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Distributed and semi-distributed hydrological modelling for catchments draining to the Great Barrier Reef coastline

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ABSTRACT

The Great Barrier Reef (GBR) is a globally significant natural wonder, threatened by pollutant loads from eastward-draining rivers. A distributed hydrological model, G2G (Grid-to-Grid), has been configured at a resolution of 0.01° (~1 km) and 1 hour to simulate these flows. A semi-distributed hydrological model, SWIFT (Short-term Water Information Forecasting Tool), has been set up for 9 catchments at 19 streamflow gauging locations within the same area, as part of the Australian national 7-day Ensemble Streamflow Forecast Service. This provided an important research opportunity to assess the two modelling approaches for different purposes. The performance of both models has been evaluated at the 19 common gauged locations and varies from site to site, but is broadly comparable. The SWIFT is slightly better because it is calibrated to each gauged catchment. In contrast, G2G is configured as a single area-wide model supported by landscape spatial datasets and time-series flow data. G2G is capable of generating outputs for any grid cell, including ungauged locations, whilst SWIFT can only generate outputs at predefined locations on the river network. In conclusion, these catchment-specific and area-wide modelling approaches are compared and their suitability discussed in relation to the modelling purpose.

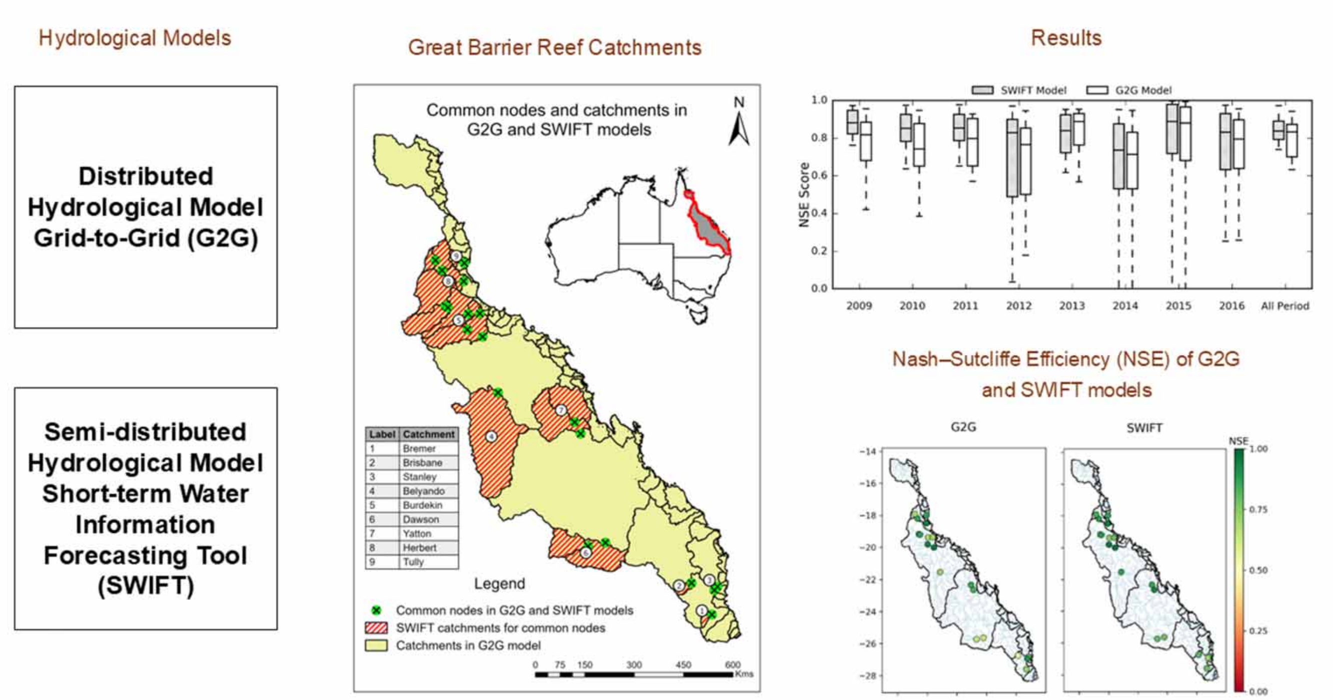
Key words: calibration, Great Barrier Reef (GBR), Grid-to-Grid (G2G), model performance, Short-term Water Information Forecasting Tool (SWIFT), streamflow

HIGHLIGHTS

- Comparison of distributed and semi-distributed hydrological models.
- Hydrological modelling for Great Barrier Reef catchments.
- Performance assessments of hydrological models using various metrics.
- Gridded versus node-link structure hydrological modelling.

GRAPHICAL ABSTRACT

Distributed and semi-distributed hydrological modelling for catchments draining to the Great Barrier Reef coastline



1. INTRODUCTION

The Great Barrier Reef (GBR) is one of the world's great natural wonders because of its extraordinary size, biological diversity and relatively undisturbed state (Furnas 2003). It is the largest contiguous coral reef ecosystem in the world and the largest that has ever existed. In 1981, most of the GBR ecosystem was inscribed onto the World Heritage Register as the Great Barrier Reef World Heritage Area (Lucas *et al.* 1997; Furnas 2003). It remains, by a very large margin, the largest World Heritage Area as well as being a major attraction for both international and local tourists. The GBR is a national icon, an international biological treasure, and a significant economic resource (Lucas *et al.* 1997; Furnas 2003).

The GBR receives runoff from the catchments of eastward-draining rivers and streams between Cape York and Fraser Island. This GBR catchment area encompasses 25% of the State of Queensland and 5.6% of the Australian continental landmass, with a varied climate that is broadly tropical or subtropical monsoonal depending on latitude (Furnas 2003). Measurement of streamflow discharge into what is now the GBR World Heritage Area began in 1910. A major expansion of the streamflow gauging network took place in the 1950s to provide information on state water resources. This expanded network was maintained until the early 1990s, when gauging stations on some smaller rivers and streams were decommissioned (Furnas 2003). Accurate streamflow measurements are indispensable for effective water resource management and environmental protection, as they underpin a wide range of applications including water supply planning, flood forecasting, infrastructure design, operational control of reservoirs and hydropower systems, pollutant load estimation, aquatic ecosystem assessment, and hydrological modelling. In recent years, artificial intelligence (AI) and machine learning (ML) based approaches have gained significant traction in flood and streamflow forecasting, with a growing number of novel methods being developed; however, the effectiveness of these data-driven models fundamentally depends on the availability and quality of historical streamflow data, which are essential for training, validating, and benchmarking model performance across diverse hydrological conditions and spatial scales (Ambika *et al.* 2025; Modi *et al.* 2025; Sattari & Moradkhani 2025). For GBR catchments, streamflows are critically important as they are used to calculate the total sediment and nutrient loads entering the reef (Cook *et al.* 2017; Khan *et al.* 2020; Livsey *et al.* 2022; Lewis *et al.* 2024). If the reef's ecosystem is repeatedly exposed to too much sediment and nutrients, it will be disturbed and changed in ways that prevent it from returning to what is regarded as a healthy and desirable state (Furnas 2003). Further, the improvement in river flow simulation over ungauged areas of the world remains an important research challenge, recognised for example by the Prediction in Ungauged Basins (PUB) initiative (Blöschl *et al.* 2013). One popular emerging solution addressing this research challenge is through AI and ML approaches that combine the static datasets on landscape properties with hydrometeorological time-series to simulate river flows for ungauged locations. Whilst showing promise, the physical-conceptual interpretations of the water balance model formulations compared here will continue to have appeal whilst AI/ML methods provide future opportunities to explore, including with regard to predictive performance and exploratory data analysis.

Streamflow can be measured at a site or can be estimated by performing hydrological modelling. Generally, a combination of both works best as streamflow gauging stations cannot be installed at every location due to significant installation and maintenance costs, and hydrological modelling without any streamflow observations will not provide reliable simulations. By applying a hydrological model, we can generate the continuous time-series of streamflow at gauged and ungauged locations, both as historical simulations and as forecasts.

In this investigation, the performance of two types of hydrological models applied for different purposes is compared: (i) a distributed hydrological model, Grid-to-Grid (G2G) (Moore *et al.* 2006) and (ii) a semi-distributed hydrological model, Short-term Water Information Forecasting Tool (SWIFT) (Pagano *et al.* 2011; Hapuarachchi *et al.* 2017). G2G has been applied to an area-wide modelling domain, encompassing the GBR catchment area at a resolution of 0.01° (~1 km) and 1 hour for the eReefs project (https://www.ereefs.org.au/, accessed on 12 March 2025), to simulate the streamflow for input to marine models used in monitoring the health of the reef environment. In contrast, SWIFT has been applied to issue the 7-day Streamflow Forecasts operationally for the entire continent at an hourly temporal resolution for specific locations (http://www.bom.gov.au/water/7daystreamflow/, accessed on 12 March 2025). With several gauged catchments common to both models, it is thus possible to compare their outputs with streamflow observations to gain insights into the strengths and limitations of the two modelling approaches for different purposes. The results of this model comparison are reported here.

G2G is a physical-conceptual distributed hydrological model for area-wide runoff and river flow forecasting at grid, catchment, regional and national scales (Moore *et al.* 2006; Cole & Moore 2009). The runoff production and routing schemes of G2G are able to capture a wide range of hydrological regimes, typically at (sub-) hourly and 0.01° (~1 km) resolution. Landscape spatial datasets on terrain, soil/geology and land-cover properties underpin the model formulation and its configuration, leaving only a small set of global and local parameters for model calibration refinement. The landscape properties are used to shape the pattern of rainfall into an evolving streamflow response across space and time. This makes G2G particularly well-suited for simulating and forecasting river flows from ungauged and gauged areas. G2G is used operationally 24/7 across Britain for Flood Guidance reporting by the Flood Forecasting Centre (England & Wales) and the Scottish Flood Forecasting Service (Cranston *et al.* 2012; Price *et al.* 2012). G2G is also used across Britain for seasonal hydrological outlooks (Bell *et al.* 2017) and for national planning when assessing spatial flood and drought risk under climate and land-cover change (Bell *et al.* 2009; Kay *et al.* 2021). In Australia, G2G was first configured and assessed for water availability forecasting in the Upper Murray Basin (Moore *et al.* 2014). Subsequently, this model was reconfigured, and its calibration was refined for the catchments draining to the Great Barrier Reef coastline (Wells *et al.* 2019; Khan *et al.* 2024, 2019, 2018). This provided simulated discharges along the coast for input to models of the Reef environment and synthesis through the Monthly Report Card on the health of the GBR (Wallace *et al.* 2008, 2015; Turner *et al.* 2013).

