Healthy Land & Water

MIRROR ANALYTICS

QUT

Riparian Bayesian Network and Visualisation Tool – Final Report

DES1221100-2023 QWMN Research and Development and Innovation Strategic Tender

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About Healthy Land & Water

Healthy Land & Water is the peak environmental group for South East Queensland. For over 20 years it has been dedicated to investing in and leading initiatives to build the prosperity, liveability, and sustainability of our 'future region'. A healthy environment also supports a vibrant economy, strong livelihoods, great lifestyles and the happiness and well-being of the community. Healthy Land & Water is focused on **delivering an environment for future generations to thrive**.

Our success and strength stems from our extensive knowledge, science and evidence which informs investment in our environment. We are experts in research, monitoring, evaluation and project management. Our team has led many thousands of projects to restore waterways and landscapes, improve native habitats, manage weeds, protect native species, inform policy and educate communities on the best ways to improve and protect the environment.

Working in partnership with Traditional Owners, government, private industry, utilities and the community, Healthy Land & Water delivers innovative and science-based solutions to challenges affecting the environment. Through a combination of scientific expertise and on-ground management works, Healthy Land & Water **leads and connects through science, big data and actions that will preserve and enhance our natural assets and support resilient regions long into the future**.

Disclaimer

Traditional Owner acknowledgement

We acknowledge that the place we now live in has been nurtured by Australia's First Peoples for tens of thousands of years. We believe the spiritual, cultural and physical consciousness gained through this custodianship is vital to maintaining the future of our region.

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Executive summary

Mirror Analytics, Healthy Land & Water and the Queensland University of Technology (QUT) have been engaged by the Queensland Department of Environment, Science and Innovation (DESI) to build a decision support tool to support riparian management in South East Queensland. Ecosystem service and intrinsic values of riparian zones are diverse and widely acknowledged, and include water quality regulation, aquatic habitat provision as well as social and cultural values. Key drivers for this project are:

- The ongoing challenge of translating bio-physical characteristics of riparian ecosystems into ecosystem service values in a spatial context.
- The relatively low awareness and utility of existing information and research on river and riparian ecosystems of South East Queensland, threats and their ecosystem service values.

To address these challenges, this project developed a prototype end-user-focused decision support system. The goal of this work is to illustrate how information can be incorporated into an adaptive process that can guide riparian management actions.

This is achieved through the development of a spatially explicit Bayesian Network (BN) and interactive visualisation that predicts the water quality regulation and aquatic habitat provision ecosystem service values under different scenarios of riparian zone management. Key elements of this work included:

1) End-user engagement: land and water managers across South East Queensland were engaged in key opportunities for improvement in decision-making processes and the design of the end-user interface (visualisation).
2) Bayesian Network and software development: A prototype Bayesian Network and supporting software were developed based on literature and expert elicitation.
3) Spatial data management: Spatial data to inform sub catchment scale predictions were synthesised to form the basis of the data inputs to the Bayesian Network.
4) Bayesian network to spatial data connection and model training: The Bayesian Network was connected to the spatial data and trained.
5) End-user interface: An interactive web-based interface was developed to allow end-users to explore the water quality and aquatic habitat outcomes under different riparian management and climate scenarios.

Through further iteration, we expect that this process will give land and water managers access to the available science on riparian ecosystems and their ecosystem service values, and thereby enable improved conservation outcomes for riparian ecosystems. However at this stage the tool should only be used to aid general discussion. It's application as an effective decision support tool is currently limited primarily by;

- Limited spatial data on river and catchment attributes of South East Queensland
- Detailed critical review of literature across all model components & scientific consensus on the relationships between model nodes

1 Introduction

1.1 Context

By 2050, nearly half of the global urban population will face water scarcity, inadequate water quality, and rapid loss of environmental services and freshwater biodiversity (Koncagül & Connor, 2023). Water-related impacts on agriculture, health, incomes, and potentially migration and conflict are expected to cost some regions up to 6% of their Gross Domestic Product (GDP), and this will be exacerbated by climate change and an increasing population (World Bank, 2016).

