A Review of Event-Based Conceptual Rainfall-Runoff Models: A Case for Australia

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Abstract: Event-based models focus on modelling of peak runoff from rainfall data. Conceptual models indicate simplified models that provide reasonably accurate answers despite their crude nature. Rainfall-runoff models are used to transform a rainfall event into a runoff event. This paper focuses on reviewing computational simulation of rainfall-runoff processes over a catchment. Lumped conceptual, event-based rainfall-runoff models have remained the dominant practice for design flood estimation in Australia for many years due to their simplicity, flexibility, and accuracy under certain conditions. Attempts to establish regionalization methods for prediction of design flood hydrographs in ungauged catchments have seen little success. Therefore, as well as reviewing key rainfall-runoff model components for design flood estimation with a special focus on event-based conceptual models, this paper covers the aspects of regionalization to promote their applications to ungauged catchments.

Keywords: rainfall runoff; event-based model; conceptual model; design flood; calibration; runoff routing; Australia

1. Introduction

Rainfall-runoff models are widely used to estimate design flood hydrographs. The estimated flood hydrograph is then used to mitigate the cost and risk of flooding through, for instance, the design of flood mitigation structures or floodplain management strategies. Therefore, a range of mathematical models (including rainfall-runoff models) has been developed to improve the accuracy of design flood estimates and ensure the optimum design and management of infrastructure; for example, the Catchment Model [1], the Soil Conservation Service (SCS) Curve Model [2], and Hydrologic Engineering Centre (HEC)-1 [3] model. The relative accuracy of each model, however, is dependent on several factors, such as its intended purpose, data availability, catchment characteristics, desired accuracy, budget, and time constraints [4–7].

Rainfall-runoff models have a long history of being used for flood risk assessment, ranging from the classical rational method [8] to the modern physically based distributed models [9,10]. These models primarily seek to generate streamflow from rainfall data, which can be categorized into a few broad groups: (i) empirical black-box type models based on the nonlinear relationship between inputs and outputs, such as the SCS Curve Number Model [2]; (ii) conceptual models based on the equations that represent water storage in catchment, such as the Topography-based Hydrological Model (TOPMODEL) [11]; and (iii) physical models based on the physical laws and equations related to the hydrologic processes, such as the “Model Based and Incremental Knowledge Engineering” (MIKE)-Topography-based Hydrological Model (SHE) [12].

The rainfall-runoff models in the second group (conceptual models) are widely used for flood modelling purposes, mainly because of their flexibility and simplified governing equations [5]. These models provide the conceptual idea of the behaviors in a catchment...
and can be implemented when computational time and data are limited; typically, either on a continuous basis or event based. Continuous simulation techniques, for instance, the “Identification of unit Hydrographs And Component flows from Rainfall, Evaporation and Streamflow data” (IHACRES) [13], Continuous Simulation Systems (CSS) [14], and the Australian Water Balance Model (AWBM) [15], are theoretically advanced; however, these require a considerable amount of data (spatially and temporally) to calibrate the model meaningfully, particularly for larger catchments with complex hydro-climatic characteristics [16].

Conversely, event-based conceptual models, being either lumped (e.g., the initial loss–continuing loss (IL-CL) and initial loss–proportional loss (IL-PL) models) or distributed (e.g., the probability distributed model (PDM) [17], TOPMODEL [11], Xinanjiang model [18], and the soil water balance model (SWMOD) [19]), conceptualize the capacity of a model to approximate the catchment runoff response in a simplistic manner but with reasonable accuracy, often by ignoring the spatial variability of the model inputs and land characteristics. However, distributed conceptual models (unlike lumped conceptual models) account for the variability with regards to both time and space throughout the duration of a rainfall event, hence they require a substantial volume of catchment and climatic data. For instance, the Xinanjiang model (commonly used in China) uses a cumulative distribution function; similarly, the PDM model (widely applied in the UK) and the SWMOD model (used in Australia) also use a probability distribution function, to describe the spatial heterogeneity in soil storage capacities across a catchment.

Both the continuous and the event-based approaches have been applied to a range of catchments (gauged and ungauged) by many hydrologists worldwide with varying degrees of success, but the selection of an appropriate model is often difficult as there is a lack of objective comparison using standard datasets across the competing models [10,14,16,20,21].

In Australia, rainfall-runoff modelling for design flood estimation in general is dominated by the lumped event-based conceptual approaches [22] as there are limited data available across much of Australia for model calibration and verification, as well as a number of models developed specifically for Australian conditions having different combinations of loss function (representing infiltration, evaporation, interception, etc.) and transfer function (representing various runoff attenuation mechanisms).

There have been significant developments and applications of event-based conceptual rainfall-runoff models in Australia, in particular for the gauged catchments [23], with varying degrees of success, but there is a lack of systematic review of these developments. Hence, the motivation for this paper is to review the rainfall-runoff modelling practices for design flood estimation in the context of Australia with a special focus on event-based conceptual models. Four lumped event-based rainfall-runoff models are considered in this study, which are Runoff Routing Burroughs (RORB) [24], the Watershed Bounded Network Model (WBNM) [25], the Runoff Analysis and Flow Training System (RAFTS) [26], and the Unified River Catchment Simulator (URBS) [27]. Although other conceptual models could have been included in this review, only four models are covered given their extensive use throughout Australian catchments. The RORB and WBNM are widely used in rural applications, while the RAFTS model is generally more suitable for complex urban catchments. URBS has been used for flood forecasting more frequently than RORB, WBNM, and RAFTS.

