content of this thesis is my own work.

This thesis has not been submitted for any degree or other purposes.

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# Thesis Summary

Climate change has increased the frequency of wildfire in the last few decades. One major ecosystem that has been affected by wildfire is forested catchments. Wildfire changes the surface vegetation of catchments and results in a change in catchment runoff and erosion; thus, has serious impacts on the hydrological cycle and water quality of forested catchments. Forested catchments usually have high water quality, and they are commonly used as an important source of drinking water supply in Australia and internationally. Monitoring short-term and long-term post-wildfire water quantity and quality change is important for catchment management. Past studies are limited by data availability and method used. In this thesis, we firstly used empirical and physical-based hydrological model to detect the effect of wildfire on forested catchment hydrology (water quantity and quality) and then built scenarios using physical-based model to investigate the cause of the catchment hydrology change and identify the wildfire sensitive areas in catchments for catchment protection. The case study used here is the 2001/2002 Sydney wildfire, 10 years of pre-wildfire and 10 years of post-wildfire water quantity and quality data were collected by WaterNSW and used in this study.

Chapter 1 sets the context in terms of significance of forested catchment water quality, describing wildfire effect on catchment water quality with a focus on total suspended sediment (TSS), total nitrogen (TN), and total phosphorus (TP) change in the post-wildfire period, and the impact these water quality change have on drinking water quality. Past studies on post-wildfire water quality change were reviewed, and two requirements for improving the studies were proposed: requirement to investigate the long-term post-wildfire water quality change and requirement to improving the method used in the study (such as using physical based model).

The long-term wildfire effect on forested catchment water quality was examined in Chapter 2. This chapter gives a description of study area and datasets used in this thesis. Linear mixed model were used in this chapter in an ANCOVA-type change detection approach to assessing the effect of wildfire. A wildfire dummy variable (0 for pre-wildfire, 1 for post-wildfire) is used as a predictor of water quality. If the wildfire dummy variable is a significant predictor in the model that indicates a possible wildfire effect which represents the average effect between pre- and post-wildfire periods. Three controls (in addition to the four burnt catchments) were used to aid the interpretation of the results and help disentangle the effects of natural climate variation and the effect of the wildfire. During the data exploration process in this chapter, a change in the flow duration curve is observed for both control and burnt catchment, to exclude the effect from flow change; we included flow as a predictor when estimating water quality concentrations changes. As a result, on average, (as compared to unburnt catchments) a 64% TSS concentration increase, a 48% TN concentration increase and 40% TP concentration increase were observed in our burnt catchments over the ten years post-wildfire period.

Chapter 2 shows an average wildfire effect on water quality over the study period. However, in forested catchments, most erosion and the subsequent larger impacts on water quality occur during events. Thus, in Chapter 3, we focussed on the water quality differences between events pre- and post-wildfire. Events are defined by flow excess 90th percentile annual flow. As observed in Chapter 2: there is a change in flow duration curve between pre- and post-wildfire period. In order to compare events with similar events, the events were classified into groups using k-mean clustering based on characteristics of their hydrograph (mean flow, maximum and minimum flow, event duration, number of turning points in hydrograph, overall rising time during events and overall dropping time during events) and antecedent conditions. We then compared the event mean concentrations for events within

the same cluster between the pre- and post-wildfire periods. Overall, compare the averaged water quality concentration change in each cluster, a 70-fold increase in TSS event concentration, 5.3-fold increase in TN event concentration, and 10.1-fold increase in TP event concentration were observed in burnt catchments as compared to control catchments.

The previous two chapters assessed the long-term effect of wildfire on water quality, and used LMMs and a clustering method to deal with the problem of sporadically collected data. However, the empirical method used in these two chapters can only detect and summarise the change. Physical-based hydrological model, on the other side, has the same capabilities as empirical models in terms of change detection, but also has the ability to build scenarios to investigate the cause of the catchment hydrology change and identify the wildfire sensitive areas in a catchment.

Chapter 4 used a physical-based distributed model SWAT (Soil and Water Assessment Tool) to assess the wildfire impact on catchment hydrology. SWAT models were built for two control catchments and three burnt catchments. Ten years pre-wildfire data was used to create and calibrate the SWAT models. The calibrated model was then used to simulate the flow and TSS for the ten years post-wildfire period while ignoring the wildfire effect. The control catchments achieved a significantly higher NSE value than burnt catchments during the post-wildfire period, the decrease in NSE value for burnt catchments are identified as an effect of wildfire. The short-term (1<sup>st</sup> year post-wildfire), medium-term (2-5 years post-wildfire) and long-term (6-10 years post-wildfire) flow and TSS output from burnt catchments were compared with observations. A decrease in TSS output in long-term period was observed.

Two major impacts wildfire has on the hydrological cycle are due to burning of surface vegetation and surface soil organic matter, namely soil organic carbon. A reduction in surface vegetation affects catchment evapotranspiration and increases erosion and runoff. A

reduction in soil top layer carbon content can make soil more easily eroded, change infiltration rates and water holding capacity. The SWAT model allows analysis of water quantity and quality change caused by different (wildfire affected) component of catchments. In Chapter 5 we created four scenarios by changing the inputs and parameters for SWAT: (i) change in soil carbon, (ii) change in surface vegetation from forest to grassland and (iii) change in surface vegetation from forest to bare ground. The unburnt models created in Chapter 4 were used as scenario (iv) unburnt scenario. To investigate the effect of wildfire on soil carbon to create scenario (i), 27 pairs (control and burnt) of soil samples were collected from 7 prescribed burnt sites in NSW. Particle size fractions and soil organic carbon were measured for all the control and burnt samples. The burn severities of these sites were calculated based on Landsat images pre- and post-prescribe burn. A regression model was then used to predict the change in soil organic carbon based on the unburnt carbon content and burn severity (adjusted  $r^2 = 0.54$ ). This model was applied to create soil carbon maps for the study catchments based on observed wildfire severity from the study catchments. The predicted carbon maps were used to run SWAT in the post-wildfire period. The flow and TSS output from these four scenarios were compared with each other. We conclude the effect from wildfire to soil top layer carbon content has minimal effect on catchment water quantity and quality. By comparison, the vegetation change is a driving factor for post-wildfire water quantity and quality change.

In Chapter 6, we investigated the correlation between soil properties, sub-catchment properties (slope, elevation, sub-catchment size) and SWAT predicted flow and TSS. We observed that the flow output in SWAT models are highly correlated to slope and soil properties under all (Forest, Grass and Bare) land-cover types. However, the correlation between inputs and TSS output is different between different land-cover types. The correlation between slope, soil properties and TSS output increases as the land-cover

decreases (from forest to bare ground). A better understanding of the correlation between inputs and water quantity and quality output can help us: 1) further investigate the sensitivity of SWAT model to soil properties to better understand the results in chapter five; 2) identify the area that is more sensitive to wildfire which may help catchment management decision made during both the pre-wildfire protection planning and post-wildfire recovery process.

The final chapter of this thesis presents the conclusion and recommendations for further research on assessing wildfire-induced changes in catchment hydrology.

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As I am writing, it is my 3918<sup>th</sup> day in Australia and my 3162<sup>th</sup> day at The University of Sydney. Sydney University to me, is my life in Australia. More than 4000 days ago sitting at home in Hangzhou China, I decided to come to Australia, because of this University (at the time solely because the name sounded cool). I think I love this University too much, I have studied here as long as I can and now, this has finally come to an end.

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离开家的那一天，我在博客留言说：“辗转多次，好事多磨，终于是真的上路了，以为会哭的，竟然未落一滴泪，该落的泪早落了，留下平静的心和全新的挑战，是的，该上路了。”

妈妈回复：“希望这种信心一直会延续，这样我的负罪感就会轻一些。”

今天，四千多个日夜过去了，我想我的信心依然还在，而且会一直延续下去，陪伴我一生。所以，我最亲爱的亲爱的妈妈：“我想这是一条正确的路，你一直都是全世界最棒的妈妈”

*The day I left home, I posted on my blog: “Finally I am on my way, I thought I will cry, but not even one drop of tear. All I have now is a peaceful heart, ready for challenge, yes, it's time to leave.”*

*Mum replied: “I wish your confidence can always stay with you, so I feel less guilty for sending you away.”*

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*In addition to the statements above, in cases where I am not the corresponding author of a published item, permission to include the published material has been granted by the corresponding author.*

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# List of Abbreviations

AGDC	Australian Geoscience Data Cube
ANCOVA	Analysis of Covariance
AWC	Available Water Contain
BD	Bulk Density
BOM	Bureau of Meteorology
CFSR	Climate Forecast System Reanalysis
CSA	Critical Source Area
DEM	Digital Elevation Model
DF	Discount Flow
dNBR	Differenced Normalized Burn Ratio
EMC	Event Mean Concentration
HRUs	Hydrological Response Units
LAI	Leave Area Index
Lin's CCC	Lin's Concordance Correlation Coefficient
LMM	Linear Mixed Models
ME	Mean Error
MUSLE	Modified Universal Soil Loss Equations
NCEP	National Centre for Environment Predictions
NIR	Near-infrared
NSE	Nash–Sutcliffe model efficiency coefficient
OM	Organic Matter
RMSE	root-mean-square error
SLGA	Soil and Landscape Grid of Australia
SSPE	Standardised-squared prediction error
STP	Sewage Treatment Plant
SWAT	Soil and Water Assessment Tool
SWIR	Mid-infrared
TN	Total Nitrogen
TP	Total Phosphorus
TSS	Total Suspended Sediment
USLE	Universal Soil Loss Equation
WQ	Water Quality
WYLD	Water Yield

# Chapter 1

---

## 1. General Introduction

The frequency of wildfire is expected to increase due to climate change in the next few decades (Lucas 2007). Already, a significant amount of forested land is frequently burnt by wildfire around the world, particularly in western North America, south-eastern Australia and the Mediterranean (FAO, 2001). In south-eastern Australia wildfire events have burnt over 3 million hectares of forested area from wildfires in 2003, 2006, and 2009 (Attiwill and Adams, 2013). In Canada, forest wildfire has burnt between 0.29 and 7.56 million hectares annually from 1975 to 2005 (Smith et al., 2011). From 1997 to 2008, 65 extreme wildfires (greater than 40,000 hectares) were recorded in the United States (Smith et al., 2011). In response to an increase in wildfire frequency, there has been an increase in research on all aspects of wildfire and forest management in Australia and internationally. From this intensification of research, the potential impact of wildfire on forested catchment hydrology, and in particular water quality has emerged as a major concern (Lane et al., 2010, Smith et al., 2011, Feikema et al., 2011, Murphy, 2012, Santín et al., 2015, Langhans et al., 2016).

Forested catchments can deliver high quality water and are used as an important source of potable water (Oliver et al., 2012, Neary et al., 2009). Among the largest cities in the world, (including the top 25 cities from Asia, Americas, Europe, Africa and five from Australia), approximately one-third (33 cities) obtain a significant amount of their drinking water from protected forested catchments (Dudley and Stolton, 2003). Additionally, water supplied from forested catchment contribute two-thirds of the freshwater supply in the United States (Council, 2008). Except for a few that are located in less wildfire-prone areas such as in wet tropical rainforests, most forested water catchments are particularly susceptible to wildfire. In Australia, wildfire has burnt forested catchments that supply drinking water to major cities in the past two decades including Sydney (2001), Canberra (2003), Adelaide (2007), and Melbourne (2009) (Smith et al., 2011).

Wildfire can have a significant impact on the hydrological cycle of forested water catchments and can affect the water quantity and quality output from these catchments. When a wildfire happens, firstly, it affects catchment flow rate: wildfire removes surface vegetation increasing the percentage of rainfall available for runoff and decreases evapotranspiration which increases the amount of water available for overland flow (Moody and Martin, 2001). Secondly, intense wildfire can affect soil chemistry creating a hydrophobic layer at 5–20 cm soil depth (Neary et al., 2005, Onda et al., 2008). This hydrophobic layer can lower soil infiltration rate, thus, increasing surface runoff. Additionally, wildfire increases the amount of available sediments and nutrients in the catchment. During wildfire, the heating and combustion of organic matter releases charcoal, ash, heavy metals, and otherwise stable nutrients that would have been previously unavailable for transport into waterways, especially during the first post-wildfire event (Johansen et al., 2003). Total suspended sediment (TSS), total nitrogen (TN), and total phosphorus (TP) are the major water quality contaminants that result from wildfire.

### **1.1.Effect of wildfire on total suspended sediments**

An increase in sediment load is a widespread consequence of wildfire (Lane et al., 2006). After wildfire in forested catchments, ash produced from wildfire and increased erosion rate promotes the amount of total suspended sediments (TSS) in streams. An increase in suspended sediment can affect the colour and turbidity of water and may also transport particulate-associated contaminants (Sheridan et al., 2007a). From a drinking water quality perspective, elevated levels of TSS in drinking water may increase the amount of adsorbed nutrients in the water column and, as a consequence, can promote bacterial growth (NHMRC, 2011). Sediment yields in streams are affected by a number of factors such as vegetation, soil, geology (elevation and slope), wildfire severity, weather patterns, and land use (Neary et al., 2005). Sediment mobility and output are greatest when discharge is highest and during the

first post-wildfire year (Silins et al., 2009). Sediment output declines as the vegetation in the catchment recovers (Neary et al., 2005). One key factor in determining post-wildfire erosion is the duration, magnitude and timing of the first post-wildfire event. The most severe erosion generally happens when a heavy rainfall event occurs shortly after wildfire, well before catchment vegetation recovers (Ryan et al., 2011).

Numerous studies have recorded an increase in TSS after wildfire. For example, Moody and Martin (2001) analysed TSS change after wildfire in Buffalo Creek, United States, and found a 20-fold increase in TSS concentration during the first year post-wildfire. Also in the United States, Silins et al. (2009) recorded 6- to 15-fold increases in levels of TSS in burnt catchments compared to control catchments after the 2003 Lost Creek wildfire. Ryan et al. (2011) investigated changes in TSS level for three years post-wildfire in Little Granite Creek, United States, and found that even when the first post-wildfire season had relatively low flow, there was still a 5-fold increase in TSS. They found that TSS concentrations declined in the second and third-year post-wildfire as the vegetation recovered (Ryan et al., 2011).

## **1.2. Effect of wildfire on nitrogen and phosphorus**

Compared to the investigation of post-wildfire changes in TSS, the effects of wildfire on nitrogen (N) and phosphorus (P) in forested catchments are less well-studied. While nutrient loss from unburnt forested catchments is usually low (Neary et al., 2005), wildfires have the ability to interrupt stable ecosystems and volatilise nutrients from the vegetation and soil. These nutrients are transferred into the atmosphere or remain on the soil surface or ash (Johansen et al., 2003) where they can be transferred into the streams and then into catchments following runoff and erosion processes. Increased concentrations of N and P in forested catchments post-wildfire can be in insoluble and soluble forms (Son et al., 2015). The insoluble N and P are transferred into the catchment with ash, soil, and sediment while

the inorganic N and P are dissolved in the runoff and transferred into catchment. Solute form N and P include phosphate ( $\text{PO}_4^{-2}$ ), nitrate ( $\text{NO}_3^-$ ), and ammonium ( $\text{NH}_4^+$ ) (Smith et al., 2011). Nitrates may affect oxygen transport in red blood cells and present a potential risk to human health whereas high level of  $\text{NH}_4^+$  may erode copper pipes. An increase in TN and TP in water may result in eutrophication, encourage the growth of algae, and increases the potential for toxic blooms which can affect the safety, taste, odour, and colour of water and interrupts aquatic ecosystems (NHMRC, 2011, Drewry et al., 2009).

Past studies have found a decrease in TN and TP stored in the surface layers of the forest floor after high severity wildfire (Drewry et al., 2006). However, changes in TN storage are greater than TP because the volatilisation temperature of P ( $>550\text{ }^\circ\text{C}$ ) is much higher than for N ( $>200\text{ }^\circ\text{C}$ ) (Murphy et al., 2006). Past studies have reported different changes in post-wildfire TN and TP, ranging from a small decline or minor increase (0.3–2-fold compared to unburnt forests) to substantial (20–431-fold) increases (Bayley et al., 1992, Townsend and Douglas, 2004, Sheridan et al., 2007b). Hart et al. (2005) observed that the amount of TN and TP lost from soil is directly linked to the amount of organic carbon in the soil destroyed by wildfire. Ranalli (2004) reviewed 39 studies on post-wildfire water quality change and found that it generally takes 1–2 years for elevated TP and 3–5 years for elevated TN to decline after wildfire.

### **1.3.Past studies for assessing the impact of wildfire**

Several past studies have investigated the impact of wildfire on water quality change. A summary of these studies regarding the study length, observation record, and methods are shown in Table 1.1. From this information, a number of knowledge gaps have been identified.

**Table 1.1 Details of studies investigating the effect of wildfire on water quality (WQ)**

Study	Description	Pre-wildfire data / post-wildfire data	Method <sup>1</sup>
Lane et al. (2006)	Severe wildfire burnt over 1 million ha of forested land in Australia	10 years / 2 years post-wildfire	ANCOVA (with control) <sup>2</sup>
Bladon et al. (2008)	The effect of wildfire on post-wildfire nitrogen concentration with three burnt catchments and two unburnt catchments	NA / 3 years	ANCOVA (with control)
Mast and Clow D.W (2008)	WQ change after a wildfire in Glacier National Park, USA	5 years/ 4 years	Compare average concentration
Townsend and Douglas (2004)	The effect of a wildfire on stream WQ and catchment water yield in a tropical savanna (North Australia) excluded from wildfire for ten years	3 years /10 <sup>th</sup> year post-wildfire	ANCOVA (No control)
Malmon et al. (2007)	Sediment change post-wildfire in New Mexico	2 years / 3 years	ANCOVA (No control)
Kunze and Stednick (2006)	Sediment change post-wildfire in 2 burnt catchments in Colorado, USA.	NA / 3 years	ANCOVA (with control)
Oliver et al. (2012)	Analysis the WQ change post a severe wildfire in lake Tahoe basin, USA	10 years / 2 years	ANCOVA

1 ANCOVA method: using regression model to account for the effect of flow on WQ.

2 Unburnt catchment used as a control, the pre- and post-wildfire WQ change are compared.

### *1.3.1. Lack of studies showing medium to long-term (>5 years) wildfire effect on water quality*

As can be seen in Table 1.1, most past studies have only assessed the effect of wildfire on water quality for a period of 1-3 years post-wildfire indicating that there is a gap in knowledge about the longer (more than 3 years) term impacts. Wildfire can impact on flow and water quality for decades (Kuczera, 1987) so it is important to study the long-term post-wildfire effect for effective catchment management.

### *1.3.2. Lack of studies with adequate pre-wildfire data*

Another issue is the absence or lack of sufficient pre-wildfire water quality data. The lack of pre-wildfire data is a major problem in relating post-wildfire water quality change and catchment erosion rates to long-term catchment conditions (Shakesby and Doerr, 2006). For example in the studies summarised in Table 1.1, studies by Bladon et al. (2008) and Kunze and Stednick (2006) had no record of pre-wildfire catchment water quality data resulting in them being unable to compare their studied catchments to the pre-wildfire conditions. Other studies such as those by Townsend and Douglas (2004) and Malmon et al. (2007) had only a short period pre-wildfire water quality data (1-3 years); the problem being that the short period of data collected may not reflect the longer term pre-wildfire hydrological conditions of the catchments (i.e. include both dry and wet period catchment conditions). The exceptions are studies by Lane et al. (2006) and Oliver et al. (2012) as they both have long-term pre-wildfire data. However, both studies only have records for two years post-wildfire. Studies without pre-wildfire water quality data rely on comparing the observed data with data collected from control (undisturbed) catchments. This method requires a high degree of similarity between the control and burnt catchments in terms of slope, soil, land use, elevation, and weather conditions. To accurately assess the impacts of wildfire on water quality, both long-term pre- and post-wildfire dataset are required.

### *1.3.3. Past studies predominantly use least-square regression models for change detection without accounting for auto-correlation in the data*

Another limitation of water quality data is how well the sampled data represents the variation in water quality, and this is also related to the validity of the models fitted to the data. This limitation results from the nature of sampling; due to the cost of water sampling and testing, monthly sampling is the most common method of data collection for catchment water quality (Wade et al., 2012). Past work has shown that monthly sampling does not reflect the overall

condition of the temporal variation in water quality in a catchment, especially over short periods of time (Lessels and Bishop, 2015a).

Additionally, monthly sampling often misses rainfall events, but monitoring of the catchment sediment output during rainfall events is important for catchment management, particularly for Australian conditions. Australia catchments are generally characterised by long durations of base flow and large rainfall events (Drewry et al., 2009) resulting in large amounts of sediment and nutrient output during rainfall events. To overcome this problem, some studies take additional samples during rainfall events to more accurately assess catchment water quality output. This sampling method does help to capture the high nutrients and sediment output, but resulting data is not collected probabilistically.

As shown in Table 1.1, nearly all past studies rely on a regression model for detecting changes, where least-square regression is used to fit the model. This method assumes the data has been collected using a probabilistic sampling design. This allows the assumption of independent observations to be made and makes least-squares model fitting valid. However, neither the fixed interval sampling nor the event-based sampling method is probabilistic. Therefore, studies using these data need to consider the auto-correlation between samples.

One approach is linear mixed models (LMM) (Lark and Cullis, 2004). This model accounts for auto-correlations between samples and gives an unbiased estimate of the variances; it allows statistically valid hypothesis testing which is crucial in change detection studies. Lessels and Bishop (2013) used LMM for predicting water quality using stream discharge and turbidity from two catchments in south-east Australia.

#### *1.3.4. Past studies have ignored the effects of events and hydrograph differences*

A common method used in past studies investigating water quality compares average yearly water concentrations with pre-wildfire averaged water quality conditions. For example, a comparison of water quality condition in the first year post-wildfire is used to detect wildfire effect and compare the following year's water quality concentration output with pre-wildfire water quality concentration to observe the catchment recovery rate. However, a higher percentage of catchment sediments and nutrients are transported into the catchment during events. The sediments and nutrients output from a catchment is effected by seasonal differences (Singh et al., 2004) and event antecedent conditions (Asselman, 2000). Thus, the same type of events needs to be compared to understand the real change within each type of events. To compare post-wildfire events to corresponding pre-wildfire events, events should be grouped based on the shape of their hydrography. One popular way of grouping events is clustering (Arabkhedri et al., 2010, Spate et al., 2003).

#### *1.3.5. Empirical models are commonly used in past studied*

While empirical models are useful for describing responses of catchment to wildfire events, their use limits the ability of past studies to:

- Investigate the effect of water quality change caused by different parts of the catchment (e.g. due to differences in terrain, vegetation and soil);
- Investigate the correlation between soil, vegetation, and post-wildfire water quality change to find the wildfire sensitive area of the catchment.

Most past studies have used empirical models for monitoring catchment water quality. However, the empirical models used do not include any spatial variability inherent in the catchment. The effect of wildfire on erosion process is spatially variable (Sheridan et al., 2007a). The physical spatial differences between catchments together with spatially variable

climate inputs result in differences in post-wildfire nutrients delivery between different catchments (Martin and Moody, 2009). Additionally, empirical models can only be used to detect a change and summarises the change while physical-based distributed model can help understand the changing process and why the change occurs. A lack of either spatial or temporal data is the main reason why past studies of water quantity and quality exports has been mainly based on empirical relationships (Prosser et al., 2001). When temporal and spatial data (such as soil type, elevation, and land-use) are sufficient for creating physical-based models, they should be used for a better description of the catchment (Prosser et al., 2001). As the availability of spatial data increases and the need for a better understanding of different components of change in different parts of the hydrological cycle, physical-based hydrological models are becoming important for studying the effects of land-use change on the hydrological cycle (Ghaffari et al., 2010).

The use of physical-based models for predicting the effect on wildfire on water quality is very limited. The study by Feikema et al. (2011) is one of the few studies that has used the E2 model with gridded rainfall data to estimate the impact of wildfire on catchment water quantity and quality. Their study investigated the changes in sediment and nutrients of four catchments in south-eastern Australia. They achieved good calibration results and found a significant effect of wildfire on water quality. They emphasized the importance of sufficient, accurate spatial data on model accuracy and indicated that correct prediction of land-use change effect on water quality can only be achieved if there are reliable historic observations of water quality for the specified change in land use.

The Soil and Water Assessment Tool (SWAT) is one of the most widely used physical-based models for predicting the long-term impact of land use change on catchment flow and water quality. The model requires recorded catchment spatial characteristics (land-use, slope, and

soil map) and weather data (rainfall, solar radiation, temperature, and wind speed) for prediction of water quantity and quality. Despite this, the number of studies investigating the effect of wildfire on changes to catchment water quality using SWAT is very limited. SWAT has been more commonly used in studies for predicting land use change caused by management decisions (Ghaffari et al., 2010, Pisinaras et al., 2010, Rostamian et al., 2008). One example is Pisinaras et al. (2010) who used SWAT to analyse the effect of wildfire on catchment water quality. Notably, the catchment was only calibrated and validated using observed data from an unburnt catchment; no burnt catchment data was used in the study. Nevertheless, the study demonstrated a way to estimate the wildfire effect on catchment water quality using SWAT.

A lack of high resolution data is one reason why physical-based models are not readily used for investigating the effect of wildfire on water quality studies. The accuracy of physical-based models relies heavily on the accuracy and resolution of input spatial data such as land-use data and soil survey maps. Soil classes are one of the most important primary units in physical-based models. Inskeep et al. (1996) used a model for predicting solute transport in soil and concluded that model prediction based on low spatial resolution might not accurately reflect the transport processes. In a similar soil study, Wilson et al. (1996) observed that model output errors significantly increased with a decrease in spatial resolution of the soil maps. In the case of simulating water quantity and quality, a change in soil properties using a physical-based model affects catchment infiltration and influences stream sediment and nutrients load.

Geza and McCray (2008) compared two sets of soil inputs using SWAT modelling and concluded that the accuracy of soil inputs is important for modelling water quality and nutrients output predictions. Properties for Australian soil types are not provided in SWAT,

therefore, users need to calculate the soil inputs required. A commonly used soil map in Australia is the Digital Atlas of Australian Soil map (McKenzie et al., 2000). Using this map as a source of data, Saha et al. (2014) modelled streamflow using SWAT for a catchment in south-eastern Australia. Their study found that soil parameters were inaccurate in some of the areas investigated which introduced inaccuracy into the model. Most soil information in Australia has come from individual surveys resulting in a significant shortage of soil data coverage in Australia at a suitable scale. To improve this, the Soil and Landscape Grid of Australia (SLGA) was recently introduced by Grundy et al. (2015). The SLGA is a grid-based map of soil properties rather than soil type. This product has created new possibilities for using such soil inputs in physical-based models in Australia.

## 1.4.Objective

With the above problems and concerns found for past studies investigating the effect of wildfire on water quantity and quality, this thesis aimed at:

1. Assessing the impact of 2001/2002 wildfires in New South Wales, Australia using empirical and physical-based distributed models with focus on dealing with sporadic water quality data.
2. Using physical-based distributed models to identify the cause of the post-wildfire water quantity and quality change and find the wildfire sensitive areas in forested catchments.

To achieve these aims, the following steps are used:

- a. Use LMM to:
  - i. Assess the medium- to long-term impacts of wildfire on water quality in forested catchments around Sydney based on ten years pre-wildfire and ten years post-wildfire catchment hydrology data to address problems detailed in 1.3.1 and 1.3.2.
  - ii. Present an approach using LMM to detect change based on sparse (as compared to discharge) water quality observations to address problems detailed in 1.3.3.
- b. To address the problem identified in 1.3.4, a matching event approach was used to:
  - i. Test the effect of wildfire on water quality (TSS, TN, and TP) during event flows.

After the above method, SWAT models were calibrated and validated using ten years of pre- and post-wildfire data for both control and burnt catchments to detect the effect of wildfire on

water quality during the ten years post-wildfire period. The calibrated models are then used to investigate the effect of wildfire on (1) catchment soil, (2) catchment vegetation and the follow-on effects on water quality. Differences in water quality output resulting from sub-catchment topography differences were also investigated. This involved the steps as shown below:

- c. Build a SWAT model to:
  - i. Test the effect of wildfire on water quantity and quality.
  - ii. Investigate the ability of the SWAT model to analyse the wildfire induced hydrology change in response to a single rainfall event.
- d. Modify soil and land-use inputs used in the SWAT model to:
  - i. Investigate the effect of wildfire on water quantity and quality output related to a wildfire-related change in soil carbon.
  - ii. Simulate and test the effect of wildfire on vegetation to investigate model sensitivity to wildfire-related vegetation change.
- e. Extract the flow and TSS output from subcatchments and compare their correlation to catchment size, slope, elevation, and soil properties.

Empirical models provide a “lumped” method for investigating disturbance. In the empirical method, this thesis focused on investigating wildfire effect on water quality only, the change of flow has been analysed for the same catchments by Heath (2014) using empirical approaches, thus, is not included in this thesis. The physical-based distributed model here has focused on both flow and TSS change. Beside detecting the change, the SWAT model method is used to investigate the cause of wildfire and identify the wildfire sensitive areas in the catchments. The use of these methods would give a better understanding of wildfire effect on forested catchment and provide useful suggestion for catchment management.