In South East Queensland, more than 70% of water consumption is urban, and rapidly growing urban development has created pressure on water quality and water supply (Head, 2014). Management challenges have increased in recent years with intensifying cycles of drought and flood, coupled with increased economic impacts of disruption in highly urbanised areas (Head, 2014).

Responses to these challenges increasingly advocate a whole-of-system approach, in which catchment and river managers must determine the optimal management strategies to improve multiple ecosystem service values (Pantus et. al. 2011). A number of toolkits and guidelines are available to assist water managers in deciding where and how to act (Grove et. al. 2023; Pantus et. al. 2011).

However, land and water managers face difficulties in implementing whole-of-system approaches, partly due to gaps in capacity and communication between scientific researchers and practitioners (Cosgrove & Loucks, 2015; Head, 2014). What remains is to incorporate this information into an adaptive process that can guide management actions while being informed by new science or changes in stakeholder values (Bunn et. al. 2010). This project creates an iterative method for modelling ecosystem service values of riparian ecosystems under different management and climate scenarios. This project established the proof-of-concept of this approach in a real-world end-user-driven application.

1.2 Riparian zone rehabilitation

1.2.1 What is a riparian zone?

Riparian ecosystems are characterised as ecotones between terrestrial and aquatic environments and encompass a diversity of ecosystem types. The word riparian is derived from the Latin word "riparius" meaning of or belonging to the river. These areas include floodplains, wetlands, forests, grasslands, and heathlands. Although rivers are influenced by physical and biological attributes of their entire catchment, it has been shown that the area of land closer to the river has the greatest influence on many characteristics of freshwater ecosystems, such as water quality and aquatic habitat (Olley et. al. 2015; Sheldon et. al. 2012)

1.2.2 Riparian and river rehabilitation in South East Queensland

The recognition of many of the adverse effects of human impacts on aquatic ecosystems has resulted in an increasing level of investment in river and riparian zone rehabilitation. Ecosystem service and intrinsic values of riparian zones are diverse and widely acknowledged (Capon et. al. 2013). In South East Queensland, riparian areas provide both water quality regulation and aquatic habitat provisioning services. For example, catchments with greater riparian vegetation cover have been found to export less suspended sediment and nutrients and have improved freshwater ecosystem health (Olley et. al. 2015; Sheldon et. al. 2012).

Although the drivers and ecological objectives of specific conservation and rehabilitation strategies vary, key objectives include: reducing fine sediment pollution originating from the highly rural upper catchments that drain into Moreton Bay; reducing the loss of high-quality agricultural soils; improving water quality at bulk water supply intake points in water supply catchments; improving freshwater aquatic ecosystem biodiversity; and enhancing cultural and recreational values (Watkinson et al. 2012; Leigh et. al. 2013).

1.3 Modelling the benefits of riparian rehabilitation

1.3.1 Modelling rivers and riparian ecosystems

Rivers and catchments are complex bio-physical systems. They encompass both biological (fish and plants) and physical (landforms, water pools, rapids) characteristics or 'components' and processes, such as water flow and sediment transport. These systems can be represented as models or abstract mathematical representations. Modelling often targets a sub-set of components or processes within an area of interest such as water flow (i.e. surface water extent, volume or hydraulics), or aquatic species distribution (i.e. potential refugia under climate change scenarios). Once developed, they can be used to enhance our understanding of these systems and in the decision-making context explore predicted outcomes under different scenarios.

1.3.2 Modelling rivers and riparian zones using Bayesian

1.3.2.1 What is a Bayesian Network?

Bayesian Network (BN) models are a well-established and widely used modelling tool that estimates the most likely state of a set of model factors given known conditions (Pearl & Russel, 2003). A BN model has a set of components that allow for calculation (Pitchforth, Wu, & Mengersen, 2013; Darwiche, 2008):

- A relationship chart (directed acyclic graph) (DAG) as shown in **Figure 1**, defining the relationships between variables in the system being modelled (structure).
- Variable (node) definitions that outline the possible node states that the variable can take (discretisation).
- Conditional probability tables that define the probability of any given state of the reference node given known conditions that affect it (quantification).