While it is not practically possible to review all aspects of rainfall-runoff modelling, we attempt to cover comparative strengths and weaknesses of these models, the major routing processes, rainfall losses, and the aspects of regionalization to promote their applications to ungauged catchments. There has been limited research on comparing and contrasting these four widely used runoff routing models in Australia. Since the publication of the fourth edition of Australian Rainfall and Runoff (ARR) in 2019, the capability of these models to implement Monte Carlo simulation has become an important consideration since this is the currently recommended method of design hydrograph simulation in Australia. It is expected that this review will promote a better understanding of the model differences, including their practical applications, recent developments, and future enhancements such as consideration of climate change impacts on simulated design hydrograph. Hence, this
paper is intended to serve as a key reference for commonly used event-based conceptual rainfall-runoff models in Australia for design flood estimation.

2. Rainfall-Runoff Models Used in Australia

The first formal rainfall-runoff model, known as the Rational Method, was proposed by Mulvaney [8] and is based on an empirical relationship between rainfall and runoff. The model has largely been applied for designing small water resource structures such as gutters and drains. Thereafter, Sherman [28] proposed the unit hydrograph approach (widely used across the UK and USA), based on the assumption of linearity, which can be viewed as the first data-driven rainfall-runoff model [29,30]. The model came about due to the need for improving rainfall-runoff models by providing the peak flow as well as the corresponding shape and volume of the flood discharge.

Snyder [31] extended upon this work by introducing the synthetic unit-hydrograph, which is based on the time–area relationship. While the assumption of linearity has been found to be appropriate in some studies [32–35], Australian catchments in particular have a nonlinear catchment response [24,36].

To overcome limitations associated with the unit hydrograph approach, Laurenson [36] developed a conceptual rainfall-runoff model based on the nonlinear relationship between stream discharge and catchment storage [37–39], widely known as the Laurenson Runoff Routing Model (LRRM) (see Figure 1). The LRRM triggered the development of several other conceptual rainfall-runoff models, including RORB, WBNM, URBS, and RAFTS, which simulate rainfall-runoff processes over a catchment for design, environmental, and ecosystem purposes. Since then, these models have been extensively applied to hydrological modelling projects, particularly for design flood estimation throughout Australia, with the underlying model structure remaining virtually unchanged from their inception. Numerous event-based conceptual rainfall-runoff models exist, with different combinations of loss and routing parameters at various spatial and temporal scales. Some of the commonly used models in Australia include RORB, WBNM, RAFTS, and URBS. These models aim at simulating the streamflow using two main components that vary between each model; initially a runoff production component produces excess rainfall, then a runoff routing component routes the rainfall excess through a conceptual representation of the catchment.

The catchment is represented by a network of sub-catchments, which are divided by watershed boundaries or by contours of equal travel time. RAFTS, for instance, delineates sub-areas using areas of equal travel time, while other models (such as RORB, WBNM, and URBS) use watershed boundaries to delineate sub-areas. These four models are lumped to some degree, in that the parameters are average values, and the input data are also spatially averaged and based on nonlinear routing concepts, each with two parameters: the first being a nonlinearity exponent and the second being the routing parameter, also known as storage delay parameter [24,40–42]. Application of these models has ranged from rural to urban catchments, small to large catchments, and arid to tropical catchments, and has also seen limited use internationally other than in Australian catchments. A brief overview of historic developments, special features, applications, and limitations of these models are presented below and also summarized in Table 1. Weinmann [23] presented a comparison of runoff routing methods.

<table>
<thead>
<tr>
<th>Aspect</th>
<th>RORB</th>
<th>WBNM</th>
<th>URBS</th>
<th>RAFTS</th>
</tr>
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<tbody>
<tr>
<td>Routing Parameter</td>
<td>$k_c$</td>
<td>$C$</td>
<td>$a$</td>
<td>$B$</td>
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<tr>
<td>Model type</td>
<td>Event-based</td>
<td>Event-based</td>
<td>Event-based or semi-continuous</td>
<td>Event-based or continuous</td>
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<tr>
<td>Sub-areas delineation</td>
<td>Watershed boundaries</td>
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<td>Watershed boundaries</td>
<td>Contours of equal travel time</td>
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Table 1. Comparison among RORB, WBNM, URBS, and RAFTS models.
Table 1. Cont.

<table>
<thead>
<tr>
<th>Aspect</th>
<th>RORB</th>
<th>WBNM</th>
<th>URBS</th>
<th>RAFTS</th>
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<tr>
<td><strong>Routing</strong></td>
<td>Nonlinear</td>
<td>Nonlinear, time delay or</td>
<td>Muskingum–Cunge</td>
<td>Muskingum–Cunge</td>
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<td><strong>Methods</strong></td>
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<td>Muskingum–Cunge</td>
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<td><strong>Loss</strong></td>
<td>IL-CL or IL-PL, Horton</td>
<td>IL-CL or IL-PL, infiltration equation (Manley–Phillips)</td>
<td>IL-CL or IL-PL, the Australian Representative Catchments Model water balance model</td>
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<td>infiltration equation</td>
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<td>or a time-varying loss</td>
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<td><strong>Special</strong></td>
<td>Monte Carlo framework;</td>
<td>Split into overland flow</td>
<td>Flood forecasting; split</td>
<td>Incorporates the percentage of urbanized/forested land and the catchment slope</td>
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<td><strong>Features</strong></td>
<td>access to the 2016 IFD</td>
<td>and channel routing;</td>
<td>into overland flow and</td>
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<td>urban, and partly urban</td>
<td>varying baseflow model;</td>
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<td>Monte Carlo framework.</td>
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Figure 1. Timeline showing major Australian rainfall-runoff and regional hydrologic modelling developments [8,22,24,26,28,31,32,36,39,42–54].
2.1. RORB

RORB is a lumped-parameter, event-based model that calculates flood hydrographs based on rainfall and other channel inputs. The catchment is represented conceptually by a network of nonlinear reservoirs and channel reaches, where the processes that control catchment response are assumed to be homogeneous. Runoff generation is modelled in RORB using one of two conceptual loss models, either the IL-CL or IL-PL models. A nonlinear storage–discharge relationship is adopted to model each reach, which is given by:

\[ S = 3600 k_c Q^m \]  