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# **Chapter 2**

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## **2. Assessment of the Decadal Impact of Wildfire on Water**

### **Quality in Forested Catchments**

**Abstract:**

Wildfire can have significant impacts on hydrological processes in forested catchments and a key area of concern is the impact on water quality, particularly in catchments that supply drinking water. Wildfire effects runoff, erosion, and increases the influx of other pollutants to catchment waterways. Research suggests that suspended sediment and nutrient levels increase following wildfire. However, past studies on catchment water quality change have generally focused on the short-term (1-3 years) effects of wildfire. For appropriate catchment management, it is important to know the long-term effect of wildfire on catchment water quality and the recovery process. In this study, a statistical analysis was performed to examine the effect of 2001/2002 Sydney wildfire on catchment water quality. This research is particularly important as the catchments studied provide drinking water to Sydney. Linear mixed models were used in this study in an ANCOVA-type change detection approach to assess the effect of wildfire. We used both burnt and unburnt catchments to aid the interpretation of the results and help disentangle the effects of natural climate variation and the effect of the wildfire. The results of this study showed persistent long-term (10-year) effects of wildfire including increases in total suspended sediment concentrations (64% higher than unburnt catchments), total nitrogen concentrations (48% higher), and total phosphorus (40% higher).

## **2.1.Introduction**

Wildfire can have a significant impact on the hydrologic cycle of forested catchments due to changes in the surface vegetation and canopy cover, combined with ash sealing of soil pores (Shakesby and Doerr, 2006, Ice et al., 2004). This is of particular concern for water quality (WQ) in forested catchments (Crouch et al., 2006, Lane et al., 2010) as in many cases they supply drinking water to urban communities (Neary et al., 2009). The frequency of wildfire is expected to increase due to climate change (Lucas, 2007). In response, there has been an increase in the number of studies on the effect of wildfire on catchment hydrology (Lane et al., 2006, Smith et al., 2011, Kuczera and Parent, 1998). Suspended sediment and nutrients (phosphorus and nitrogen) are two important measures of catchment water quality (Drewry et al., 2006). An increase in total suspended sediment (TSS) in rivers limits light penetration and effect primary productivity within the river (Wood and Armitage, 1997). Increases in total phosphorus (TP) and total nitrogen (TN) levels can result in excessive algal growth (Townsend and Douglas, 2004).

Increases in TSS and nutrient levels arise from the effects of wildfire on erosion, runoff, infiltration, and the combustion of organic matter. When a catchment is burnt the wildfire reduces surface vegetation cover, which increases the percentage of rainfall available for runoff. Furthermore it decreases evapotranspiration which increases overland flow and subsequently the amount of flow in streams (Moody and Martin, 2001). These conditions promote higher levels of soil erosion. Erosion can also be driven by the reduction in infiltration as ash seals soil pores and soil heating produces hydrophobic soil layers (Neary et al., 2005, Onda et al., 2008, Heath et al., 2015). Additionally, during a wildfire, burning and heating of organic matter releases charcoal, ash, heavy metals, and other stable nutrients that might be previously unavailable for transport into waterways (Johansen et al., 2003).

Table 2.1 presents a summary of studies that assessed the impact of wildfire on WQ with a focus on TSS, TP, and TN. Most only examined the effects 1-4 years post-wildfire which identifies a gap in knowledge about the long-term impacts. This is especially important given that some studies have shown wildfire can impact flow for decades post-wildfire (Kuczera, 1987). Challenges facing long-term wildfire research are centered around the lack of pre-wildfire water quality data and more generally the need for fine-scale spatial and temporal data both before and after wildfire to increase the sensitivity of change detection approaches. Shakesby and Doerr (2006) identified that lack of pre-wildfire data as a major problem in relating post-wildfire erosion rates to long-term conditions. In some studies such as Bladon et al. (2008), they were unable to compare their catchment state with catchment pre-wildfire conditions due to the absence of pre-wildfire WQ data. The exception is Lane et al. (2006), Oliver et al. (2012) who both had long-term pre-wildfire data. In terms of assessing the impacts of wildfire on WQ both a long pre- and post-wildfire dataset is required.

Another issue with past studies is the nature of sampling in terms of how well they represent the variation in WQ, which also relates to the validity of the statistical models fitted to the data to assess change. For example, Oliver et al. (2012) indicated their pre-wildfire WQ data was collected on a monthly time step and occasionally during an event. This is a common method used in most catchments WQ monitoring programs (Bartley et al., 2012) due to the high cost of environmental sampling. Past work has shown that monthly sampling does not reflect the range of hydrological conditions in a catchment, especially over the long-term (Lessels and Bishop, 2015a).

In order to detect change, least-square regression is used to fit a regression model of some form in nearly all cases. However this assumes the data has been collected using a probabilistic sampling design which in this context involves randomisation of the sample

times. This allows us to assume that the observations are independent which makes least-squares model fitting valid. However, in the studies in Table 2.1, the fixed interval sampling or event-based sampling is not randomised. Therefore, we need to account for potential auto-correlation by using model-based approaches as exemplified by linear mixed models (LMM) (Lark and Cullis, 2004). This approach calculates an unbiased estimate of the variances and allows statistically valid hypothesis testing which is crucial in change detection studies.

In terms of detecting WQ change, a typical approach is to account for the difference in discharge between pre-and post-wildfire periods with an analysis of covariance (ANCOVA) model which compares two regression lines to detect whether there is a difference between the model parameters, e.g. slope, for the pre- and post-wildfire periods (Salavati et al., 2016, Ravichandran, 2003). Alternatively, a paired approach may be adopted where a neighbouring unburnt catchment is used. During the pre-wildfire period a regression model between WQ from these 2 catchments is created, the model is then used to predict the burnt catchment's WQ for the post-wildfire period. The observed prediction error indicates a possible wildfire effect. Importantly, a paired study requires high similarities between the paired catchments in terms of slope, soil, land use and climate conditions. An issue with this approach and an ANCOVA is that the regression model which uses discharge only to model WQ may be overly simplistic and does not represent antecedent conditions and hysteresis, i.e. rising/falling limb, which control the discharge-WQ relationship (Drewry et al., 2009).

**Table 2.1 Past Studies on wildfire effect on WQ.**

Study	Description	Pre-wildfire data / post-wildfire data	Method <sup>1</sup>	Limitation
Lane et al. (2006)	Severe wildfire burnt over 1 million ha of forested land in Australia	10 years / 2 years post-wildfire	ANCOVA (with control) <sup>2</sup>	Long-term impact were hard to compare due to the high variations in climate and the effect of logging.
Bladon et al. (2008)	The effect of wildfire on post-wildfire nitrogen concentration with 3 burnt catchments and 2 unburnt catchments	NA / 3 years	ANCOVA (with control)	Lack of pre-wildfire WQ data and there is a shortage in assessing the initial wildfire effect on WQ and recovery of the catchments.
Mast and Clow D.W (2008)	Post-wildfire WQ change after a wildfire in Glacier National Park,USA	5 years/ 4 years	Compare average concentration	No control (unburnt) catchment studied. Result effected by snow melt event ( first flow released during long period of time).
Townsend and Douglas (2004)	The effect of a wildfire on stream WQ and catchment water yield in a tropical savanna (North Australia) excluded from wildfire for 10 years	3 years /10 <sup>th</sup> year post-wildfire	ANCOVA (No control)	Only the WQ 10 years post-wildfire was described, no earlier observation was compared with pre-wildfire data.
Malmon et al. (2007)	Sediment change post-wildfire in New Mexico	2 years / 3 years	ANCOVA (No control)	Only 2 years pre-wildfire data was used in the study.
Kunze and Stednick (2006)	Sediment change post-wildfire in 2 burnt catchments in Colorada, USA.	NA / 3 years	ANCOVA (with control)	No available pre-wildfire data. First year post-wildfire, WQ data were collected only after events.
Oliver et al. (2012)	Analysis the WQ change post a severe wildfire in lake Tahoe basin, USA	10 years / 2 years	ANCOVA	Pre-wildfire sample collected monthly and during events, no information on daily or annual discharge.
Hauer and Spencer (1998)	Phosphorus and nitrogen concentration change after wildfire in Columbia	NA / 5 years	Compare average concentration	Lack of pre-wildfire data Limited data were collected at some sites due to funding limit.

1 ANCOVA method: using regression model to account for the effect of flow on WQ.

2 Unburnt catchment is used as a control, the pre- and post-wildfire WQ change are compared.

Additionally, most past studies (such as studies mentioned above) used empirical models for water quality predicting and monitoring, this process ignored the topographic differences e.g. soil, topography, in the modelling process (Lessels and Bishop, 2015b). However, these models require high level of input spatial and climate data which is not always available for most studies. Thus, this method is not discussed in this study.

In summary gaps in existing research are:

- lack of studies showing > 5 years post-wildfire impact on WQ;
- lack of studies with adequate pre- and post- wildfire data;
- past studies predominantly use least-square regression models for change detection without accounting for auto-correlation in the data and therefore hypothesis testing is erroneous;
- past studies rely on simple discharge-WQ models to detect change due to wildfire.

The 2001/2002 wildfires around Sydney provide an opportunity to address all of these issues due to the fact that they were widespread and predominantly in water supply catchments meaning that the pre- and post-wildfire WQ data was numerous. More specifically this work aims to

- assess the long-term impacts of wildfire on WQ in the forest catchments around Sydney based on a 10 years pre-wildfire and 10 years post-wildfire dataset;
- present an approach using LMM to detect change based on sparse (as compared to discharge) WQ observations to address the shortcomings identified previously.

## **2.2. Materials and Methods**

### *2.2.1. Study area*

In the period between December 3rd 2001 and January 14th 2002, wildfire burnt an area of approximately 7333 km<sup>2</sup> around Sydney, Australia (Winter and Watts, 2002). Much of the area burnt was located in the catchment area of Lake Burragorang, which is impounded by Warragamba Dam and provides 80% of Sydney's drinking water and within the catchment there are approximately 200,000 residents (Lessels and Bishop, 2013). Due to its importance, many streams in the area are monitored for water quality by a government agency, WaterNSW, and have WQ measurements before and after the wildfire. The criteria used to select monitoring stations include: have adequate WQ data pre- and post-wildfire, and also have extensive forest cover (>65%) in the catchment area above each monitoring station, which yielded a total of seven monitoring stations. These criteria were used as the focus of this work is the impact of wildfire on the WQ of forested catchments. The location of the 7 catchments is presented in Figure 2.1 where four catchments were unburnt (control) and 3 catchments were burnt.

The four burnt catchments have an area ranging from 56 km<sup>2</sup> to 436 km<sup>2</sup>, had forest cover from 69-97% pre-wildfire, and annual rainfall ranged from 694 mm to 1182 mm. The three unburnt catchments have areas that range from 72 km<sup>2</sup> to 1447 km<sup>2</sup>, had forest cover from 73-90% pre-wildfire, and annual rainfall range from 889 mm to 1263 mm. A summary of the key features of the study catchments is presented in Table 2.2.

10 years pre-wildfire and 10 years post-wildfire flow and WQ data were provided by WaterNSW. For each catchment, flow was recorded at an hourly interval for the entire study period (1991-2011). For most catchments, WQ data were sampled on a monthly basis before 2000. After 2000, automatic event samplers were installed at most of the sites, which are designed to automatically collect samples during event-flow. Flow values that exceed the annual 90th percentile of stream flow were defined as event-flow. In this work we focus on TSS, TP, and TN as the response variables.

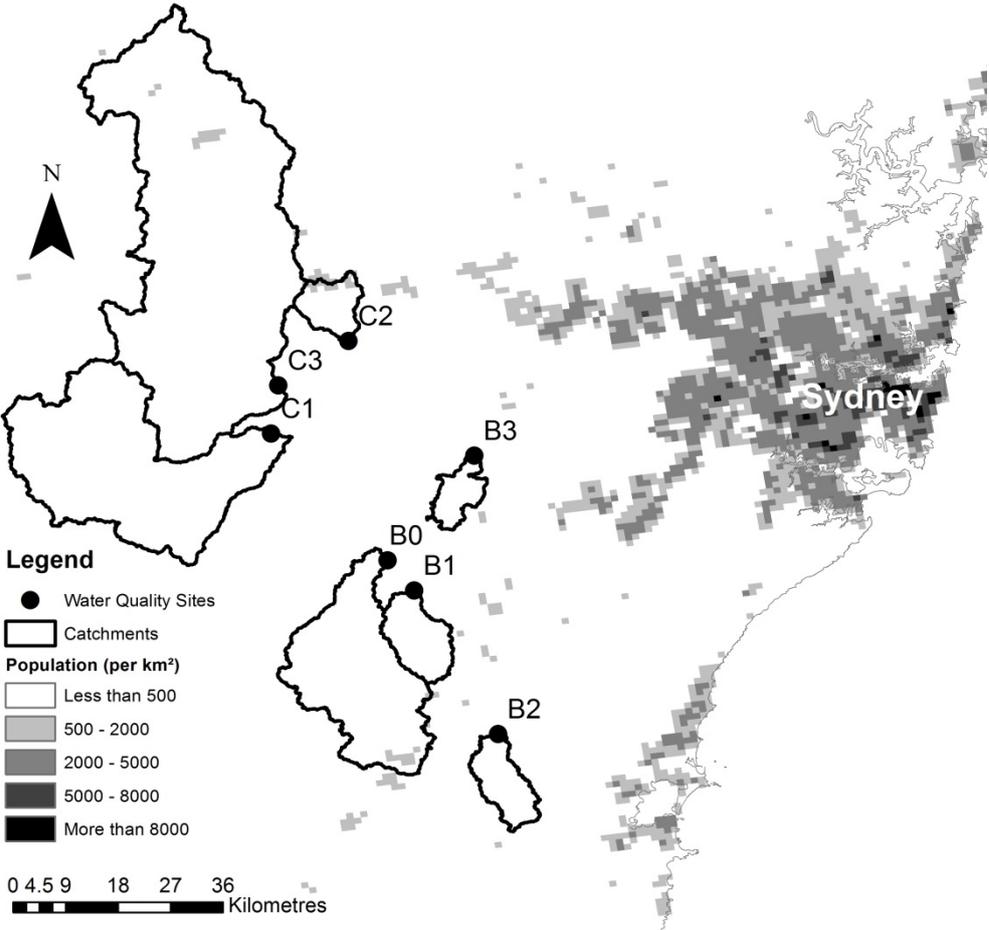


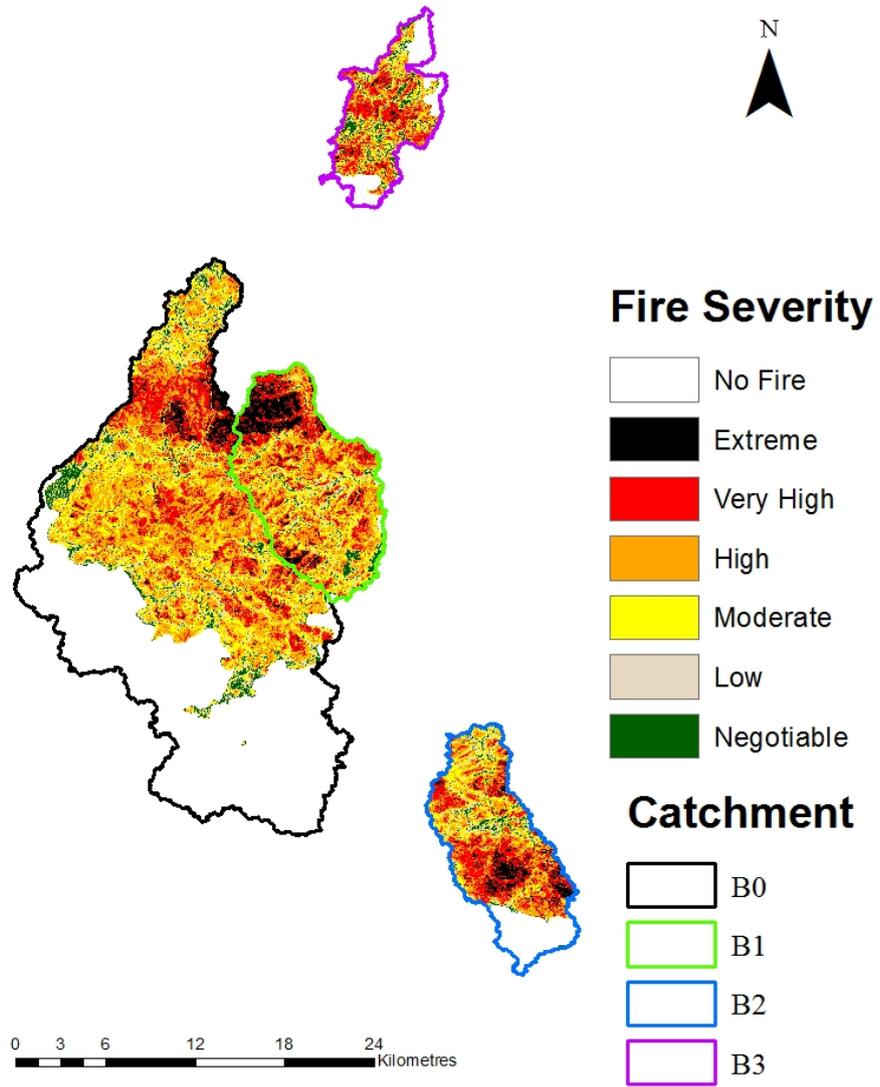
Figure 2.1 Location of the studied area

**Table 2.2 Catchment characteristics.**

Catchment	Area (km <sup>2</sup> )	% Burnt	% Grass land	% Forest	% Urban	Annual rainfall (mm)	Mean Flow (ML/ year)
C1	719	0	9	90	0	932	3445519
C2	72	0	0	85	14	1263	341462
C3	1447	0	25	73	1	886	2968759
B0	436	57	12	86	1	857	576706
B1	104	100	2	97	0	824	137954
B2	88	83	4	95	0	1182	420889
B3	56	79	29	69	1	694	240910

### 2.2.2. Wildfire severity

In this study, the three catchments not burnt during wildfire were used as control catchments (C1, C2, and C3) to interpret the change detection results rather than being strict experimental controls. The four other catchments were heavily impacted by the wildfire of 2001 (Shakesby et al., 2007), especially catchment B1. The severity of wildfire was classified by Heath et al. (2014) based on the satellite interpretation of the wildfire behavior in the burnt catchments. The fire severity map is showed in Figure 2.2. Catchment B1 was intensely affected by extreme wildfire, as showed in Table 2.2, 100% of the catchment was burnt in this wildfire with the most intense wildfire occurring next to the monitoring station. Similar to B1, catchment B0 was significantly affected by extreme wildfire near the monitoring station. However, compared to B1, the percentage of area burnt in B0 (57% burnt) catchment is smaller than B2 (83% burnt) which also experienced less severe wildfire around the monitoring station compared to the other burnt parts of the catchment. The wildfire severity of catchment B3 (79% burnt) was more evenly distributed.



**Figure 2.2 Wildfire severity maps of burnt catchments (Heath et al. 2014)**

### 2.2.3. Catchment terrain

Figure 2.3 presents elevation maps of the studied catchments. It shows the differences in elevation and terrain shape between the catchments. Catchment B0 has an elevation range from 105 m to 867 m, median slope of 8%. Catchment B1 has an elevation range from 175 m to 632 m, median slope 10%. Compared to these two catchments, catchment B3 and B2 are relatively flatter. Catchment B3 has a median slope 3%, elevation ranges from 205 m to 519 m. B2 has a minimum elevation of 328 m, maximum elevation of 777 m, median slope 4%.

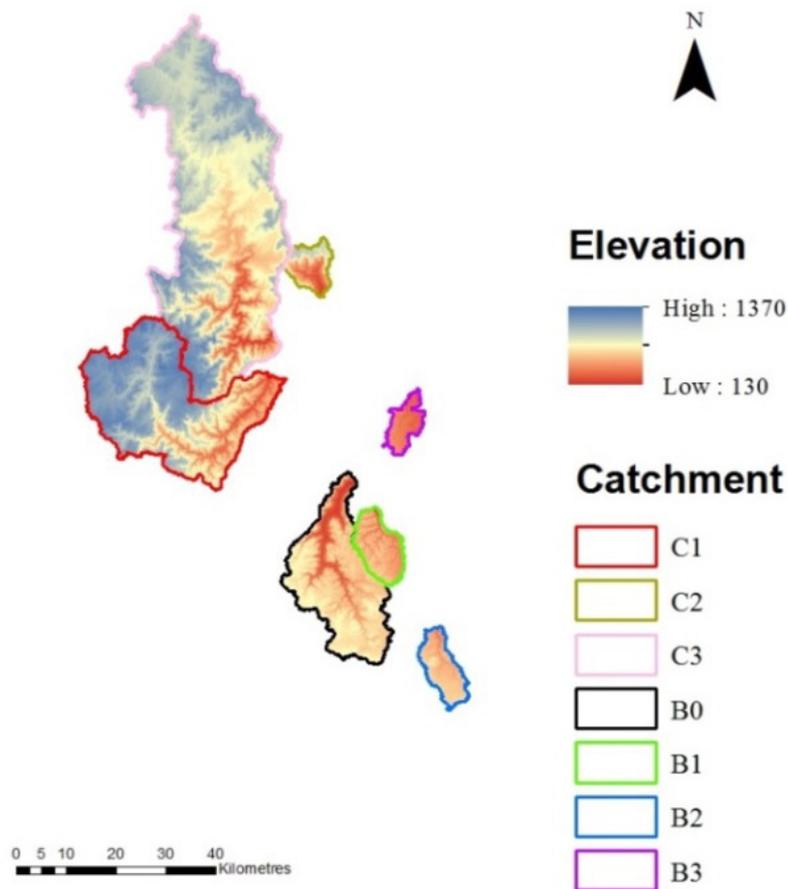


Figure 2.3 Elevation maps of studied catchments

#### *2.2.4. Change detection method*

In order to assess the long-term effect of wildfire on WQ, a linear mixed model (LMM) was used, with the focus being on modelling TSS, TN, and TP concentrations. The use of a linear mixed model (LMM) allows for an auto-correlation in the residuals to be modelled (Lessels and Bishop, 2013). This is crucial as the WQ samples have been collected systematically, so we cannot assume we have independent observations which would allow us to use least-squares regression (Lark and Cullis, 2004). The impact of this incorrect assumption would be biased standard errors which has follow on effects on variable selection and hypothesis testing (Lessels and Bishop, 2013).

In this work we used a similar approach to Lessels and Bishop (2013), who used flow and derivatives of flow to model WQ. The LMMs were fitted using the *geoR* package (Ribeiro Jr and Diggle, 2001) in R (R Core Team, 2015). To detect change due to the wildfire, a wildfire dummy variable (0 for pre-wildfire period, 1 for post-wildfire period) was created and used as a predictor in all models irrespective of whether the catchment was burnt or unburnt. Our assumption is that: in the burnt catchments, the presence of the wildfire dummy variable in the final model indicates that there was an impact of wildfire. The value of the coefficient associated with the wildfire dummy variable indicates the mean change in WQ between pre- and post-wildfire periods, assuming all of the other predictors are held to be constant. The interpretation of this has to be considered in the context of the unburnt catchments, which in an idealised situation would have a non-significant wildfire dummy variable, and therefore the coefficient would equal to 0. This approach is analogous to an

analysis of covariance (ANCOVA) except here we use a more complex model to account for differences in flow and flow-related variables between the pre- and post-wildfire period, which are also related to WQ.

In addition to the wildfire dummy variable, the predictors we considered were event direction, event distance, discount flow (DF), and flow. The event distance is the time since the last event flow. An extended dry period will cause a buildup of easily erodible material in the catchment, which will cause higher concentrations (in terms of sediments and nutrients) during the first flow, and generally in the rising limb (Wang et al., 2011). The event direction specifies whether the stream is in base flow conditions, the rising limb, or the falling limb of an event. The discount factor (*DF*) value, introduced by Wang et al. (2011) represents a weighted average of past flow that provides a measure of antecedent conditions. The DF value with discount factor *d* is defined as;

$$DF(d) = \frac{\sum_{i=1}^j d^{j+1-i} \hat{q}_j}{\sum_{i=1}^j d^{j+1-i}} \quad (2.1)$$

In summary, a weight, *d*, is given to historical observations to calculate a temporally weighted average of past flow. This weight diminishes exponentially with time at a rate that varies with the DF value. In general, a smaller DF value indicates recent flows have more weighting, while a large DF value indicates the DF flow represents longer term flow conditions (Wang et al., 2011). For the LMM, five levels of DF (0.50, 0.75, 0.9, 0.95 and 0.99) were considered as candidate predictor variables. The predictors were selected using

backward elimination based on Wald tests using a P-value of 0.05 as the criteria for keeping predictors in the model.

After the model is predicted, the partial regression coefficient of the “wildfire” dummy variable was back-transformed to assess the impact of wildfire in terms of the proportional increase or decrease in its effect on WQ on the original scale.

#### 2.2.5. *Assessment of model quality*

Leave-one-out cross-validation was used to assess the model quality of the LMM. Measures of model quality were assessed by the mean and median standardised-squared prediction error (SSPE), mean error (ME), root-mean-square error (RMSE) and Lin’s Concordance Correlation Coefficient (Lin’s CCC) The SSPE for time,  $i$ , is

$$SSPE(i) = \frac{\{z(i) - \hat{Z}(i)\}^2}{\sigma_i^2} \quad (2.2)$$

where  $z$  is the observed value,  $\hat{Z}$  is the predicted value, and  $\sigma_i^2$  is the prediction variance. A mean SSPE value close to 1 indicates that model estimates of uncertainty (the prediction variances) match the prediction errors meaning that model correctly represents the variation in WQ (Lark and Cullis, 2004). This is crucial as the variance estimates associated with the partial regression coefficients are used to perform variable selection, and ultimately assess the change in WQ attributable to wildfire.

Root-mean-square error (RMSE) is the standard deviation of the residuals, it is a measure of the accuracy of the model. As the predictions get better, the RMSE becomes closer to 0.

The mean error is a measure of the bias of the model (2.3);

$$ME = \frac{1}{n} \sum_{i=1}^n z(i) - \hat{Z}(i). \quad (2.3)$$

It measures the average tendency of the predicted values to be larger or smaller than the observed values. The optimum value is 0.

Lin's CCC ( $\rho_c$ ) is a measure of how far pairs of observed and predicted values deviate from the line of perfect concordance, that is the 45 degree line of a scatter plot of observed versus predicted. It is scale-independent and allows comparisons between properties with different magnitudes or units. The perfect value of Lin's CCC is 1. When the two variables compared have a length of N,  $\rho_c$  is calculated as showed below (2.4);

$$\rho_c = \frac{2s_{xy}}{s_x^2 + s_y^2 + (\bar{x} - \bar{y})^2} \quad (2.4)$$

where  $\bar{x}$  and  $\bar{y}$  are the corresponding mean,  $s_x^2$  and  $s_y^2$  are variance,  $s_{xy}$  is the covariance.

The flow and WQ data were log transformed to meet the assumption of normality for the LMM.

## **2.3.Results**

### *2.3.1. Exploratory Data Analysis*

A summary of the available water quantity and quality data is shown in Table 2.4. The number of observations for WQ data is limited to around one per month; therefore, 200-300 observations are available for each catchment during both the pre-wildfire and post-wildfire period. Some big exceptions are C1 which had 500+ observations during the post-wildfire period and B1 which only had 69 observations collected in the post-wildfire period. For catchment B1, most available data are collected before 2007, this might have resulted in a higher maximum and mean TSS value in this catchment because the catchment has had less time to recover during the post-wildfire period.

During 2001 to 2009, in the post-wildfire period, the studied catchments were affected by the millennium drought (van Dijk et al., 2013), especially during the first 5 years post-wildfire. The millennium drought was described as the worst drought on record for southeast Australia. Table 2.3 presented the average annual rainfall estimated for each catchment using Thiessen polygons with data obtained from nearby Bureau of Meteorology weather stations. As summarised in Table 2.3, all catchments experienced a rainfall decrease during the first 5 years post-wildfire period. The decrease in catchments B0, B1, and B2 are most severe.

**Table 2.3 Average annual rainfall during pre-wildfire, 1-5 years post-wildfire and 6-10 years post-wildfire for all catchments (ML/day)**

Catchment	Pre-wildfire	1-5 years post-wildfire	6-10 years post-wildfire
C1	912.79	796.50	1111.44
C2	1214.06	1080.18	1556.01
C3	851.94	757.99	1091.89
B0	903.51	697.83	914.69
B1	869.25	671.38	880.01
B2	1246.38	962.65	1261.80
B3	670.72	592.18	849.14

As a result, all the catchments showed a lower maximum flow value in the post-wildfire period compared to the pre-wildfire period (Table 2.4). A lower TSS maximum value is also observed in most catchments except catchment B1. Catchment B1 had a larger maximum TSS concentration during the post-wildfire period. This significant difference might be a result of the wildfire effect. In contrast to the maximum value, a higher post-wildfire median flow value is observed in most catchments except B0 and B1. A higher post-wildfire median TSS concentration is observed in all catchments, as compared to the pre-wildfire period. A higher post-wildfire maximum value of TN is observed in C3, B0, B1, and B2, as compared to the pre-wildfire period. In terms of TP a higher post-wildfire value is observed in C3, B0, and B1. Most catchments observed a higher median TN and TP value during the post-wildfire period except catchment C2.