In contrast to data-hungry machine learning models which are more popular in the digital ecosystem (Mihaljevic, Bielza, & Larranaga, 2021), BNs have an advantage in disciplines where natural variation is difficult to handle such as risk calculations for agriculture (Drury et. al. 2017), military operations planning (Falzon, 2006), medicine (Arora et. al. 2019), and ecology (Ramazi et. al. 2021; Johnson & Mengersen, 2012). BNs are popular in both statistics and machine learning since they make fewer assumptions and are more transparent than many alternative approaches.

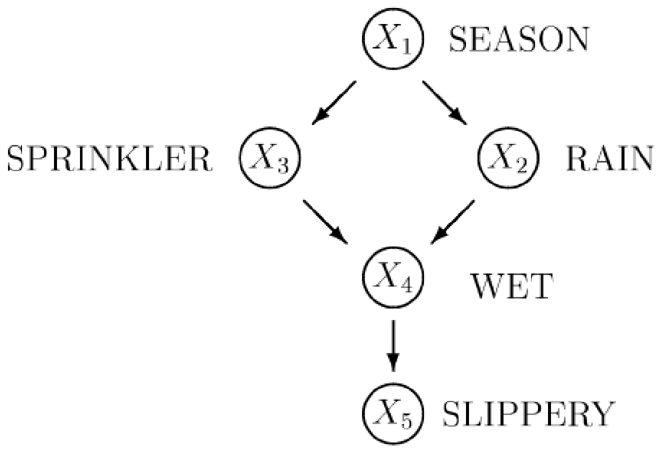

***Figure 1**: Causal DAG of a Bayesian Network as depicted in Pearl & Russel 2003.*

For example, in the above DAG (**Figure 1**), the probability of a slippery surface is depicted as conditional on the probability of that surface being wet, which in turn is conditional on both the probability that it has rained and the probability that a sprinkler is activated. Rain and sprinkler are both causally affected by the season, but in different directions. The direction and magnitude of each causal relationship in the Bayesian Network, depicted in the DAG by an arrow, is contained in a conditional probability table. Together, the conditional probability tables represent the unique probability distribution that covers the set of potential states of the system resulting in a slippery surface.

Data is included in the Bayesian Network by transforming input data into probability tables. The conditional probability tables can be quantified using diverse data relevant to the different nodes in the network. Transforming input data to probability tables provides a common representation for disparate types and amounts of data, puts data on the same scale, and enables fast computation. Once quantified by data, the Bayesian network can be used to highlight data gaps, inform about important causal variables, and facilitate evaluation of "what-if" scenarios by changing the inputs and assessing the change on the target output, taking into account the other factors in the network.

There are multiple benefits of Bayesian Network based models:

- High transparency.
- The possibility of combining empirical data with expert knowledge.
- The ability to integrate multiple data formats.
- Highly flexible to update with new information.

1.3.2.2 Applying BN modelling in river systems

The potential of Bayesian Networks to link biophysical attributes of ecosystems to a quantified ecosystem service has been demonstrated extensively, although most BN models of ecosystem services focus on a single service only (Landuyt et. al. 2013). Further, previous work has rarely had the aim of direct impact on decisions, in favour of providing accurate predictions. Here we describe how the ecosystem services of riparian zones can be represented within a Bayesian Network model using the example of water quality regulation.

Water quality regulation is a key ecosystem service of riparian zones and is affected by other components and processes of a river catchment. In any section of the river water quality is dependent on, amongst other things, the sediment, nutrient and pathogen loads, and streamflow. Each of these are also dependent on several other components of the catchment. The sediment load, for example, depends on the amount of sediment derived from streambank, gully, and hillslope erosion, plus the amount of rainfall, run-off and streamflow, and the extent and condition of vegetation in the riparian zone (Olley et. al. 2015, 2024).