(1)

where \( S \) is the storage in \( m^3 \), \( Q \) is the discharge in \( m^3/s \), \( m \) is the nonlinearity exponent and \( k_c \) is the storage delay parameter in hours. The parameter \( m \) is often fixed at 0.8 (but is within the range 0.6 to 1) based on recommendations in the *Australian Rainfall and Runoff* (ARR) national guide, 1987 [43] and similarly in the RORB user manual [43,45]. The parameter \( k_c \) is therefore the key calibration parameter, which is selected interactively to match the selected observed and modelled streamflow events. Being that RORB is one of the most widely recognized rainfall-runoff models in Australia [46], a significant amount of research has been carried out, particularly on its principal parameter \( k_c \) [42,44–59]. Uncertainties in the estimated \( k_c \) value can introduce bias into the estimated design floods. Dyer et al. [45], for example, found that \( k_c \) flood prediction equations in New South Wales (NSW) are associated with errors ranging from −30% to +50%.

The first edition of RORB was released by Mein et al. [24] as a simple conceptual rainfall-runoff model for rural catchments. The model later experienced six major and several minor modifications, with the current version (version 6.14) being released in January 2010. RORB evolved from the LRRM model [36], which was also modified by Porter and McMahon [60], Mein et al. [24], Laurenson and Mein [40], and Laurenson et al. [43]. In 2005, a range of additional features were introduced into the fifth version of RORB, including stochastic simulation within a Monte Carlo simulation framework, allowing for the initial loss and/or temporal patterns to be stochastically varied [46]. A subsequent release of RORB, MiRORB v1.1 [61], was designed to facilitate the adoption of the ARR 2019 guidelines by allowing access to the updated Intensity–Frequency–Duration (IFD) dataset [62] (shown in Table 1). Apart from Australia, RORB has been applied successfully in parts of Asia. For instance, Selvalingam et al. [63] used RORB in a tropical urban catchment in Singapore to simulate flood runoff hydrographs to analyze the performance of existing drainage systems.

2.2. WBNM

WBNM, developed by Boyd et al. [39], is a flood hydrograph model with the advantage of being able to split the catchment storage into overland flow and channel routing [25,64, 65]. Rainfall excess can be derived from historic storm events or design storm parameters using one of four runoff generation models [65,66]. This includes three conceptual rainfall loss models, being the IL-CL or IL-PL, the time varying loss model or the Horton infiltration equation (shown in Table 1). Sub-catchment lag times are related to various physical characteristics, particularly to catchment area with the intention of developing a simple yet realistic flood hydrograph model [66]. Apart from a major revision in 1987 [25], WBNM has also experienced updates in 1996 [64], 1999 [67], and in the 2012 version (WBNM2012). While the original version focused on modelling the flood response of natural catchments, later versions focused on its applicability to flood studies on natural, urban, and partly urban catchments.

WBNM implements the same routing model applied in RORB (nonlinear routing) with the same nonlinear storage–discharge (S-Q) relationship in general (Equation (1)); it also incorporates two other models; specifically, a simple time delay or Muskingum–Cunge routing. In WBNM, the lag time varies with sub-catchment discharge \( Q \), area \( A \), and the controlling parameter \( C \), as follows:
\[ K = \alpha 0.6 C A^{0.57} Q^{-0.23} \]  

(2)

where \( \alpha \) is the additional stream lag factor i.e., time delay which lags the flows by \( x \) minutes. A study on lag time in a wide range of natural gauged catchments (with areas ranging from 0.1 to 8000 km\(^2\)) suggested that a reduction factor of 0.6 in the lag time calculation provides better results [64].

The lag time can be divided into two components, namely overland flow (Equation (3)) and channel (or stream) flow (Equation (4)).

\[ K_{\text{overland}} = C A^{0.57} Q^{-0.23} \]  

(3)

\[ K_{\text{stream}} = 0.6 C A^{0.57} Q^{-0.23} \]  

(4)

Equation (3) transforms rainfall via overland flow and minor drainage networks into a runoff hydrograph at the sub-catchment outlet. Equation (4) receives runoff from upstream sub-catchments and routes it through the mainstream. It also transforms rainfall from the associated sub-catchment into the local runoff hydrograph [25,65].

2.3. URBS

The rainfall-runoff model URBS is based on a network of distributed nonlinear sub-catchments, whose inflows are routed along channels to generate a streamflow hydrograph [68]. It was initially developed in 2001 by Brisbane City Council for planning purposes [47]. The model can be used as an event-based model (similar to RORB and WBNM) for design flood hydrology, or as a semi-continuous model for flood forecasting. The model can be categorized as either (i) a basic model, which assumes that each sub-catchment can be represented by a single nonlinear reservoir, similar to RORB, or (ii) a split model, which assumes that the channel storage is proportional to channel length, which is similar to WBNM. The basic model, however, is not suitable for large catchments (greater than 50 km\(^2\)); the split model, on the other hand, is more flexible, modelling the physical processes of each sub-catchment in a more realistic manner [62]. Similar to RAFTS, sub-catchments in the URBS model can be represented as percentage of urbanized/forested land and uniquely, the model can be integrated with sediment wash-off and traffic disruption models (as mentioned in Table 1) [27]. URBS is useful for the hydrologic assessment of land-use change and flood forecasting for real-time flood monitoring systems.