SWIFT is a comprehensive streamflow modelling package designed for operational continuous streamflow forecasting and hydrological research (Perraud *et al.* 2015; Hapuarachchi *et al.* 2022). The package offers a diverse set of modelling tools, including conceptual hydrological models, catchment routing models, channel flow routing models, streamflow error-correction models, provisions for multi-objective Pareto optimisation, and semi-distributed hydrological modelling. These tools enable users to access a wide array of functions, allowing them the flexibility to mix-and-match different hydrological and routing models and calibration strategies tailored to their specific needs and applications. SWIFT is currently used operationally for delivering the Australian national 7-day ensemble streamflow forecasting service (Hapuarachchi *et al.* 2022; Bari *et al.* 2024). While SWIFT has gained popularity in academic and research organisations across Australia, its adoption by the water industry has been limited due to intellectual property rights constraints.

In this investigation, historical streamflow simulations were generated using two distinct hydrological modelling approaches and compared against observed streamflow data at common gauging locations across the Great Barrier Reef (GBR) region. This comparative analysis was designed to evaluate the relative performance, strengths, and limitations of each modelling framework under regional hydrological conditions. Notably, this is the first study to undertake such a dual-model assessment for the GBR catchments, providing a novel contribution to the understanding of model behaviour in tropical and subtropical environments. The results offer critical insights into the applicability, accuracy, and operational feasibility of each approach, thereby informing future model selection for both retrospective analyses and predictive streamflow forecasting. These findings are expected to support researchers, water resource managers, and policy-makers in making evidence-based decisions regarding hydrological model deployment, ultimately contributing to improved water management and ecological conservation strategies in the GBR region and other comparable areas of the world. The paper is organised as follows. Section 2 describes the background of both hydrological models. Section 3 describes the study area and data used. The methodology is outlined in Section 4. Section 5 presents and discusses the results of the comparative assessment of model performance, with Section 6 providing the overall conclusions of the investigation.

2. BACKGROUND OF HYDROLOGICAL MODELS

2.1. Grid-to-Grid model

The Grid-to-Grid Model, or G2G, represents the storage and translation of water through the landscape on a grid-cell basis: summarised as a model schematic in Figure 1 (Moore *et al.* 2006; Cole & Moore 2009). Considering a single grid-cell, surface runoff is generated from its soil-water storage in response to rainfall, fewer losses from evaporation to the atmosphere and drainage to groundwater, along with lateral flow (interflow) exchanges with neighbouring cells.

Soil-water storage capacity varies randomly across the grid cell, represented by a probability distribution of Pareto form with a shape parameter controlling the nature of the variation (Moore 1985, 2007; Moore *et al.* 2006). The total storage capacity of the cell (as a depth of water over the cell area) is specified, for a given soil class, through the product of soil depth and water content per unit volume (saturation less residual content). The maximum capacity within the cell is related to this total storage capacity and, along with the shape parameter, to the mean topographic gradient of the cell relative to that of other cells in the class.

Drainage to groundwater (percolation) is a nonlinear function of soil-water storage, following Clapp & Hornberger (1978), controlled by the vertical saturated hydraulic conductivity of the soil as a multiplier and a percolation parameter as an exponent (Figure 1).

Lateral flow (interflow) employs a Brooks & Corey (1964) based nonlinear function of soil-water storage with a pore size distribution factor as exponent and a multiplier involving a conveyance term that includes topographic slope and the horizontal saturated hydraulic conductivity of the soil.

The cell's groundwater store is added to by soil percolation (recharge) from above and by groundwater inflows from neighbouring cells. *Groundwater flow* from the cell is assumed to be governed by Darcy's law with dependence on groundwater

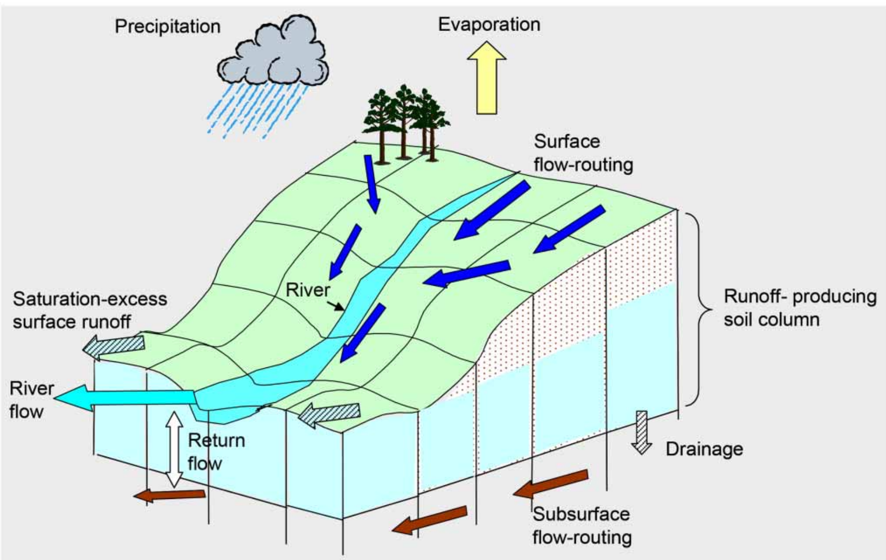


Figure 1 | G2G model schematic (Moore *et al.* 2006).

storage and a multiplier that depends on the horizontal hydraulic conductivity of the aquifer and the slope of the bedrock. In the absence of information on bedrock slope, this is further generalised to a nonlinear function of groundwater storage. The direction of groundwater flow from cell to cell is assumed to be governed by the topographic slope at the surface.

Surface runoff generated from the cell's soil-water storage contributes to its *channel flow* (or hillslope flow if in the headwater) along with inflows from neighbouring cells upstream. Channel flow routing through the cell is represented by a form of Horton-Izzard equation with physically-based links through a conveyance term based on Manning's equation: this introduces the geometric properties of the channel (length, width and slope) along with Manning's roughness.

Storage-related transfers of water, called *return flows*, between the groundwater and the channel represent groundwater-channel interactions, whilst a similar function between soil-water and channel-water storages represents hillslope-channel interactions.

The overall G2G scheme thus employs surface (channel) and subsurface (groundwater) pathways of lateral water movement through the landscape, incorporating interactions between them and soil-water hillslope interactions with the channel. Spatial datasets on soil/geology and terrain properties underpin the distributed model formulation, leaving only a few global parameters to be calibrated.

The runoff production and flow routing schemes employ depth-integrated formulations, so are computationally efficient, making G2G fast to run for real-time operational use with regional to national coverage and enabling a degree of offline model calibration. Flow conductance and return flow parameters can be subject to local calibration for gauged river reaches as a further refinement (invoking direct flow insertion as described below).

For real-time use, G2G employs data assimilation of gauged river flows captured through telemetry to improve forecast accuracy. At gauged locations, modelled flows are replaced by observed flows as they become available through a process called *direct flow insertion*, thereby inhibiting modelling errors propagating downstream. Model simulated flows are compared to observations, and the errors are used to adjust the model states upstream using an *empirical state-updating scheme*. The scheme is configured conservatively, serving particularly to keep baseflows aligned to those observed. Model errors can show a tendency to persist with runs of overestimation and underestimation. This property is exploited to forecast future errors using an *error predictor* of Auto Regressive Moving Average (ARMA) form to improve the overall accuracy of river flow forecasts.

Finally, some functionality is provided to account for artificial influences such as abstractions, returns, reservoir/lake controls (Moore & Cole 2022), and urbanisation. A profile of water flows (positive or negative) that is fixed or time-varying can be set. A conceptual storage with a rate constant can be used to emulate the damping effect of reservoirs/lakes. Direct flow insertion can be invoked for lakes/reservoirs with gauged outflows, with future outflows set to the latest observed flow or to a profile as previously described. The effect of urbanisation on river flow response is captured by reducing the effective soil depth and increasing the channel-flow routing speed, supported by a land-cover dataset.

G2G has evolved as a distributed hydrological modelling toolkit representing runoff production and flow routing processes across a landscape. Different options, not detailed here, allow a range of hydrological regimes to be represented, whilst a modular design facilitates functionality being modified or added to.

2.2. SWIFT model

Short-term Water Information Forecasting Tools (SWIFT) is a comprehensive streamflow modelling package designed for operational continuous flow forecasting and hydrological research (Perraud *et al.* 2015; Hapuarachchi *et al.* 2022). SWIFT is built on a modern C++ core, ensuring speed, stability, flexibility, and compatibility with both Windows and Linux operating systems. It is optimised for high-performance computers, making use of multithreading functionality to minimise performance overheads. Furthermore, SWIFT's modular structure makes it easy to add new modules and facilitates integration with other software packages such as Python, MATLAB, and R through its C Application Programming Interface (API). SWIFT is used operationally for delivering the Australian national 7-day ensemble streamflow forecasting service (Hapuarachchi *et al.* 2022; Bari *et al.* 2024). Despite SWIFT's growing popularity among academic and research organisations across Australia, its uptake in the water industry has been restricted by concerns over intellectual property rights.

This study implements the GR4H rainfall-runoff model (Bennett *et al.* 2014), an hourly adaptation of the daily GR4J model (Perrin *et al.* 2003), alongside Lag & Route channel flow routing in the SWIFT modelling package (Figure 2). Previous research conducted in Australia (Perrin *et al.* 2003; Coron *et al.* 2012; Van Esse *et al.* 2013), as well as elsewhere, has shown that GR4J, and its variant GR4H, perform at least as well as other conceptual models in a range of environments at daily and hourly time-steps. GR4H has four independent parameters and is relatively simple to calibrate (Kabir *et al.* 2024).