The change in the maximum values might indicate a change in flow duration curve, this might result in a WQ concentration change. An example of duration curves pre- and post-wildfire is shown for catchments C1 and B0 in Figures 2.4 and 2.5. During the post-wildfire period, the catchments experienced a change in the distribution of flow and WQ as represented by the duration curves. The flow duration curve for catchment C1 shows that

compared to the pre-wildfire period, the post-wildfire period showed a decrease in flow for the top decile and an increase in the middle decile of the graph. This explained the increase in median value of the data as summarised in Table 2.4. The bottom decile of the flow duration curve showed a similar pattern to pre-wildfire period. A similar pattern was also evident in the WQ duration curves for the control catchments, a decrease in top and bottom decile of the curve and an increase in the middle decile. Catchment B0 experienced a greater rainfall decrease, which result a more obvious decrease in both peak flow and base flow in the flow duration curves as shown in Figure 2.5. Opposite to the control catchment, a decrease in flow in the middle decile of the graph is observed. However, an upshift of the WQ duration curves was observed in all WQ duration curves for catchment B0. The change in the maximum and median flow value and the change in duration curves shows the WQ change might be effected by the change of flow, and it is important to account for flow when detecting the effect of wildfire on WQ.

**Table 2.4 Summary of hydrological data.**

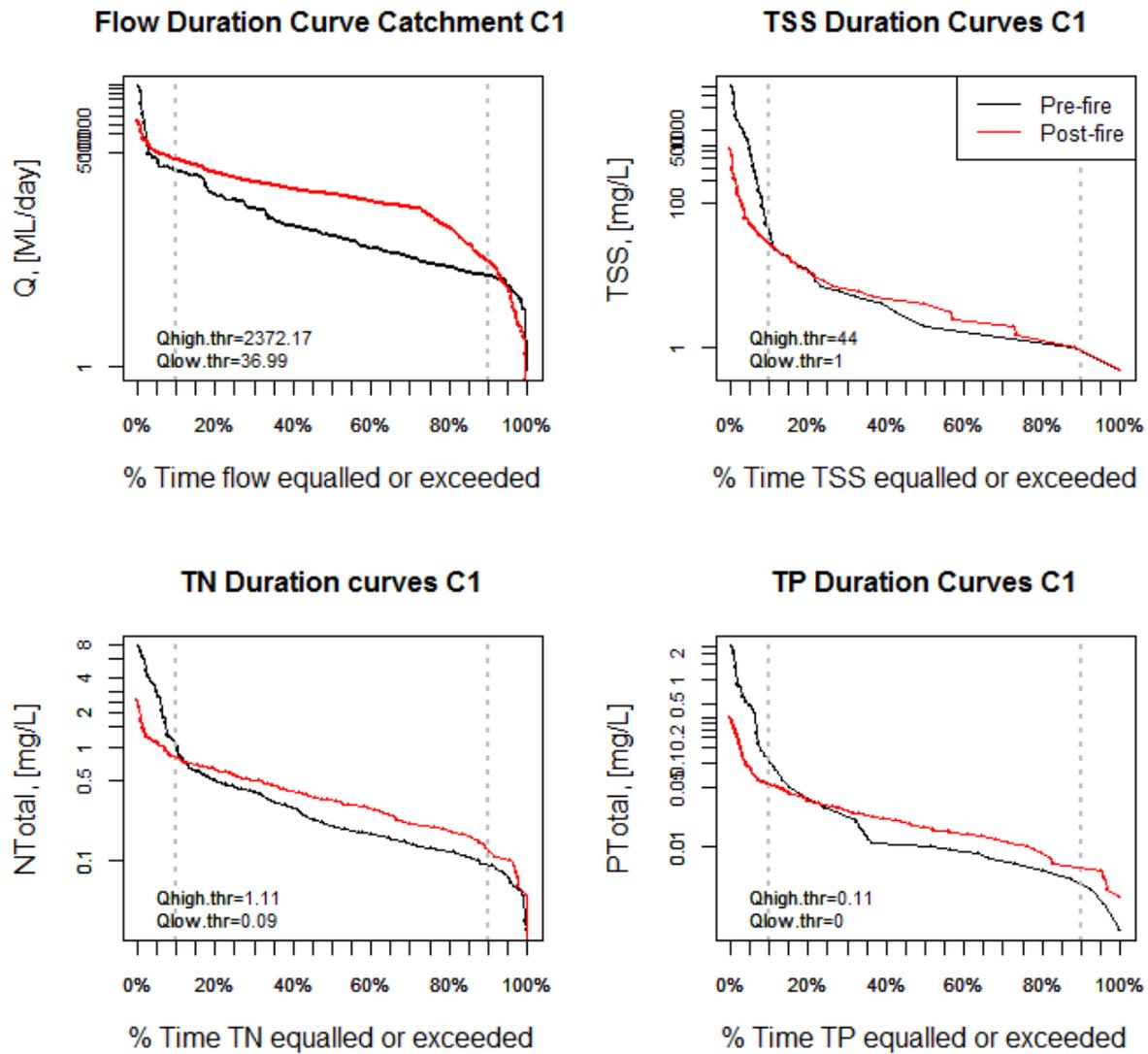
Catchment	Pre/Post-wildfire	Flow (ML/day)			TSS (mg/L)			TN(mg/L)			TP (mg/L)			Available data
		Min	Max	Median	Min	Max	Median	Min	Max	Median	Min	Max	Median	
C1	pre	0.88	65000	181.51	0.5	3829	1.00	0.03	7.52	0.20	0.001	2.42	0.01	244
	post	0.23	16673.89	908.45	0.5	532	4.00	0.005	2.25	0.31	0.003	0.34	0.02	536 <sup>1</sup>
C2	pre	5.66	6238.66	31.51	0.5	1316	3.00	0.2	15.8	1.13	0.001	1.5	0.16	220
	post	1.736	2202.96	87.48	0.5	536	6.00	0.005	2.08	0.36	0.002	0.39	0.01	284
C3	pre	11.11	101778.8	191.10	0.5	2807	1.00	0.06	7.84	0.18	0.001	0.92	0.01	213
	post	3.28	8879.39	646.18	0.5	2149	5.00	0.05	13.2	0.30	0.002	1.92	0.01	331
B0	pre	0.54	2.39	0.62	0.5	15110	1.00	0.05	6.3	0.32	0.001	0.53	0.02	288
	post	0.53	0.99	0.56	0.5	1998	7.00	0.17	11.8	0.42	0.003	2.3	0.02	126
B1	pre	1.57	6828.59	6.77	0.5	97	1.00	0.005	9.4	0.10	0.001	0.26	0.004	218
	post	0.34	1126.86	5.48	0.5	3950	1.00	0.05	21.2	0.20	0.003	2.45	0.005	69 <sup>1</sup>
B2	pre	3.43	7491.3	21.80	1	149	1.00	0.03	0.79	0.16	0.001	0.17	0.009	157
	post	1.54	4067	55.77	0.5	35	1.25	0.005	0.95	0.17	0.001	0.06	0.008	381
B3	pre	0	14299.22	9.565	0.5	803	4.0	0.05	6.8	0.42	0.001	0.73	0.01	233
	post	0	1184.46	32.29	0.5	496	7.0	0.005	2.65	0.44	0.003	0.5	0.02	351

1: Outliers compared to other catchments. Abbreviations: C = Control; B = Burnt; TSS = Total Suspended Sediment; TN = Total nitrogen; TP = Total phosphate.

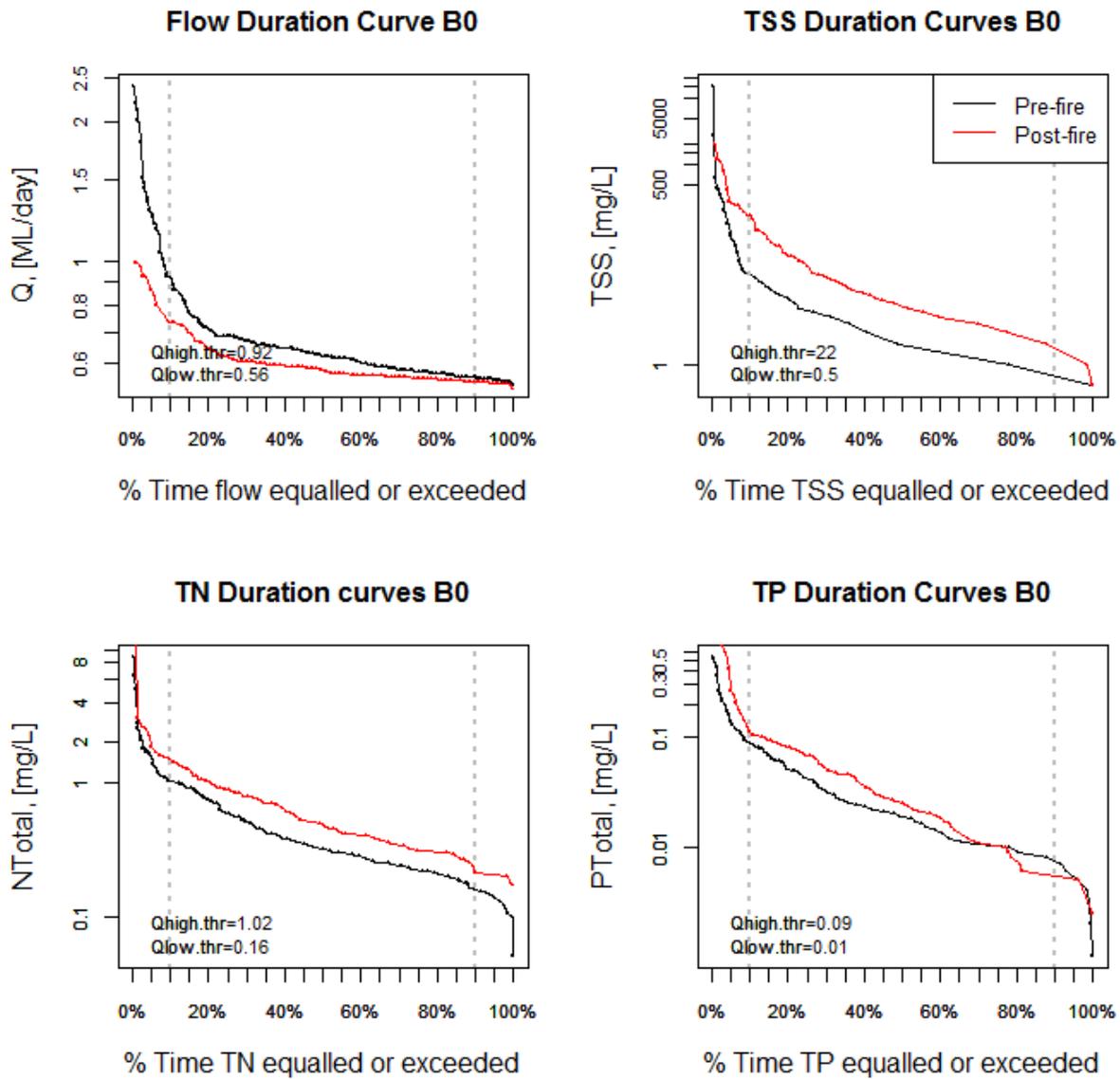
**Table 2.5 Model performance**

Catchment	TSS				TN				TP			
	Mean SSPE	ME	RMSE	Lin's CCC	Mean SSPE	ME	RMSE	Lin's CCC	Mean SSPE	ME	RMSE	Lin's CCC
C1	0.96	-0.03	0.94	0.79	0.96	-0.03	0.43	0.85	0.96	-0.04	0.61	0.83
C2	1.02	0.00	1.12	0.76	0.97	0.01	0.59	0.81	1.03	0.00	0.87	0.84
C3	0.99	-0.03	0.97	0.76	1.03	-0.02	0.55	0.78	0.99	-0.01	0.69	0.73
B0	0.98	-0.01	1.04	0.81	0.96	-0.01	0.51	0.73	0.90	-0.01	0.69	0.78
B1	0.98	-0.01	0.89	0.74	0.97	-0.01	0.87	0.71	0.97	0.00	0.84	0.70
B2	1.00	0.01	0.73	0.65	1.05	-0.01	0.48	0.74	0.98	0.00	0.54	0.70
B3	1.00	-0.03	0.93	0.77	0.96	-0.03	0.43	0.77	0.94	-0.01	0.53	0.81

Abbreviations: C = Control; B = Burnt; TSS = Total Suspended Sediment; TN = Total nitrogen; TP = Total phosphate.



**Figure 2.4** Duration curves for catchment C1. Abbreviations: C = Control; Q = Flow; TSS = Total Suspended Sediment; TN = Total nitrogen; TP = Total phosphate.



**Figure 2.5 Duration curves for catchment B0 Abbreviations: B = Burnt; Q = Flow; TSS = Total Suspended Sediment; TN = Total nitrogen; TP = Total phosphate.**

### 2.3.2. *Linear Mixed Modelling*

All models showed a mean SSPE close to 1 and a negligible bias (Table 2.5) indicating a good model performance. This means that we can be confident that the variances are unbiased and our variable selection is valid. The model performance was also quite consistent between catchments and WQ variables as evidenced by the Lin's CCC values ranging from 0.65-0.85 for all models. Each catchment had a different combination of predictors for predicting TSS, TN and TP (Table 2.6, 2.7, and 2.8). All models found flow to be a significant predictor for predicting WQ. Furthermore, models for predicting TSS generally found event direction to be a useful predictor. Much less (2 models in TN and 3 models in TP prediction) catchments found this to be significant in models predicting TN and TP. One possible reason is TN and TP includes soluble N and P which are not as tightly coupled to runoff and erosion events. The models for C2 and B2 as shown in Table 2.6, have indicated both event direction and event distance as a predictor for TSS while other models included either event direction or event distance. C3, B0, B1, and B3 models indicated wildfire as a predictor for TSS. For TN, model C2, B0, B1, B2, and B3 predicted a wildfire effect. For TP, catchment C2, B1, and B2 indicated that wildfire is a significant predictor.

**Table 2.6 Selected predictors for model predicting total suspended solids**

TSS	logFlow	eventDirection	eventDistance	DF50	DF75	DF90	DF95	DF99	wildfire
C1									
C2									
C3									
B0									
B1									
B2									
B3									

**Table 2.7 Selected predictors for model predicting total nitrogen**

TN	logFlow	eventDirection	eventDistance	DF50	DF75	DF90	DF95	DF99	wildfire
C1									
C2									
C3									
B0									
B1									
B2									
B3									

**Table 2.8 Selected predictors for model predicting total phosphorus**

TP	logFlow	eventDirection	eventDistance	DF50	DF75	DF90	DF95	DF99	wildfire
C1									
C2									
C3									
B0									
B1									
B2									
B3									

**Table 2.9 Back-transformed model coefficients for wildfire dummy variable indicating effects of wildfire on WQ.**

Catchment	TSS	TN	TP
C1	X	X	X
C2	X	0.37	0.1
C3	1.46	X	X
B0	3.32	1.35	X
B1	1.84	2.88	2.45
B2	X	0.7	1.13
B3	1.32	X	X
Average for control	1.23	1	1
Average for burned	1.87	1.48	1.40
Net change (burnt-control)	0.64	0.48	0.40

\* for calculating the Average, when the effect of wildfire was not significant a value of 1 was used.

\* catchment C2 was not used to calculate the mean due the STP upgrading during the post-wildfire period.

The back-transformed model coefficients are shown in Table 2.9. Among the three control catchments, catchment C3 showed an increased in TSS during the post-wildfire period. The lower amount of available data for the C3 catchment may have contributed to this result (Table 2.4). This is because during pre-wildfire period, there were no auto-samplers, so the number of event samples would have been small, resulting in an under-estimation of the mean WQ values in the pre-wildfire period. This would not be the case in the other catchments as with more samples, the entire range of flow conditions is represented as found by the work of (Lessels and Bishop, 2015b) in the same catchments. Additionally, catchment C2 showed a decrease in TN and TP level (Table 2.9). Catchment C2 is located downstream of a sewage treatment plant (STP) which was upgraded around the time of wildfire, which would have improved the WQ in catchment C2 and effected our results, thus, the results from C2 were removed before calculating the mean effect for Table 2.9. However, the TN and TP decrease observed in the modelling process gives confidence in our approach and shows its applicability to change detection studies in general. All burnt catchments except B2 showed a wildfire effect on TSS. Catchment B1 showed the largest TSS increase during the post-wildfire period. The wildfire effect on TSS in catchment B2 was not observed. Table 2.9 also presents the average of the back transformed regression coefficient for the control and burnt catchments. The burnt catchments show a 40 – 87% increase in TN, TP, and TSS respectively, for the post-wildfire period, whereas the control catchments observed a 23% increase in TSS and no change for TN or TP.

## 2.4. Discussion

An increase in TSS value after wildfire is a main observation in many studies (Smith et al., 2011). It is also observed in this study at a decade scale. In terms of individual catchments there were fluctuations in the impacts of wildfire. On average, in the 10 years post-wildfire period, catchment B0 showed the highest increase in TSS (3.32-fold more than pre-wildfire), followed by B1 (1.84-fold increase over pre-wildfire) and catchment B3 showed a relatively lower effect (1.32-fold increase over pre-wildfire). Catchment B2 did not show a statistically significant TSS concentration change. This can be caused by several reasons: firstly, catchment B2 had a small amount of pre-wildfire data relative to the post-wildfire data. Therefore, the standard errors associated with the dummy wildfire variable would be large, making it less likely to find a significant difference. Secondly, this result could also be caused by the lower wildfire severity in the catchment. Finally, the monitoring station is located further away from most severely burnt parts of the catchment (Figure 2.1 and 2.2), which possibly make changes in WQ being modelled less sensitive to wildfire effects.

Amount the past studies observed an increase in TSS concentration, the study results varies: Malmon et al. (2007) observed 33-fold increase in TSS in their study on the water quality change 3 months post-wildfire; Sheridan et al. (2007b) observed a 32-fold increase in TSS after one year of the wildfire. Conversely, some catchments were less effected by wildfire, for example, Gallaher et al. (2002) observed a 1.76-folds increase in TSS level 5 months post-wildfire. Past studies also showed that the recovery time of catchment varies between studies based on different burnt severity and other catchment conditions, for example at one extreme, Hicke et al. (2012) found that catchment recovery to pre-wildfire conditions took 3 months post-wildfire. On the other side, another study indicates complete catchment flow condition recovery may take as

long as 150 years (Kuczera and Parent, 1998). Compared to past studies focused on the WQ in the first 3 years post-wildfire, our study tested the 10 years average effect. As a result, our predictions of the effect of wildfire on TSS in long-term are considerably smaller than studies using short-term post-wildfire data. Compare to Townsend and Douglas (2004)'s studied on the 10<sup>th</sup> year post-wildfire WQ, their study observed no obvious WQ change, our study on 10 years average WQ change observed a more obvious change. This can be explained by a few reasons: firstly, the fire severity in their catchments was low: their catchment was burnt in May, which is a wet season for the catchment. Secondly, only three years pre-wildfire data were used in their study, this may not fully reflect the pre-wildfire conditions of the catchment. Thirdly, their study tested the WQ collected on the 10<sup>th</sup> year after wildfire, this will make the WQ change observation less intense than our test on the 10 year average of post-wildfire period which includes the early years post-wildfire when the change would be larger.

Relative to TSS, the impact of wildfire on TN and TP is less pronounced (Bladon et al., 2008, Abramson, 2009, Feikema et al., 2011, Lane et al., 2008). Past studies have shown small declines to minor increases of TN and TP (0.2-, 2-fold respectively) and also large increases (between 20 to 432-fold) (Townsend and Douglas, 2004, Mast and Clow D.W, 2008, Sheridan et al., 2007a). Our LMM results showed that in long-term, a 2.88-fold increase in TN for the most severely burnt catchment, catchment B1 and 2.45-fold increase in TP. Catchment B1 has a shorter record of post-wildfire available data (up to 6 years post-wildfire only) which might be the reason for the large change in WQ. Additionally, the higher averaged change in 6 year averaged WQ concentration change compare to longer (10 years) average change demonstrated a sign of catchment recovery as WQ concentrations recover towards the pre-wildfire level. This also indicates this catchment was still significantly impacted by wildfire up to 6 years post-wildfire.

This is far longer than several other studies who found that TN and TP concentration returns to pre-wildfire level 1-2 years post-wildfire and TN may decrease in the long-term (Smith et al., 2011, Hopmans and Bren, 2007, Porporato et al., 2003). A decrease in TN was also reported by our catchment B2. The increases in TN and TP concentration during post-wildfire period may result from remobilisation of sediment store in colluvial deposits, channels and floodplain, as well as from atmospheric and runoff inputs of ash (Smith et al., 2011). The nutrient loss from unburnt forested catchments are usually low (Neary et al., 2005). In contrast, wildfire volatilises nutrients from vegetation and soil. These nutrients are either released into atmosphere or remain in the ash deposited on the soil surface (Hicke et al., 2012). Nutrients that remain in the surface ash layer may be transported into streams during run-off and erosion events (Neary et al., 2005). The amount of N and P lost from soil is directly related to the amount of organic matter destroyed during wildfire (Hart et al., 2005). One observation from our study is post-wildfire TN and TP is sensitive to flow but less sensitive to event type (event duration and event antecedent condition) than TSS. This might indicate that the post-wildfire TN and TP are less related to catchment erosion and runoff from the surface layer during rainfall events, rather a large proportion of TN and TP is transferred into streams from infiltration.

One major limitation of this study is ignoring the effect of wildfire on different parts of the hydrograph, for example base flow vs event flow. Further research should focus on examining the effect of wildfire on event WQ, and also distinguish between short-term (0-2 years post-wildfire) and medium-term (2+ years post-wildfire) impacts on WQ. Additionally, in this study, only empirical models has been reviewed and used for detecting change. Empirical models, compare to physical-based distributed model, requires less data and processing time. However, the empirical methods used here are lacking the ability to incorporate within-catchment spatial

variability, e.g. soil, topography, into the modelling process (Lessels and Bishop, 2015b). Future research should consider use distributed model for analysis of fire effect on water quality so the topography differences can be included in the modelling/analysis process.

## **2.5. Conclusion**

In this study we have used LMM to compare 10 years pre- and post-wildfire TSS, TN, and TP change after a wildfire in Australia. On average, there is a 64% TSS concentration increase, a 48% TN concentration increase and 40% TP increase during the 10 years post-wildfire period. This study has shown that wildfires can have a significant effect on water quality over long-term, decadal timescales. For efficient catchment monitoring and management, a long-term (10+ years) water quality monitoring is essential.

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## **Chapter 3**

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### **3. Change detection for assessing the effect of wildfire on water quality during event flows**

## **Abstract:**

Wildfire affects the water quality of forested catchments. Therefore, it is important to monitor the water quality during the post-wildfire period as these catchments are in many cases sources of drinking water to surrounding cities. Since most sediments and nutrients are exported during events in a forested catchment it is especially important to monitor the water quality change during high flow events. As both antecedent conditions and event size impact on water quality during events we need to compare similar events between the pre-wildfire and post-wildfire period to assess changes in water quality induced by wildfire. Past studies have been limited by data availability and influenced by the proportion of samples taken within events. In this study, we examined the effect of 2001/2002 Sydney wildfires on catchment water quality during events. Ten years pre- and post-wildfire water quality (total suspended sediment, total nitrogen, and total phosphorus) data was separated into unique hydrological events based on flow data. The events were then classified into groups using k-mean clustering based on characteristics of their hydrograph and antecedent conditions. We then compared the event mean concentrations for events within the same cluster between pre- and post-wildfire periods. We use both burnt and unburnt catchments to aid the interpretation of the results and help disentangle the effects of natural climate variation and the effect of the wildfire on catchment hydrology. We observed a decrease in total suspended sediment, total nitrogen, and total phosphorus concentration in our control catchments. For burnt catchments, we observed an increase in total suspended sediment concentration (4.14-fold), an increase (1.38-fold) in total nitrogen event mean concentration, and no observable average concentration change in total phosphorus as compared to pre-wildfire concentration.

### **3.1.Introduction**

Current research has indicated that there is an increase in the frequency of extreme weather events such as heavy rainfall events and high temperature events (Khan et al., 2015). Change in temperature and precipitation patterns can have the potential to increase the frequency of wildfire, effect forest mortality, and impact on potable water supplies in both the short- and long-term (Stanford, 2013). One of the most direct effects of wildfire is the removal of surface vegetation (Heath et al., 2014, Jorgenson et al., 2013, Leon et al., 2012, Isabella Bovolo et al., 2009). Vegetation cover in a catchment can be greatly reduced by wildfire and hydrophobic soil can form post-wildfire (Shakesby and Doerr, 2006), and this effects soil infiltration and leads to increased runoff and erosion during precipitation events (DeBano, 2000).

Wildfire also increases the amount of available sediments and nutrients in the catchment: during wildfire, the burning and heating of organic matter releases charcoal, ash, heavy metals, and other stable nutrients that might be previously unavailable for transport into waterways, especially during the first post-wildfire rainfall event (Johansen et al., 2003). Debris flows and landslides after wildfire can also increase the sediments entering streams (Meyer and Pierce, 2003). Another source of sediment is the transport of ash into streams. Ash is one of the major products of wildfire, is highly mobile and transported into streams and reservoirs within days or weeks post-wildfire (Robert et al., 2016). Past studies reported wildfire effect on total suspended sediment (TSS) level range from a small change, quick recovery to significant long-term effects. For example, Lane et al. (2006) reported a 200% and 50% TSS concentration increases compared to the pre-wildfire period during the first post-wildfire year in two burnt catchments in south-eastern Australia. Both catchments reported a TSS level lower than the pre-wildfire sediment level the second post-wildfire year. Mayor et al. (2007) on the other hand, reported a

37,000-fold greater average TSS level over the first 7 years post-wildfire period than the adjacent unburnt catchment, however, their catchments experienced a much larger flow value during the post-wildfire period as compared to the flow value observed in the pre-wildfire period.

Runoff from wildfire burnt surfaces includes suspended sediment with associated adsorbed nutrients, as well as soluble nutrients contained in the ash and water (Bodí et al., 2014). An increase in total nitrogen (TN) and total phosphorus (TP) are the most commonly reported due to wildfire (Smith et al., 2011). Lane et al. (2008) reported an average of 5 to 6-fold increases in nitrogen and phosphorus exports three years after wildfire in north eastern Victoria, Australia. Nitrogen and phosphorus in the form of particulate matter dominated the first year (69% and 94% respectively), and dissolved forms increased in importance in subsequent years.

Most past studies have only reported averaged post-wildfire water quality concentration change, however this ignored the effect of the hydrograph stage and averages the effect of wildfire to water quality during base flow and event periods. Many past studies on wildfire effect on forested catchment water quality use daily total stream flow instead of hourly stream flow values. This is often too coarse to represent flow events, particularly those events in smaller catchments.

A high percentage of catchment pollutant loads are transported into the catchment during storm events (Lawrence and Lin, 1989, Drewry et al., 2009). Excess loading of pollutants such as TSS, TN, and TP may cause water quality problems such as eutrophication and algal blooms. Australia streamflow has highly variable patterns (Croke and Jakeman, 2001), this is why event based sampling method are used in some catchments in Australia as the typical monthly sampling scheme will not capture the high sediment and nutrients output during events.

Additionally, we need to account for the sample being taken during different types of events: the sediment and nutrients outputted from a catchment is effected by seasonal differences (Singh et al., 2004) and event antecedent conditions (Asselman, 2000). Therefore, in order to detect the water quality change, it is important to monitor water quality pre- and post-wildfire based on event types, as events with similar antecedent conditions, and event size and shape, need to be compared together to observe the real change caused by events.

Therefore, in this study, we aim to analysis the effect of wildfire to forested catchments during events by:

- 1: Grouping events based on their hydrograph shape and antecedent conditions;
- 2: Use this grouping to testing the effect of wildfire on water quality (TSS, TN, and TP) during event periods.

## **3.2.Method**

### *3.2.1. Study area*

Five catchments, two control and 3 burnt are used in this study. Full details about the studied catchments can be found in Chapter 2. Catchment C3 that was used in Chapter 2 was eliminated due to upgrading of a sewage treatment plant during the post-wildfire period and catchment B3 was not included here due to a small dataset size. A summary of key features of the study catchments is presented in Table 3.1. During the post-wildfire period, the studied catchments were affected by the Millennium Drought (van Dijk et al., 2013), as showed in Table 3.1, and there is a drop in rainfall during this period especially the first 5 post-wildfire years.

**Table 3.1 Catchment characteristics**

Catchment	Observation Record	Area (km <sup>2</sup> )	% Burnt	% Grass	% Forest	% Urban	Annual rainfall (mm)		
							Pre-wildfire	1-5 years Post-wildfire	6-10 years Post-wildfire
C1	01/1991 - 12/2011	719	0	9	90	0	912	797	1111
C2	01/1991 - 12/2011	72	0	0	85	14	1214	1080	1556
B0	01/1991 - 12/2011	436	57	12	86	1	903	697	914
B1	01/1991 - 02/2007	104	100	2	97	0	869	671	880
B2	01/1991 - 12/2011	88	83	4	95	0	1246	962	1261

### 3.2.2. Datasets

For each catchment, flow and water quality data were provided by WaterNSW for the period from 1991 to 2011. For each catchment, as recorded in Table 3.1, flow was recorded at an hourly interval for the entire study period (1991-2011) except catchment B1 where observations were only available until 2007. Water quality data was sampled on a monthly basis before 2000, after that, automatic event samplers were installed (at most of the sites), which automatically collect samples during event-flow. Events were selected for each catchment based on hourly flow data. Event flow was defined as flow greater than the annual 90<sup>th</sup> percentile of flow. Other flow data was defined as base flow. A set of continuous flow data observations were assigned to one event, rogue individual measurements or events without water quality observations were removed before clustering.