Similar to RORB and WBNM, URBS incorporates the basic storage–discharge (S-Q) relationship (Equation (1)). However, in URBS the routing parameter \( k^i_c \) is calculated per sub-catchment \( i \) based on several sub-catchment characteristics:

\[ k^i_c = \alpha f \left[ \frac{nL(1 + F)^2}{\sqrt{S_c(1 + U)^2}} \right] \]  

(5)

where \( \alpha \) is the storage lag parameter, \( L \) is the stream length, \( S_c \) is the channel slope, \( f \) is the reach length factor, \( U \) is the urbanized fraction of the sub-catchment, \( F \) is the forested fraction of the sub-catchment, and \( n \) is the channel roughness. Stream length and catchment area are required to determine the catchment extent and the rainfall excess, respectively, while other variables are optionally included in the calibration process depending on the problem at hand.

In URBS, three runoff generation models are employed, with two conceptual rainfall loss models (the IL-CL and IL-PL models) and one infiltration equation (the Manley–Phillips model). In addition to these event-based runoff generation models, URBS also provides a continuous loss model, being the recovering initial loss model. The resulting rainfall excess is routed through each sub-catchment using the Muskingum method. Distinctive from previously discussed models (RORB and WBNM), URBS allows for baseflow estimates to be modelled within the program using either a constant or varying baseflow model.
URBS is able to implement on a Monte Carlo framework; however, the model should typically be used within the observation boundary as the model is primarily used in flood forecasting \[69,70\]. Outside of Australia, URBS has been used in Asia for flood hydrograph assessment; for example, Punpim and Nutchanart \[71\] applied the model to the Ping River catchment in Thailand. The study derived the regional flood estimates using the model parameters from 11 hydrologically similar gauged catchments and the corresponding catchment characteristics for applying to ungauged catchments.

2.4. RAFTS

RAFTS was originally developed to overcome the lack of models focusing on complex drainage systems, such as heavily urbanized catchments or areas of intense development. Its root began in the Regional Stormwater Drainage Model (RSWM), which was developed by Willing & Partners and the Snowy Mountains Engineering Corporation (SMEC) \[26,38\]. Unlike the previous models discussed, RAFTS divides each sub-catchment into ten sub-areas, which allows streamflow hydrographs to be extracted at any sub-catchment outlet. The ten sub-areas are divided using isochrones of equal travel time, and assume that the travel time \( t \) for the given area is dependent on the reach length \( L \) and the average reach slope \( S \), as follows:

\[
t \propto \sum_{i=1}^{n} \frac{L}{\sqrt{S}}
\]

(6)

Similar to URBS, RAFTS incorporates the catchment slope in the regional storage discharge relationship \[22\]. It adopts the Muskingum–Cunge method for reservoir routing to deal with multiple hydraulically connected detention catchments and storage configurations. The basic storage–discharge equation can be expressed as:

\[
S = K(q)q
\]

(7)

where \( S \) is the storage (m\(^3\)) and \( q \) is the discharge (m\(^3\)/s). The storage delay time \( (K(q)) \) for each sub-catchment is:

\[
K(q) = B q^n
\]

(8)

where \( B \) is the storage delay time coefficient and \( n \) is the nonlinearity exponent (with a default value of \(-0.285\)). Combining these two equations (Equations (9) and (10)), results in a storage–discharge relationship similar to previous models:

\[
S = B q^{n+1}
\]

(9)

It can be seen that the nonlinearity exponent in RAFTS \( (n) \) is equivalent to \((m^{-1})\) in other models (RORB, WBNM, and URBS). Furthermore, the storage delay time coefficient for each sub-catchment \( (B_{av}) \) is calculated as:

\[
B_{av} = 0.285 A^{0.52} (1 + U)^{-1.97} S_c^{-0.5}
\]

(10)

where \( A \) is the sub-catchment area (km\(^2\)), \( U \) is the urbanized fraction of the sub-catchment and \( S_c \) is the main drainage slope of the sub-catchment (%).

RAFTS incorporates three loss models, namely the IL-CL model, IL-PL model, and the Australian Representative Catchments Model \[72,73\]. Due to the inclusion of the Australian Representative Catchments Model, RAFTS can either be modelled continuously or on an event basis. The model does not rely on the user to define a suitable number of sub-catchments, thereby moderating the risk of uncertainty. Kemp and Daniell \[74\] noted that the model gives better results in simple catchments rather than complex urbanized catchments; however, using more sub-areas than necessary can adversely impact the model outputs. The current version of RAFTS does not have the capability to undertake Monte Carlo simulation, but recently this too has been integrated for a case study project to predict
flood response in Tasmania. The study demonstrates the efficiency of the model simulation processes and compares the results to a traditional hydraulic modelling approach [75]. Hence, these four lumped event-based conceptual models are fairly similar, with a few key differences shown in Table 1.

3. Model Components

The conceptual event-based rainfall-runoff models for design flood estimation are typically composed of two components: the loss model that determines the effective rainfall for an event and the runoff routing model that routes the flow through the catchment.

3.1. Rainfall Losses

Numerous models have been developed to derive the rainfall excess, being the total rainfall minus losses; however, they are usually conceptually based or founded on point infiltration equations. Among all the loss components, for instance, infiltration, interception, evapotranspiration, depression storage, and transmission losses, infiltration is considered as the most significant loss component depending on the soil properties, vegetation cover, and surface conditions [76]. Larger catchments tend to be heterogeneous, in that the soil surface conditions, vegetative cover, and soil properties rapidly change in both space and time. In practice, the infiltration capacity is generally assumed to be uniform, thus making it difficult to estimate a representative loss value for the entire catchment of interest. Additionally, losses show a wide variability from event to event; many researchers have therefore recommended stochastic losses [77–79], which are generally used with the Monte Carlo simulation techniques as detailed in Section 7.

In Australia, conceptual lumped loss models are the most commonly used loss models, primarily due to their simplicity and ability to predict overall catchment response, thus ignoring spatial variability [80]. Examples of these types of models include the IL-CL model [79,81], the IL-PL model [82,83], and the SCS Curve Number model (widely used in America by the US Department of Agriculture [2]). Each of the four rainfall-runoff models mentioned earlier (RORB, WBNM, URBS, and RAFTS) can model rainfall excess using two conceptual loss models, being the IL-CL model based on the concept of Hortonian overland flow, or the IL-PL model based on the saturated overland flow concept.