In modelling water quality, each of the contributing components can be pictured as a box (or node) and the interactions between components are drawn as arrows or links between components. This provides a graphical representation of the factors contributing to water quality and their interactions. For sediment load streambank, gully, and hillslope erosion, streamflow and riparian vegetation all have influence. They form a network of components (nodes) and interactions (arrows) which influence sediment load, and ultimately water quality (directed acyclic graph (DAG)).

1.4 Aims and objectives

This project developed a spatially explicit Bayesian Network of key riparian ecosystem services linked to an interactive web-based application. This takes advantage of a long history of investment in catchment and waterway mapping, monitoring and research as the basis for model relationships and data inputs.

The goal of this project is to deliver South East Queensland decision-makers an interactive platform that:

- Presents ecosystem service values of riparian ecosystems under different management and climate scenarios at the sub catchment scale.
- Allows users to explore management scenarios and predicted ecosystem service benefits of riparian areas.

This was achieved through the development of a spatially explicit Bayesian Network linked to an interactive visualization dashboard. The project delivers three products:

- Synthesised and standardised spatial dataset that collates relevant spatial data related to catchments and riparian ecosystems.
- A geographic information system (GIS) linked Bayesian Network model that simulates the riparian system and its ecosystem services.
- A dashboard of visualisations representing the predictions of the GIS-lined Bayesian Network model.

This demonstration project has two work packages with associated deliverables:

1. A Bayesian Network model constructed using an established method for information synthesis.
2. A prototype software application, that allows the Bayesian Network model to be queried directly and applied in the relevant spatial context.

This two-part approach allows future refinement and expansion of the tool to accommodate changes in scientific understanding as well as incorporating new datasets. This allows for:

- Including additional threats and values, climate drivers, and species-specific phenomena as the scientific community builds consensus.
- Changing spatial and temporal scale of analysis for new user groups and use cases.
- Updating model parameters quickly as new datasets and research papers are released.

This reflects our approach to addressing our primary priority (model improvement and integration) based on the modern software principles of continuous deployment and service-oriented architecture, allowing for continuous improvement of the product far beyond the project window.

1.4.1 First Nations

Waterways and associated riparian zones hold deep spiritual and cultural importance for First Nations peoples. Engagement with Traditional Owners in South East Queensland under this project aims to understand how these values can be integrated into decision frameworks to improve how these values are reflected in land and water management. It is expected that the exact piece of targeted work with First Nations will be negotiated. Engagement as part of this project has included:

- Initial relationship building with Jinibara People and the Jinibarra Peoples Aboriginal Corporation (JPAC).
- Meeting with Jinibara Traditional Owners on Country to discuss opportunities for further engagement – March 2024.

The project is currently under consideration by the JPAC board, and the project team is awaiting a response from the Jinibara Peoples Aboriginal Corporation on a time to meet to discuss this work addition to projects under the federally funded Regional Delivery Partnerships Program.

2 Approach and methodology

2.1 Governance

For this project, the core team members include scientists involved from inception through to execution. The project also engaged a wider stakeholder network, which included a Scientific Advisory Committee and a User Advisory Committee. For the committees, scientific experts in the field of water management, including riparian management, water quality, water modelling, and aquatic biodiversity experts were identified. From these identified groups, individuals were identified who were senior or lead authors of relevant published scientific work, especially in relation to the study area of South East Queensland, Australia, and the research team's professional networks. Engagement with these stakeholder committees included workshops, surveys, and ongoing consultations.

2.2 Constructing a spatially explicit Bayesian Network (process)

The modelling process consisted of four main steps (see **Figure 2**):

a) Developing a conceptual model, consisting of a directed acyclic graph structure and conditional probability tables.
b) Developing a spatial dataset to map the input nodes and allow geographic predictions.
c) Linking the model to the spatial dataset to create a predictive model.
d) Creating a user-friendly interactive dashboard that could be used to deliver the model.

This process builds on the GIS-linked Bayesian network development process reported in Smith *et al.* (2007). A summary of the process is given below, with more detail given in each of the following sections of this report.