### 3.2.3. Clustering of events

For each event, ten features were calculated as shown in Table 3.2. These features were selected with the aim to group events with a similar magnitude, shape of hydrograph, and a measure of antecedent conditions. All of these are conceptually related to water quality.

**Table 3.2 Features used for event clustering**

Abbreviation	Description	Calculation method
anc	Antecedent condition of the flow	Time since the end of last event to the beginning of this event
meanfl	Mean flow	Mean flow rate during the event time
minfl	Minimum flow	The minimum flow rate during the event
maxfl	Maximum flow	The maximum flow rate during the event
duration	Event duration	Time from the beginning to the end of the event
peak	The number of peaks during the events	Counting the times the event changed from "rising" to "dropping"
ristim	Overall rising time	Time that flow is increasing during the event
risflow	Overall rise in flow	Increase in flow during the event
dptim	Overall dropping time	Time that flow is decreasing during the event
dpflow	Overall decrease in flow	Decrease in flow during the event

These events were then clustered into groups using k-means clustering by using the “kmeans” function in R (R Core Team, 2015). The Elbow method (Kodinariya and Makwana, 2013) was used to determine the number of clusters for each catchment. After clustering, clusters that had both pre-wildfire and post-wildfire events were retained for further analysis.

### 3.2.4. Data analysis

After clustering, we investigated the overall change in the event mean concentration (EMC) change in TSS, TN, and TP caused by wildfire. To achieve this, the EMC for the pre- and post-wildfire period was calculated separately for each cluster and then averaged for each catchment. The results were compared between control and burnt catchments to aid the interpretation of the results in terms of disentangling effects due to wildfire and climate.

### **3.3.Results and discussion**

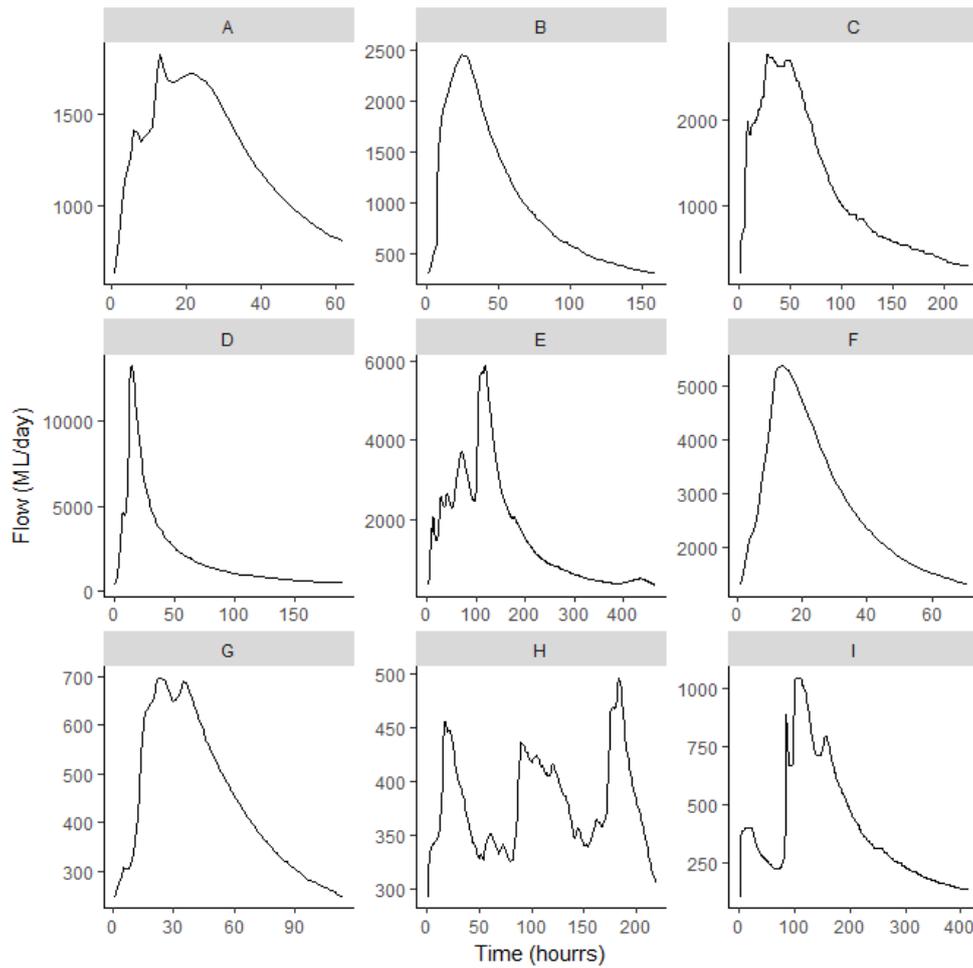
#### *3.3.1. Cluster results*

Several events have been recorded for all catchments during both pre- and post-wildfire periods. The control catchments recorded a similar number of events during both pre- and post-wildfire periods. Burnt catchments, however, showed a variation in the number of events. Catchment B1, for example, had much less events than other burnt catchments during the post-wildfire period. This is likely due to limited data being recorded for this catchment: the flow data of this catchment is only recorded until February 2007. This coincided with the Millennium Drought. However as shown in Table 3.3, during the five years post-wildfire time, only seven events were observed. This observed number is lower than the average yearly event numbers observed in other catchments. Catchment B0 showed a decrease in observed event numbers during the post-wildfire period: only fifteen events were observed for post-wildfire period while thirty events were observed during the pre-wildfire period. Overall, the control catchment observed more events during the post-wildfire period than the burnt catchments. This observation is different to Mayor et al. (2007)'s study where only thirteen events were observed in their control catchments but thirty-one events were observed in their burnt catchment during the seven years post-wildfire period. The low number of events observed in our study during post-wildfire period can be a result of decrease in rainfall.

**Table 3.3 Number of events and clusters in each catchment**

Catchment	No. events (before clustering)		No. events (after clustering)	
	Pre- wildfire	Post- wildfire	Pre- wildfire	Post- wildfire
C1	31	32	30	29
C2	36	38	36	38
B0	30	15	15	15
B1	16	7	4	4
B2	24	33	23	31

After the events were identified, they were extracted and clustered, clusters with only pre-wildfire or post-wildfire data were eliminated. The number of events after clustering is shown in table 3.3. To illustrate the approach, one example event flow in each cluster for a control catchment C1 are shown in Figure 3.1 and the averaged flow, event duration, and event antecedent condition are shown in Table 3.4. As summarised in Table 3.4, cluster E has the longest average flow duration, cluster F has the highest averaged flow and antecedent condition. One example event flow in each cluster for burnt catchment B0 is shown in Figure 3.2 and the averaged flow, event duration, and event antecedent condition are shown in Table 3.5. Compared to C1, B0 has a much lower flow. As indicated in Table 3.5, cluster E has the highest flow and longest average flow duration, cluster D has the highest antecedent condition which is the longest time since the last event flow.

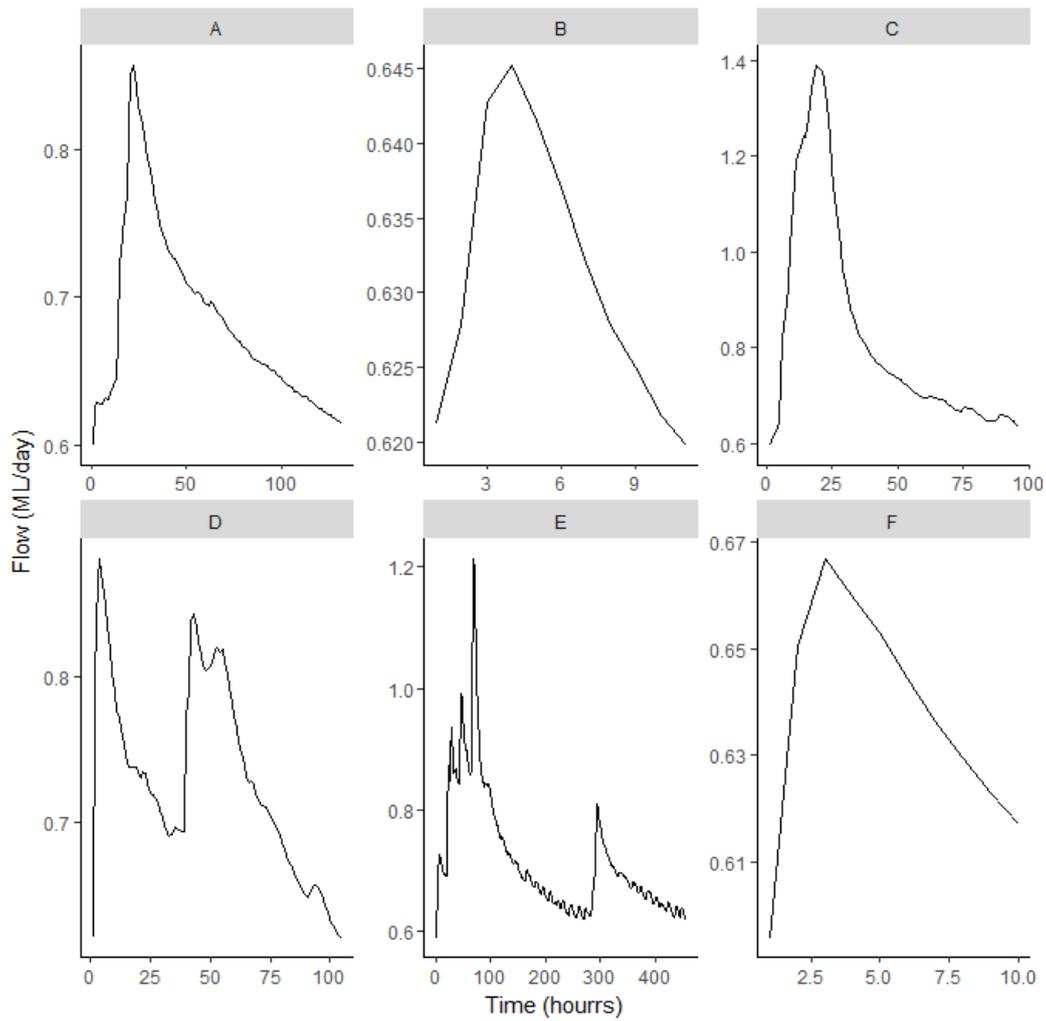


**Figure 3.1 Sample event flow for catchment C1 in different clusters**

**Table 3.4 Catchment C1 cluster averaged flow, duration and antecedent condition**

Cluster	No. Events	Average flow (ML/day)	Average duration (hours)	Average anc* (hours)
A	7	1165.53	58.00	829.29
B	4	825.76	161.75	96.00
C	4	957.41	192.75	1068.75
D	4	1677.48	183.50	2791.25
E	4	1555.48	523.75	1656.75
F	3	3783.55	97.33	3081.67
G	5	365.54	101.20	680.60
H	5	384.99	287.60	454.20
I	4	409.76	422.50	433.25

\*anc = Antecedent condition



**Figure 3.2 Sample event flow for catchment B0 in different clusters**

**Table 3.5 Catchment B0 cluster averaged flow, duration and antecedent condition**

Cluster	No. Events	Average flow (ML/day)	Average duration (hours)	Average anc* (hours)
A	5	0.68	120.60	28.80
B	2	0.62	7.50	4.00
C	9	0.76	117.78	257.56
D	6	0.72	75.33	991.33
E	4	0.77	406.75	372.00
F	4	0.62	10.75	216.00

\*anc = Antecedent condition

### *3.3.2. Compare the water quality observations during the pre- and post-wildfire period*

After clustering, the average water quality concentrations were calculated for each cluster in the pre-wildfire period and in the post-wildfire period. Table 3.6 and 3.7 presents the averaged cluster water quality for one control and one burnt catchment.

On average for all clusters, the C1 catchment recorded a mean event TSS concentration value of 96.77 mg/L during the pre-wildfire period. This value decreased to 12.04 mg/L during the post-wildfire period. However, the median concentration value of pre-and post-wildfire TSS for C1 were observed to have similar value. An averaged higher concentration of TN and TP was also observed in pre-wildfire event period for catchment C1, TN concentration of 0.71 mg/L was observed for pre-wildfire period while post-wildfire period recorded 0.59 mg/L. The concentration for TP is relatively smaller compared to TN, however, a significantly higher value is still observed in the pre-wildfire period (0.06 mg/L pre-wildfire, 0.03 mg/L post-wildfire). Compared to C1 catchment, catchment B0 showed an opposite concentration change. A higher TSS value is observed for post-wildfire period (47.11 mg/L) compare to pre-wildfire period (8.68 mg/L). This concentration change trend is also observed to TN, with 0.74 mg/L observed for pre-wildfire and 0.57 mg/L observed for post-wildfire period. The concentration of TP however, showed the same value for both pre-wildfire and post-wildfire period.

As shown in Table 3.6, cluster F in C1 observed a large amount of TSS, TN, and TP output, this might be the effect of the high flow and a long time since the previous event flow. Additionally, cluster E in B0 (Table 3.7) showed the highest TSS, TN, and TP output during the pre-wildfire period. This might be the combination effect of highest averaged event flow rate and event duration. The extreme output observed in these clusters proved the importance of clustering.

Further research should consider the effect of different event characteristics (averaged flow, duration and antecedent condition) and how they impact on water quality.

**Table 3.6 Catchment C1 cluster averaged pre- and post-wildfire water quality**

Cluster	TSS (mg/L)		TN (mg/L)		TP (mg/L)	
	Pre-wildfire	Post-wildfire	Pre-wildfire	Post-wildfire	Pre-wildfire	Post-wildfire
A	10.88	16.76	0.33	0.49	0.02	0.03
B	11.00	13.70	0.80	0.70	0.02	0.02
C	83.91	1.50	0.70	0.57	0.07	0.02
D	11.50	38.99	0.48	0.95	0.03	0.07
E	5.37	12.33	0.32	0.72	0.02	0.03
F	653.00	13.86	2.85	0.73	0.36	0.03
G	93.25	1.90	0.56	0.28	0.05	0.02
H	1.00	3.23	0.17	0.34	0.01	0.01
I	1.00	6.11	0.20	0.51	0.00	0.02
Median	11	12.33	0.48	0.57	0.02	0.02
Average	96.77	12.04	0.71	0.59	0.06	0.03

**Table 3.7 Catchment B0 cluster averaged pre- and post-wildfire water quality**

Cluster	TSS (mg/L)		TN (mg/L)		TP (mg/L)	
	Pre-wildfire	Post-wildfire	Pre-wildfire	Post-wildfire	Pre-wildfire	Post-wildfire
A	2.00	14.33	0.54	0.48	0.04	0.02
B	1.00	92.00	0.47	0.58	0.02	0.09
C	12.59	18.00	0.76	1.06	0.06	0.05
D	1.00	29.40	0.21	0.80	0.01	0.05
E	34.50	69.75	1.22	0.93	0.14	0.05
F	1.00	59.17	0.25	0.58	0.01	0.03
Median	1.5	44.29	0.51	0.69	0.03	0.05
Average	8.68	47.11	0.57	0.74	0.05	0.05

The averaged cluster concentration for all catchments are calculated and presented in Table 3.8. Overall, comparing 10 years pre-wildfire and 10 years post wildfire EMC change, the control catchments observed an EMC drop for all water quality properties (0.4-fold for TSS, 0.56-fold for TN, and 0.31-fold for TP). The burnt catchment observed a 4.2-fold (6.24 to 25.88 mg/L)

increase in TSS EMC, 1.4-fold (0.38 to 0.53 mg/L) increase in TN, and no change to TP. It can also be noticed that, the increase in water quality concentration is much higher in catchment B1. Catchment B1 showed a severe TSS, TN, and TP EMC increase during the five years post-wildfire period. The EMC TSS concentration of catchment B1 increased from 1.5 mg/L to 219.25 mg/L (146-fold) this value is significantly higher than studies focused on the general post-wildfire flow (average of event and base flow) (Nyman et al., 2011, Smith et al., 2011, Shakesby et al., 2007, Sheridan et al., 2007a, Malmon et al., 2007). A high increase in TN (15.58-fold) and TP (19-fold) is also observed in catchment B1. Compared to catchment B1, the ten years post-wildfire EMC change from catchment B0 is a less severe 5.4-fold increase in TSS (8.68 to 47.11 mg/L). Catchment B2 shows an even smaller EMC concentration change. The lower concentration change might indicate a sign of catchment recovery. Compared to TSS, the TN and TP concentration change in catchment B0 are less pronounced, over the ten year's event period, 0.21 mg/L averaged TN increase is observed while the TP level has recovered to pre-wildfire levels. Catchment B2 showed a similar pattern in this, a 0.12mg/L averaged increase in TN and no change in TP. This indicated that TP has a faster recovery rate than TN. This result is also concluded by Ranalli (2004) who reviewed thirty-nine studies on the wildfire effect on water quality. In their review, they had found that in general, elevated TP levels started to decline one to two years post-wildfire while elevated TN concentration take three to five years. Further studies with sufficient data can compare events in the same cluster at different times during the post-wildfire time to investigate the post-wildfire catchment recovery.

**Table 3.8 Average change in water quality during event period**

Catchment	TSS (mg/L)		TN (mg/L)		TP (mg/L)	
	Pre-wildfire	Post-wildfire	Pre-wildfire	Post-wildfire	Pre-wildfire	Post-wildfire
C1	96.77	12.04	0.71	0.59	0.06	0.03
C2	40.94	46.10	1.35	0.57	0.19	0.04
B0	8.68	47.11	0.57	0.74	0.05	0.05
B1	1.50	219.25	0.12	1.87	0.01	0.19
B2	3.80	4.65	0.19	0.31	0.01	0.01
Average C	68.85	29.07	1.03	0.58	0.13	0.04
Average B*	6.24	25.88	0.38	0.53	0.03	0.03

\*B1 were excluded when calculating average B as only 5 years' post-wildfire data were recorded for B1.

### 3.4. Conclusion

This study compared the long-term (ten years) post-wildfire TSS, TN, and TP concentration change during events. We found a severe post-wildfire TSS concentration changes during events in post-wildfire period. An increase in TN EMC is also observed for ten years post-wildfire, while the TP concentration were similar on average to pre-wildfire levels over the ten years post-wildfire period. The EMC observed in this study is much higher than the water quality change observed in Chapter 2 especially for TSS concentration. This shows the importance of monitoring post-wildfire water quality change during event flows. The clustering analysis used in this study demonstrated this method's capability for comparing fixed interval sparse data such as data collected by event based auto sampler. The method used in this study can be used to detect change for other water quality studies such as the water quality change after deforestation and monitoring the water quality improvement after sewage treatment plant upgrades.

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## **Chapter 4**

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### **4. Modelling the effect of wildfire on forested catchment hydrology using the SWAT model**

## **Abstract:**

Wildfire reduces the surface vegetation, releases ash and soil, increases erosion and runoff, and therefore effects the hydrological cycle of a forested water catchment. It is important to understand the change induced by wildfire and how the catchment recovers. These processes are spatially sensitive and affected by interactions between wildfire severity and hillslope, soil type and surface vegetation. Thus, one approach is to use physical-based spatially-distributed models. In this study, the Soil and Water Assessment Tool (SWAT) is used to examine the effect of the 2001/02 Sydney wildfire on catchment water quantity and quality. Five catchments (two control, three burnt) with ten years of pre-wildfire data are used to create and calibrate the SWAT models. The calibrated model was then used to simulate the flow and total suspended sediment (TSS) for the ten years post-wildfire period while ignoring any effects of wildfire on vegetation and soil. The simulated water flow and TSS are compared with post-wildfire discharge and water quality. The NSE values for control and burnt models were compared, a lower NSE value during the post-wildfire period for burnt catchment models (as compared to control) indicates a possible wildfire effect. Catchment Control 2 (C2) was calibrated at daily steps with a NSE of 0.62 and 0.77 for flow and TSS respectively, the validation period of C2 showed a NSE of 0.58 for flow and 0.53 for TSS. Control 1 (C1) which affected by lower quality rainfall data, showed a low NSE of 0.47 for flow and 0.42 for TSS during calibration period and lower NSE value for validation period. All the burnt catchments showed good calibration results with a mean NSE value across all of 0.68 for flow and 0.73 for TSS. All burnt models predicted poorly during the validation period. We then compared the observed and simulated TSS for short (1 year post-wildfire), medium-(2-5 years), and long-(6-10 years) term periods post-wildfire to analyse catchment recovery and observed a TSS output decrease in long-term period.

## **4.1.Introduction**

Forested catchments are an important source of drinking water supply around the world. It is reported that among the top 105 world's largest cities, approximately one-third of them (33 cities) obtain a significant amount of their drinking water from protected forested catchments (Dudley and Stolton, 2003). One reason for this is the high quality of water in these areas. However, the catchment hydrology (water quantity and quality) can be significantly affected by wildfire. Although some of these catchments are located in wet tropical rainforest areas that may be less prone to wildfire, a large number of other catchments located in other forested areas are susceptible to wildfire events. In Australia, in the past decade wildfire has burnt forested catchments which supply drinking water to major cities such as Sydney (2001), Canberra (2003), Adelaide (2007), and Melbourne (2009) (Smith et al., 2011). More recently, 12,694 ha (0.7%) of Sydney's drinking water supply catchments were affected by the Balmoral wildfire in 2013 (Santín et al., 2015). Wildfire can change the surface vegetation of a catchment and cause an increase in runoff and erosion; thus, have serious impacts on the hydrological cycle and aquatic health of forested catchments. Large areas of forest land are burnt by wildfire around the world, particularly in western North America, south-east Australia and the Mediterranean (FAO, 2001). More than 65 wildfires greater than 40,000 hectares were recorded in the United States from 1997 to 2008 (Smith et al., 2011). Wildfire events burnt over 3 million hectares of the forested area from 2002 to 2009 in south-eastern Australia. These burnt forest lands contribute 40% of the public land of the state of Victoria in Australia (Attiwill and Adams, 2013). The effect of wildfire on catchment hydrology has become a major area of concern in Australia and internationally (Lane et al., 2010, Smith et al., 2011, Feikema et al., 2011, Murphy, 2012, Santín et al., 2015, Langhans et al., 2016).

Wildfire can have a potential impact on catchment vegetation and soil infiltration, this changes the catchment runoff rate, erosion rate and causes flashier flows (Calder, 1993). Additional to change in catchment flow, an increase in total suspended sediment output (TSS) is a widespread consequence of wildfire (Lane et al., 2006). Following wildfire, increased erosion rates together with the ash produced from wildfire elevates TSS in adjacent waterways. Increase in TSS in waterways affects the turbidity of the water and may transport particulate-associated contaminants (Sheridan et al., 2007a). The elevated TSS level in catchments may increase the level of adsorbed nutrients in the water column, and as a consequence, promoting bacterial growth (NHMRC, 2011). In addition, there is a significant correlation between parasites and bacterial concentration; and suspended particles can carry bacteria pathogenic to humans and foster their development (Robert et al., 2016).

There are numerous past studies that have investigated the effect of wildfire on catchment hydrology, one of the most common methods for studying post-wildfire catchment hydrology change is the paired catchments approach with, in most cases, short (1-3 years) pre-wildfire catchment hydrological data (Brown et al., 2005, Scott, 1993, Ruprecht and Schofield, 1989). The paired catchment approach creates a regression model between catchment hydrology in control and burnt catchment during the pre-wildfire period. The model is then used to predict the catchment hydrology for the burnt catchment as if the catchment was not burnt. The difference between the observed value and the predicted value are then assumed to be caused by wildfire. This method is commonly used with annual and monthly data, it has also been used with the peak flow and base flow component of streamflow (Bari et al., 1996). However, Watson et al. (2001) argued that the calibration period in most of the past paired catchment studies are too short, and this limits the strength of the regression model. The major reason studies use a short

calibration period are the lack of pre-wildfire data as the location and occurrence of wildfire is hard to anticipate. Shakesby et al. (2007) have identified lack of pre-wildfire TSS data as the major problem for analysing post-wildfire erosion rates in catchments, especially for the long-term. Scott (1993) observed an increase in TSS output during the six months post-wildfire in their studied catchment, but couldn't conclude a significant increase due to lack of pre-wildfire catchment hydrological data. Moreover, the empirical regression model used in paired catchment studies and most other past studies are lacking the ability to include spatial variability of land use, slope, and soil in the model. The effect of wildfire on erosion processes are spatially variable (Sheridan et al., 2007a), and this effect, together with spatially variable post-wildfire rainfall, results in punctuated deliveries of greater than the expected TSS deliveries (Moody and Martin, 2001). Prosser et al. (2001) identified the lack of both temporal and spatial data as the main reason that catchment hydrology studies have been based on empirical relationships. He suggested the use of physical-based approaches that account for spatial patterns such as soil type, elevation and land-use as these could predict the effect of wildfire but also provide a mechanistic understanding of the effect of wildfire.

For these reasons, physical-based distributed models are becoming important for studying land-use change effects on the hydrological cycle (Ghaffari et al., 2010). These models require spatial and temporal inputs related to climate, soil, land use and terrain. The Soil and Water Assessment Tool (SWAT) is one of the most important and widely used physical-based distributed models (Arnold et al., 2012) for predicting the long-term impact of land use change on catchment hydrology using recorded catchment physical characteristics (land use, slope and soil type) and weather data. It was developed to evaluate the effect of alternative management decisions on water resources and nonpoint-source pollution (Arnold et al., 2012). SWAT model operates on a

daily time step. This enables the possibility of predicting and comparing the effect of single rainfall events.

SWAT has been commonly used in studies for predicting land use change caused by management decisions (Ghaffari et al., 2010, Pisinaras et al., 2010, Rostamian et al., 2008). However, there have been very limited studies found using SWAT or other physical-based distributed models to examine the wildfire effect on catchment hydrology. Feikema et al. (2011) used the E2 model with gridded rainfall data in their study to estimate the impact of wildfire on TSS and nutrients in four catchments in south-eastern Australia. Their models achieved good calibration results and observed a significant wildfire effect on catchment hydrology during the first post-wildfire year. They indicate the quality of model prediction is largely dependent on the data used to support the model and accurate prediction of land use change on catchment hydrology can only be achieved if there are reliable historic observations of catchment hydrological data for the specified change in the land use. Pisinaras et al. (2010) used several land use change scenarios in their research and suggested SWAT can be used for predicting the effect of wildfire. However, in their study, the catchment was only calibrated and validated with observed data from an unburnt catchment; no actual observed post-wildfire data from burnt catchment was used to compare with the simulated results.

Besides high quality catchment hydrology observations, high resolution GIS data such as soil and land use information are also important for good model quality. The accuracy of physical-based distributed models are highly dependent on the quality of input data, for example, Inskeep et al. (1996) used a physical-based model to predict solute transport in soil and concluded that model prediction based on a low spatial resolution soil map may not accurately reflect the transport processes. In a similar study, Wilson et al. (1996) concluded that model output errors

significantly increases with decreased spatial resolution of soil maps. Tozer et al. (2012) compared gridded rainfall data and station observed data and suggested that gridded rainfall data brings more error into the model predictions and should be used carefully.

Another primary input in physical-based distributed models is soil inputs. Soil properties (as represented by soil classes) effects catchment infiltration and influences TSS and nutrients load to waterways. However, the accuracy of soil inputs in physical-based distributed models are less discussed in past studies. Geza and McCray (2008) compared two different sets of soil inputs provided in SWAT for the USA, and emphasized the importance of the accuracy of soil inputs. Saha et al. (2014) used a soil map from the Digital Atlas of Australian Soil (McKenzie et al., 2000) in their study modelling streamflow using SWAT, they indicated that, the inaccuracy of some soil inputs introduced uncertainty into the model and made the calibration process difficult. Most soil information in Australia has come from individual surveys, this has left the continent significantly short of complete soil data coverage at suitable scales for multiple purposes. Grundy et al. (2015) introduced a new soil information and spatial data delivery system, the Soil and Landscape Grid of Australia (SLGA). The SLGA is a grid based soil map that provides a logical way to harmonise existing soil information and was designed around clearly stated current and future end-user needs. It provide maps of soil attributes include soil particle fractions, soil bulk density, soil available water capacity, soil nutrients content, and other soil properties. This product might create new possibilities for estimating soil inputs in physical-based distributed models in Australia and globally as similar products are now available for the world, for example SoilGrids (ISRIC, 2013).

In this study, the SWAT model is used to predict the effect of the 2001/02 Sydney wildfire on catchment hydrology. Ten years pre-wildfire data is used to create and calibrate the SWAT

model. The calibrated model was then used to simulate the flow and TSS for the ten years post-wildfire period without wildfire effect. The simulated hydrological data are compared with recorded catchment hydrological data to analysis the wildfire effect. Control catchments are used to help interpret the results. In addition we illustrate the use of digital soil maps such as the SLGA as an input for the SWAT model.