In ARR 1987 and ARR 2019, the IL-CL model is largely recommended for use in Australia; though in some studies the IL-PL model indicated better performance [45,84]. Additionally, several studies [85,86] have detailed the use of an empirical method, the SCS Curve Number method, to model runoff generation processes in Australia; however, they had little success in design flood estimation practices. The limitation of using conceptual lumped loss models is that it ignores the actual temporal patterns of storm losses and the variations in the rainfall-runoff process. However, more sophisticated loss models, for example, distributed loss models that consider the dynamic nature and spatial variability of runoff generation across a catchment [9,87,88] are data-driven models, and hence are seldom applied in Australia due to data limitations.

Other models, such as semi-distributed loss models, an example of which include the Xinanjiang model [18], attempt to overcome data issues and represent the physical processes more realistically by considering the spatial variability throughout a catchment but in a more simplistic manner [79,89]. The probability distributed model (PDM) [17] is one example, which uses a probability distribution function to describe the variability in soil storage capacities. While it is widely used overseas, it has seen limited use in Australia. A similar model developed in Australia is SWMOD [19], which describes the spatial variability of the soil water storage using a probability distribution function. The model is extensively used in the western part of Australia but has had limited use in eastern Australia.

3.2. Runoff Routing

A runoff routing model provides two main uses: firstly, the technique determines the design flood estimates for flood management studies, and secondly, the model forecasts
the flood peak between an upstream and a downstream section on a watercourse. There are many different runoff routing methods based on varying degrees of complexity; however, the common objective of each method is to route the rainfall excess through the catchment storage to obtain an estimate of the surface runoff hydrograph. For instance, the hydrologic routing method such as the Muskingum routing method compares the computed and observed hydrographs through the optimization of a functional relationship with observed data.

A simpler method is reservoir or level-pool routing, which assumes that the water surface of a reservoir is horizontal along its entire length and that the reservoir outflow is a function of stage, varying with time. Methods in practice include the storage indication method, the modified Puls method and the Runge–Kutta method, among others. The unit hydrograph method is most likely still in use today globally as it is relatively simple to apply and the results are seen to be reasonable for many engineering purposes; however, it is not generally used in Australia, particularly due to the assumption of linearity. Alternatively, channel or streamflow routing is used for river channels with varied flow conditions, where the assumption of the water surface being horizontal is inappropriate to use. In channel routing, storage is considered as a function of both inflow and outflow and is determined by either direct measurement or by analyzing the observed upstream and downstream hydrographs.

RORB adopts the nonlinear routing approach depending on the sub-catchment reach length. The three remaining models (WBNM, URBS, and RAFTS) separate overland flow routing from channel routing. These overland flow calculations vary in complexity between each model, with WBNM primarily dependent on the catchment area, while URBS and RAFTS consider additional factors, such as the imperviousness ratio and channel slope. Channel routing also varies in these three models; URBS adopts the Muskingum method, while the other two models (WBNM and RAFTS) implement three routing methods, specifically the Muskingum, Muskingum–Cunge, and time-delay routing methods. In Australia, the storage–discharge relationship is often assumed to be nonlinear, with the nonlinearity exponent \( m \) typically fixed. Values often range from 0.6 to 1, although the equivalent value in RAFTS is calculated as \( n = m^{-1} \). Recommendations for the nonlinearity exponent in RORB and URBS are for a fixed value of 0.8, while WBNM and RAFTS are for fixed values of 0.77 and 0.715, respectively [43].

For RORB, WBNM, URBS, and RAFTS, the channel routing parameters are \( k_c \), \( C \), \( \alpha \), and \( B \), respectively. McMahon and Muller [42] introduced an equation relating the RORB \( k_c \) parameter to the average flow distance \( d_{av} \) of a catchment:

\[
c = \frac{k_c}{d_{av}}
\]

(11)

The equation was later adopted in several studies, including Yu [54], Dyer [45], and Pearse et al. [59]; each of these studies found reasonable accuracy while developing regression equations for regional relationships, with the coefficient of determination \( (R^2) \) between 0.9 and 0.5. Each of these studies regionalized \( k_c \) using catchment areas; however, given that \( k_c \) is implicitly dependent on the average flow distance \( d_{av} \), which is highly correlated to catchment area, it would be more appropriate to regionalize \( c \) [51].

Boyd and Bodhinayake [65] also found that WBNM’s \( C \) parameter is also directly proportional to RORB’s \( k_c \) parameter, using the following relationship:

\[
C = 1.45 \frac{k_c}{d_{av}}
\]

(12)

Similarly, URBS’s \( \alpha \) parameter and RAFTS’s \( B \) parameter are also proportional to \( k_c/d_{av} \) but an alteration is required in RAFTS for consideration of its slope parameter [65]. For the same \( m \) value, the relationship between \( \alpha \) and \( k_c \) is:

\[
k_c = f_{av} \alpha
\]

(13)
\[ f_{av} = \sum_{i=0}^{n} \frac{f_i A_i}{A} \]  

(14)

where \( A_i \) is the \( i \)-th sub-catchment area (for \( n \) sub-catchments) and \( f_i \) is the sum of routing constants, i.e., \( L_i \) along the routing path from the centroid of the sub-catchment to the outlet.