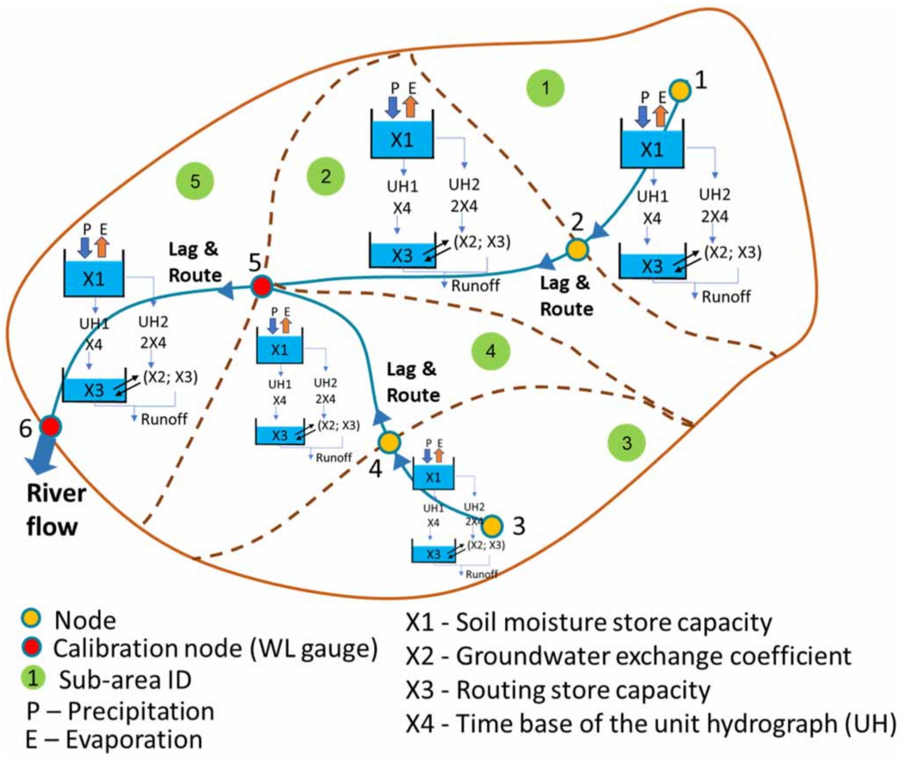


Figure 2 | SWIFT model schematic.

3. STUDY AREA AND DATA

3.1. Study area

The GBR region extends more than 2,300 km along the Queensland coast in Australia and covers 35 major catchments (Figure 3) that drain to the GBR lagoon (Furnas 2003; Steven *et al.* 2014). G2G has been applied across 25 major catchments covering a total area of 426,339 km^2 (Figure 3), whilst SWIFT has been applied to 9 internal catchments at 19 streamflow gauging locations (Figure 3, Table 1). Model coverage of G2G is greater because of its exclusive application for the eReefs project to estimate the streamflow from a large part of the GBR catchments. In contrast, SWIFT has been applied to various catchments across Australia for issuing ensemble 7-day Streamflow Forecasts operationally (http://www.bom.gov.au/water/7daystreamflow/, accessed on 12 March 2025). This study deals only with those 19 locations where outputs from both models are available: their catchment areas vary from 91 to 35,864 km^2 (Table 1).

3.2. Spatial data

In this study, G2G is configured to use the Geocentric Datum of Australia (GDA94) geographic (latitude and longitude) coordinate system at a 0.01° resolution (~1 km). Various types of spatial gridded data were used to set up the G2G hydrological model. These include flow direction, flow accumulation, the slope of the grid-cell, main river length and slope, land/river designation, land cover (urban fraction), and dominant soil type, along with the soil hydraulic property information. A grid-cell drained-area dataset specifies the area drained by each grid-cell, and a routing cell-length dataset gives the distance between centroids of cells aligned to the flow direction. These data have been prepared at a 0.01° resolution cell size.

The hydrologically enforced GEODATA 9″ (0.0025°) Digital Elevation Model (DEM-9S) and D8 flow directions (D8-9S), available across Australia, were utilised to develop some of the spatial datasets. The flow direction grid was calculated by the ANUDEM procedure as used in deriving the DEM-9S. ANUDEM is a computer program developed by the Australian National University (ANU) Fenner School of Environment & Society for processing data into a digital elevation model (DEM). Details of these datasets are available from the Geoscience Australia website at: https://www.ga.gov.au/products/servlet/controller?event=GEOCAT_DETAILS&catno=66006, accessed on 12 March 2025.

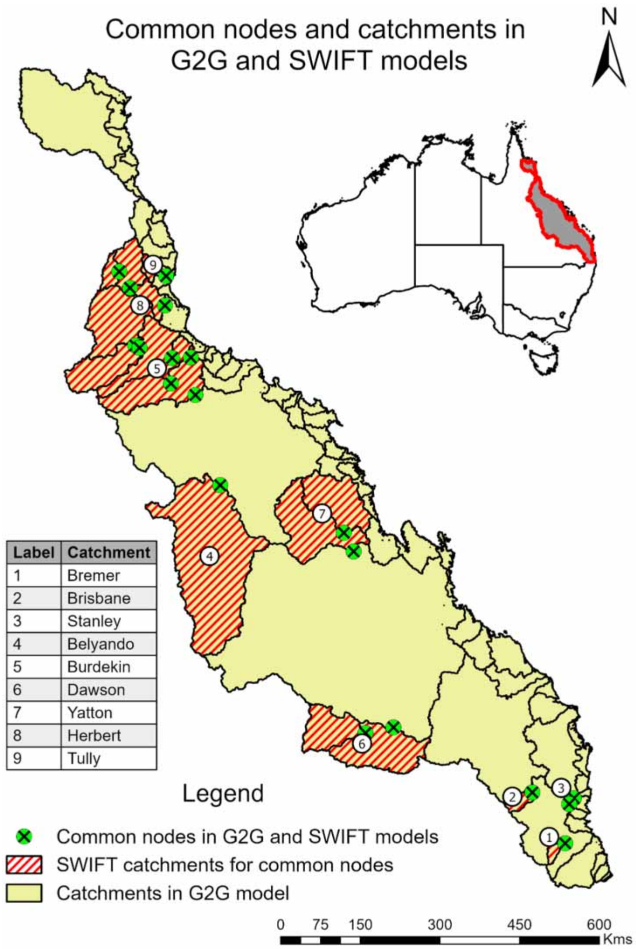


Figure 3 | Map of study area catchments.

The Australian Hydrologic Geospatial Fabric (Geofabric) from the Bureau of Meteorology, Australia (the Bureau) provides additional information on the water bodies, stream network and associated attributes (http://www.bom.gov.au/water/geofabric/, accessed on 12 March 2025). Geofabric (Atkinson *et al.* 2008) proved useful in understanding the river network connectivity for the case study area. The Geofabric dataset was used to derive several supporting datasets at a 0.01° resolution for use by G2G over the study area, including average terrain slope, slope of the river channel and river length.

G2G requires flow directions derived at the resolution of the model, 0.01° in this case. The COTAT+ method, developed by Reed (2003) and improved by Paz *et al.* (2006), was used to derive the 0.01° resolution flow directions from the finer 0.0025° base resolution (GEODATA 9″). Tests over mainland Britain by Davies & Bell (2009) have shown that COTAT+ successfully reproduces the catchment areas derived by the finer scale DEM regardless of the topography to which it is applied.

The soil property dataset at a 0.01° resolution was derived from the Digital Atlas of Australian Soils (DAAS) soil types (Northcote *et al.* 1968) through the use of pedotransfer functions (McKenzie & Hook 1992; McKenzie *et al.* 2000). DAAS soil classes were summarised on a 0.01° grid using the dominant soil class within each grid-cell. The soil component of the G2G formulation was treated as a single depth-integrated column characterised by the soil properties of depth, lateral and vertical saturated hydraulic conductivity, and volumetric water content (water volume per unit volume of soil) at saturation, field capacity and residual conditions. Pedotransfer function derived properties estimated by McKenzie *et al.* (2000) have been used in their derivation.

In the SWIFT model's application, Geofabric (Atkinson *et al.* 2008) was used for delineating the catchment into sub-areas. This was achieved by identifying desired sub-area outlet nodes and determining the upstream catchment area using Geofabric's catchment (polygon) and stream (link) layers and associated upstream to downstream connectivity attributes. The area,

Table 1 | The study area catchments

Catchment	AWRC ID	Station Name	Area (km^2)
Bremer	143107A	Bremer River at Wallon	628
Brisbane	143015B	Cooyar Creek at Taromeo Creek	956
Stanley	143303A	Stanley River at Peachester	102
	143901A	Stanley River at Woodford	246
Belyando	120301B	Belyando River at Belyando Crossing	35,455
Burdekin	120107B	Burdekin River at Blue Range	10,478
	120122A	Burdekin River at Gainsford	26,260
	120110A	Burdekin River at Mt Fullstop	17,241
	120002C	Burdekin River at Sellheim	36,225
	120112A	Star River at Laroona	1,208
	120102A	Keelbottom Creek at Keelbottom	195
Dawson	130302A	Dawson River at Taroom	15,836
	130324A	Dawson River at Utopia Downs	6,029
Yatton	130404A	Connors River at Pink Lagoon	8,701
	130401A	Isaac Rive at Yatton	19,673
Herbert	116006B	Abergowrie at Herbert River	7,488
	116004C	Gleneagle at Herbert River	5,268
	116016A	Gunnawarra (Rudd Creek)	1,477
Tully	113006A	Tully River at Euramo	1,388

sub-area centroid, channel length, and sub-area connectivity were then calculated from the delineated sub-areas. In practice, this was achieved through an automated GIS process. The minimum to maximum range and average size of sub-areas for each catchment are presented in Table 2. Out of all catchments, the smallest and largest sub-areas are 24 and 3,502 km^2 for the Burdekin and Belyando catchments, respectively. The Brisbane catchment (site 143015B, Cooyar Creek at Taromeo Creek) comprises a single sub-area, so its minimum, maximum and average sizes are the same. Notably, all sub-area sizes exceed the ~1 km^2 spatial resolution of the G2G model, confirming that the computational units used in SWIFT modelling are coarser than those of the G2G framework.

3.3. Hydrometeorological data

3.3.1. Streamflow data

Historical hourly observations of streamflow from 284 gauging stations were used in G2G modelling, sourced from the Water Data Online product of the Bureau (http://www.bom.gov.au/waterdata/, accessed on 12 March 2025). The data portal

Table 2 | The minimum to maximum ranges and the average size of sub-areas

	Size of sub-areas (km^2)		
Catchment name	**Min**	**Max**	**Average**
Belyando	84	3,502	1,313
Bremer	231	397	314
Brisbane	956	956	956
Burdekin	24	2,993	906
Dawson	232	1,695	990
Herbert	303	1,610	1,070
Stanley	33	59	49
Tully	564	825	694
Yatton	47	1,484	656

contains streamflow data from across Australia. These data were collated from state and local government agencies responsible for recording water level data at monitoring stations and providing the associated rating tables enabling conversion to streamflow data. Where available, the streamflow data from 1 January 2007 to 1 November 2022 were used for G2G modelling.