## **4.2.Method**

### *4.2.1. Study area*

Full details about the study area can be found in Chapter 2, and in particular Section 2.1 has a detailed description of the catchments. Catchments C3 and B0 are not included in this chapter due to the size of the pre-wildfire catchment hydrological dataset being too small for calibration in SWAT. Catchment C1 was affected by a sewage treatment plant (STP), however, it is still included in this chapter because we are only examining the effect of fire on TSS and not nutrients. As shown in Chapter 2 the STP upgrade had no effect on TSS concentration.

## **4.3.Model description**

### *4.3.1. SWAT*

SWAT is a physical-based spatially-distributed model widely used for simulating flow, TSS, and nutrients in waterways. It requires land use, soil properties, elevation, and weather data. SWAT runs on a daily time step, it has the option to input a stream network or generate a stream network from a digital elevation model (DEM). Based on the stream network, catchments are divided into sub-basins, and further divided into hydrological response units (HRUs) based on the physical characteristics (land use, slope, and soil type) of the catchment. HRUs are units that

have homogenous responses to precipitation, and are formed by selecting the areas that have similar geomorphological properties (Pisinaras et al., 2010). For each HRU the model predicts hydrology with input climate data using the water balance equation. The model calculates the runoff using curve number equations, and uses the Modified Universal Soil Loss Equations (MUSLE) (Williams and Berndt, 1977) to calculate soil erosion. The model provides output data such as flow, TSS, and nutrient concentration at a specific point on the channel network. The hydrological response to climate data change are produced individually in each HRU, aggregated for each sub-basin, and then accumulated for the specific channel monitoring sites (Arnold et al., 2012). The hydrological component in SWAT is based on equation 4.1,

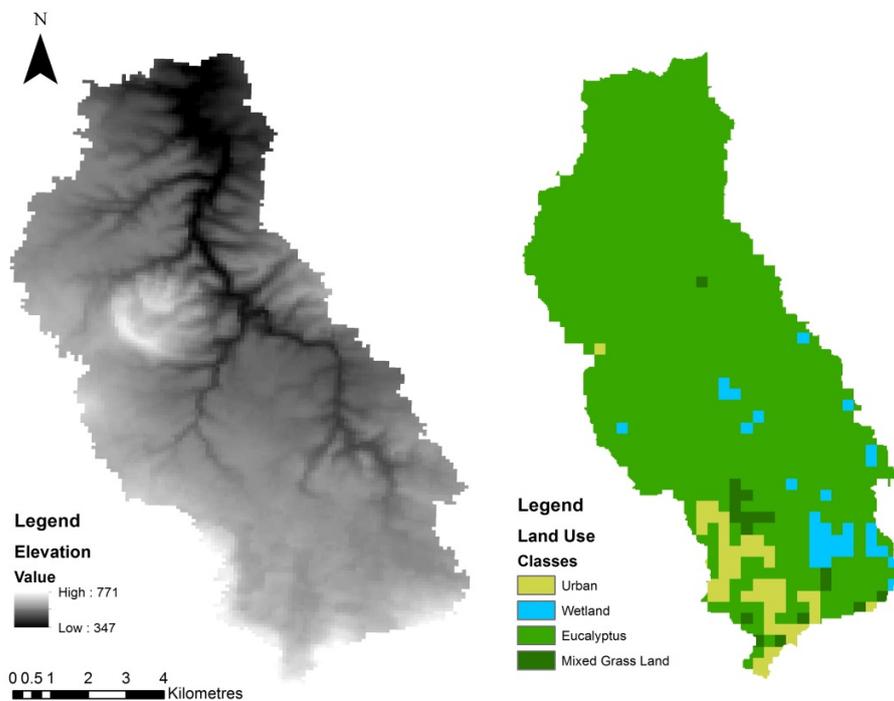
$$SW_t = SW_0 + \sum_{i=1}^t (R_{\text{day}} - Q_{\text{surf}} - ET_i - W_{\text{seep } i} - Q_{\text{gw}}), \quad (4.1)$$

where  $SW_t$  is the final soil water content,  $SW_0$  is the initial soil water content,  $t$  is the time in days,  $R$  is the amount of precipitation on day  $I$ ,  $Q_{\text{surf}}$  is the amount of surface runoff on day  $i$ ,  $ET_i$  is the evapotranspiration on day  $i$ ,  $W_{\text{seep } i}$  is the amount of water entering the vadose zone from the soil profile on day  $i$ , and  $Q_{\text{gw}}$  is the amount of return flow on day  $i$ . The Penman-Monteith method is used in this study for calculating potential evapotranspiration. Actual canopy evaporation is calculated based on leave area index (LAI), maximum interception capacity and potential evapotranspiration. LAI is limited by soil water content (Neitsch et al., 2011).

TSS in SWAT is calculated for each HRU with the MUSLE equation, MUSLE uses the runoff instead of rainfall as an indicator for calculating TSS, this increases the prediction accuracy and also enables the estimation of TSS from a single storm event.

#### 4.3.2. Model inputs

The quality of the model and the accuracy of the model simulation are highly dependent on the quality of the input data (King et al., 1999). SWAT requires DEM, land use map, and soil map to create HRUs as the first step for creating a SWAT model. We used a 90 m resolution DEM (Figure 4.1 left) from Geoscience Australia. From this, SWAT automatically determined the catchment channel network, separation of sub-basins as well as channel length and width.



**Figure 4.1 DEM (left) and Land Use (right) input for catchment B2**

#### *Soil properties*

The soil maps were downloaded from the Atlas of Australian soils (McKenzie et al., 2000). SWAT requires input for soil properties for all layers in the soil profile, which include many properties such as soil depth, bulk density, available water capacity, saturated hydraulic

conductivity ( $K_{sat}$ ), and soil composition. The soil organic carbon content, soil bulk density, soil particle size, and soil available water capacity were obtained from the SLGA (Grundy et al., 2015) at 90 m resolution. An example of the soil organic carbon map is shown in Figure 4.2 (left). However, SWAT uses the polygon representation of soil to represent its spatial variability where each polygon represents one soil type and requires associated soil inputs. For this, we used polygons as defined by Soil-Landscape mapping data (McKenzie et al., 2000). These are shown on the right in Figure 4.2. For each soil polygon, the median value of soil organic carbon, soil bulk density, soil composition, and soil available water capacity was calculated for six soil layers from the SLGA data. The soil layers were separated into depth ranges of 0-5 cm, 5-15 cm, 15-30 cm, 30-60 cm, 60-100 cm and 100-200 cm as available from the SLGA. The  $K_{sat}$  value is not provided in SLGA, thus, we used pedotransfer functions described by Minasny and McBratney (2000) for calculating  $K_{sat}$ , as shown in equation 4.2 and 4.3:

$$K_{sat} \left( \frac{\text{mm}}{\text{d}} \right) = \exp \left( 2.41 - 8.12 \tanh \left( 0.5 \left( (-3.96) + 2.86\theta_{-10} + 1.90 \text{ bulk density whole} \right) \right) - 3.67 \tanh \left( 0.5 \left( (-14.40) + 20.90 \theta_{-10} + 3.68 \text{ bulk density whole} \right) \right) \right); \quad (4.2)$$

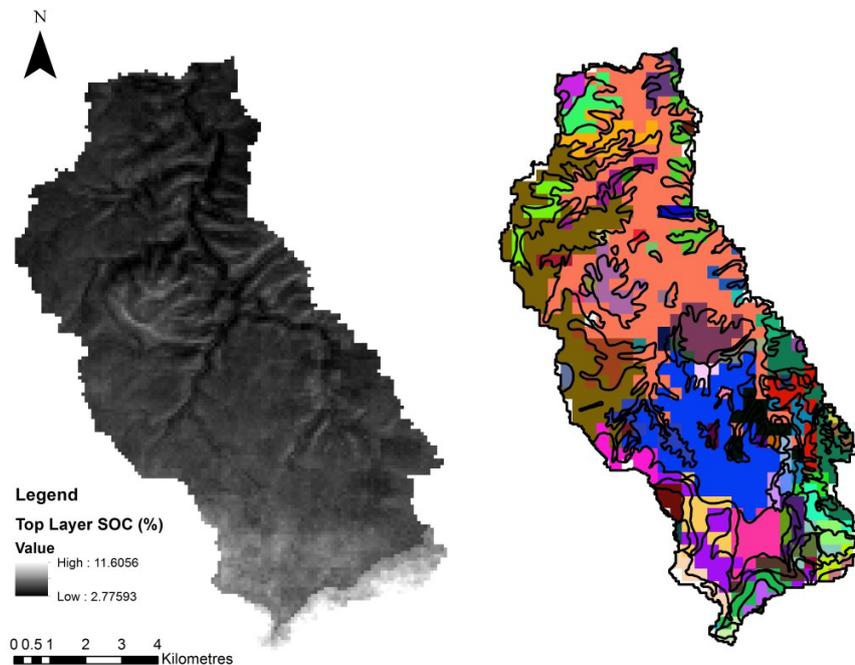
$$\theta_{-10} \left( \frac{\text{cm}^3}{100\text{cm}^3} \right) = 0.5255 - 2.76 \times 10^{-5} \text{ sand}^2 - 0.05195 \text{ bulk density whole}^2; \quad (4.3)$$

where field capacity ( -10 kPa ( $\theta_{-10}$ )) is calculated using equation 4.3, sand is the percentage of sand of the layer calculated from SLGA and bulk density whole is the bulk density of the layer calculated from SLGA.

### *Land use*

The land use map used in this study is NSW land use data collected during 2000 (Emery, 2010). Land use was aggregated into six land use classes in SWAT: urban land, eucalyptus land, mixed

forest land, grassland, bare ground and wetland. Figure 4.1 (right) shows an example land use map for catchment B2.



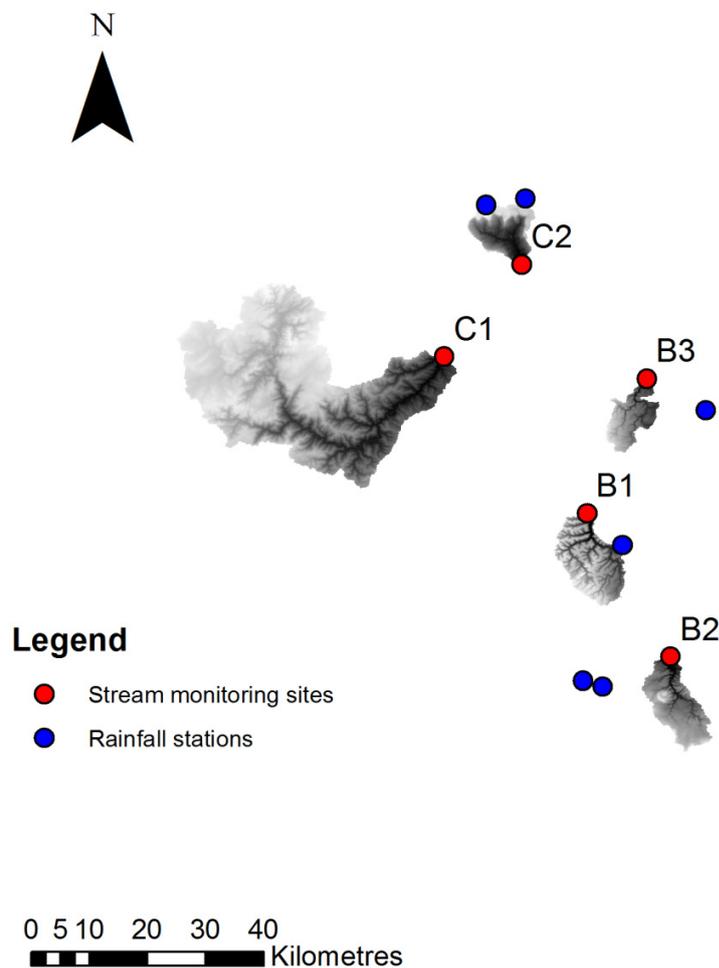
**Figure 4.2 SOC raster (left) and soil types (right) for Catchment B2**  
\*each colour in soil types map represent one soil type.

### *Weather inputs*

The weather input data requirements in SWAT include daily rainfall, temperature, humidity, solar radiation, and wind speed. The daily rainfall data used in this study were downloaded from Bureau of Meteorology (BOM) stations within 30 km of each catchment (Figure 4.3). SWAT also requires daily inputs for temperature, humidity, solar radiation, and wind speed during the calibration and validation period. There was limited station data for these properties, thus, the Climate Forecast System Reanalysis (CFSR) data created by National Centre for Environmental Prediction (NCEP) in USA (resolution of  $0.5^{\circ} \times 0.5^{\circ}$ ) for solar radiation, wind, and temperature was used (Kalnay et al., 1996), because this is the only data that satisfied all the criteria for our

research period. The CFSR data project was completed over a 36 years period from 1979 to 2014, and has been commonly used in SWAT models (Dile and Srinivasan, 2014).

The location of the climate data inputs are showed in Figure 4.3. SWAT automatically picks the closest climate station to each HRU to calculate catchment hydrology output for the HRU and accumulates these for each catchment to calculate the final output.



**Figure 4.3 Locations of climate stations**

#### *4.3.3. Model implementation and model quality analysis*

The models were calibrated in SWAT-CUP, which is a semi-automatic calibration program used for model calibration. SWAT-CUP provides different methods for calibration: PSO, SUFI-2, MCMC, ParaSOI, and GLUE. In this research, the SUFI-2 algorithm (Abbaspour et al., 2007a) was used for calibration and uncertainty analysis. The SUFI-2 algorithm is one of the most commonly used calibration methods used by SWAT users and previous studies have shown that the SUFI-2 algorithm is very efficient in calibration and uncertainty quantification for large watersheds (Faramarzi et al., 2009, Schuol et al., 2008, Yang et al., 2008) and small watersheds (Abbaspour et al., 2007b, Rostamian et al., 2008). In SUFI-2, all uncertainties in the model are quantified by the P-factor, which is the percentage of measured data bracketed by the 95% uncertainty (95PPU). This 95PPU is calculated at the 2.5% and 97.5% of the cumulative distribution of the catchment hydrology variables obtained through Latin Hypercube Sampling. The program starts by assuming large parameter uncertainty and decreases the parameter range to decrease uncertainty until (1) most observations fit into 95PPU brackets, and (2) the average distance between the upper and lower parts of the 95PPU is smaller than the standard deviation of the measured data (Abbaspour et al., 2007a).

Five separate models (one for each catchment) were created in ArcSWAT 2012 to predict catchment hydrology. All five models were calibrated for ten years (1991-2000) pre-wildfire with a further five years used as a warm up period (1986-1990) and validated for ten years (2002-2012) during the post-wildfire period. Flow and TSS were calibrated and validated. Year 2001 was excluded as it contains both pre-wildfire and post-wildfire data.

To investigate the wildfire effect on catchment hydrology:

1. The model quality was assessed by the Nash Sutcliffe Efficiency (NSE) value at daily level. The model's ability to predict the post-wildfire period catchment hydrology for control and burnt catchments was compared and analysed. The models are calibrated based on catchment features and their interaction with weather, therefore the poor performance of SWAT models for burnt catchments in the post-wildfire period indicates a change in catchment condition between the pre-wildfire and post-wildfire period, thus, a possible wildfire effect.
2. To investigate the catchment recovery process post-wildfire flow and TSS output were compared for 3 periods: short-term (1 year post-wildfire), medium-term (2-5 years post-wildfire) and long-term (6-10 years post-wildfire).
3. The observed and predicted post-wildfire flow and TSS output during the first post-wildfire rainfall event were analysed to investigate the effect of fire on the first post-wildfire event.

## 4.4. Results and Discussion

### 4.4.1. Input data

A summary of catchment hydrological data availability during the pre- and post-wildfire period is shown in Table 4.1. During the entire study period, the flow data was recorded at an hourly interval. TSS data were sampled on a monthly basis before 2000, and after 2000, samples were collected during events by an automatic event sampler. SWAT requires daily flow and TSS observations for the calibration and validation process. The observed hourly flow data was aggregated to estimate the flow value for the day. SWAT requires TSS outputs in metric tonnes for the calibration and validation process. Our observations were recorded in concentrations (mg/L). To estimate the TSS in tonnes, our TSS observations were multiplied by the flow rate observed at the time and converted to tonnes per day. If there was more than one TSS observation in a day, the average value was used. Each catchment had flow data during the entire 10 year pre-wildfire and 10 year post-wildfire period except catchment B1 which only has data until the end of July 2007. The number of observations for TSS ranges from 63 to 187 per catchment. Similar to flow data, catchment B1 has fewer TSS observations for the post-wildfire period. During 2001 to 2009, the catchments were affected by the worst drought on record for southeast Australia – also known as the Millennium drought (van Dijk et al., 2013). As a result, all the catchments observed a higher maximum and median flow value during pre-wildfire period. All catchment observed a higher maximum TSS daily output during pre-wildfire periods except catchment B1 which had an extremely high TSS (3950 tonnes/day) load in the post-wildfire period. However, most catchments observed a lower median TSS value during the pre-wildfire period with the exception of B1 which had the same median TSS value observed for both pre- and post-wildfire periods.

**Table 4.1 Summary of input data**

Catchment	Pre/Post-wildfire	Flow (m <sup>3</sup> /s)			TSS (tonnes/day)				
		Min	Max	Median	Flow Available Data (Daily)	Min	Max	Median	TSS Available Data (Daily)*
C1	pre	0	114373	152	97729(3510)	0.5	3829	1	244(187)
	post	0	19936	96	89992(3615)	0.5	532	4	536(184)
C2	pre	0	29088	21	96754(3475)	0.5	1316	3	220(173)
	post	0.5	4206	16	84352(3421)	0.5	536	6	284(162)
B1	pre	0.4	8750	6	94465(3503)	0.5	97	1	218(160)
	post	0	5114	5	41848(1740)	0.5	3950	1	69(63)
B2	pre	3.2	18812	13	100176(3559)	1	149	1	157(114)
	post	1.1	5198	8	85780(3512)	0.5	35	1.2	381(187)
B3	pre	0	26440	3	109793(3440)	0.5	803	4	233(155)
	post	0	6927	2	83963(3449)	0.5	496	7	351(162)

\*daily values are calculated by averaging values observed on the same day

The parameters of all five catchments were calibrated for flow and TSS for the ten year (1991-2001) pre-wildfire period. Detail sets of parameter ranges are listed in Table 4.2. For each catchment, all parameters were calibrated for flow first and then for TSS. The initial parameter sets were selected based on the literature and the SWAT user manual (Winchell et al., 2013). The five catchments showed different sensitivities and calibrated ranges to different parameters. The global sensitivity test showed curve number (CN2) as the most sensitive parameter for flow estimation for all studied catchments. Catchment B1 and B2 had maximum canopy storage (CANMX) as the second most sensitive parameter while other catchments have a higher sensitivity to effective hydraulic conductivity (CH\_K2). CANMX is a parameter used to calculate surface runoff, and is determined by the density of plant cover and the morphology of the plant species which was determined by the land use input layer. CH\_K2 is determined by soil type. The groundwater "revap" coefficient (GW\_REVAP) was determined by both the soil property and the root depth of the plants and was found to be the most sensitive ground water

parameter for catchments C1, C2, B1, and B2, while catchment B3 is more sensitive to threshold depth of water in the shallow aquifer required for return flow to occur (GWQMN). For TSS simulations, the exponent parameter for calculating TSS re-entrained in channel sediment routing (SPEXP) was the most sensitive parameter for catchments B1, B2, and B3. The control catchments C1 and C2 are more sensitive to linear parameters for calculating the maximum amount of TSS that can be re-entrained during channel sediment routing (SPCON). The parameter sets showed sensitivities to surface runoff, ground, soil, and sediment parameters. It is crucial to have an accurate estimation of the parameter ranges for accurate estimation of the runoff and TSS output. Parameter sets were selected and calibrated individually for the catchments and the calibrated parameter ranges are checked against critical values to make sure the value does not fall outside range of theoretical values.

**Table 4.2 Descriptions of selected parameters used for calibration.**

Parameter Name*	Description	Calibrated range									
		C1		C2		B1		B2		B3	
		Min	Max	Min	Max	Min	Max	Min	Max	Min	Max
a__CANMX.hru	Maximum canopy storage [mm].	N/A*	N/A	35.74	107.26	22.68	76.75	29.88	54.96	16.57	32.76
r__OV_N.hru	Manning's "n" value for overland flow	-0.20	0.13	-0.06	0.42	-0.09	0.07	-0.16	0.06	-0.01	0.10
r__CN2.mgt	SCS CN II value.	-0.01	0.59	0.00	0.60	0.05	0.30	0.28	0.50	0.38	0.40
a__USLE_P.mgt	USLE support practice factor.	0.07	0.48	0.20	0.73	0.30	0.30	N/A	N/A	N/A	N/A
a__CH_K2.rte	Effective hydraulic conductivity [mm/hr]	N/A	N/A	N/A	N/A	139.55	251.14	44.63	87.66	36.70	73.22
a__CH_COV1.rte	Channel erodibility factor	-0.11	0.24	0.06	0.42	N/A	N/A	N/A	N/A	0.02	0.15
a__RCHRG_DP.gw	Deep aquifer percolation fraction.	N/A	N/A	0.45	1.34	-0.08	0.64	N/A	N/A	0.07	0.74
r__RCHRG_DP.gw	Deep aquifer percolation fraction.	N/A	N/A	N/A	N/A	N/A	N/A	0.13	0.38	N/A	N/A
a__GW_REVAP.gw	Groundwater "revap" coefficient.	0.10	0.28	0.11	0.28	-0.04	0.12	0.00	0.01	0.11	0.18
r__GWQMN.gw	Threshold depth of water in the shallow aquifer required for return flow to occur (mm).	-0.30	-0.26	0.30	0.30	N/A	N/A	-0.15	0.16	-0.45	-0.12
r__GW_DELAY.gw	Groundwater delay (days).	-0.30	-0.13	N/A	N/A	N/A	N/A	-0.13	0.22	-0.20	0.12
r__GWQMN.gw	Threshold depth of water in the shallow aquifer required for return flow to occur (mm).	-0.30	-0.26	0.30	0.30	N/A	N/A	-0.15	0.16	-0.45	-0.12
a__PRF_BSN.bsn	Peak rate adjustment factor for sediment routing in the main channel	1.30	2.35	0.99	2.96	N/A	N/A	N/A	N/A	N/A	N/A
r__PRF_BSN.bsn	Peak rate adjustment factor for sediment routing in the main channel	N/A	N/A	N/A	N/A	-0.59	0.00	-0.14	0.17	-0.35	0.08
a__SPEXP.bsn	Exponent parameter for calculating sediment reentrained in channel sediment routing	-0.30	0.30	1.11	1.37	0.05	0.30	N/A	N/A	N/A	N/A
r__SPEXP.bsn	Exponent parameter for calculating sediment reentrained in channel sediment routing	N/A	N/A	N/A	N/A	-0.21	0.13	0.08	0.25	-0.43	0.06
a__SPCON.bsn	Linear parameter for calculating the maximum amount of sediment that can be reentrained during channel sediment routing	0.01	0.01	0.00	0.01	0.00	0.01	0.00	0.01	0.00	0.01
r__SOL_K(1).sol	Saturated hydraulic conductivity for the second layer.	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	0.01	0.22
r__SOL_K(2).sol	Saturated hydraulic conductivity for the first layer.	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	-0.15	0.04
r__SOL_AWC(1).sol	Available water capacity of the first soil layer.	N/A	N/A	N/A	N/A	N/A	N/A	-0.13	0.08	N/A	N/A
r__SOL_AWC(2).sol	Available water capacity of the second soil layer.	N/A	N/A	N/A	N/A	N/A	N/A	0.07	0.38	N/A	N/A
r__Precipitation()1986001-2012365.pcp	Precipitation	-0.04	-0.03	-0.03	0.02	N/A	N/A	N/A	N/A	N/A	N/A

\* r\_: parameter changed by ratio; a\_: parameter changed by adding value. N/A = parameter is not used for calibrating this catchment.

#### 4.4.2. Calibration and Validation

The NSE values for all catchments (Table 4.3) showed a good calibration result except for catchment C1. The bad calibration result of catchment C1 may be a combined result of inaccurate precipitation data and a high complexity in the catchment topography. Catchment C1 is the biggest catchment with the greatest slope and elevation variation across all studied catchments. In addition, the closest rainfall station is located 30 kilometres away from the catchment (Figure 4.3). Additionally, the rainfall station is at an elevation of 1015 m, more than 800 metres higher than the catchment monitoring site. This increases the difficulty for model calibration and validation. Precipitation is often the most important climate input data for simulating runoff and in SWAT the closest rainfall station is used for simulation of runoff in each sub-basin. This precipitation value is corrected by the elevation method where the precipitation value is calculated for each elevation band in the model as a function of the respective lapse rate and the difference between the elevation of rainfall station and the average elevation specified for the band. Three elevation bands were defined in our models at 33%, 66%, and 100% of the maximum elevation value. However, when stations are located far away from the catchment or when a catchment has complex topography, this leads to an inaccurate representation of the sub-basin's precipitation variability (Tuo et al., 2016). The inaccurate precipitation input for catchment C1 made the calibration and validation difficult. After calibration, catchment showed a NSE of 0.47 for flow and 0.42 for TSS and lower NSE value for the validation period. Evidence of inaccurate precipitation data was events occurring when no rainfall fell in the catchment.

On the other hand, catchment C2 showed good calibration and validation results, after calibration, the catchment showed a NSE of 0.62 and 0.77 for flow and TSS respectively, 0.58 and 0.53 for

validation period. This model's result showed SWAT's ability to predict catchment hydrology at daily steps with reliable climate inputs.

All the burnt catchment models showed good calibration results with a mean NSE value of 0.68 for flow and mean NSE value of 0.73 for TSS. However, all burnt catchment models predicted poorly in the validation period. This indicates a difference between catchment behaviour during the pre- and post-wildfire period, which indicates a possible wildfire effect.

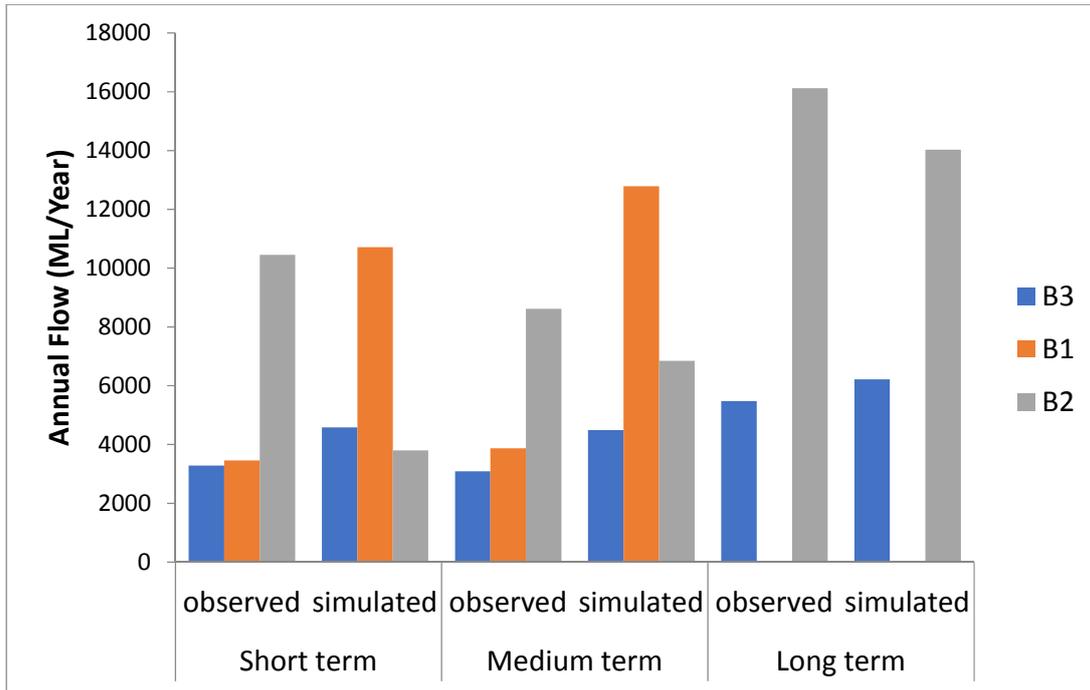
**Table 4.3 NSE values for catchments during calibration and validation period**

Catchment	Pre-wildfire		Post-wildfire	
	Flow	TSS	Flow	TSS
C1	0.47	0.42	0.23	-0.05
C2	0.62	0.77	0.58	0.53
B1	0.70	0.92	-5.78	-0.01
B2	0.63	0.63	-0.01	-0.20
B3	0.72	0.63	0.34	-0.03
Average C	0.55	0.59	0.41	0.24
Average B	0.68	0.73	-1.82	-0.08

#### *4.4.3. Total post-wildfire flow and TSS output*

The annual averaged flow and TSS output values for burnt catchments were calculated for short-term (1<sup>st</sup> year post-wildfire), medium-term (2-5 years post-wildfire) and long-term (6-10 years post-wildfire). The outputs were separated into different time frames to separately investigate catchment behaviour at different times since the wildfire to analyse catchment recovery. As the catchment soil and vegetation recovers, the effect from the wildfire is expected to decrease, therefore the observed flow and TSS value should get smaller to show that the catchment behaviour are recovering back to pre-wildfire levels.