Flavell et al. [90] developed the relationship between the length of the main channel within each subarea \( L_i \) and the average flow distance \( d_{av} \) for natural catchments. They found \( L_i \) to be approximately a tenth of the total length \( L \) and the average flow distance was half of \( L \). These studies established a relationship between RAFTS’s \( B \) parameter and RORB’s \( k_c \) parameter (Equation (15)), based on Western Australian and Victorian catchments:

\[ B = 0.2 \, k_c \]  

(15)

4. Parameter Calibration

In general, rainfall-runoff modelling for design flood estimation requires a long-duration, high-quality river gauge along with one or more concurrent continuous rainfall gauges of equal quality to calibrate the parameters of the routing model [5,76]. Calibration is performed by optimizing or systematically adjusting parameters to match observed and simulated flood hydrographs [91]. In gauged locations, models can be calibrated either independently (independent parameter sets will be produced for each catchment) or jointly (a single set of parameters will be derived for all the gauges within that group). The traditional approach to calibration is the trial-and-error approach, which iteratively adjusts the parameter set until a reasonable match between the observed and simulated streamflow is found. Automated optimization is a more sophisticated calibration approach, where an optimizer algorithm runs the model hundreds to thousands of times with different parameter sets.

Objective functions that are used to optimize the selected parameter set include the relative error of the peak flows, time to peak, and volumes or hydrograph shape. In ungauged catchments, calibration is performed using regression-based regionalization methods. However, one common issue with calibration is equifinality [55,92], where a range of parameter sets may produce similar results which in turn affect parameter and predictive uncertainty. For successful calibration, the calculated hydrograph should be fitted as much as possible with the peak discharge, time to rise, slope of the rising and falling limbs, recession curve, and runoff volume of the recorded hydrograph. If the catchment is ungauged or poorly gauged, the model parameters may be estimated using the available information from the neighboring catchments or hydrologically similar catchments [22].

5. Prediction in Ungauged Catchments

In many situations, there are insufficient or no data available to calibrate the rainfall-runoff model parameters. Such circumstances require data to be pooled in space, given the limitations of data in time. Parameter regionalization is one technique that allows parameters from neighboring or similar gauged catchments to be transferred to the catchment of interest [93], although the design floods predicted by the regionalization are likely to have greater uncertainty than those from a well calibrated catchment modelling system [22]. These techniques typically regionalize flood data, then use predictor variables (such as catchment physiographic, geomorphologic or climatic characteristics) to estimate the flow for a given catchment, thus enabling model parameters to be estimated without the need of observed rainfall and runoff data at the site of interest [94,95].

A number of regionalization studies have been undertaken, with one of the first regional methods being the index flood (IF) method [1], which relies on the assumption that catchments are similar within each region, referred to as regional homogeneity. Alternative methods were derived so that each site has its own region, defined in predictor variable space; for instance, the region of influence (ROI) approach or canonical correlation analysis. Many of the regionalization studies (shown in Table 2) initially calibrated model parameters at gauged catchments with similar characteristics before regionalizing the data to ungauged
catchments. However, limited data availability, the conceptual nature of parameters, and equifinality restrict the innovation and development of regionalized rainfall-runoff model parameters \[9,96\].

**Table 2.** Key publications in Australia on regional prediction equations for rainfall-runoff model parameters in Australia.

<table>
<thead>
<tr>
<th>Author</th>
<th>No. of Catchments</th>
<th>Area (km(^2))</th>
<th>Region</th>
<th>m</th>
<th>Routing Parameter</th>
<th>Remarks</th>
</tr>
</thead>
<tbody>
<tr>
<td>Weeks and Stewart [44]</td>
<td>15 (QLD) 27</td>
<td>158 to 3430</td>
<td>QLD and south-west of WA</td>
<td>0.73 (QLD)</td>
<td>(k_c)</td>
<td>(k_c) value for WA found to be higher than in the eastern states</td>
</tr>
<tr>
<td>Morris [97]</td>
<td>25 (QLD) 16 (VIC)</td>
<td>20 to 5170</td>
<td>QLD, VIC, WA, TAS</td>
<td>0.75 (VIC)</td>
<td>(k_c)</td>
<td>(k_c) value for the drier part of VIC found to be lower for small catchments</td>
</tr>
<tr>
<td>Sobinoff, Pola and O'Loughlin [98]</td>
<td>26</td>
<td>0.1 to 4560</td>
<td>NSW (Newcastle, Sydney, Wollongong)</td>
<td>0.8</td>
<td>(k_c)</td>
<td>No regional trends were apparent, except some lower values of (k_c) in the upper Hunter Valley</td>
</tr>
<tr>
<td>McMahon and Muller [42]</td>
<td>10</td>
<td></td>
<td>South-East QLD</td>
<td></td>
<td>(k_c/d_{av})</td>
<td>Covered coastal areas</td>
</tr>
<tr>
<td>Flavell, Belstead, Chivers, and Walker [90]</td>
<td>52</td>
<td>5 to 6526</td>
<td>WA (4 regions)</td>
<td>0.8</td>
<td>(k_c)</td>
<td>Regressions involving stream length were better than those using area slope</td>
</tr>
<tr>
<td>Weeks [99]</td>
<td>88</td>
<td>2.5 to 16,400</td>
<td>QLD (coastal and inland areas)</td>
<td>0.8</td>
<td>(k_c)</td>
<td>No relation was found between (k_c) and other parameters such as catchment slope</td>
</tr>
<tr>
<td>Hansen et al. [100]</td>
<td>19 (East VIC) 21 (West VIC)</td>
<td>20 to 3910</td>
<td>VIC (Eastern and Western part)</td>
<td>0.8</td>
<td>(k_c)</td>
<td>Predicted (k_c) values are similar for catchments greater than 2000 km(^2)</td>
</tr>
<tr>
<td>Pilgrim [48]</td>
<td>&lt;100 (SA); approx. 1000 (TAS)</td>
<td></td>
<td>SA, TAS</td>
<td>0.75</td>
<td>(k_c)</td>
<td>Predicts larger (k_c) values for smaller catchments</td>
</tr>
<tr>
<td>Yu [54]</td>
<td>30 (VIC), 51 (WA), 41 (NT)</td>
<td></td>
<td>VIC, WA, NT</td>
<td></td>
<td>(k_c/d_{av})</td>
<td>(k_c/d_{av}) increased with the increase in mean annual rainfall in VIC and WA</td>
</tr>
<tr>
<td>Kemp [101]</td>
<td>24</td>
<td>5 to 6020</td>
<td>SA</td>
<td>0.8</td>
<td>(k_c/A^{0.57})</td>
<td>For areas with mean annual rainfall (MAR) greater than 500 mm predicts lower (k_c) value</td>
</tr>
<tr>
<td>Walsh and Pilgrim [102]</td>
<td>46</td>
<td>0.1 to 13,000</td>
<td>NSW</td>
<td>0.8</td>
<td>(k_c), area, and stream length</td>
<td>No trends for (k_c) to vary with event size</td>
</tr>
<tr>
<td>Dyer et al. [103]</td>
<td>72</td>
<td>All over Australia</td>
<td></td>
<td>0.8</td>
<td>(k_c/d_{av})</td>
<td>Developed regression relationships for seven groups based on hydrological similarity utilizing Andrews curves rather than geographical regions</td>
</tr>
<tr>
<td>Perera [58]</td>
<td>32</td>
<td></td>
<td>VIC</td>
<td>0.8</td>
<td>(k_c/d_{av})</td>
<td>Following Dyer et al. [103] unable to identify group for 20 catchments</td>
</tr>
<tr>
<td>Pearse, Jordan, and Collins [59].</td>
<td>220</td>
<td></td>
<td>QLD, NSW, VIC, WA, TAS</td>
<td>0.8</td>
<td>(k_c/d_{av})</td>
<td>Similar results found to those of Perera [58]. (k_c/d_{av}) was found at the range of 0.96–1.25 depending on the particular region</td>
</tr>
<tr>
<td>Bodhinayake [104]</td>
<td>252 storms on 17 catchments 164 to 7300</td>
<td></td>
<td>QLD (From North Johnstone to the Mary River)</td>
<td>0.8</td>
<td>(k_c/d_{av})</td>
<td>No strong trends were found with any variables, similar to Pearse et al. [59]. Mean value of parameter C was found as 1.47</td>
</tr>
<tr>
<td>Boyd and Bodhinayake [65]</td>
<td>46</td>
<td>0.2 to 6910</td>
<td>QLD, NSW, VIC, SA</td>
<td></td>
<td>(C)</td>
<td>Obtained a mean value of (C = 1.64) for all 54 catchments</td>
</tr>
</tbody>
</table>