The Water Data Online product served as the main source for historical streamflow data from 1 January 2007 to 31 December 2016, which was used for SWIFT modelling. Additional data from water agencies were incorporated as needed. The data from all the sources were merged while taking into account their quality codes and timestamps, whether in Universal Time Coordinate (UTC) or local time.

For G2G modelling, all streamflow data were processed using an internal hydrometeorological data Quality assurance and Quality control (QaQc) tool that removes data points that were: (i) negative in value, (ii) linearly interpolated (identified by a constant gradient across at least 24 time-steps), (iii) data with values of 12 standard deviations above the median value for the location, and (iv) constant in value for at least 24 time-steps. The resulting streamflow data for each location were then plotted for each year and visually inspected for any remaining abnormalities indicating poor-quality data. Such data points were then also removed from the dataset.

For SWIFT modelling, the SDF QaQc tool was used and has similar functionality to that employed for G2G model development. This tool flags suspected data and allows users to compare streamflow data with rainfall data from nearby stations. Flagged data were manually inspected to verify their quality and suitability for SWIFT modelling. After flagged data were removed, the dataset was cleaned further by visually checking for any remaining abnormalities indicating poor-quality data.

3.3.2. Rainfall data

Gridded hourly rainfall data at 0.01° resolution were generated for G2G modelling. To generate this dataset, hourly gauged historical rainfall data and daily gridded rainfall data at 0.01° resolution from the Bureau's Australian Gridded Climate Data (AGCD) were used (Evans *et al.* 2020). The inverse distance weighting approach was used to generate hourly gridded rainfall data. Daily AGCD data were disaggregated linearly to an hourly timescale. The AGCD dataset was used only in those places where the density of rainfall gauges was low, particularly in inland western regions (Figure 3); otherwise, in most of the regions, interpolated hourly rainfall gauge data were used. These gridded rainfall data align with the G2G grid-cells across the model's domain.

For SWIFT modelling, hourly rainfall data (2007–2016) were extracted from the Bureau's internal databases. Due to the limited availability of hourly rainfall data before 2007, daily rainfall data were extracted from the Australian Water Availability Project (AWAP) (Raupach *et al.* 2009) and disaggregated linearly to an hourly timescale. The disaggregated hourly rainfall data (from 1990 to 2006) were used for the hydrological model warmup. Though the quality of disaggregated hourly rainfall data was low, it provided good estimates of model states in hourly hydrological models (Bennett *et al.* 2016). Comprehensive quality checking was performed for all rainfall observations using a semi-automated workflow. The area-averaged observed rainfall for each sub-area was calculated using the inverse distance weighted approach by taking the distance from the centroid of the sub-area to the rainfall gauges.

3.3.3. PE data

Daily Potential Evaporation (PE) data at a 5 km resolution were sourced from the Australian Water Resources Assessment Landscape (AWRA-L) model (https://awo.bom.gov.au/, accessed on 12 March 2025). This dataset was converted into monthly profiles and mapped to a 0.01° grid for use as input to the G2G model. The PE data were extracted from January 2007 to October 2022.

For the SWIFT model development, monthly gridded PE data from 1990 to 2016 were extracted at a 5 km resolution from the AWAP (Raupach *et al.* 2009). A linearly weighted downscaling method was used for preparing an hourly PE dataset for model calibration.

4. METHODOLOGY

4.1. Setting up the G2G model

G2G employs gridded and point scale time-series hydrometeorological datasets as model input, static spatial datasets that support its configuration to a given model domain, and model parameters that control how the model responds (Moore *et al.* 2006, 2013; Wells *et al.* 2018). Preparation of the input datasets used for setting up G2G has been discussed previously in Section 3. The G2G products – the G2G gridded and point scale outputs – are configurable to meet the needs of the application. Figure 4, in its upper part, provides an overview of the G2G setup process in flow chart form, with the lower part showing the running, postprocessing/analysis and output packaging steps for the model.

4.1.1. Modes of running the G2G model

The G2G model can be run in various modes during calibration, verification and simulation (Moore *et al.* 2014; Wells *et al.* 2018). These modes are outlined below.

Pure simulation mode. Observed flows are normally not used (other than for model initialisation), and rainfall and potential evaporation data are converted into river flows by the G2G model (Figure 4). This mode is primarily used for model calibration and determining 'global' values of model parameters.

Simulation mode with state updating. In this mode, observed flows at a gauging station are used to apply an adjustment to the water storage within deep soils in the upstream gauged catchment/sub-catchment. This conservative scheme adjusts the water in storage gradually over time with the aim that modelled and observed baseflows are better matched.

Simulation mode with state updating and flow insertion. In this mode, the model is run as in simulation mode with state updating except that direct flow insertion – where model flows are replaced with observed flows at gauged locations – is used at sites upstream (Figure 4). Note that, for the gauged site under assessment, the model simulation before inserting the observed flow at that site is used for assessment. Therefore, flow insertion will have no impact on gauging stations with no gauged sites upstream.

4.1.2. Accounting for artificial influences

To accommodate the effects of artificial influences, such as river abstractions/discharges and reservoirs/lakes, simple functionality is provided in G2G to set a constant flow (negative or positive), to apply an annual profile of monthly flows and to represent a damped response using a conceptual storage with a rate-constant parameter (Wells *et al.* 2018).

A number of artificially influenced locations were identified as potentially having an impact on the natural flow regime. These were: the Fairbairn Dam, the Burdekin Falls Dam, Claire Weir and Paradise Dam. An improvement was noted by damping the modelled flow at grid cells aligned to the outlets of Fairbairn Dam and Burdekin Falls Dam, but not much improvement was noticed in damping the outflow from Clare Weir and Paradise Dam.

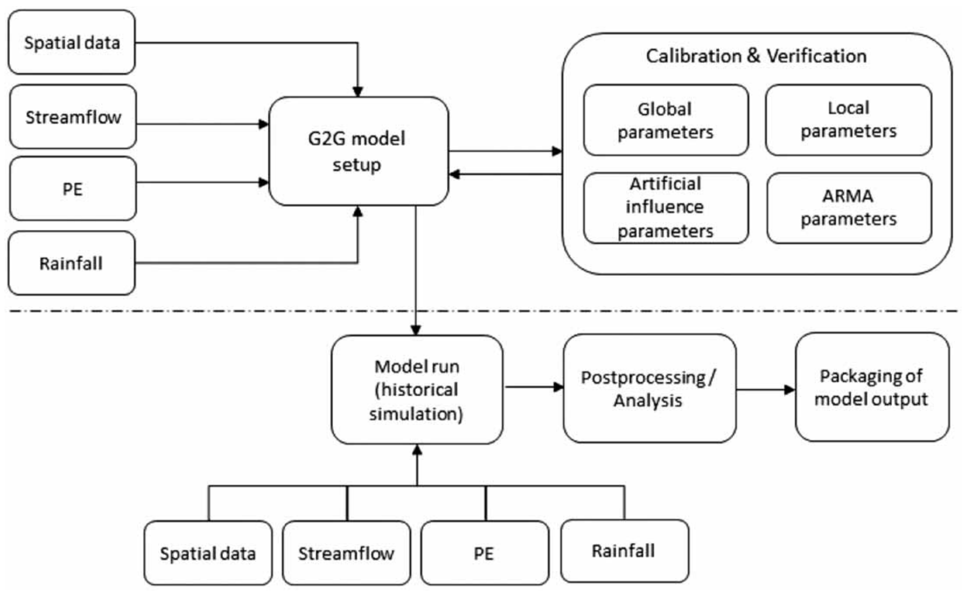


Figure 4 | Flow chart of G2G model setup.

4.1.3. Model calibration

The G2G model formulation allows model properties to be linked directly to spatial datasets on terrain, soil/geology and land cover, leaving only a few 'global' parameters that require calibration across the model domain (Figure 4). Subsequently, 'local' values for parameters affecting channel flow routing (flow conductance) and soil store return flow fraction can be calibrated for a gauged river reach by invoking direct flow insertion for gauged inflows to the reach (Wells *et al.* 2018).

The initial stages of 'global' model calibration were focused on making the best use of the supporting spatial datasets (particularly the soil datasets) and gaining a better understanding of the hydrological regime. This stage was primarily manual and used the model in 'pure' simulation mode so as not to allow data assimilation to confound interpretation. Modelled and observed hydrographs were heavily used to aid understanding of model performance at various stages. This provided an initial calibration of the model and identified the model structure to use.

The second phase of 'global' model calibration continued to use simulation-mode (without error-prediction) but invoked state-updating and (upstream) flow insertion, and employed specified parameter sweeps of the 'global' parameter space. This involved hundreds of model runs, and whilst automated calculation and analysis of performance metrics (NSE and RBias) were useful, visual inspection of the model hydrographs was also important. Finally, a global calibration was achieved that balanced both the performance statistics and visual acceptance of the hydrographs (e.g. capturing the dominant characteristics of the observed response).

Once 'global' model calibration had been completed, the 'local' parameter values for the flow routing (flow conductance) and soil store return flow fraction were identified for each gauged river reach having upstream gauged inflows. This was achieved by running the model in simulation-mode with state-updating and (upstream) flow-insertion, sweeping through a range of values for the two parameters and then selecting the 'local' parameter values giving the best balanced performance across the NSE and RBias performance statistics. Finally, the ARMA model parameters used for error-prediction were also calibrated for each gauged location using the simulation mode flow output and flow observations.

In performing the G2G model calibration, the streamflow data for 284 sites over the period 1 January 2007–31 December 2014 were used, with the remaining period 1 January 2015–1 November 2022 employed for assessment.

4.2. Setting up the SWIFT model

4.2.1. Semi-distributed model structure

Semi-distributed modelling brings simplicity compared to distributed modelling and provides sophistication compared to lumped modelling by accommodating in part the spatial variability of rainfall and model states and routing variables within a catchment while maintaining computational efficiency. In the SWIFT model application, a catchment is delineated into sub-areas, which are the smallest divisions within a catchment, to represent a semi-distributed model structure (Figures 2 and 5, Table 2). Sub-area connectivity from upstream to downstream is described using a node-link structure (Figure 2). The number of sub-areas varies for each catchment and depends on catchment size, topography and the availability of gauging locations. A collection of sub-areas forms a sub-catchment, where a streamflow gauge exists at the outlet. Multiple sub-catchments together constitute the entire catchment.