However, as shown in Figure 4.4, overall, there is an increase in observed and simulated annual flow value for all catchments. This is possibly due to the increase in annual rainfall, during the post-wildfire period, there is an increase in annual rainfall (Table 4.4). During post-wildfire period, catchment vegetation starts to recovery, this increased water usage of the catchment, however, the rainfall increase during post-wildfire period may be greater than the increase in water usage increase from catchment vegetation recovery. Thus, an increase in flow is observed. However, the differences between observed and simulated flow value for catchment B2 and B3 are decreasing as the time goes by. The flow difference for catchment B2 and B3 are smallest during the long-term period. This might indicate a sign of catchment recovery. Heath et al. (2016) performed a study on the post-wildfire flow change after the same fire with B2 and other different burnt catchments. In their study, they identified that catchment B2 recovered to pre-wildfire vegetation condition within 5 years post-wildfire. Our result showed a similar result for catchment B2, the simulated flow and observed flow has similar value during the long-term period.



**Figure 4.4 Averaged annual flow value for different post-wildfire periods.**

**Table 4.4 Annual rainfall during different post-wildfire period**

	Short-term (mm)	Medium-term (mm)	Long-term (mm)
B1	528.43	728.71	880.01
B2	757.69	1044.86	1261.80
B3	543.51	625.08	849.14

Our catchment experienced a low rainfall period at the beginning of the post-wildfire period. This has brought some uncertainty to our modelling process. The model constantly over-predicted the flow during low rainfall period, this problem might be fixed by calibrating the dry and wet period separately. When compare the simulated flow between short and medium period: a higher flow is simulated for medium-term for all the catchments, but a higher annual flow value is observed for catchment B1 and B2 in the short-term (as compared to the observed flow in medium-term). This might indicate an effect from wildfire and an increase in annual flow values during the first post-wildfire period. The annual TSS outputs value exceeds the simulated TSS value for all periods (Table 4.5). The TSS output from catchment B1 indicated a severe

wildfire effect. This catchment observed an extreme TSS value during the short-term (2007 tonnes/year), this value decreased to 595 tonnes/year. This indicates a catchment recovery. The TSS observation for long-term period was not recorded, we were not able to analyse the long-term recovery process. However, the simulated value of this site observed minimum to no TSS output during short- to medium-term period. This represents the significant damage caused by wildfire.

Catchment B2 and B3 showed an increase in TSS output in the long-term, however, the increase in simulated value are much less significant than observed value. Therefore, the increases in TSS for these 2 catchments were not a result of increase in flow change only. This increase indicates a slow recovery of the catchment. This slow recovery could be a result of a drier landscape and lower annual rainfall in the first few years post-wildfire period (Heath et al., 2016). Our study on TSS output here observed a longer recovery time than flow. This can indicate that, even the catchment flow has recovered to pre-wildfire condition; catchment TSS output can still be affected by wildfire.

**Table 4.5 Averaged annual TSS output (tonnes/year) for different post-wildfire periods.**

	Short-term		Medium-term		Long-term	
	Observed	Simulated	Observed	Simulated	Observed	Simulated
B1	2007	1	595	0	N/A*	0
B2	3	3	20	5	24	5
B3	15	70	8	10	47	22
Total	2025	74	623	14	71	28

\*No water quality data were recorded during this period.

#### 4.4.4. *Post-wildfire events*

The first post-wildfire flood is always identified as the most severely impacted event by wildfire. Russell-Smith et al. (2006) reported an estimated volume of 7,000 cubic feet (200 cubic metres) per second flood and a loss of 15-20 tonnes of soil per acre (6-8 tonnes per hectare) during the first post-wildfire event in Buffalo Creek, United States. Moody and Martin (2001) observed that the flow output of the first post-wildfire event was one half of the largest observed flow during the pre-wildfire period. Their study also investigated the average TSS output for the following four years and concluded a decrease in TSS output. However, no pre-wildfire TSS output data was used for comparison. Also, the catchment in the study experienced a drier period during the post-wildfire period, received less rainfall, and produced less flash floods. Thus, the real impact of the event was not analysed. The extended heat from wildfire increases the available TSS and nutrients in a catchment, and also creates charcoal and ash. This increased the TSS output from the catchments especially during the first post-wildfire event (Johansen et al., 2003). It is important to monitor the catchment behaviour during the first post-wildfire event. However, the lack of data and the higher variation in rainfall make it particularly difficult to examine the immediate post-wildfire hydrological response (Cerdà and Lasanta, 2005).

With the help of SWAT, we were able to simulate daily observations during the post-wildfire period and generate “unburnt” conditions for the study catchments and compare observed events with simulated events based on climate input data. This enables the possibility of investigating the first post-wildfire event impact and the impact of the following events. We first investigated the impact of the first post-wildfire event: the simulations in 3 burnt catchments, both catchment B1 and catchment B2 showed a significant higher flow and TSS observation (Table 4.6). Catchment B2 showed a flow observation of 25.08 m<sup>3</sup>/s at the first post-wildfire event while the

simulated flow only estimated a value of 2.16 m<sup>3</sup>/s. Catchment B1 showed an extremely high TSS observation of 856 mg/L during the first post-wildfire event even with a low flow observation. The simulated TSS showed 0 mg/L TSS output during that event. Catchment B3 however, observed a higher value in both simulated flow and simulated TSS. This can be a result of inaccuracy of the rainfall, the inaccurate rainfall may have resulted an increase in flow, and the increase in flow estimation resulted in an overestimation of catchment erosion rates, resulted a higher simulated TSS concentration.

**Table 4.6 Observed and simulated flow and TSS during first post-wildfire event**

Catchment	First event time	Observed flow (m <sup>3</sup> /s)	Simulated flow (m <sup>3</sup> /s)	Observed TSS (mg/L)	Simulated TSS (mg/L)
B1	10/4/2002	2.66	0.11	856	0
B2	6/2/2002	25.08	2.16	2.66	1.35
B3	5/2/2002	4.07	8.27	2.03	3.50

Most catchment sediment output in a forested catchment happens during event periods (Hopmans and Bren, 2007). Wildfire enhanced the threat of soil erosion especially during high-intensity rainfall events (Keeley, 1986). When monitoring post-wildfire catchment hydrology the first post-wildfire rainfall events should be closely monitored.

## **4.5. Conclusion**

The effect of wildfire on post-wildfire flow and TSS concentration were analysed using the SWAT model. For the 10 years post-wildfire period, the TSS concentrations observed from burnt catchments were much higher than TSS concentration estimated based on pre-wildfire calibrated models. The result of this study suggested that, one of the most severe wildfires in Sydney's drinking water catchments in the past hundred years had a significant effect on medium to long-term TSS output. This study proved SWAT is an effective tool for detecting catchment hydrology changes cause by wildfire. The studied catchments in this chapter are effected by drought during the short- and medium-term period. However, a higher flow response to rainfall during short-term and medium post-wildfire period is still observed (as compared to the flow change in simulated models). The flow value recovered to pre-wildfire levels during the long-term period (5+ year after the wildfire).

This study also provided evidence indicating the first post-wildfire event produced significant amounts of flow and TSS output. Heath et al. (2016) studied the flow change of catchment B2 effected by the same wildfire, and observed flow value recovered to pre-fire condition 5 years after wildfire. Our result for B2 flow recovery showed similar results. The catchment with shorter length post-wildfire dataset, B1, was observed to have the highest TSS output during the short-term and a slower recovery rate. The TSS recovery time observed in this study is longer than the flow recovery time observed in this study. This indicates the importance of long-term post-wildfire water quality monitoring. One reason for different recovery time can be the different recovery rate from different component of hydrology cycle such as different recovery rate of catchment vegetation change and catchment soil. Investigate the different impacts and recovery rates of these components can give us a better understanding of the recovery process,

thus, increase the accuracy of prediction. Further research should focus on identifying what is the dominant cause of fire-induced change on catchment water quality.

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## **Chapter 5**

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**5. Assessment of the relative contributions of wildfire induced impacts on soil and vegetation, and their effect on forest catchment hydrology using SWAT**

## **Abstract:**

Wildfire may affect the hydrological cycle of forested catchments, both in terms of quantity and quality of the stream water. Two major reasons for this are the effect that wildfire has on surface vegetation and soil organic carbon content. A reduction in surface vegetation affects catchment evapotranspiration, and increases erosion and runoff. Another important but less considered wildfire effect (in terms of the impact on catchment hydrology) is the reduction in soil organic carbon content. The surface organic layer are important sources of nutrients and help maintain soil structure, any reduction can make soil more easily eroded, change infiltration rates, and water holding capacity.

While there are many empirical studies that show wildfire impacts on surface vegetation and soil organic carbon, the relative impacts that each of these has on catchment hydrology (water quantity and quality) is less clear. Therefore, in this study we use the Soil and Water Assessment Tool (SWAT), a physical-based hydrological model, to assess the individual and combined effects of each on catchment hydrology. The case study is the 2001/2002 wildfire around Sydney, New South Wales. Five catchments were used to calibrate the SWAT model with 10 years' pre-wildfire water quantity and quality data and simulations were then performed for the first year post-wildfire under four scenarios (i) Unburnt, (ii) Burnt soil (change soil carbon to estimated post-wildfire level based on burn severity), (iii) Bare ground (change soil carbon to post-wildfire level and change surface vegetation of burnt area to bare ground to present extreme severity wildfire), and (iv) Grass (change soil carbon to post-wildfire level and change surface vegetation of burnt area to grass to present moderate severity wildfire). The wildfire severities of these burnt catchments were calculated based on the difference between pre- and post-wildfire Landsat

images. To investigate the effect of wildfire on soil carbon, 27 soil samples were collected from 7 prescribed burnt sites in NSW. The control (unburnt) sites were adjacent (within 50 metres) to the burnt plots. Particle size fractions and soil organic carbon were measured on the samples. In addition, the burn severities of these sites were calculated based on Landsat images using the same method as for the study catchments. A regression model was then used to predict the change in soil organic carbon based on the unburnt carbon content and burn severity (adjusted  $r^2 = 0.54$ ). This model was applied to create soil carbon maps for the study catchments based on observed wildfire severity. The predicted carbon maps were used to run SWAT in the post-wildfire period. The modelled value of flow and water quality (total suspended sediment) outputted from the four scenarios were then compared with each other and with observed post-wildfire discharge and water quality observations. We compared the observed and simulated mean, minimum, and maximum values. The differences between these values represent the sensitivity of the model predictions to wildfire related changes. We estimated a carbon drop (22-88%) in burnt soil. This carbon drop resulted in a minimal change in catchment hydrology predicted by SWAT. Vegetation changes due to wildfire resulted in substantial differences in the post-wildfire catchment hydrology were predicted by SWAT.

## **5.1.Introduction**

Wildfire has a significant effect on the hydrological cycle of forested catchments and causes an increase in runoff and erosion; therefore, affecting the hydrology (water quantity and quality) of a forested catchment. Two major effects of wildfire are the effect it has on surface vegetation and soil organic carbon content. In south-eastern Australia, wildfire events from 2003 to 2009 burnt a combined area of over 3 million hectares of forest (Smith et al., 2011). In western North American, wildfire is considered to be one of the most threatening natural disturbances due to its impact on vegetation (Leon et al., 2012). The removal of vegetation alone in severe wildfire is sufficient enough to produced significant effects on catchment hydrology (Neary et al., 2009). A reduction in surface vegetation effects catchment evapotranspiration, increases erosion and runoff, and increase the percentage of rainfall for runoff (Moody and Martin, 2001).

The amount of soil organic matter varies between different ecosystems. In most soil types, the organic matter is concentrated in the top layer and decreases downward through the soil. The wildfire effect on soil depends on the depth of penetration of the heat and its duration (Heath et al., 2015). When the wildfire is severe enough to expose bare soil, the infiltration rates can be reduced. This is due to several reasons such as a collapse of the soil structure and removal of organic matter, impact of raindrops on the soil surface, and ash and charcoal residues clogging soil pores (Brooks et al., 2012). The soil surface and organic layer are important sources of nutrients and help maintain soil structure, any reduction can make soil more easily eroded, change infiltration rates, and water holding capacity. Additionally, the removal of vegetation changes the surface soil moisture and temperature level. This might result in a change in microbial activity and in nutrient cycling. In higher severity wildfire events, heat is also transferred into soil which effects underground biological processes such as decomposition and

mineralisation, which in turn, effects the quantity and quality of organic matter (Neary et al., 2005).

The study by Humphreys (1981) investigated the soil temperature generated during different wildfire conditions in Australian and found that during wildfire, the temperature only reaches 200 °C at 1 mm below surface. The soil temperature never exceeds the ambient temperature at 2-3 cm below ground. However, the loss of soil organic carbon starts at temperature between 100 and 200 °C (Kang and Sajjapongse, 1980). The change in soil organic carbon post-wildfire varies between different wildfire severity, vegetation type and soil type. These effects ranges from almost total destruction to a 30% increase in the surface layer (González-Pérez et al., 2004). In soils heated under laboratory conditions, 100% loss of organic carbon is frequently reported (Almendros et al., 1984, Fernández et al., 1997). Fernández et al. (1997) reported a 50% organic carbon loss in the top 10 cm soil post-wildfire in pine forest. González-Pérez et al. (2004) reviewed the effect of wildfire on soil organic matter in the past studies and conclude the effect is highly dependent on the environment factors. No general trends can be suggested for individual wildfire events. Neary et al. (2005) suggested that additional research is needed to further elucidate the consumption of organic matter in soil during wildfire with the consideration of burnt severity or heat transfer during the wildfire.

The change in surface vegetation and soils structure effects catchment hydrology. Soil erosion post-wildfire varies from less than 0.1 Mg/ha/year in low severity wildfire to 369 Mg/ha/year in severe wildfire with high slope (Neary et al., 2009, Robichaud and Miller, 2000, Abramson, 2009, Anderson, 1976, Bartley et al., 2012). Most of the hydrological change occurs during the first year post-wildfire. (DeBano, 2000, Brown et al., 2005). An 8-9 times total suspended sediment (TSS) increase during the first year post-wildfire was reported by Lane et al. (2006)

following a wildfire in southern Australia. Reneau et al. (2007) reported a 106-fold increase in TSS year compare to unburnt catchments in New Mexico, USA. Sheridan et al. (2007b) studies 6 catchments affected by wildfire in Victoria, Australia and observed TSS increase from 1.3 times to 1459 times during the first post-wildfire year, compared to pre-wildfire conditions.

The different effects of wildfire on TSS depends on different factors include rainfall, catchment slope, burn severity, catchment scale, and others. It is also affected by the method used for estimating TSS output for unburnt catchments. Empirical models are the most commonly used in change detection studies. In this method, regression models are used to predict the catchment's condition. However, by using an empirical model, studies are only able to detect the effect of wildfire on catchment hydrology, but not able to analyse or identify the cause of this effect.

As a result studies on wildfire effects on catchment hydrology have only focused on summarising the overall post-wildfire catchment hydrology change. It would be required to include in the modelling process spatially varying data about soil, land use, terrain, and weather to better identify susceptible locations and components of the catchment, e.g. soil versus vegetation. This would improve catchment management and protection decisions.

Physical-based spatially-distributed hydrological model are one method to deal with the above limitations and improve the modelling process. Physical-based models, as described by the name, use physical inputs, such as digital elevation model (DEM), land-use maps, and soil maps to simulate hydrology in a catchment. Another benefit of this model is it allows user to modify input data individually and investigate the output results separately. This would allow us to introduce different wildfire effects such as the effect on soil or vegetation, and compare the corresponding outputs. Additionally, physical-based models allow investigation of hydrological

outputs from different part of the catchments as these models separating catchments into sub basins, and runoff are calculated in each sub basin first and then routed through several channels to calculate the total runoff (Pisinaras et al., 2010). The same process is followed for sediments. This may help improving the catchment protection decisions in the future. The Soil and Water Assessment Tool (SWAT) is one of the most popular hydrological models used worldwide (Arnold et al., 2012). This model uses a large range of parameters and has a high flexibility in input (Abbaspour et al., 2007b). It was developed for the purpose of predicting effect of land use change (Neitsch et al., 2001).

In this study, we aim to assess the relative effects that wildfire induced changes in soil and vegetation have on catchment hydrology. In particular we focus on flow and TSS under four scenarios:

1. Unburnt scenarios;
2. Burnt soil (change soil carbon to estimated post-wildfire level based on burn severity);
3. Bare ground (change soil carbon to post-wildfire level and change surface vegetation of burnt area to bare ground to present high severity wildfire);
4. Grass land (change soil carbon to post-wildfire level and change surface vegetation of burnt area to grass to present moderate severity wildfire).

## 5.2. Methods

### 5.2.1. Wildfire sites

Three catchments located southwest of Sydney, New South Wales, Australia, are used in this study (Figure 5.1). The hydrology of these catchments are important in these catchments as it delivers drinking water for Sydney's residents (Heath et al., 2014). These catchments were burnt by wildfire which occurred from 3<sup>rd</sup> December 2001 to 14<sup>th</sup> January 2002. The three selected catchments have areas from 56 km<sup>2</sup> to 104 km<sup>2</sup> with the burnt area ranging from 79.1% (B3) to 100% (B1) during this wildfire. The key features of these studied catchments are summarised in Table 5.1

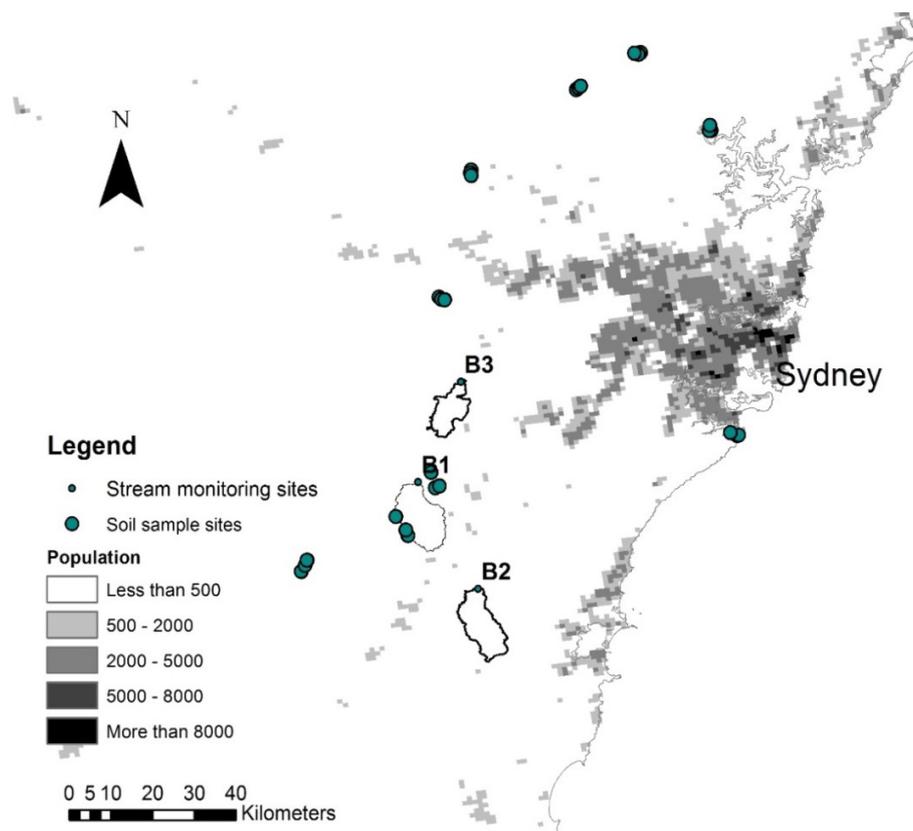


Figure 5.1 Location of studied catchments and soil sample sites

**Table 5.1 Catchment characteristics**

Catchment	Area (km <sup>2</sup> )	Burnt %	Grass land%	Forest %	Other%	Annual rainfall (mm)	Annual Flow (ML)
B1	104	100	2	97	1	824.65	137954
B2	88	83.2	4	95	1	1182.54	420889
B3	56	79.1	29	69	2	694.95	240910

### 5.2.2. SWAT

The input data and the calibration process of the models can be found in Chapter 4 section 4.3. The following sections focus on what parts of the SWAT model were modified to reflect burnt conditions.

#### *Universal Soil Loss Equation (USLE)*

The USLE equation is an equation used for estimating long-term average annual soil erosion, it is created by Wischmeier and Smith (1978) as shown below;

$$A = R \times K \times L \times S \times C \times P, \quad (5.1)$$

where A (average soil loss) is predicted by 6 factors: rainfall and runoff erodibility factor (R), soil erodibility factor (K), slope length (L) and steepness (S), C is the cropping factor and P is short for support practice factor. In SWAT, the C factor is controlled by crop type, it is changed accordingly based on land use. K factor is a property of soil type. Support practice include terracing, strip cropping and contouring, it is assigned to individual HRU based on slope and specific practice. In this study, only K and C factors were modified while updating soil and land use information.

*USLE equation soil erodibility factor ( $K_{USLE}$ )*

$K_{USLE}$  value is important for calculating soil erodibility factor. This is the only factor directly related to catchment hydrology affected by soil carbon change in SWAT.

Wischmeier and Smith (1978) define the soil erodibility factor as the soil loss rate per erosion index. SWAT uses the USLE equation soil erodibility factor ( $K_{USLE}$ ).

$$K_{USLE} = \frac{0.00021 \times M^{1.14} \times (12 - OM) + 3.25 \times (c_{soilstr} - 2) + 2.5 \times (c_{perm} - 3)}{100} \quad (5.2)$$

This equation was developed by Wischmeier et al. (1971) for calculating the soil erodibility based on soil composition. As showed in equation 5.2, M is the particle size parameter, OM is organic matter content,  $c_{soilstr}$  and  $c_{perm}$  are the soil structure code and soil permeability class. OM value is calculated as 172 times organic carbon content.

The particle size parameter is calculated by as:

$$M = (m_{silt} + m_{vfs}) \times (100 - m_c) \quad (5.3)$$

where  $m_{silt}$  is silt content in percent,  $m_{vfs}$  is the very fine sand content and  $m_c$  is the percent clay content. The very fine sand is calculated based on the percentage of sand use RUSLE2 equation (Foster et al., 2003) where:

$$P_{vfs} = (0.74 - \frac{0.62P_{sd}}{100})P_{sd} \quad (5.4)$$

### 5.2.3. Scenarios

For each catchment, four scenarios were built:

Scenario 1: Unburnt model: The models were built with available data and calibrated for 10 years pre-wildfire period, and simulated with the calibrated data for 1 year post-wildfire period.

Scenario 2: Burnt soil model: during the post-wildfire period, the top layer soil carbon was modified based on soil burnt severity. The USLE\_K value is also modified accordingly. The process of estimating post-wildfire soil carbon map is explained in section 2.4.

Scenario 3: Bare ground model: during the post-wildfire period, soil carbon and catchment land use were both modified. The burnt forest areas were changed to bare ground (standard SWAT land use type), indicate the most intense burning within the catchment.

Scenario 4: Grass model: during the post-wildfire period, the soil carbon and land use were both modified. The burnt forest land model was changed to grass land (standard SWAT land use type).

The four scenarios were run for one year post-wildfire period. Simulated results were compared to observe what post-wildfire change effect the post-wildfire catchment hydrology the most and what's a better way to predict post-wildfire catchment hydrology. We only investigated the catchment hydrology change for one year post-wildfire period for two reasons: 1, hydrology change during the first post-wildfire year is most severe and requires close monitoring. 2, there is less vegetation recovery happening during the first post-wildfire year. In the longer-term post-wildfire, the catchment hydrology will recover as the catchment vegetation recovers. However, it is hard to simulate the vegetation recovery process in our models.

Scenario 3 and 4 represent 2 different wildfire effects on forest land use change, Scenario 4 represent land use change under moderate wildfire effect while scenario 3 represents land use change under extreme wildfire effect. Therefore we model the lower and upper bounds of what could happen post-wildfire. A detailed explanation of vegetation updating in SWAT is will be present in section 5.2.5.

#### *5.2.4. Calculate post wildfire soil carbon and other soil inputs*

The soil carbon change caused by wildfire are estimated based on a regression model including the differenced normalised burn ratio (dNBR) and pre-wildfire soil properties such as clay content and organic carbon.

#### *Prescribe burnt sites and soil samples*

To test the effect of wildfire on top layer soil carbon content and the relationship of change in carbon content and wildfire severity, we took samples from prescribed burn sites and tested their soil carbon content change. 9 prescribed burn sites were selected in NSW as showed in Figure 5.1. Each site was burnt at different ignition dates with different burn size (Table 5.2). Three pairs of plots were selected for each burnt sites. The burnt plots were selected randomly in the burnt area and the control (unburnt) plots were adjacent (within 50 metres) to the burnt plots but in the area that were not burnt. Samples were taken at the same time, both plots were visually identified to have minimum difference in dominant canopy species, slope and aspect.

**Table 5.2 Burn size and ignition date of prescribe burnt sites**

Site	Burn size (ha)	Ignition date
HT	611.90	19-24 August 2015
SG	166.18	14 August 2015 to 24 August 2015
HES	634.17	17-24 August 2015
PTS	319.27	19-24 August 2015
LAK	807.86	13-18 September 2015
MTC	916	8-10 March 2016
JOD	46.04	5-8 April 2016
KIF	591.16	14,15,16,17 April 2016
LEF	2669.26	1, 2, 3 April 2016

The top layer soil from each site was taken using a soil core. These samples were stored separately in a zip bag at 4 °C and sieved to 2 mm in laboratory. For each soil sample, particle size analysis was done using hydrometer method to determine the percentage of soil, clay, silt, and sand content in soil. A separated subsample was oven-dried at 40 °C, grounded and analysed for total C and N.

To build scenario 2, the top layer soil C content of all polygons were updated based on polygon's median dNBR and soil inputs. One thing need to be noticed here is, the SLGA's soil layer separation method assigned top 5 cm soil as the top layer soil. This value is different to our soil samples collected in prescribed burn sites (top 10 cm). However, only the top layer soil carbon content was modified. This is because past studies on soil carbon change has concluded that wildfire only effect the surface layer of the soil. The carbon content or temperature change never exceeds 2-3 cm below ground (Humphreys, 1981).

#### ***Burnt severity (dNBR)***

For both wildfire catchments and prescribed burnt sites, the dNBR were calculated based on Landsat 7 ETM+ satellite images. The dNBR is calculate based on the difference between pre-

burnt landscape NBR and the post-burnt landscape NBR, which is calculated using near infrared (NIR) and mid infrared (SWIR) bands using equation 5.5

$$NBR = \frac{NIR - SWIR}{NIR + SWIR} \quad (5.5)$$

The NBR ranges between -1 to 1, a higher NBR indicates a higher vegetation density of the area. The difference between pre-burnt NBR and post-burnt NBR presents the vegetation cover differences, hence, burnt severity. The pre-burnt and post-burnt SWIR and NIR band of calibrated Landsat 8 images were downloaded from Australian Geoscience Data Cube (AGDC) (Cube, 2015)

#### 5.2.5. *Vegetation effect*

In addition to scenario 1 and 2, two other scenarios were created to represent burnt lands. Scenario 3: the burnt areas were changed to Range – Grass (RNGE) to present wildfire effect at moderate severities. Scenario 4: burnt forest areas were change to bare ground to represent the area which were most severely affected by wildfire. Vegetation changes in SWAT results in changes in soil erosion and plant evapotranspiration. In SWAT, plant evapotranspiration is calculated using the Penman-Monteith function (Monteith, 1965). Plant water uptake is calculated as a function of leave area index (LAI), plant stomatal conductance plant height and plant root depth. It is limited by soil water content. Land cover change also effect USLE C factor in USLE function (Renard, 1997). The USLE C factor in SWAT effects the maximum decrease in erosion for a set land cover. The input values are showed in Table 5.3.

**Table 5.3 Value of main vegetation inputs in different model settings**

Name	Input	Unburnt	Bare	Grass
Maximum potential leaf area index	BLAI	5	0.01	2.5
Maximum canopy height (m)	CHTMX	10	0.01	1
Maximum root depth (m)	RDMX	3.5	0.1	2
Optimal temperature for plant growth (degree C)	T_OPT	30	25	25
Minimum temperature for plant growth (degree C)	T_BASE	0	12	12
USLE C Factor	USLE C	0.001	0.2	0.003
Maximum stomatal conductance	GSI	0.002	0.005	0.005
Manning's "n" value for overland flow	OV_N	0.1	0.14	0.15
Initial SCS runoff number for moisture condition II	CN2	55	86	69

### 5.3.Results

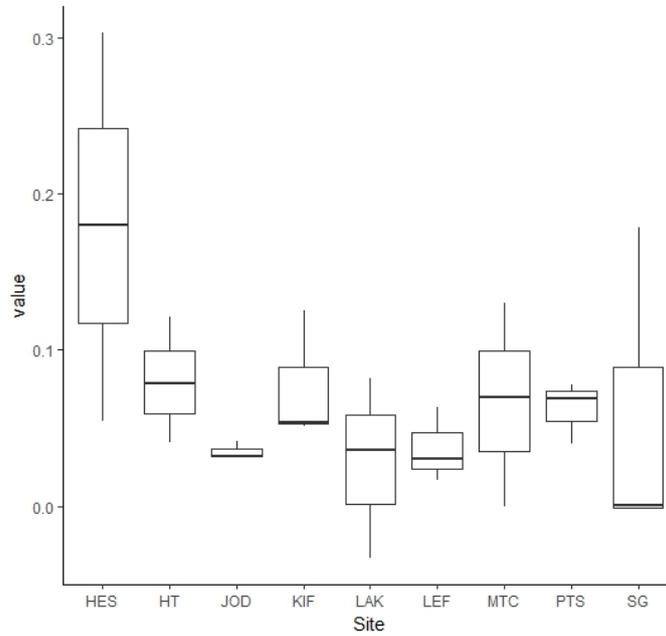
Three catchments were calibrated for 10 years pre-wildfire (1991 – 2001) time at daily steps in SWAT-CUP for flow and TSS. These catchments showed an average NSE of 0.68 for flow and 0.69 for TSS calibration (Table 5.4). It should be noted here, even the model’s TSS values are simulating at daily steps, there is on average, only one to two TSS observations for each catchment in each month. Thus, SWAT only compares the predicted and observed TSS output on the corresponding day. The high NSE values suggested the ability of the model to predict stream flow and TSS output based on soil, weather, terrain and vegetation inputs.