Similar to other countries, Australia has numerous ungauged catchments and hence different forms of regional relationships have been applied to Australian catchments for conceptual rainfall-runoff models (shown in Table 2). For instance, the third edition of ARR (1987) included a set of equations to regionalize the RORB \(k_c\) parameter for a number of Australian states, as developed by Weeks and Stewart [44]. McMahon and Muller [42] related the RORB \(k_c\) parameter to \(c\) (a parameter representing a catchment’s hydrologic response), which is readily correlated to \(k_c\) by a factor \(d_{av}\) (see Equation (13)). Yu [54] developed regression equations to regionalize \(c\) for the south-west of Western Australia and Victoria, which proved to be reasonably accurate with values for \(R^2\) of 0.8 and 0.5, respectively.
Similarly, Dyer et al. [103] developed regional prediction equations for both the $c$ and $k_c$ parameters across seven Australian regions; results showed considerably higher $R^2$ values (ranging from 0.75 to 0.99) for the $c$ parameter as compared with the $k_c$ parameter. In their study, the authors adopted a cluster analysis technique to group of 72 Australian catchments into seven homogenous groups using several predictor variables, which included geometric, morphological, geological, meteorological, and vegetation catchment characteristics. The study found that once an ungauged catchment was allocated to a predefined homogeneous group by the proposed method, the error in prediction was much smaller than those associated with the relationships previously published in the literature. However, this regionalization technique (using RORB model) was applied by Perera [58] to design flood estimation in 32 catchments in Victoria and by Pearse et al. [59] in 220 catchments in Victoria and Tasmania, and they observed similar difficulties while classifying the catchment to a particular group.

The WBNM C parameter has also been investigated; for instance, Bodhinayake [104] investigated the nature of the C parameter by considering a range of rainfall-runoff event characteristics, such as the peak discharge, rainfall depth, rainfall excess depth, rainfall intensity, and spatial distribution of rainfall, along with a number of catchment characteristics such as the catchment area, shape, elevation, and mean annual rainfall. Boyd and Bodhinayake [65] also calculated the average value for 54 catchments located in Queensland, New South Wales, Victoria, and South Australia. Neither study was able to find any strong regional relationship between the C parameter and catchment or rainfall-runoff event characteristics. These studies indicated the fact that one value (for instance, $A^{0.57}$ as the catchment factor shown in Equations (4) and (5)) is typically accounted for in the model structure over a wide range of areas. Additional research is therefore required to estimate rainfall-runoff model parameters for ungauged catchments to enhance the accuracy of flood estimates for future application.

The key publications on regional prediction equations of the rainfall-runoff model parameters in Australia are summarized in Table 2.

### 6. Current Situation and Future Trends

The rainfall-runoff models—RORB, WBNM, URBS, and RAFTS—had their genesis in the LRRM model, where its application to gauged catchments was proposed. Considerable research has been undertaken on these models and regionalization over the past four decades (as summarized in Figure 1 and Table 2). More recently, attention has shifted to consider the stochastic nature of model parameters/inputs from the traditional Design Event Approach, as recommended in ARR 1987 [43], where the parameters/inputs are treated as fixed values with the exception of rainfall depth [22,53].