The hydrological model is independently applied to each sub-area (Figures 2 and 5). Each sub-area within a sub-catchment has the same model parameterisation except for parameter *X4*, the time base of the unit hydrograph in hours (Figures 2 and 5). For the j'th sub-area in a sub-catchment, the parameter is calculated as

$$X4_j^* = X4\left(\frac{A_j}{250}\right)^{1/2} \quad (1)$$

using the calibrated value of *X4* for the whole sub-catchment. Here, A_j is the area of the sub-area in km^2, with 250 km^2 used as a reference area of a sub-area: it is an arbitrary number based on previous model calibration results and is used consistently for all the catchment models.

Runoff generated in each sub-area is routed (catchment routing) to its outlet. Then, lag and route channel routing is used to sequentially route discharge from each sub-area from upstream to downstream (Figures 2 and 5). Model parameters are automatically calibrated for each sub-catchment and manually fine-tuned considering the catchment characteristics such as known travel times, the existence of reservoirs, and backwater and tidal impacts.

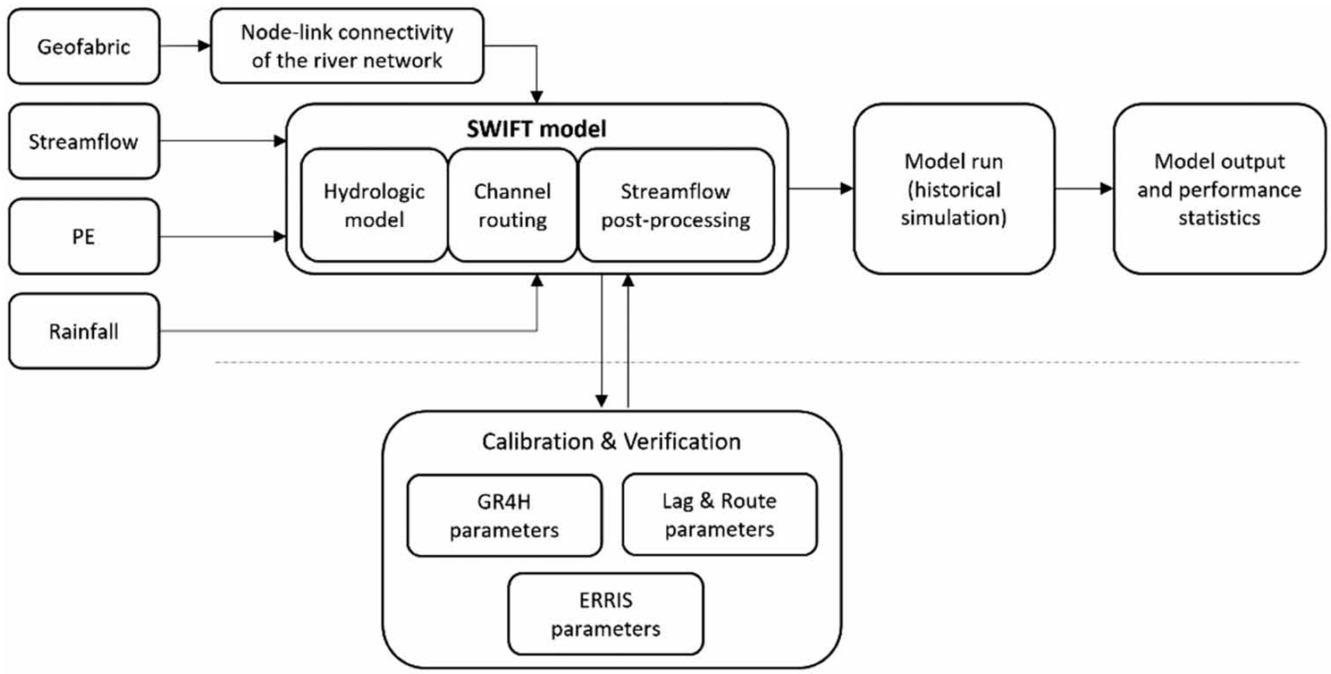


Figure 5 | Flow chart of SWIFT model setup.

The streamflow at each sub-catchment outlet is post-processed using the Error Representation and Reduction In Stages (ERRIS) (Bennett *et al.* 2021) model within the SWIFT package (Figure 5). ERRIS is applied to address different statistical properties of the streamflow error in four stages: (i) hydrological model forecast and data normalisation, (ii) non-linear bias correction, (iii) restricted autoregressive (AR) model updating, and (iv) adjustment of residual distribution. The impact of ERRIS on model performance is significant (Hapuarachchi *et al.* 2022), especially in the forecast mode.

4.2.2. Input data preparation

Following the extraction and quality control of hourly gauged rainfall data for all stations, the sub-area average rainfall was calculated using the inverse-distance weighted approach using the four rainfall gauges nearest to the sub-area centroid. Any data gaps in the sub-area average rainfall were filled using the disaggregated AWAP rainfall data. Observed hourly discharge data for the sub-catchment outlets were first extracted and quality checked, and then used for calibrating the model, post-processing the simulated discharge, and evaluating the model performance.

The monthly PE values were initially disaggregated to daily values by assuming that the values occur on the middle day of each month and applying linear interpolation between them. These daily PE data were then disaggregated linearly to produce an hourly PE dataset for use in model calibration. Note that the PE disaggregation method did not consider diurnal patterns or any correlation with rainfall and temperature, but was considered adequate for the modelling purpose of this study. Previous research by Andreassian *et al.* (2004) using the GR4J model demonstrated little performance sensitivity to the precise form of PE input used, provided model parameters are adapted to suit. Climatological averages of PE calculated over the period from 1990 to 2016 were used to run the model in forecast mode.

4.2.3. Model cross-validation

A 'leave-two-year-out' cross-validation approach (Hapuarachchi *et al.* 2016) was implemented using observed hourly data from 2007 to 2016. A longer leave-out period was preferred, but this would shorten the data available for model calibration. The duration of two years was determined as appropriate after considering the limited data available. The first year (D1 in Figure 6) of the leave-out period in each iteration was used for model validation. The purpose of the second year (D2 in Figure 6) was to avoid propagating any hydrological effects from the validation period into the model calibration and to maintain the independence of the calibration and validation periods (Hapuarachchi *et al.* 2016).

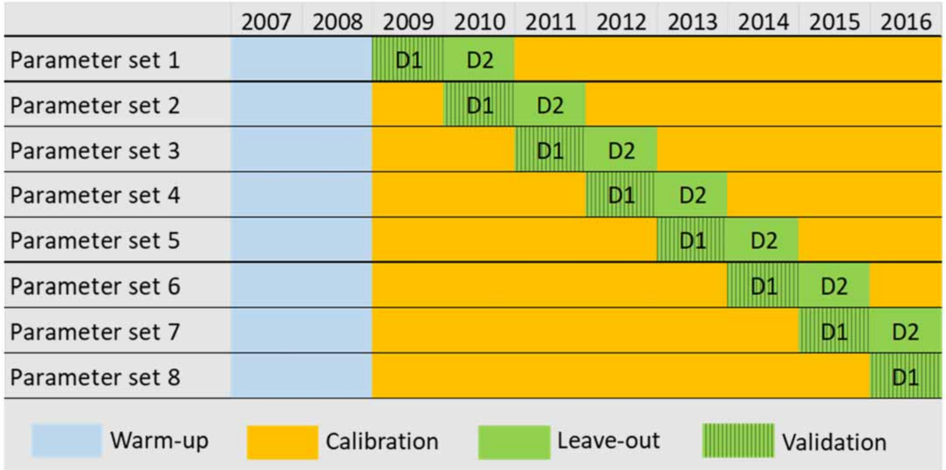


Figure 6 | Schematic of the cross-validation process.

The automatic model calibration functionality built-in to SWIFT – the Shuffled Complex Evolution (SCE-UA) algorithm (Duan *et al.* 1994) – was used to calibrate all the model parameters (GR4H, Lag & Route, and ERRIS) for each sub-catchment and then further tuned manually. The model was warmed up using the quality-checked observed data from 1 January 2007 to 31 December 2008 and automatically calibrated for the period from 1 January 2009 to 31 December 2016.

As shown in Figure 6, the model was warmed up using the first two years of data and calibrated eight times using the remaining data, leaving out two years each time (D1 and D2). Then, each calibrated parameter set was used to run the model for the relevant leave-out period and collate the first year of the output (D1) to create a continuous validation dataset from 2009 to 2016.

Once the model was validated, the whole dataset (2009–2016) was used to calibrate the model to obtain the final parameter set (operational parameters) for a sub-catchment. The final parameter set was compared with the parameter sets obtained in the cross-validation and was manually fine-tuned if necessary. It was assumed that the final parameter set performs better than or equal to the parameter sets obtained in the cross-validation. The cross-validation methodology was used to calibrate model parameters for all the sub-catchments from upstream to downstream. Once the model was calibrated for an upstream sub-catchment, the parameter set was fixed, and the post-processed simulated flow using the ERRIS model was passed to the downstream sub-catchment. It ensures that cumulative model errors were not passed from upstream to downstream in model calibration, leading to finding a robust model parameter set.

4.3. Intercomparison and evaluation metrics

Model performance in simulation mode was assessed by visually inspecting the modelled and observed hydrographs and using the three statistical performance measures Nash-Sutcliffe Efficiency (NSE) (Nash & Sutcliffe 1970), Mean Absolute Error (MAE) and relative model bias, RBias.

NSE gives the proportion of variance in the observations that is accounted for by the model. It is defined as

$$\mathrm{NSE} = 1 - \frac{\sum_{t=1}^{n} e_t^2}{\sum_{t=1}^{n} (Q_t - \overline{Q})^2} \tag{2}$$

Here, $e_t = (Q_t - q_t)$ is the model error at time t with Q_t and q_t the observed and modelled flow, and $\bar{Q} = n^{-1} \sum_{t=1}^{n} Q_t$ is the mean flow over n observations. NSE is a dimensionless measure and allows meaningful comparisons across different events, catchments, and models. This statistic has a value of 1 for a perfect simulation and takes negative values if the simulations are worse than those provided by the mean observed flow.