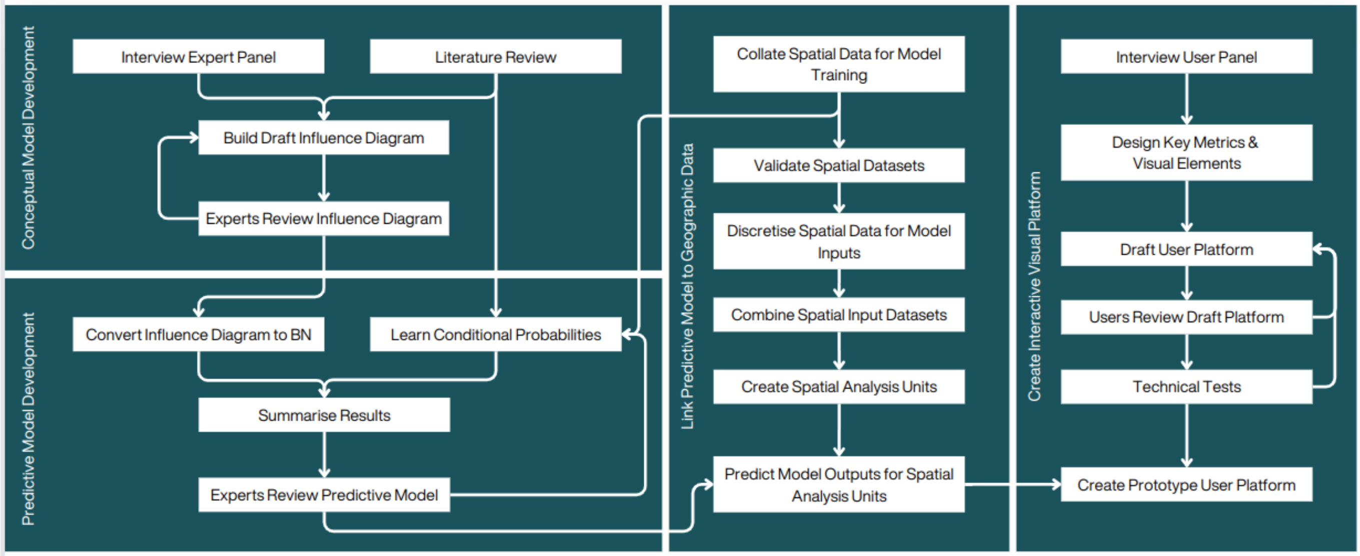

Figure 2: *Conceptual model development.*

2.2.1 Conceptual model development

The purpose of the conceptual model development stage was to build an influence diagram capturing the key variables believed to affect riparian management, and the key outcomes of riparian management believed to be important to users (Section 3). Successful riparian management was defined as the delivery of ecosystem services linked to riparian areas – in this case, water quality and provision of habitat for aquatic biodiversity. To identify the variables in the model, a first set of predictor variables was collated based on a literature review. This version was then reviewed by an expert panel. The final version of the influence diagram contained input variables that could be observed in spatial datasets, as proxies for key environmental variables influencing riparian ecosystems. Importantly, the final set of predictor variables necessarily reflected available spatial data on river and catchment attributes, rather than the ideal variables.

2.2.2 Predictive model development

To build a predictive model, the conceptual model was converted into code using the statistical software *R*. In this step, the conditional probability tables were quantified for each set of node-state combinations included in the model. First, states were defined for each node, such that the states of a node were mutually exclusive and cumulatively exhaustive: for example, a node labelled "Riparian Woody Vegetation Cover" could take the observed states "High" or "Low". Second, these states were assigned thresholds for observed values based on the spatial datasets (Section 5) and based on literature. Thresholds for the state categories were determined based on agreed definitions with reference to literature, the distribution of values in the spatial dataset, and in consultation with domain experts. For example, the node "Riparian Woody Vegetation Cover" would be observed in the "High" state if more than 70% of the riparian area was covered in woody vegetation (Olley et. al. 2015). Finally, the conditional probability tables were constructed. These conditional probability tables represent the total probability distribution of all possible combinations of discretised variables represented in the model. The full conditional probability tables are available via querying the model API.