Some of the recent investigations on rainfall-runoff modelling considered the stochastic nature of the flood generation process using the Monte Carlo simulation technique, which facilitates deriving many realizations of flood events based on all possible sets of inputs and dependencies relating to emergency response, dam operations or flood damages, etc. [70,77,79,105–112]. For example, Patel and Rahman [110] used RORB within a Monte Carlo framework to estimate the design flood for the Cooper’s Creek catchment in NSW. The authors found that the dominant parameter of the model $k_c$ exhibited a high degree of variability from event to event, and hence the use of a fixed value of $k_c$ for a given catchment (as is carried out traditionally) is not justified.

Another recent study by Caballero and Rahman [112] examined the stochastic nature of the storage delay parameter of a one-storage/lumped conceptual model using data from 86 pluviograph stations and six catchments from NSW and noted that its storage delay parameter should not be considered as a fixed input in design flood estimation, as it showed a high degree of variability from event to event. However, Loveridge et al. [109] argued that stochastic routing parameters are unrealistic, as the routing parameter theoretically represents the hydrologic response of a catchment (being the soil characteristics, channel network, etc.) and should therefore be fixed (although longer term changes may occur). The
authors’ state that any variability noted in the routing parameter in these studies is more likely due to the inherent model uncertainties and errors in key inputs (which vary from event to event). More recently, the new ARR 2019 [22] has advocated for the use of Monte Carlo simulation in rainfall-runoff modelling and requires the stochastic nature of model inputs/parameters to be considered. Recommendations in ARR 2019 [22] also consider the routing parameter to be fixed unless a full uncertainty analysis is being performed.

A regional design hydrograph prediction model can be developed similar to the regional flood frequency estimation (RFFE) model provided in the Australian Rainfall and Runoff (ARR) 2019 guidelines. Here, a simple runoff routing model with a single node can be considered for smaller catchments. This model should be equipped with regional equations to generate rainfall duration, rainfall intensity, rainfall temporal pattern, initial loss, continuing loss, and storage delay parameters at any arbitrary location in Australia. Such a model could be useful to the water industry in a similar way to the RFFE model.

An additional tool to evaluate the impacts of climate change on design hydrographs need to be integrated with each of the commonly used runoff routing models in Australia. Several recent studies have shown the importance of considering the impacts of climate change on runoff hydrographs [113–116]. Catchment homogeneity [117] is also important in regionalization of runoff routing parameters. Furthermore, runoff routing models lack the tools needed to carry out comprehensive uncertainty analysis under changing climate [118–121]. Artificial intelligence-based methods can also be incorporated with the runoff routing models to enhance the uncertainty analysis due to data limitation [112–124].

7. Conclusions

This paper presents a review of commonly used rainfall-runoff models (RORB, WBNM, URBS, and RAFTS) for design flood estimation in Australia and summarized their practical applications, recent developments, and modelling approaches including prediction in ungauged catchments. These four rainfall-runoff models are lumped event-based conceptual models based on nonlinear runoff routing with a few basic differences; for instance, WBNM and URBS allow for both overland flow and channel routing while the remaining models consider channel routing alone; RORB and URBS contain Monte Carlo simulation frameworks; and while all four can adopt the IL-CL and IL-PL models, WBNM and URBS have an infiltration equation and time-varying loss model.

The basic structure of these rainfall-runoff models has not gone through significant changes since their inception; however, Monte Carlo simulation has been increasingly applied with these models to account for the probabilistic nature of model inputs. In ARR 2019, Monte Carlo simulation has been recommended over the traditional Design Event Approach; however, some gaps primarily exist around uncertainty and regionalization of key parameters.

The application of the RORB, URBS, WBNM, and RAFTS models in ungauged catchments for prediction of design flood hydrographs is a relatively difficult task as these models cannot be calibrated directly in ungauged catchments and particularly the case in Australia where the majority of catchments have little to no data available. The application of the new RFFE Model 2019, rather than relying on long datasets (with respect to time), using surrounding streamflow records (with respect to space) can provide design flood estimates (peak flows) at ungauged location in Australia; however, the technique is appropriate for certain conditions, for instance, small catchments with uniform hydro-climatic and catchment characteristics.

It is suggested that new regionalization studies along with validation studies be carried out using data from gauged catchments covering a wide range of hydrologic and catchment characteristics that would enable development of prediction equations of design flood estimation at ungauged catchments with a greater confidence. Based on the outcomes of this new research, a new application tool could be developed (similar to regional flood frequency estimation (RFFE) 2019 software in the Australian Rainfall and Runoff guidelines) that would allow estimation of design flood hydrographs at ungauged catchment locations.
While not explicitly covered in this study, a rainfall-runoff model within a Monte Carlo framework would be beneficial, as it treats the event duration and the other variables in a stochastic manner through the use of real-world inputs, models, and methods. This review paper, which aimed to promote a better understanding of the principal approaches of the commonly adopted rainfall-runoff models in Australia, concludes with the hope that future generations will enthusiastically meet the new emerging research needs in rainfall-runoff modelling (e.g., incorporation of climate change, uncertainty analysis, and artificial intelligence-based techniques). Rainfall-runoff models should be made more versatile so that they can incorporate land-use changes and rainwater harvesting to manage floods [125]. A future review study on the selected hydrological models should focus on applying these models to a number of selected catchments and examine their performances in estimating the observed design flood hydrographs.

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References


120. Farsi, N.; Mahjouri, N. Evaluating the contribution of the climate change and human activities to runoff change under uncertainty. J. Hydrol. 2019, 574, 872–891. [CrossRef]


122. Shekar, P.R.; Mathew, A.; Yeswanth, P.V.; Deivalakshmi, S. A combined deep CNN-RNN network for rainfall-runoff modelling in Bardha Watershed, India. Artif. Intell. Geosci. 2024, 5, 100073. [CrossRef]


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