The Mean Absolute Error (MAE) is a measure of errors between the observed and simulated flows. MAE is calculated as the sum of the absolute value of each model error divided by their number such that

$$\mathrm{MAE} = \frac{\sum_{t=1}^{n} |e_t|}{n} \tag{3}$$

The relative model bias, RBias, indicates over (positive) or under (negative) estimation of the modelled flows relative to the observed flows, and is defined as

$$\mathrm{RBias} = -\left(\frac{1}{n\bar{Q}}\sum_{t=1}^{n} e_t\right) \tag{4}$$

Long-term bias values that significantly deviate from 0 can suggest where there are water balance issues, such as due to abstractions, affecting the flow response.

5. COMPARATIVE ASSESSMENT OF MODEL PERFORMANCE

This section presents the comparison of G2G and SWIFT models using various metrics and comparison plots for different durations.

5.1. Model performance during calibration and evaluation

Here, the performance of G2G and SWIFT models is compared during the calibration and assessment period.

5.1.1. G2G model performance

NSE values for all 284 streamflow gauging locations over the calibration period (1 January 2007–31 December 2014), assessment period (1 January 2015–1 November 2022) and full period (1 January 2007–1 November 2022) are presented in Figure 7. The performance of G2G during calibration, assessment and the full period is almost similar. Median values of NSE across the sites are 0.66 (calibration period), 0.66 (assessment period) and 0.65 (full period). These values are very close, indicating that model performance is stable over the calibration, assessment, and full period. Figure 7 shows that though the median values of NSE in all three boxplots are close, the inter-quartile ranges are slightly different, particularly for the assessment

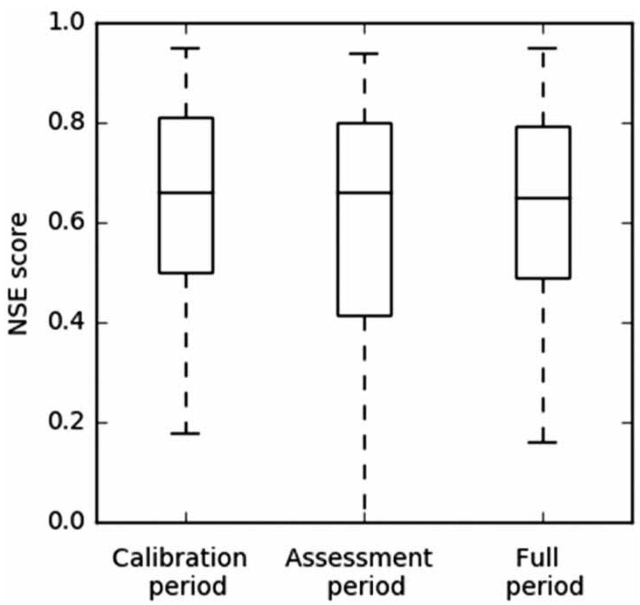


Figure 7 | Boxplots of NSE during the calibration (2007–2014), assessment (2015–2022) and full period (2007–2022) for all 284 sites.

period, which is wide, and the whisker corresponding to the 5th percentile is negative. This is mainly due to the presence of a few dry years in the assessment period, such as 2017, 2018 and 2019. The year 2019 in particular was the hottest and driest on record in Australia (http://www.bom.gov.au/climate/current/annual/aus/2019/, accessed on 12 March 2025). The weights of these dry years have less impact when NSE values are calculated for the full period in comparison to when calculated only for the assessment period. From all three boxplots, it is evident that there is variation in NSE values from site to site, and this depends on various factors such as the existence of any upstream site for flow insertion, the number of rainfall gauges in the vicinity, the size of the catchment, the presence of perennial or ephemeral streams and storage structures upstream. Over the calibration period, NSE values for all 284 sites are above zero, whereas over the assessment period, some sites go negative, again due to a long dry period of a kind not experienced during the calibration period.

5.1.2. SWIFT model performance

As described in Section 4.2.3, the cross-validation method enables independent calibration and validation of the model for the same period. The results of the SWIFT model's cross-validation (assessment period) and calibration (full period) for 2009–2016 are presented in Figure 8. NSE values for all calibration sites exceed 0.5 for the assessment period and 0.7 for the full period. The median NSE for the assessment period is 0.75, while for the full period, it is 0.85. These values indicate excellent performance in both calibration and validation of the model.

5.2. Comparison of G2G and SWIFT model performances

The NSE, MAE and RBias of both G2G and SWIFT models for the common period 2009–2016 are presented in Table 3. Out of 19 locations, the NSE is slightly higher at 17 locations for SWIFT in comparison to G2G. Also, MAE is slightly lower at 14 locations and RBias is slightly lower at 12 locations for SWIFT than G2G. Further, the RBias values are negative for most of the locations for both models. These results indicate that the SWIFT model performance is slightly better than that of G2G across all comparison metrics. Though for the majority of locations, all performance metrics provide consistent results, for some locations, the results are not consistent. For example, for site 143107A (Table 3), the NSE and RBias of SWIFT are slightly better than for G2G, whereas the MAE for G2G is slightly better than for SWIFT: this indicates that SWIFT is slightly better in high flows, whereas G2G is slightly better overall.

Boxplots of NSE, MAE and RBias for hourly simulated streamflow from G2G and SWIFT models for individual years and the entire common period (2009–2016) for all locations in common are presented in Figure 9(a)–9(c). The NSE, MAE and

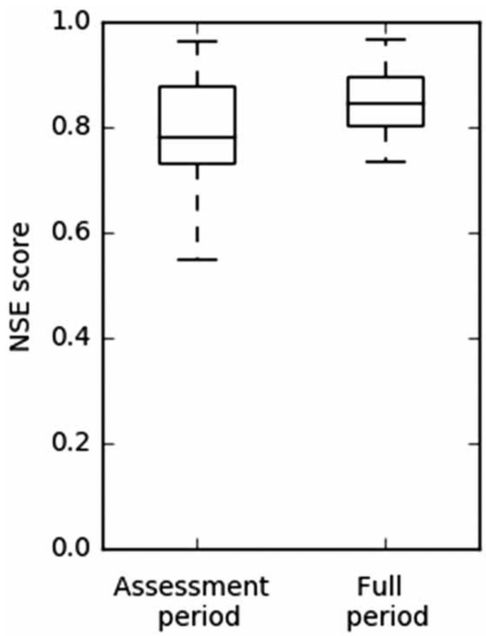


Figure 8 | Boxplots of NSE during the assessment (cross-validation 2009–2016) and full period (2009–2016) for all 19 sites where the SWIFT model is available.

Table 3 | Comparison of NSE, MAE and RBias for G2G and SWIFT models for the entire common period 2009–2016 for all 19 locations

		NSE		MAE		RBias	
	AWRC ID	G2G	SWIFT	G2G	SWIFT	G2G	SWIFT
Bremer	143107A	0.71	0.79	1.81	2.27	−0.34	−0.07
Brisbane	143015B	0.58	0.81	3.06	1.48	0.72	0.01
Stanley	143303A	0.76	0.82	1.59	1.13	−0.05	−0.08
	143901A	0.90	0.71	1.81	2.23	−0.09	−0.20
Belyando	120301B	0.71	0.87	17.35	9.81	0.19	−0.04
Burdekin	120107B	0.85	0.74	24.90	35.31	0.04	−0.03
	120122A	0.94	0.97	37.22	25.43	−0.03	0.02
	120110A	0.87	0.89	30.37	25.78	−0.04	−0.07
	120002C	0.97	0.98	37.11	35.55	−0.04	−0.04
	120112A	0.69	0.74	17.00	18.22	−0.10	−0.18
	120102A	0.71	0.80	3.01	3.00	−0.21	−0.20
Dawson	130302A	0.63	0.78	18.94	14.09	−0.29	−0.06
	130324A	0.65	0.80	10.00	5.39	0.35	−0.08
Yatton	130404A	0.85	0.86	38.21	28.78	0.20	0.08
	130401A	0.83	0.93	43.76	20.97	−0.03	−0.08
Herbert	116006B	0.94	0.95	23.91	20.46	−0.08	−0.07
	116004C	0.87	0.89	14.69	15.97	−0.02	−0.20
	116016A	0.69	0.84	4.37	3.01	−0.04	−0.10
Tully	113006A	0.87	0.87	26.74	24.13	−0.16	−0.02

RBias values of hourly simulated streamflow for 2009–2016 for all common locations for G2G and SWIFT models are presented spatially in Figure 10(a)–10(f). The median NSE across sites for all individual years and entire periods is greater than 0.6 for both models (Figure 9(a)). The median NSE of SWIFT is slightly higher than for G2G in most years except 2013: this again indicates that SWIFT performs slightly better than G2G (Figure 9(a)). The interquantile range and its variation for both models are narrower in 2009, 2010, 2011, 2013 and for the entire period than for 2012, 2014, 2015 and 2016: a reflection of the latter period being slightly drier than the earlier period for some of the locations (Figure 9(a)). The performance of both models over the entire period (2009–2016) is good, with median NSE higher than 0.8 and the lower whiskers above 0.6 for both (Figure 9(a)). The spatial plots of NSE also indicate that the performance of both models over the entire period (2009–2016) is good, whereas the performance of G2G at some locations along the western/inland region is adversely affected by the poor availability of hourly gauged rainfall data (Figure 10(a) and 10(b)). Lower NSE is generally associated with low rainfall-low runoff catchments for both G2G and SWIFT models.

The median MAE of SWIFT is slightly lower than for G2G in most years except 2011 and 2013 (Figure 9(b)). The interquantile range and its variation for both models are wider in 2009, 2010, 2011, 2012 and for the entire period than for 2013, 2014, 2015 and 2016: the latter period being slightly drier than the earlier period for some of the locations, and the peak flow values are lower, which resulted in less MAE (Figure 9(b)). The performance of both models over the entire period (2009–2016) is almost similar (Figure 9(a)). The spatial plots of MAE also indicate that the performance of both models over the entire period (2009–2016) is almost similar (Figure 10(c) and 10(d)).

The median RBias for both G2G and SWIFT for most of the years and the entire period are close to zero (Figure 9(c)). The interquantile range and its variation for both models are narrower from 2009 to 2013 and for the entire period than for 2014 to 2016, as the latter period is slightly drier than the earlier period for some of the locations (Figure 9(c)). The spatial plots of RBias further confirm that the performances of both models over the entire period are comparable, whereas the performance of G2G at some locations along the western/inland region is adversely affected by the poor availability of hourly gauged rainfall data (Figure 10(e) and 10(f)).