2.2.3 Link predictive model to spatial data

Spatial data was aggregated to the chosen level of spatial analysis for this study: stream segments as defined by the Australian Hydrological Geospatial Fabric Attribute HydroID. For the GIS variables in the riparian quality model, prior probabilities were assigned to the states based on the percentage of the stream segment covered by each state. For example, a stream segment with 90% natural and 10% urban land use according to the land use dataset would be mapped as: land use natural 90%, urban 10%. Where we could not locate a dataset for a GIS input variable, we applied a uniform probability distribution that could be used as a switch to produce output for alternative management scenarios. Baseline predicted values for each stream segment were calculated using an exact inference algorithm implemented in the R package gRain (Højsgaard, 2012).

2.2.4 Validate the model

The Bayesian Network underwent internal and external validation. A validation workflow was applied with qualitative and quantitative checks (**Figure 3**). Validation checks included tests of the data, tests of the DAG, and tests of the model predictions. This work was completed in four phases. First, we assessed the content validity of the data and model with scientific experts and practitioners. Second, we refined the model based on expert input, causal modelling logic, and assessment of the available data with the beta prototype. Third, we lab-tested the refined candidate model for validity and reliability. Fourth, we created the modified datasets, network structure, and application layout for the prototype application.

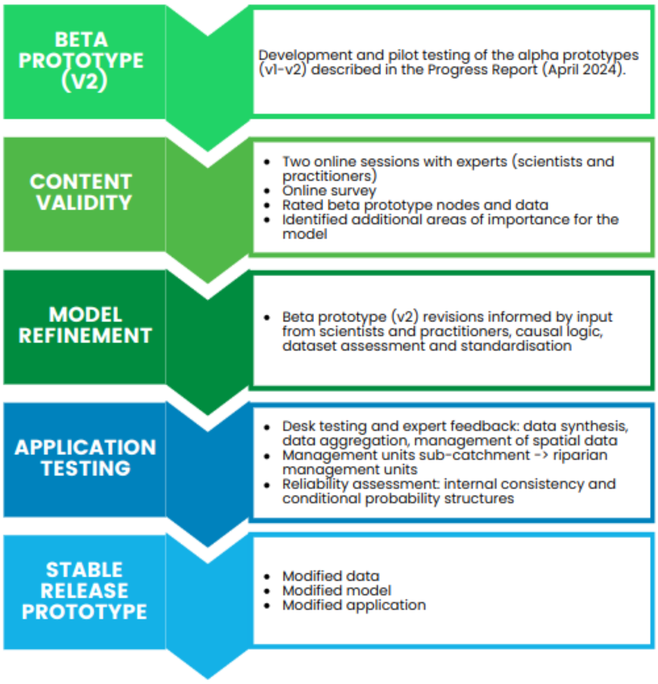

Figure 3: *Phases of the validation process*

2.2.5 Create interactive visual platform

Due to the exponential number of possible states of the riparian system according to the Bayesian Network, a software solution was devised to allow users to query certain scenarios as combinations of input states. An interactive visual platform was developed in R package RShiny and hosted on a web server so that users could access it online.

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3 End-user engagement

3.1 End-user-focused design

Decades of waterway management research offer a variety of models with strong relevance to the policy, practice, and environmental changes that contribute to catchment management. However, the implementation of these models in practice is frequently challenged by low adoption. Enhancing the success of waterway management models requires a shift towards user-focused design and easily accessible data. To address this gap, this project developed and is testing a user-focused approach to model design, in the context of best-established science and evidence synthesis.

3.2 End-user working group

An end-user working group was established to provide insight into:

- How waterway managers are currently using decision support tools.
- Opportunities for improvement in decision-making process and the role of modelling.
- Technical requirements of the Bayesian Network and the visualisation tool (this project).