**Table 5.4 Calibration results**

Catchment	NSE	
	Flow	TSS
B1	0.70	0.92
B2	0.63	0.63
B3	0.72	0.63
Average	0.68	0.69

#### 5.3.1. Carbon change

The prescribed burnt sites showed a different dNBR for different sites (Figure 5.2). With the highest dNBR of 0.303 in HES sites. LAK3 and SG2 sites indicate a dNBR of -0.03 and -0.002 indicate a strong post-burn regrowth. The prescribed burnt sites showed an average dNBR of 0.07. On average, there is a decrease of 0.195% soil carbon due to wildfire, with the highest carbon drop of 1.191%. The highest carbon drop site also has the highest burn severity value.

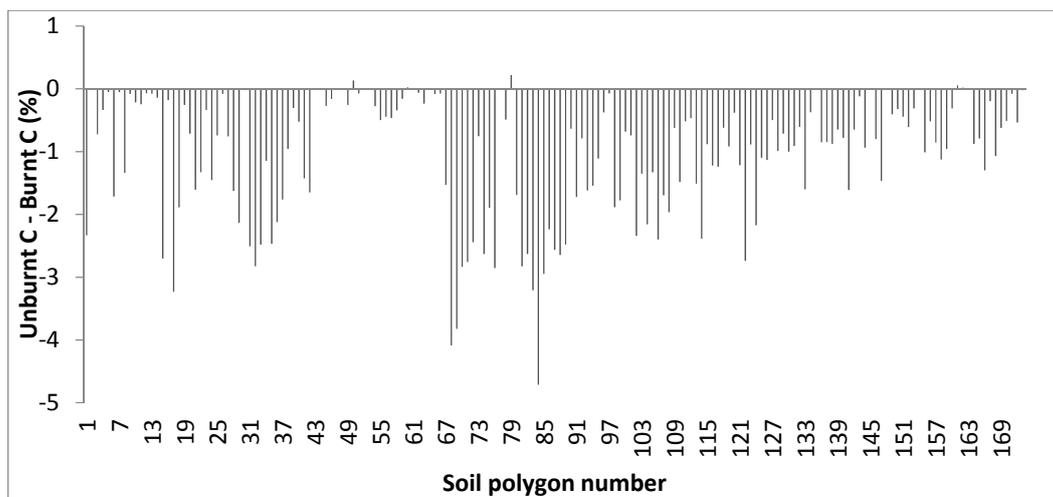


**Figure 5.2 dNBR value of prescribe burnt sites**

The regression model between soil initial clay content, soil carbon change and dNBR indicated that soil clay content is not a sensitive factor for predicting post-wildfire soil carbon. The final model is shown below and had an adjusted  $r^2$  value of 0.59.

$$PostC = 0.89 \times PreC + 4.2 * \Delta NBR - 1.8 \times PreC \times \Delta NBR \quad (5.5)$$

The post-wildfire carbon was calculated individually for each of 173 soil polygons (Figure 5.3). in the study catchments. 8 polygons showed a small increase in carbon level (0.001% - 0.22%), 6 polygons showed no change to carbon while the rest showed a decrease of soil carbon level with the highest soil carbon decrease of 4.71%. On average, there is a decrease of 1.1% carbon.



**Figure 5.3 Soil carbon change after wildfire**

The soil carbon change resulted in a small change in soil erodibility factor. The minimum soil erodibility factor has showed a 0.15% increase (from 0.154 to 0.15423) and the maximum erodibility factor increased from 0.165 to 0.16525.

### 5.3.2. Different model setting results during first year post-wildfire

A detailed report of model flow output values are shown in Table 5.5. Four different model scenarios have been used for simulating the model behaviour during the first post-wildfire year. In terms of flow, the Unburnt and Burnt soil model showed same flow prediction; Bare models showed the highest flow prediction between all models. The mean flow of Grass models were similar observed flow in catchment B2 and B3. All predicted mean flow in catchment B1 predicted higher flow than the observed flow. All models in B1 and B3 over predicted the event flow and very low flow, this might be result from poor rainfall data. In catchment B2, the Bare model predicted similar event flow to the observed flow value.

The TSS estimations are shown in Table 5.6. Catchment B3 showed the highest TSS output in all models, this might be due to lower forest land cover in this catchment. Between all simulated

models, as can be expected, Bare model for all catchments showed extremely high amount of TSS output, Grass models estimate much higher TSS output than forest lands.

Compare the model estimations with observed TSS outputs: 4 models in B2 and B3 all over predicted mean TSS output, the Unburnt and Burnt soil model in B1 observed no TSS output while a high mean TSS concentration was observed. This observed mean TSS is higher than the Grass model output but lower than the Bare model output. All models for catchment B3 overestimated the TSS output during event flow. The event TSS observed in B2 is higher than the Unburnt model. Catchment B1 output the highest event TSS output. This value is lower than the Bare model but higher than the Grass model.

**Table 5.5 Flow output during first year post-wildfire in different models (m<sup>3</sup>/s)**

		Unburnt	Burnt Soil	Bare	Grass	Observed
B1 Flow	Min	0.06	0.06	0.27	0.16	0.02
	Mean	0.94	0.94	1.6	1.23	0.15
	Max	60	60	112	74	2.92
	SD	3.70	3.70	6.95	4.59	0.35
B2 Flow	Min	0	0	0	0	0.02
	Mean	0.4	0.4	1	0.4	0.37
	Max	11	11	28	13	26.04
	SD	1.38	1.38	3.58	1.48	2.08
B3 Flow	Min	0	0	0.02	0.01	0
	Mean	0.14	0.14	0.58	0.09	0.1
	Max	14	14	23	18	4.45
	SD	0.74	0.74	1.94	1.07	0.40

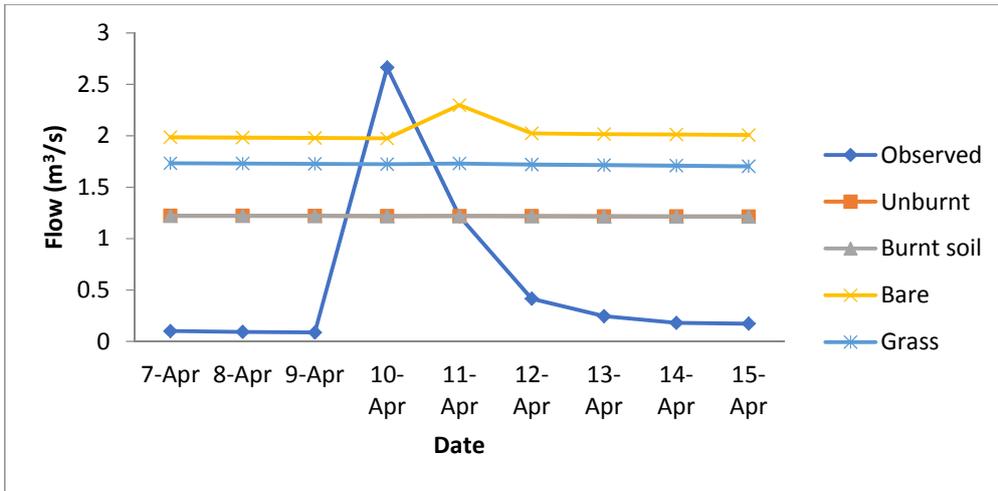
\*SD: Standard deviation

**Table 5.6 TSS output during first year post-wildfire in different models (Metric Tons/Day)**

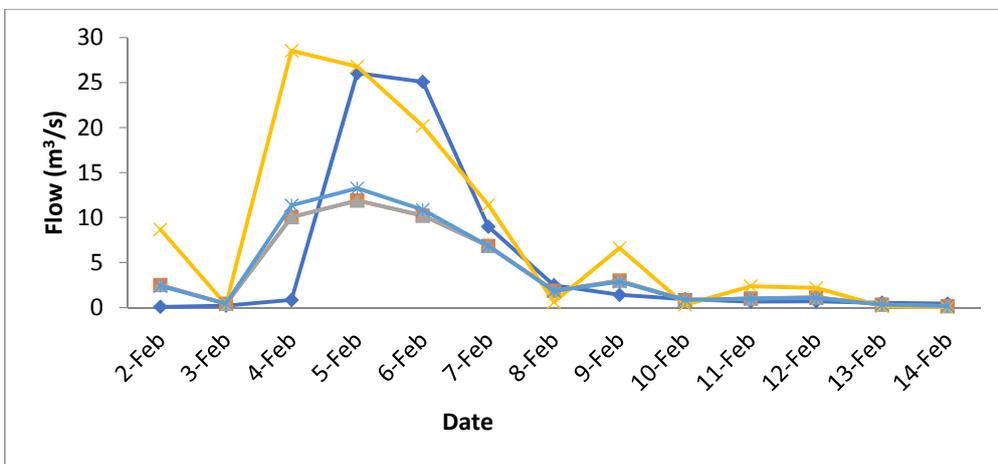
		Unburnt	Burnt Soil	Bare	Grass	Observed
B1 TSS	Min	0	0	0	0	0.005
	Mean	0	0	359	0.97	154
	Max	0	0	4667	12	1971
	SD	0	0	1294.39	3.52	546.03
B2 TSS	Min	0	0	0	0	0.002
	Mean	0.4	0.4	13096	2.3	0.2
	Max	2.4	2.4	107900	16	2.6
	SD	0.89	0.89	30252.54	5.16	0.68
B3 TSS	Min	0	0	0	0	0.005
	Mean	13	14	15804	1310	0.014
	Max	183	188	66780	11340	8.28
	SD	45.41	46.87	24780.46	2888.25	2.47

\*SD: Standard deviation

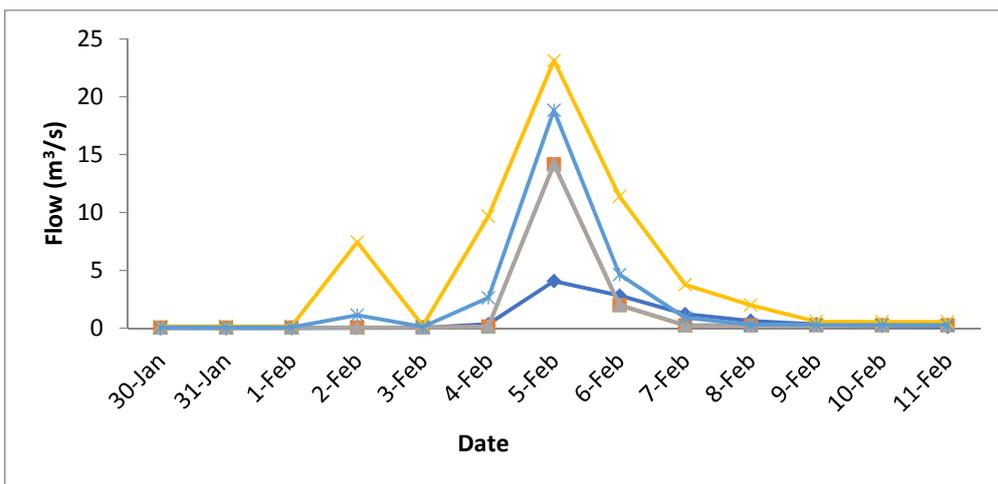
All catchments were severely burnt during this wildfire event. Past studies has indicated that one of the most significant flow and TSS change was during the first post-wildfire event (Nyman et al., 2011). Figure 5.4 shows the flow observations for the 3 catchments during the first post-wildfire event. Catchment B2 and catchment B1 received peak rainfall of 35.6 mm and 24.2 mm, and had observed peak flows of 26.04 m<sup>3</sup>/s and 2.66 m<sup>3</sup>/s accordingly. The magnitude of flow was predicted by Bare model. However, in catchment B2, the flow peak was predicted one day earlier than observed flow peak, catchment B1 estimate the flow peak one day later than observed. All the other model scenarios predicted much lower flow output than Bare ground model or observed flow peak. Compared to catchment B2 and B1, catchment B3 received the highest rainfall of 69.4 mm, but only observed a small flow peak of 4.07 m<sup>3</sup>/s (dark blue). All models for this catchment over predicted flow value.



B1



B2



B3

**Figure 5.4 First post-wildfire event flow output for observed and simulated models.**

The TSS observation is limited by the data availability and also effected by the time of the day an observation was made. The TSS output during the first flow event is showed in Table 5.7. For catchment B3, All models over predicted the TSS output. This might be a result caused by over predicting of flow. In catchment B2, the observed TSS is higher than the Unburnt and Burnt soil model but still lower than the other 2 models Catchment B1 is the most severely burnt catchment. During the first post-wildfire event, this catchment received the smallest rainfall but observed the highest amount of TSS. The Unburnt model predicted no TSS output in this event. However, this output value is still lower than the Bare ground model output. Additionally, the peak TSS level in this event is predicted one day later than the observed TSS output.

**Table 5.7 TSS output during the first post wildfire event (Metric Tons/Day)**

Catchment	Date	Observed	Unburnt	Burnt soil	Bare	Grass
B3	2/5/2002	8.2845	183	188.9	66780	11340
B2	2/6/2002	2.6612	1.889	1.889	28870	11.76
B1	4/10/2002	1971.406	0	0	0	0
	4/11/2002	35.69301	0	0	4667	12.69

## 5.4. Discussion

### 5.4.1. Soil carbon change post-wildfire

In this study, we used soil samples collected from prescribed burnt sites and dBNR value calculated from Landsat images to estimate the correlation between soil carbon change, soil clay content, and dBNR. No similar past studies has been found. Several studies have investigated the correlation between soil clay content and soil carbon content. A strong correlation between soil carbon content and soil clay content has been observed in several studies (Nichols, 1984, Spain, 1990, Arrouays et al., 1995, Alvarez and Lavado, 1998). However, some other works has shown that soil carbon storage is controlled by climate (Burke et al., 1989, Alvarez and Lavado, 1998). Percival et al. (2000) studied the factors controlling soil carbon levels in New Zealand soil and concluded soil carbon content is not an important factor. Davidson and Lefebvre (1993) observed that the clay content was unrelated to soil carbon in forest ecosystems in Maine and concluded that the soil carbon content is more correlated to soil drainage. In our study, we have observed that soil clay content was not found to be a significant factor for predicting wildfire effect on soil carbon content.

Burn severity and pre-wildfire soil carbon content were identified to be the only factors used to predict post-wildfire soil carbon content. We estimated a carbon decrease ranging from 0.195% to 1.191% in the post-wildfire top layer soil. A reduction in soil carbon content post-wildfire has been observed in several past studies, however the results varies from slightly increase (Úbeda et al., 2005) to 50% decrease (Fernández et al., 1997). In soils heated under laboratory condition, 100% of the organic carbon destruction is frequently reported (Almendros et al., 1984, Fernández et al., 1997). This agrees with our estimated carbon content change from our

regression model. Our regression model estimated a decrease from 50-88% for the 20 most severely burnt polygons and one third of the soil polygons estimated a 20-50% decrease in soil carbon.

#### *5.4.2. SWAT model's output under different input setting*

An increase in soil organic carbon has been reported to increase soil water holding capacity by several studies (Maynard, 2000). However, the significance of this increase on flow output needs future research. Minasny and McBratney (2018) analysed a large dataset to explore the relationship between soil organic carbon and soil water content at saturation and conclude the effects are very limited.

The change in soil organic carbon content mainly results in a slight change in the soil erodibility factor in the model. This change did not result in any observable change in model flow or TSS output in our simulated results. This indicates SWAT model's insensitivity to soil carbon change, or the change in soil carbon does not have impact on the hillslope hydrology and therefore stream hydrology. In this study, in terms of TSS, only the organic carbon content in the KUSLE function is modified. However, wildfire may have effects on soil structure (DeBano, 1991). This might affect some other soil inputs in SWAT such as the *csoilstr* in equation 5.2. Additionally, wildfire creates a water repellent layer on top of the soil (Heath et al., 2015) and this change might have an effect on the soil permeability (e.g. *cperm*) in the SWAT model. The sensitivity of SWAT hydrology output with these inputs should be tested in further studies.

There is very limited studies used SWAT for predicting the effect of wildfire. In these limited studies, the curve method is used. In the cases, the curve number of the model is adjusted and recalibrated after a set date (Neitsch et al., 2011, Canfield et al., 2005). The process of changing

the curve number in SWAT model first, converted the method in a similar way it is processed in empirical method. Also, this method requires recalibrating of the catchment inputs, which might have altered catchment response to the environment and violate the original purpose of using physical based model. Tufekcioglu et al. (2017) attempted to simulate the wildfire effect on catchment hydrology, however, they did not calibrate the models. In our study, we altered the land-used change to calibrated models to simulate land-used change result from wildfire at two different severity levels. One limitation of this study is we did not apply different wildfire severity to different locations in the catchment. The vegetation cover of entire burnt catchment area was treated at the same burnt severity for each scenario. Future studies can use similar method we used for soil profile, but create different vegetation profiles for land-use area burnt at different burnt severity. In our work we used to two extremes, bare soil and grassland.

## **5.5. Conclusion**

In this study, we attempt to simulate the wildfire effect on soil carbon content and vegetation, and the consequences of these changes to catchment hydrology on the first post-wildfire event and during the first post-wildfire year. Our study has estimated a big carbon drop after wildfire (22%-88%) in the top layer of soil. However, this carbon change did not result in a significant change in catchment hydrology. Vegetation changes due to wildfire are observed to be the main reason for post-wildfire hydrological change.

This attempt is not only for the purpose of simulating the wildfire effect, but also for testing the model's sensitivity. In our result, one of the most affected catchment (B2) showed similar flow output to the Bare model in terms of mean, maximum, minimum, and the first post wildfire event behaviour. Additionally, we have found the TSS output value for the first post wildfire event lies between Grass model and Bare ground model output. The observations from our results opened a possibility for a physical based way to predict post-wildfire catchment hydrology in future studies.

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## **Chapter 6**

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### **6. Effect of subcatchment spatial variability on post-wildfire hydrology**

## **Abstract:**

Forested catchments are critical source for downstream drinking water supply. The stable forest ecosystem can be disturbed by wildfire and result in severe effects on catchment hydrology (catchment water quantity and quality). Past studies focused only on summarising the wildfire induced change in catchment hydrology, and only give suggestions for post-wildfire catchment hydrology monitoring during catchment recovery period. Very little attention has been paid to identify the wildfire sensitivity areas of a catchment for wildfire protection. In this study, we used the physical-based distributed model SWAT (Soil and Water Assessment Tool) to assess the correlation between subcatchment spatial variation and post-wildfire catchment hydrology. The data used to calibrate SWAT model is collected from a catchment located near Sydney, New South Wales, Australia. This catchment was affected by wildfire which started in December, 2001. Ten year's pre-wildfire catchment hydrology data are used to calibrate the model and simulations were then performed for 1 year post-wildfire under 3 different vegetation scenarios: 1) no change (forest), 2) forest land changed to grass land, and 3) forest land changed to bare ground. The catchment was separated into 22 subcatchments by SWAT based on the catchment elevation. The water yield and total suspended sediment (TSS) output from each subcatchment was extracted. The correlation between catchment yield (water and TSS) and catchment spatial characteristics (digital elevation model and soil) were calculated to identify the catchment characteristics that may lead to a higher post-wildfire damage. The correlations indicated that, catchments with: 1) higher percentage slope increases, 2) shorter slope length, and 3) small soil top layer bulk density, clay, and carbon content, have the highest catchment hydrology impact post-wildfire. We suggest more attention should be paid to catchments with these characteristics when making catchment protection plans.

## **6.1.Introduction**

Global climate change has increased the frequency of wildfire. Wildfire in forested catchments can have a significant effect on the catchment hydrology (water quantity and water quality) over the short-term and long-term. Several studies have analysed the effect of wildfire on post-wildfire catchment hydrology (Smith et al., 2011, Feikema et al., 2011, Lane et al., 2010, Shakesby et al., 2007, Lane et al., 2006, Townsend and Douglas, 2004, Heath et al., 2015). However, most of these past studies used empirical models. The problem with empirical models is that it does not have the ability to include or investigate spatial variability (in land use, digital soil model, and soil) within a catchment, which limits these studies to only focus on summarising catchment hydrology change resulting from wildfire. Very little attention has been paid to identifying the sensitivity area of a catchment for wildfire protection. Smith et al. (2011) did a review of wildfire effect on catchment hydrology and suggested future model development should not only focus on the understanding the wildfire effect but also provide catchment management guidelines.

Compared to empirical models, physical-based spatially-distributed models are more useful at supporting the design and evaluation of water catchment management, for example, identifying the wildfire sensitive areas in forested catchment for catchment protection. Aust and Blinn (2004) indicated that forest protection is one of the most important aims when making forestry management practices plans. The nature of the physical-based distributed models allows a multi-objective evaluation of the impacts of physical inputs on the catchment hydrological responses. This property has made physical-based distributed hydrological models more attractive and popularly used for evaluating land-use change and water catchment management options.

However, physical-based distributed models are infrequently used for water management problems such as assessing the wildfire effect on catchment hydrology. One major drawback is the data required for these models. Physical-based distributed models require continuous catchment hydrology data, weather data and spatial inputs for calibrating and simulation. Insufficient data has been reported as the major reason for low quality simulation in several studies (Romanowicz et al., 2005). Additionally, there is a lack of the understanding of the robustness, sensitivity and calibration process of physical-based distributed models (Romanowicz et al., 2005). Many of these models are characterised by a multitude of input data and have a high complexity. Due to the spatial variability in the simulated process, the values of many of these inputs may not be exactly known (Cibin et al., 2010). Thus, most of these models require a calibration process after the model is built to estimate a more accurate range of inputs. The calibration process helps reduce the input uncertainty which in turn, reduce the output uncertainty. However, the calibration process can be complex and computationally extensive when the number of inputs is large (Sorooshian and Gupta, 1995). Analysis of the input sensitivity to hydrological model output can help increase the understanding of the catchment hydrological process and help the calibration process (Turanyi and Rabitz, 2000). Additionally, understanding the sensitivity and correlation of spatial inputs to catchment hydrology changes gives a better understanding of the catchment processes.

The Soil and Water Assessment Tool (SWAT) model is one of the most popular physical-based hydrological models used for investigating land-use change effect on catchment hydrology (Arnold et al., 2012). It has been proven by a large amount of studies on its ability to simulate catchment hydrology (e.g. Tuo et al., 2016, Yang et al., 2014, Pisinaras et al., 2010, Abbaspour et al., 2007b). It is an important and popular tool for catchment management. SWAT model

operates on daily steps, it is characterised by a large amount of spatial and weather inputs. Despite the excess amount of studies using SWAT, studies on the sensitivity of inputs are a minority. A few studies have studied the sensitivity of inputs (Arnold and Fohrer, 2005, Holvoet et al., 2005, Arabi et al., 2007, Muleta and Nicklow, 2005, Stow et al., 2007, Muttiah and Wurbs, 2002). However, these studies are focused on selecting the inputs that may be considered for the calibration process. There's very limited to no details reported about the correlation of specific inputs to model output. Cibin et al. (2010)'s study is an exception, in their study on the sensitivity of inputs to stream flow generation, they reported a positive correlation of catchment flow output with catchment slope percentage increase (SLOPE) and slope length (SLSUBBSN), they also observed a negative correlation between flow output and soil available water capacity (SOL\_AWC).

SWAT model provides output at different scales (catchment, subcatchment and HRU). HRU (hydrological response units) are the basic units of the model, subcatchment in SWAT are defined by the digital elevation model (DEM) and HRU are defined by soil, land-use and slope (Arnold et al., 2012). However, all of the reviewed studies have focused on testing the input sensitivity at the catchment level (main channel output). Understanding input sensitivity at a finer level may help understand calibration process from a different angle and investigating the effect of subcatchment separation. But in the context of this work, it could assist with catchment wildfire protection plans.

In this paper, we investigate the correlation between catchment DEM, soil inputs, and catchment hydrology output with SWAT in a small catchment located in NSW, Australia. This catchment provides drinking water to Sydney, and was effected by wildfire in December 2001. The

correlation between models inputs and simulated catchment hydrology outputs (from unburnt, burnt at moderate severity, and burnt at high severity) were tested.

This will help us to:

1. Have a better understanding of relationship between subcatchment spatial variability and catchment hydrology.
2. Identify wildfire sensitive subcatchments which should be the focus for catchment protection during pre-wildfire period.

## **6.2.Method**

### *6.2.1. Study area*

The studied catchment is located in west of Sydney, it is impounded by Warragamba Dam, the water quality of this catchment is important as it provides drinking water to Sydney. This catchment has an area of 56.4 km<sup>2</sup> with 35% grass land, 5% urban land, 59% forested (eucalyptus) land, and 1% mixed land. Most of the forested land was affected by wildfire between December 3rd 2001 and January 14th 2002. 10 years of pre-wildfire catchment hydrology data had been recorded by WaterNSW.

### *6.2.2. Model description and parameter extraction*

Physical-based distributed model, SWAT, is built with spatial (DEM, land use, and soil map) and climate (precipitation, temperature, solar radiation, and wind speed) inputs. Detailed descriptions about the input data and the calibration process can be found in Chapter 5.

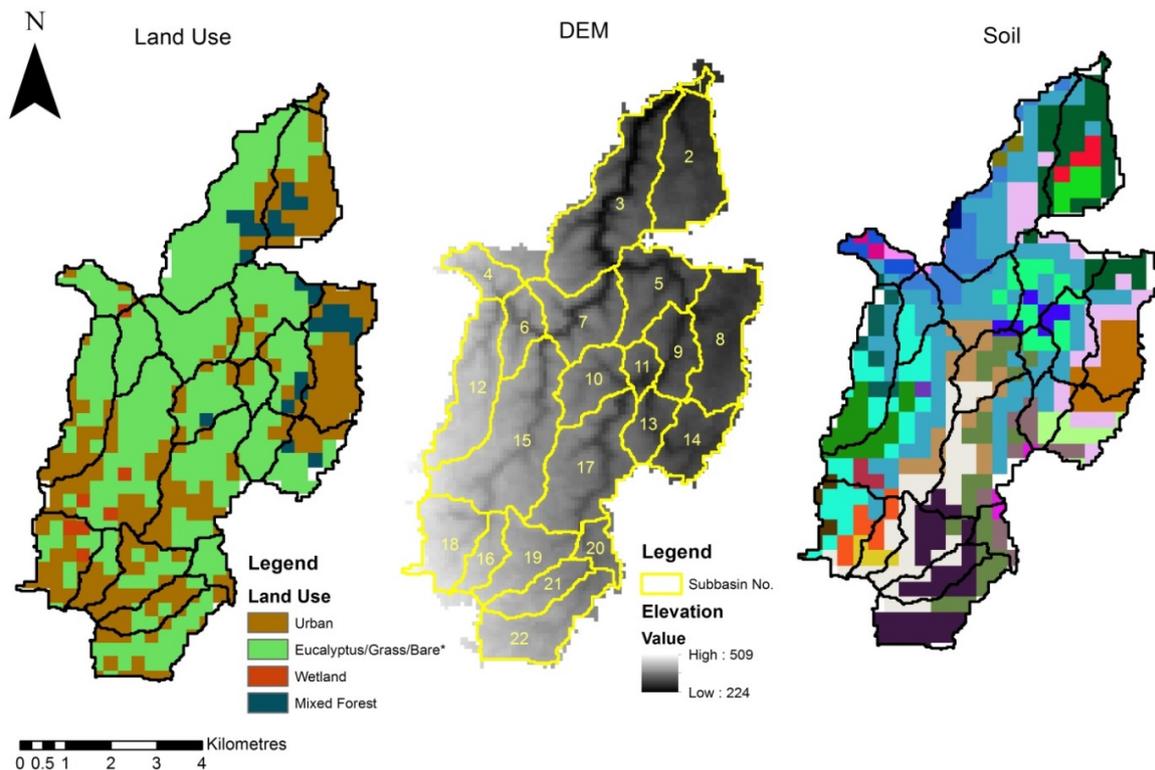
After calibration, the burnt areas in the catchment were changed from Eucalyptus land to grass land and then bare ground. The water yield (WYLD), is net amount of water that leaves individual subcatchment and contributes to channel output, and total suspended sediment (TSS), is the sediment yield from subcatchments that is transported into the channel. Each was extracted at daily steps for each subcatchment. The first year (2002) post-wildfire annual WYLD and TSS were calculated by aggregating the daily simulated values.