Since it is difficult to show in concise form the hourly hydrographs for all 19 locations, three have been selected from the north, middle and south of the GBR: Tully River at Euramo, Isaac River at Yatton, and Stanley River at Woodford (Figure 3, Table 1). Hourly hydrographs and flow duration curves are presented in Figures 11(a)–11(c) and 12(a)–12(c); note that the

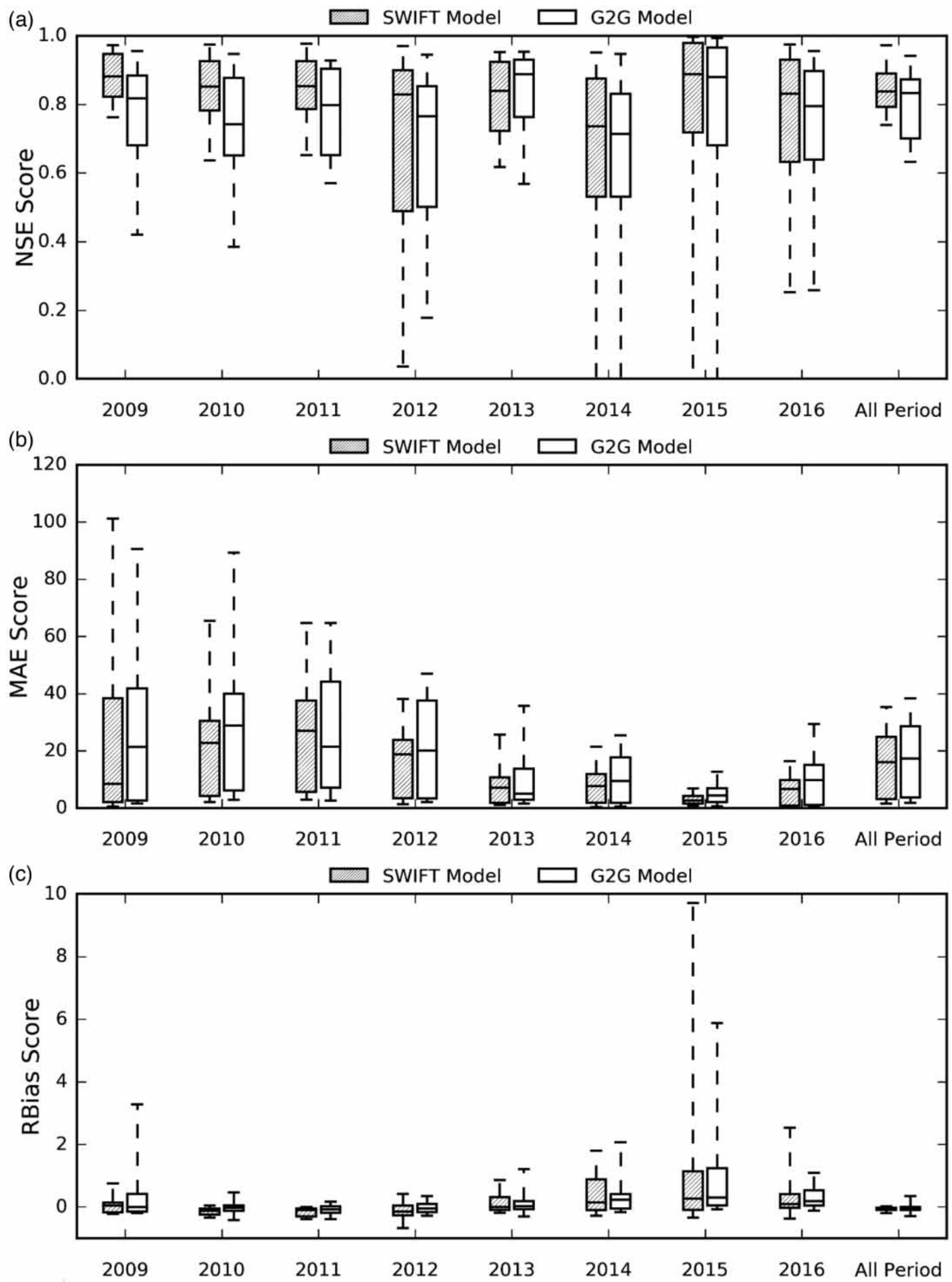


Figure 9 | Boxplots of (a) NSE, (b) MAE and (c) RBias for hourly simulated streamflow from G2G and SWIFT for individual years and the entire common period (2009–2016) for all 19 common locations.

maximum range of streamflow differs due to the size of the catchments and the rainfall they received. Close examination of Figure 11 indicates that G2G overestimates peak flows for some of the events in 2011, 2013, 2014, and 2015 for the Tully River at Euramo, 2011 for the Isaac River at Yatton, and 2012, 2013, and 2015 for Stanley River at Woodford. Similarly, SWIFT overestimates peak flows for some of the events in 2009 and 2014 for the Tully River at Euramo and 2013 for Stanley River at Woodford. These results indicate that model performance varies with the model from event to event and site to site. It is not always the case that one single model consistently performs well or poorly for all events and all sites. The flow duration curve indicates that in high flows, the performances of both models are comparable whereas in low flows SWIFT performed better for Tully River at Euramo (Figure 12(a)) and Isaac River at Yatton (Figure 12(a) and 12(b)), whereas for Stanley River at Woodford, none of the models performed well as this catchment is small in size and flows are close to zero during low flow

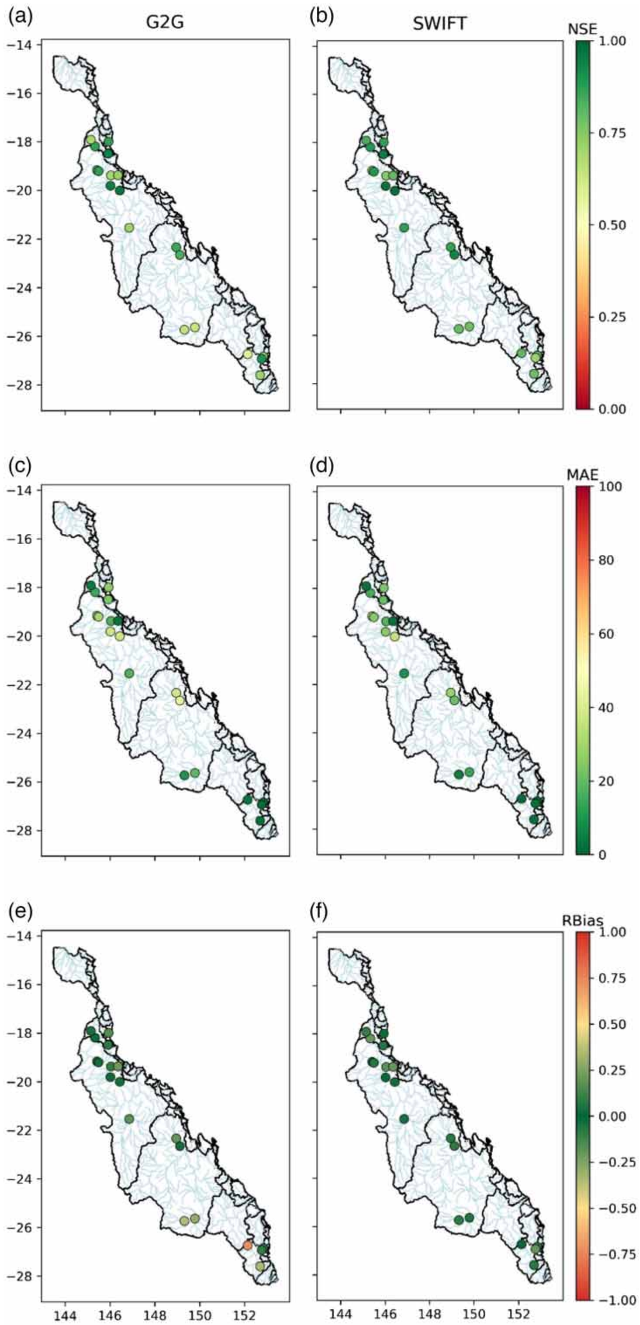


Figure 10 | Spatial plots of NSE for (a) G2G, (b) SWIFT, MAE for (c) G2G, (d) SWIFT, and RBias for (e) G2G and (f) SWIFT for hourly simulated streamflow over the period 2009–2016 for all 19 common locations.

conditions (Figure 12(c)). Note that, in Figures 11 and 12, the hydrographs and flow duration curves show that the performance of both models varies across the three sites. Overall, SWIFT performs slightly better than G2G mainly because it is calibrated to individual catchments and locations.

5.3. Strengths of both modelling approaches

The performance of both modelling approaches has been assessed at gauged locations and is broadly comparable, although the NSE, MAE and RBias of SWIFT are slightly better than G2G (Table 3, Figures 9 and 10). This is to be expected as G2G is a single area-wide distributed model configured to make use of all gauged streamflows in the GBR catchments, whereas