To analyse the correlation of spatial inputs to WYLD and TSS output from each subcatchment, the spatial inputs were extracted from each subcatchment. These inputs include: DEM inputs (area, slope increase in % (slope%), slope length, longest path, tributary slope increase in percentage (tributary slope %), tributary width, tributary depth, difference between maximum elevation and lowest elevation (elev.diff), and soil inputs for top soil layer which include: average bulk density (meanBD), average clay content (mean clay), average carbon content (average C), and average available water content (mean AWC). The correlation between input parameters and output WYLD and TSS are calculated in R using Pearson's correlations.

## 6.3.Results

### 6.3.1. Catchment spatial inputs

The Land Use, DEM and soil map of the studied catchment is shown in Figure 6.1 together with the location of the subcatchment discretisation. As shown in the land use map, the catchment is dominated with Eucalyptus forest during the pre-wildfire period. Subcatchment 2 and 8 are covered mainly by urban land and subcatchments 12, 18 to 21 are covered with a high percentage of urban land. The catchment has the highest elevation at the bottom left of the catchment (subcatchment 18), elevation decreases as the subcatchment number decreases, with catchment 1 containing the lowest point of the catchment.



**Figure 6.1 Land use, Dem, Soil classes of the catchment** (Eucalyptus/Grass/Bare are the areas modified to create different burnt severity different burnt severity).

### *6.3.2. Annual WYLD and TSS outputs from each subcatchment*

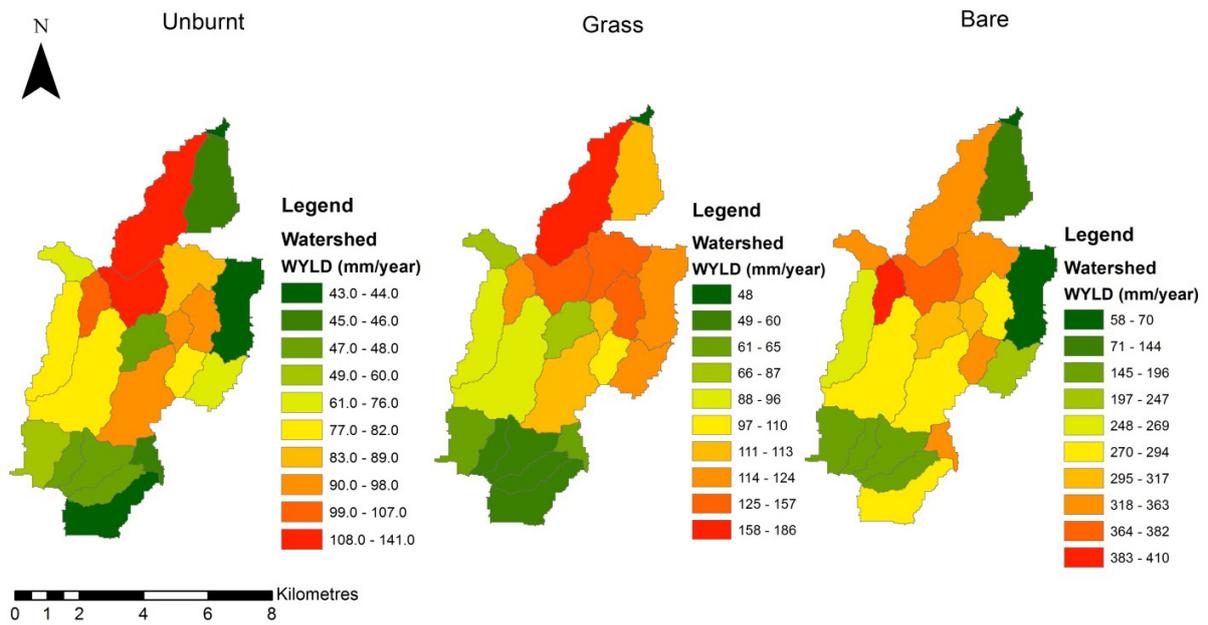
Figure 6.2 and 6.3 showed the WYLD and TSS output from each subcatchment during the first post-wildfire year. Catchment 3, 6, and 7 are identified to be the subcatchment with high sensitivity to wildfire as they have the highest catchment hydrology outputs in the wildfire effected (grass and bare) scenarios. One thing should be notice here, in the Unburnt scenario, catchments TSS output was dominated by urban lands, where the subcatchments containing the highest % of urban land generated the highest TSS output. However, in the grass and bare ground simulations, due to the land-use change, the TSS output from each subcatchment changed dramatically.

The result of this simulation identified the subcatchments with high sensitivity to wildfire, as they produced the highest WYLD and TSS during the first post-wildfire year, a higher protection level should possibly be applied to these catchments for better catchment management. Additionally, it is also important to know the driving reason for these subcatchments to have the highest WYLD and TSS output value. Table 6.1 shows the rank of different input values for each subcatchment, and those with the high sensitivity to wildfire are highlighted. These catchments were found to have a higher slope % in the subcatchment, a lower (shorter) slope length, and a higher rank in elevation difference. These 3 catchments also observed to ranked lower in soil property parameters: lower value of top layer soil bulk density, top layer clay, and carbon content. In other words sandier soils with low carbon so easily eroded as compared to heavier textured soils with more carbon.

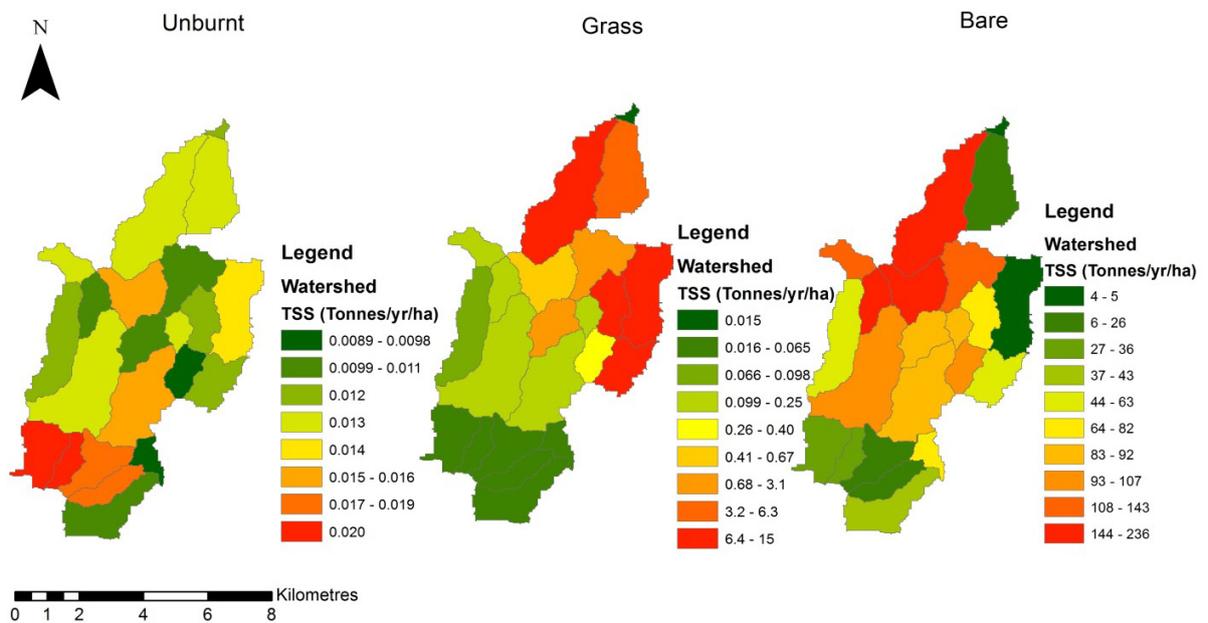
The correlation graph in Figure 6.4 and 6.5 also proved the importance of the slope %, slope length, and soil properties to WYLD and TSS output. For the flow output simulation: as shown

in Figure 6.4, the WYLD from catchments are positively correlated with slope % and negatively correlated with slope length and soil inputs (clay, carbon and bulk density).

The TSS output in unburnt simulations showed a more evenly distributed sensitivity to all the input parameters. As the vegetation cover reduces from unburnt (eucalyptus) to grass to bare ground. The effect of slope % and slope length increases, additionally, it can also be observed in Figure 6.5 that, the soil inputs (soil bulk density, soil mean clay and soil carbon content) have a more significant effect on catchment TSS output as the ground cover decreases. One reason of this is the vegetation changes in the catchments interrupted the stable environment of a forested catchment, while the catchment recovery decreases the leaching and erosion in the catchment increases, therefore there is a greater direct response to catchment spatial differences in soil.



**Figure 6.2 Annual WYLD generated from each subcatchments under different land-use scenarios**



**Figure 6.3 Annual TSS generated from each subcatchments under different land-use scenarios**

**Table 6.1 Rank of input value (from largest to smallest) used in each subcatchment (yellow cells = subcatchment with high sensitivity to wildfire).**

Rank (Largest to smallest value)	Area	Slope %	Longest path	Slope length	Tributary slope%	Tributary width	Tributary depth	PCP	Elev.diff*	meanBD	Mean clay	Mean carb	Mean AWC
1	15	7	3	8	4	15	15	7	15	2	1	19	20
2	3	3	15	15	6	3	3	19	3	14	2	21	17
3	17	6	12	12	7	17	17	10	7	1	8	2	10
4	2	5	17	17	11	2	2	9	17	8	16	12	22
5	8	4	8	2	1	8	8	21	19	19	19	1	14
6	12	17	5	22	18	12	12	6	6	21	21	22	16
7	22	13	2	19	19	22	22	13	12	20	12	15	13
8	5	11	22	21	10	5	5	16	18	10	18	8	18
9	7	9	19	18	21	7	7	11	4	16	15	10	19
10	18	15	21	10	13	18	18	15	22	22	10	16	21
11	19	14	7	16	15	19	19	5	21	9	22	4	3
12	14	12	18	9	16	14	14	3	10	5	9	17	6
13	10	10	10	13	22	10	10	18	5	13	13	9	11
14	9	18	16	14	17	9	9	17	2	17	4	18	7
15	21	20	9	20	14	21	21	4	16	11	20	3	15
16	6	1	13	4	3	6	6	22	13	15	17	5	8
17	13	16	14	11	5	13	13	2	14	18	3	13	5
18	4	2	6	1	12	4	4	8	9	7	5	6	9
19	16	22	20	5	2	16	16	20	11	3	6	14	4
20	20	19	4	6	9	20	20	12	8	12	11	7	12
21	11	21	11	3	20	11	11	14	20	4	14	20	1
22	1	8	1	7	8	1	1	1	1	6	7	11	2

\*elev.diff is calculated by the highest elevation- the lowest correlation in the subcatchment; meanBD= mean bulk density;

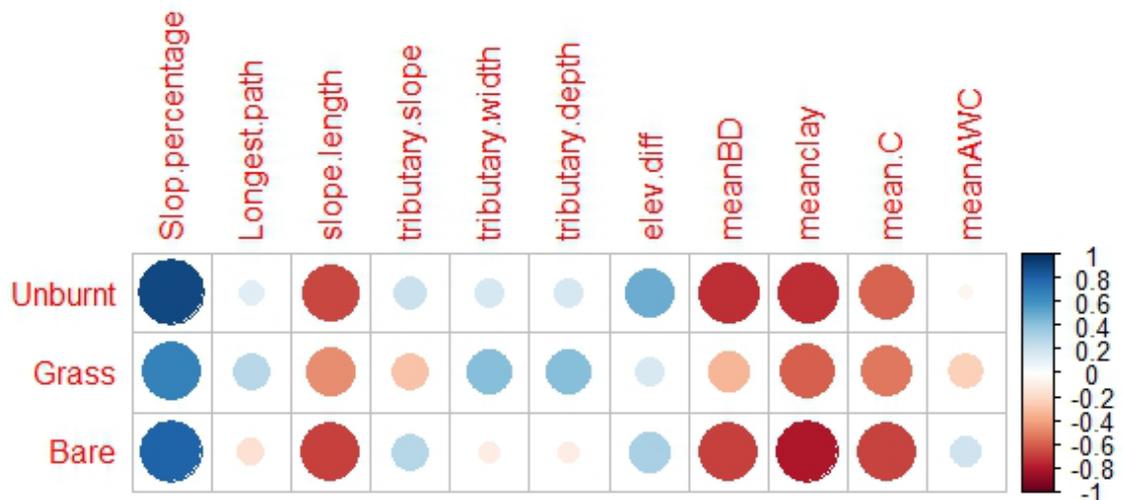


Figure 6.4 Correlations between flow output and input data

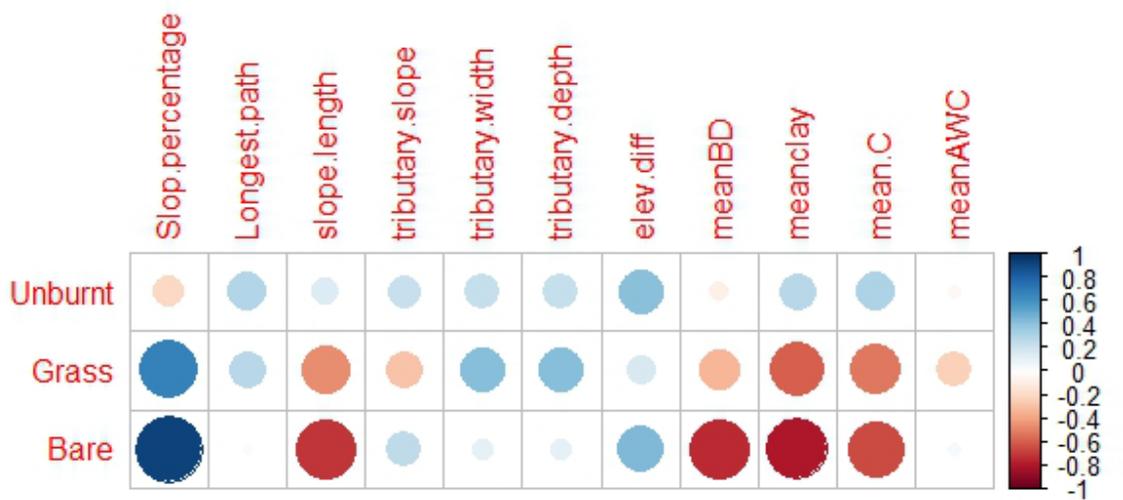


Figure 6.5 Correlations between TSS output and input data

## 6.4. Discussion

This study investigated the correlation between subcatchment spatial characteristics and catchment hydrology. There are few, if any, studies researching soil inputs correlation with wildfire effect on forested catchment hydrology. However, other studies on soil properties might give an indication on the indirect effect of soil on catchment hydrology. Soil bulk density is correlated to soil carbon content and soil clay content (Chaudhari et al., 2013). Akgül & Özdemir (1996) studied the relationship between soil bulk density and soil properties and concluded that these constants can be estimated by means of regression model. Several studies have researched the correlation between soil carbon content and soil bulk density (Sakin, 2012, Morisada et al., 2004, Gifford and Roderick, 2003, Leifeld et al., 2005, Chaudhari et al., 2013). They have concluded a negative correlation between the two. A negative correlation between soil bulk density and soil clay content is also found by Chaudhari et al. (2013). This result is supported by the correlation result between soil inputs and TSS output (Figure 6.5) for the unburnt catchment. As shown in Figure 6.5 soil bulk density is negatively correlated to TSS output while soil clay and carbon content are positively related to TSS output. Additionally, in the two post-wildfire models, all three soil properties found a negative correlation on flow and TSS output.

No study has been found investigating the direct correlation between catchment average slope and post-wildfire catchment hydrology. However, this correlation can be investigated through comparing post-wildfire catchment hydrology using multiple catchments with different slope. Duggan (1994) examined the relationship between catchment TSS outputs with: soil type, slope angle, length, litter- ground- and foliage-cover in undisturbed forested land in Kakadu National park in Australia and concluded the erosion rate is only effected by litter cover. This result is similar to what we have observed from our unburnt catchment: unburnt catchment is highly

stable despite its spatial characters. Silins et al. (2009) investigated the TSS output on 3 burnt catchments in Alberta Canada and found the highest TSS output from the catchment with the highest valley gradient and channel slope. Townsend and Douglas (2004) compared their post-wildfire TSS output from catchment with 0.5% slope catchment to other studies with higher slope percentage and observed a much lower TSS output. However, all the studies reviewed above focused on the relationship between spatial variation and hydrology output at catchment level. No study has been found analysing this relationship at the subcatchment level.

## **6.5. Conclusion**

This study provides a first attempt on investigating the relationship between subcatchment spatial variation and the wildfire effect on catchment hydrology using physical-based distributed model SWAT. The result found from this study can help identify subcatchments that contribute most to flow and sediment at catchment outlets and may assist catchment management and catchment protection decision making in the future.

This study investigated the correlation between subcatchment spatial variability and catchment hydrology. Our result indicated the subcatchment that has most the impact on post-wildfire catchment hydrology is the subcatchment with: 1) Higher percentage slope increases; 2) Shorter slope length. 3) Lower soil top layer bulk density, clay, and carbon content. The effect of these 3 factors increases as the wildfire severity increases (ground cover reduces). Thus, our suggestion is that subcatchments with these properties should receive more wildfire protection to lower the threat of wildfire on catchment hydrology.

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## **Chapter 7**

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### **7. Conclusions and suggestions for future research**

The theme of this thesis has been to improve change detection methods with an emphasis on detecting the effect of wildfire on catchment hydrology (water quantity and quality) for better catchment management. Detecting the effect of wildfire on catchment hydrology has always been a challenge due to the different effects of natural variation. The lack of water quality data (as compared to discharge data) and the sporadic sampling method has made this even more difficult. The questions then arise: what's the short-term and long-term effect of wildfire to catchment hydrology, are these changes caused by soil or vegetation, and are there certain parts of the catchment contributing most to catchment hydrology change at monitoring site?

Several empirical and physical based modelling methods have been used in this study to disentangle these problems for better catchment management, which include:

1. Linear mixed model (LMM)
2. Event clustering
3. SWAT (Soil and Water Assessment Tool)
  - a. SWAT with soil carbon change.
  - b. SWAT with vegetation change.
  - c. Correlation between sub-catchment characteristics and catchment hydrology.

The modelling process has been organised in this way as we investigated the problem from a macro view (the overall water quality change in 10 years) to micro view, individual events and we also specifically investigated the wildfire effect on different components of the hydrological cycle. Not only the findings, but also the methods used in this thesis deliver important and valuable information for future change detection studies.

As a result, the empirical model observed a long-term (5-10 years) post-wildfire water quality change; this change is more considerable during post-wildfire event period. The result from physical-based hydrological models also indicated a long-term change in TSS concentration post-wildfire. The catchment flow level recovered to pre-wildfire level during the long-term period, this observation from the physical-based hydrological model is similar to Heath et al. (2016)'s result. In their study, they used empirical method to investigate the same wildfire's effect on catchment flow; they observed that catchment recovered to pre-wildfire level in long-term (5 years post-wildfire). In addition to the change detected on post-wildfire catchment hydrology, our scenario in physical-based models also observed that post-wildfire soil carbon change has limited effect on catchment hydrology and vegetation change is the main cause of post-wildfire catchment hydrological change. The final chapter using physical-base hydrological model also identified the high wildfire sensitive area in a catchment.

## **7.1.Key findings**

This thesis started by using LMM model (in Chapter 2) to give a quick and accurate overview of the post-wildfire water quality change on decadal scale. LMM used in this context are an ANCOVA-type change detection approach but account for range of predictors rather than relying on linear relationships with flow. This method is used to deal with the data collected non-probabilistically. This chapter proved LMM's ability to deal with data that does not meet the randomisation assumption of regression models. And it is a useful tool for detecting water quality change. In this chapter, 7 forested catchments (3 controls, 4 burnt) were selected for the LMM analysis. All burnt catchments were observed to be affected by wildfire on average across the 10 years post-wildfire. On average, there is a total suspended sediment (TSS) concentration increase (64% higher than control), a total nitrogen (TN) concentration increase (48% higher

than control), and a total phosphorus (TP) concentration increase (40% higher than control) during the 10 years post-wildfire period. However, the method presented in this chapter only gave a broad guide of post-wildfire water quality change, the effect of wildfire is only analysed on average over a period of time. Therefore, this method missed the effect of hydrograph and the change of water quality during event period.

Water quality change during events is important because a large percentage of sediments and nutrients are exported during events (Lane et al., 2008). However the effect of events to catchment hydrology depends on the size and length, and antecedent conditions of the event. Since both antecedent conditions and event size impact on water quality during events we need to compare similar events between the pre-wildfire and post-wildfire period to assess changes in water quality induced by wildfire. Thus, in Chapter 3, we used k-mean clustering method to match events pre- and post-wildfire and compared the Event Mean Concentration (EMC) of TSS, TN, and TP. As a result, during the 10 years post-wildfire period, the control catchments observed an EMC drop for all water quality EMC terms (0.4-fold for TSS, 0.56-fold for TN, and 0.31-fold for TP). The burnt catchment observed a 4.2-fold increase in TSS EMC, 1.4-fold increase in TN, and no change to TP. The EMC of TSS observed in this study is much higher than the TSS change observed in Chapter 1. This indicated that event flows has more effect on TSS concentration, and may indicate a faster recovery rate of TN and TP or the soluble nitrogen and phosphorus included in TN and TP are less affected by wildfire. This chapter proved the importance of assessing the post-wildfire water quality change during events especially for TSS and the importance of comparing like with like in terms of events.

The two empirical methods used in the first two chapters provided an overview of the post-wildfire water quality change. These two chapters focused on the post-wildfire water quality

change only, this is because Heath (2014) has investigated the post-wildfire water quantity change for the same wildfire using an empirical method. However, the empirical method only provides a lumped summary of the wildfire effect, but does not provide an understanding of why the change has occurred and the effect of catchment topography differences.

Physical-based distributed models on the other hand, have the ability to include both spatial and temporal differences. It can be used to not only detect the changes, but also to build scenarios to solve questions such as analysis the impact from burning different part (e.g. soil and vegetation) of the catchment or find the wildfire sensitive area of a catchment. Thus, in the next step, a physical-based distributed model SWAT (Soil and Water Assessment Tool) is used to analyse the wildfire effect on catchment hydrology. Chapter 4 presented the calibration process for 2 control catchments (catchments with insufficient data were removed) and 3 burnt catchments (1 burnt catchment was removed as it didn't have sufficient data). The 5 catchments were calibrated for flow and TSS. Catchment C2 was calibrated at daily steps with a NSE of 0.62 and 0.77 for flow and TSS respectively, the validation period of C2 showed a NSE of 0.58 for flow and 0.53 for TSS. C1 was affected by inaccurate rainfall value, showed a NSE of 0.47 for flow and 0.42 for TSS during calibration period and lower NSE value for validation period. All the burnt catchments showed good calibration results with a mean NSE value of 0.68 for flow and mean NSE value of 0.73 for TSS. All burnt catchment predicted poorly in the validation period. The change of NSE value during validation period indicates an effect of wildfire. During the post-wildfire time, the studied catchments were effected by drought but still observed a higher flow response to rainfall (as compare to simulated) during the short and medium post-wildfire term. The flow rate recovered to pre-wildfire level in the long-term post-wildfire period. Compare to flow recovery, TSS recovery took longer. We observed a TSS output of 2025

tonnes/year for short-term (1<sup>st</sup> year post-wildfire), 623 tonnes/year for medium-term (2-5 years post-wildfire), and 71 tonnes/year for long-term (6-10 years post-wildfire); while the simulated value of TSS is 74 tonnes/year, 14 tonnes/year, 28 tonnes/year respectively. This chapter proved SWAT's ability to detect wildfire effect on catchment hydrology change, the calibrated model is then used in the following chapters to assess the other questions mentioned earlier: what is the impact from burning different part (e.g. soil and vegetation) of the catchment and where is the most wildfire sensitive area in a catchment. Chapter 5 tested the effect of burning of soil carbon and catchment vegetation on catchment hydrology. The burnt catchment models calibrated in Chapter 4 were modified to simulate the wildfire effect on soil carbon content and vegetation. The first year post-wildfire was simulated for discharge and TSS. A 22-88% carbon drop for the top layer soil was estimated based on burnt severity. The vegetation covers of the catchments were modified to bare ground and grass land uses to represent moderate and extreme fire severities. The carbon change did not lead to a catchment hydrology prediction change. Vegetation change was observed to be the main reason for hydrology changes in the catchment. The flow output for the most severely burnt catchment showed similar flow output to bare model during the first year post-wildfire. We have also found the TSS output value for the first post-wildfire event lies between bare ground model and grass model's simulation. This chapter tested SWAT model's sensitivity to wildfire related inputs. The observations from this study opened the possibility for investigating wildfire effect on catchment hydrology using a physically based model in future studies. One of those is shown in Chapter 6.

In all the above chapters, we focused on investigating the catchment hydrology output at catchment level as represented by the catchment outlet. In Chapter 6 we analysed the effect of sub-catchment spatial characteristics on catchment hydrology to identify the wildfire sensitive

area in a catchment for pre-wildfire catchment protection. In this chapter, we extract the sub-catchment hydrology output and correlated them with sub-catchment terrain and soil characteristic. The correlation test indicated that, catchment with: 1) higher percentage slope increases, 2) shorter slope length, and 3) smaller soil top layer bulk density, clay, and carbon content, have the highest post-wildfire catchment hydrology impact. We suggested that catchments with these characteristics may result in the most severe damage to the catchment water quality after wildfire; therefore, they should receive the most wildfire-protection to minimise the wildfire effect.

## **7.2.Future research**

Both empirical and physical-based models were found to be useful tool for detecting change. However, physical-based models have the ability to create different scenarios to understand the cause of the change. The methods used in this study can be used to detect other hydrological change caused by mining, logging, and other disturbances. We recommend future studies to use empirical models if only detecting the change is required as empirical models require less input data and less complexity. Physical-based model should be used to understand the cause of the change and investigating on location sensitive questions.

The outcomes of this thesis suggests further studies on wildfire effect to water quality should focus on two aspects: 1) Consider more wildfire related parameters to increase the wildfire predicting model's accuracy, and 2) investigating additional catchment characteristics.

### *7.2.1. Increase model accuracy*

More wildfire affected parameters can be considered while modelling wildfire. This may help increase model's accuracy while simulating wildfire effect. For example, the soil carbon change

method used in Chapter 5 only changed soil carbon content. More studies on wildfire effect on soil structure are needed and the corresponding inputs (such as `csoilstr` in SWAT) should be modified. The post-wildfire vegetation change methods used in our models are crude. We used the existing vegetation parameters in SWAT for post-wildfire vegetation. The post-wildfire vegetation parameters can be investigated in a more detailed way with field observed and satellite data (such as MODIS ET data for post-wildfire vegetation evapotranspiration). Moreover, the current vegetation change method treated burnt area as a whole (with the same burnt severity), the burnt severity at different locations in the burnt area was not considered. The post-vegetation profile can be updated in a similar way we did for soil carbon in Chapter 5 to consider burnt severity effect on different parts of the catchment vegetation. Moreover, further studies should focus on simulating the recovery process of soil carbon and catchment vegetation. For simulating the soil carbon recovery process, RothC model (Coleman and Jenkinson, 1996) can be embedded into the SWAT model to predict the soil recovery process and update the soil carbon as it reverts to pre-wildfire levels. One example of running RothC spatially is demonstrated by Karunaratne et al. (2015). The vegetation parameters should be updated during the post-wildfire period as well. The post-wildfire plant growth parameters can be modified to suit the post-wildfire vegetation condition. And plant evapotranspiration (ET) and leaf area index (LAI) can be calibrated and validated with real time MODIS ET and LAI data. Such as demonstrated by Strauch and Volk (2013), who used MODIS ET and MODIS LAI data to validate their updated SWAT model for simulating catchment hydrology in tropical area. Updating all these model features may help the model accurately simulate the post-wildfire hydrology and post-wildfire catchment recovery. This allows the model to be used for longer term simulation.

Current paired catchment studies on water quality using paired catchment method mostly paired catchments based on their location (Hopmans and Bren, 2007, Brown et al., 2005, Watson et al., 2001). However, in this study, we have observed that catchment post-wildfire outputs are highly correlated to slope, soil, and land use. Further change detection studies using paired catchment method can consider matching control and burnt catchments based on these catchment characters using methods such as clustering. This can reduce the water quality change caused by natural variations.

#### *7.2.2. Investigate more catchment characteristics for better catchment management*

Further studies should apply this method to other areas such as the mountain ash area in Victoria Australia. The accuracy of the model while predicting wildfire effect under different catchment condition should be tested. And the different wildfire response from different catchment conditions can be compared to help future catchment management decision making.

This effect can be investigated by applying different vegetation type to SWAT model and compare the output. Moreover, there is a shortage of data on stream exports or catchment post-wildfire contaminations, in this study, we only focused on investigating the effect of wildfire on flow and TSS studies with sufficient data should also test the effect of wildfire on other nutrients.

Addressing the above questions will help improve the understanding of the fundamental processes of post-wildfire water quality change. It may also lead the future model development to not only focus on summarising the wildfire effect on catchment water quantity and quality change, but also providing guidance to catchment managers on catchment protection.

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