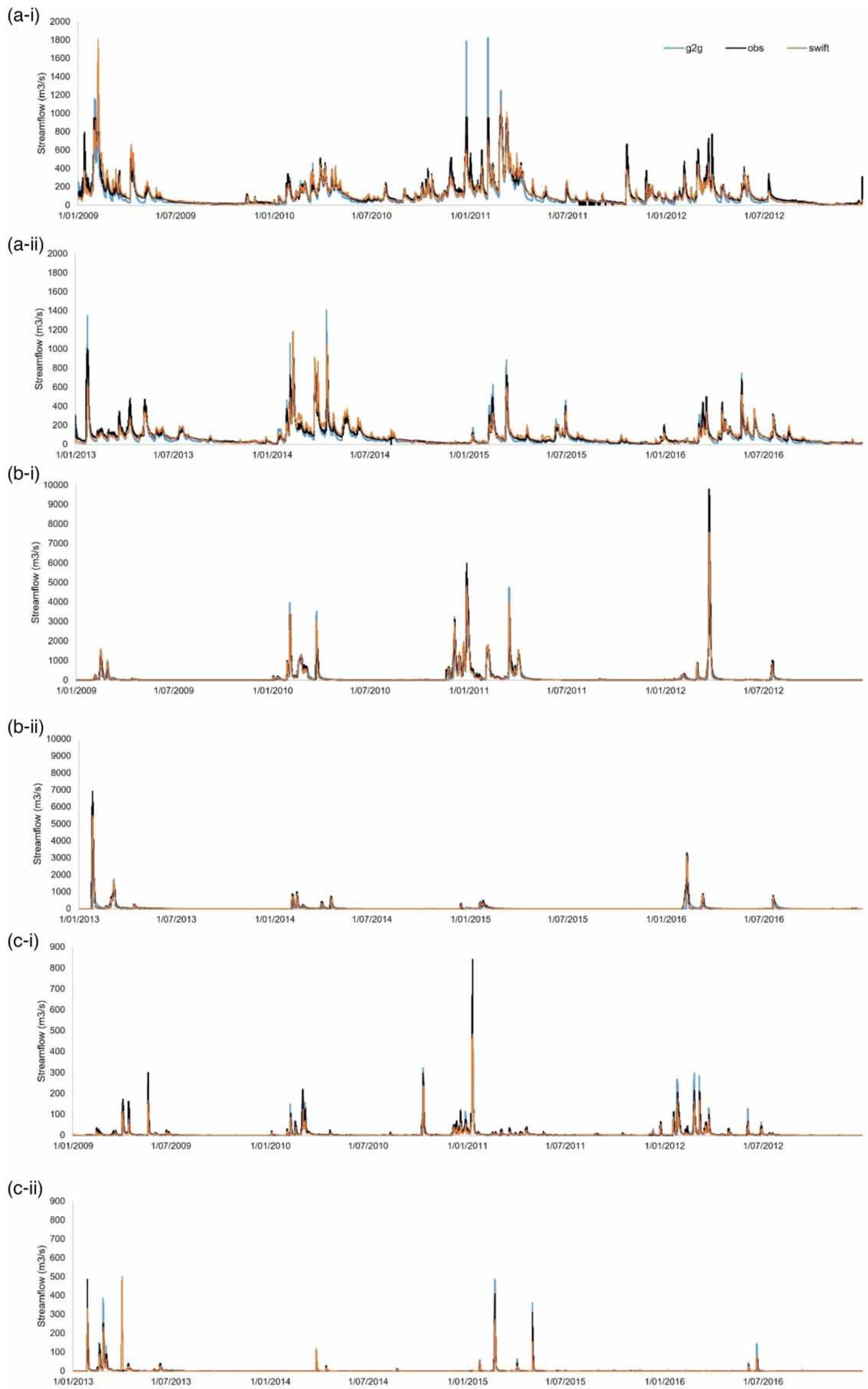


Figure 11 | Hourly hydrographs for three selected locations: (a-i to a-ii) Tully River at Euramo (in north of GBR), (b-i to b-ii) Isaac River at Yatton (in middle of GBR) and (c-i to c-ii) Stanley River at Woodford (in south of GBR). For all three locations, the figures (i) are for the period 2009–2012, and (ii) are for the period 2013–2016.

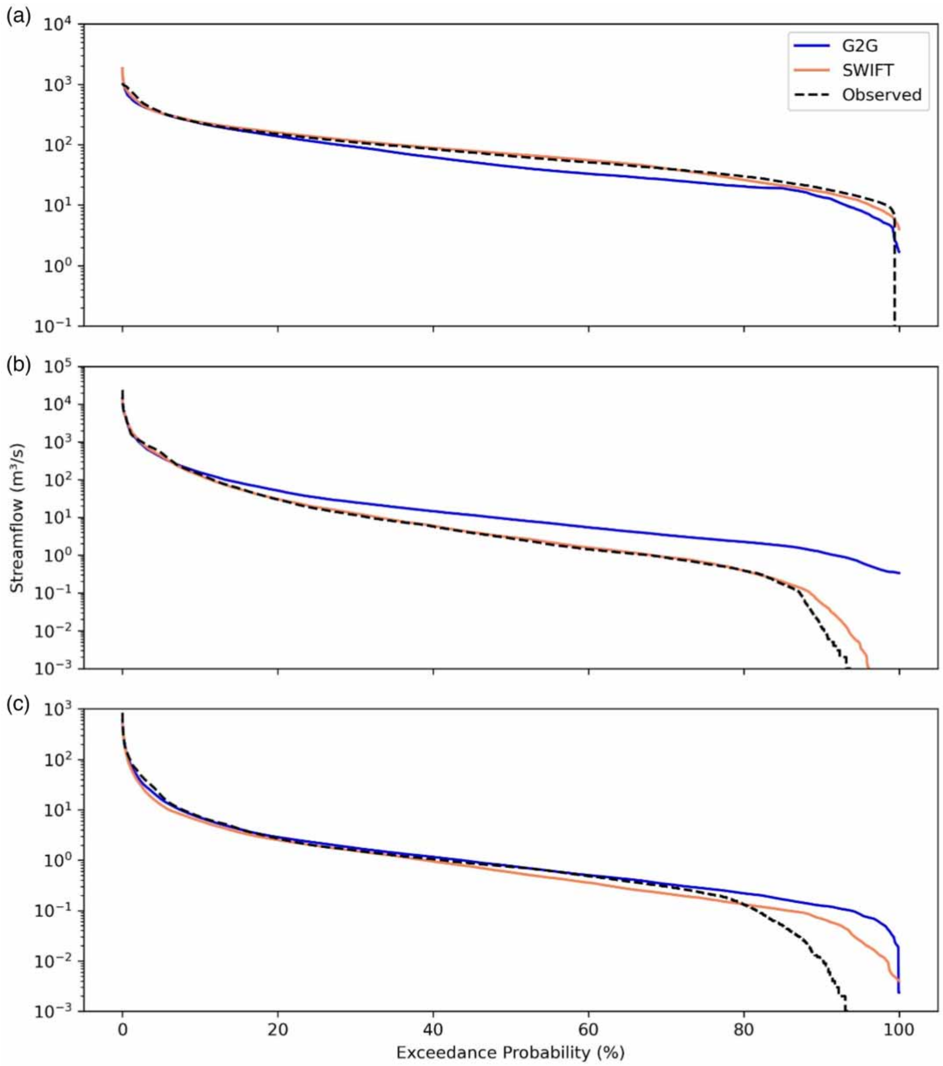


Figure 12 | Flow Duration Curve for three selected locations: (a) Tully River at Euramo (in the north of GBR), (b) Isaac River at Yatton (in the middle of GBR) and (c) Stanley River at Woodford (in the south of GBR).

SWIFT, as a semi-distributed model, is calibrated to specific gauged locations and configured to produce outputs only for a limited number of gauged locations in selected catchments. As G2G is a distributed hydrological model, it has the capability to generate the hydrological fluxes at any grid-cell in the GBR modelling domain encompassing both gauged and ungauged areas. G2G provides a coherent space-time picture of streamflow over a larger area (gauged and ungauged) whilst SWIFT is restricted to give hydrographs at gauged locations but with slightly better model performance. Further, G2G, as a distributed hydrological model, has larger, although still modest, computational and system requirements in comparison to the SWIFT semi-distributed model.

In this study, G2G modelling was conducted at a spatial resolution of 0.01° (approximately 1 km). This resolution is consistent with previous applications of G2G in Australia, such as in the Upper Murray Basin (Moore *et al.* 2014), and aligns with its operational use across Britain for Flood Guidance reporting (Cranston *et al.* 2012; Price *et al.* 2012). A resolution of 0.01° is considered appropriate for large-scale modelling domains such as the GBR catchments. This follows from a consideration of the hydrological processes operating, the available hydrometeorological observation data, the supporting spatial datasets on landscape properties relating to terrain, soil/geology, and land-cover, and the level of granularity of G2G outputs required. Finer resolutions would increase computational demands, while coarser resolutions would compromise model accuracy and granularity, particularly for smaller and more heterogeneous catchments.

SWIFT modelling was implemented at the sub-area level, representing the smallest hydrological divisions within a catchment to support a semi-distributed modelling framework (Table 2). The number and size of sub-areas vary across catchments, influenced by factors such as catchment size, topography, and the availability of streamflow gauging stations. Sub-areas are grouped to form sub-catchments, each typically associated with a streamflow gauge at its outlet. The delineation of sub-areas was informed by extensive national-scale experience with SWIFT, ensuring that they are neither too small – thereby avoiding excessive computational load – nor too large, which would reduce spatial resolution to that of the sub-catchments themselves.

6. CONCLUSION

This study presents the application and comparison of the distributed hydrological model G2G with the semi-distributed hydrological model SWIFT over a common set of catchments draining to the GBR. G2G has been applied at a resolution of 0.01° (~1 km) and 1-hour for the eReefs project to simulate streamflow from the gauged and ungauged areas to the input node coastal locations of marine models used in monitoring the health of the reef environment. Whilst SWIFT is applied operationally to issue the 7-day Streamflow Forecasts over the entire continent of Australia at an hourly timescale, here only the GBR draining catchments are used to facilitate a comparison with G2G. The calibration techniques of both hydrological models are different, as one is distributed and the other semi-distributed.

The performance of both models has been assessed individually over the calibration, validation and full period. There are 9 catchments and 19 locations common to both models, allowing their outputs over the common period (2009–2016) to be compared. Three performance metrics – NSE, MAE and RBias – along with visual inspection of the hydrographs, are used to compare model performance. In general, the performance of both models is good with high NSE values, low MAE and RBias, and with the simulated hydrographs closely matching the observations. SWIFT slightly outperforms the G2G model mainly because it is calibrated to observed streamflow for each gauged catchment in turn. G2G, as a single area-wide model, is calibrated using observed streamflow across all sites in its model domain. This approach allows G2G to simulate the hydrological fluxes at any grid-cell across the domain in a consistent way, whereas SWIFT can only simulate at a node along the stream network.

Both models have their strengths and limitations, and choosing which to utilise depends on what purpose the model is applied for. If the aim is to generate consistently the hydrological fluxes at all grid-cells in the domain, including gauged and ungauged areas, then G2G is a better option; but if the aim is to get more accurate fluxes at nodes on the stream network in a well-gauged catchment, then SWIFT can be a better choice. Where rainfall variability within a catchment is significant and can be captured through monitoring and/or rainfall ensembles, then G2G has merit. The sensitivity of G2G to spatial rainfall as a gridded time-series can prove a particular benefit, notably during localised convective rainfall (as illustrated in Figures 8 and 9 of Moore *et al.* (2006)) and for probabilistic streamflow forecasting using rainfall ensembles in such situations. The accuracy of modelled streamflow across the GBR catchments assessed here has been seen to be limited, particularly by the sparse rainfall gauge network coverage in the more remote interior areas, regardless of model type.

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DATA AVAILABILITY STATEMENT

Data cannot be made publicly available; readers should contact the corresponding author for details.

CONFLICT OF INTEREST

The authors declare there is no conflict.

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