This working group included representatives from water utilities and bulk water suppliers of South East Queensland, including Urban Utilities, Unitywater, and Seqwater, as well as Local Government representatives and Natural Resource Management bodies (Healthy Land & Water). A workshop was held on 28 February 2024 with the end-user working group.

3.3 End-user online survey

An online survey was also distributed through Healthy Land & Water's Ecosystem Health Monitoring Program (EHMP)/ Report Card network, to elicit feedback on specific topics (Appendix 1). The specific objectives of the end-user survey were to:

- Establish a baseline understanding of riparian management priorities and the challenges encountered by practitioners in waterways.
- Identify opportunities and trends for future innovation in riparian management.
- Encourage water practitioners to engage with the project and express interest.
- Identify practitioners who were willing and motivated to contribute to the further development of the model and tool and who wanted to be kept informed.

The user survey ran from January to May 2024. It gathered 26 responses from local government (N = 13), water service providers (N = 5), non-profit organisations (N = 4), and community groups (N = 1). Respondents rated their current decision-making process an average of 6.4 out of 10, with 10 representing "completely satisfied".

3.4 How are waterway managers currently using decision support tools

Waterway managers currently use a diversity of resources and approaches to inform decision making. These include State Government Guidelines, purpose-built decision support systems, local knowledge, regional and catchment-based plans, rules of thumb, and knowledge exchange through communities of practice. When asked about the frequency of use of publicly available resources survey respondents reported relatively regular use (30% report using State Government Guidelines regularly). Purpose-built decision support systems were noted as being used by 30% of respondents, highlighting the importance of organisational context. Waterway managers are generally satisfied with their decision-making process; however, there are identified key areas for improvement.

3.4.1 Opportunities for improvement in decision making processes

When asked what would improve decision making processes, 50% of survey respondents highlighted clearer information about trade-offs and synergies as an area of focus. The quality of data and improved consideration of context were also highlighted as important (38% and 34% respectively). This emphasised the importance of a key objective of this project, to model multiple-ecosystem service values of riparian ecosystems under various scenarios. Additional insights that users would like to see or value of the project included clearer information on management actions in the landscape that will have optimal return on investment.

"*Science and data are key. The challenges come when digital technology (modelling) is overlayed, and limitations are not understood*" – End-user survey response

3.4.2 Key outputs and technical requirements of the BN

Through discussion with end users, high-priority outputs for the model include the quantification of ecosystem service value of riparian ecosystems for water quality regulation and aquatic habitat provision in relation to the condition of riparian ecosystems.

The model must:

- Guide the spatial prioritisation of investment that provides optimal return on investment.
- Identify trade-offs and synergies.
- Be transparent and well-documented information on data inputs and uncertainties.

End-users also highlighted they have their own decision-making tools for core activities. Understanding how these tools overlap and can be used to complement each other was identified as a useful outcome. Model outputs under management and climate scenarios were also identified as a key desirable functionality of the model.

3.4.3 Spatial extent and scale of model outputs

The scale of information that was most identified as most appropriate for the application was sub catchment areas. It was recognised that decision-making regarding river rehabilitation at scales smaller than sub catchments is influenced by broader social and economic considerations.

4 Bayesian Network structure

4.1 Bayesian Network development process

The BN structure including nodes and links has been developed interactively through engagement with the expert advisory panel and end-users, as this project had a stated goal of developing a proof-of-concept. In line with the iterative development approach adopted by the project team, the conceptual model structure of the riparian Bayesian Network (RIP-BN) went through four iterations based on expert feedback (**Table 1** and **Table 2**). The final prototype network is shown in **Figure 4** and full documentation is provided in **Appendix 2**, which includes BN nodes and definitions, BN node connections supporting literature and summary justifications, node states, thresholds and units, and spatial context variables and associated spatial data.

Table 1: *Number of nodes and links in each version of the network.*

Version	Nodes	Links
1	30	33
2	26	27
3	27	27
4	22	24

Table 2: *Number of nodes shared by each version of the network.*

Version	Nodes	Links
1	30	33
2	26	27
3	27	27
4	22	24

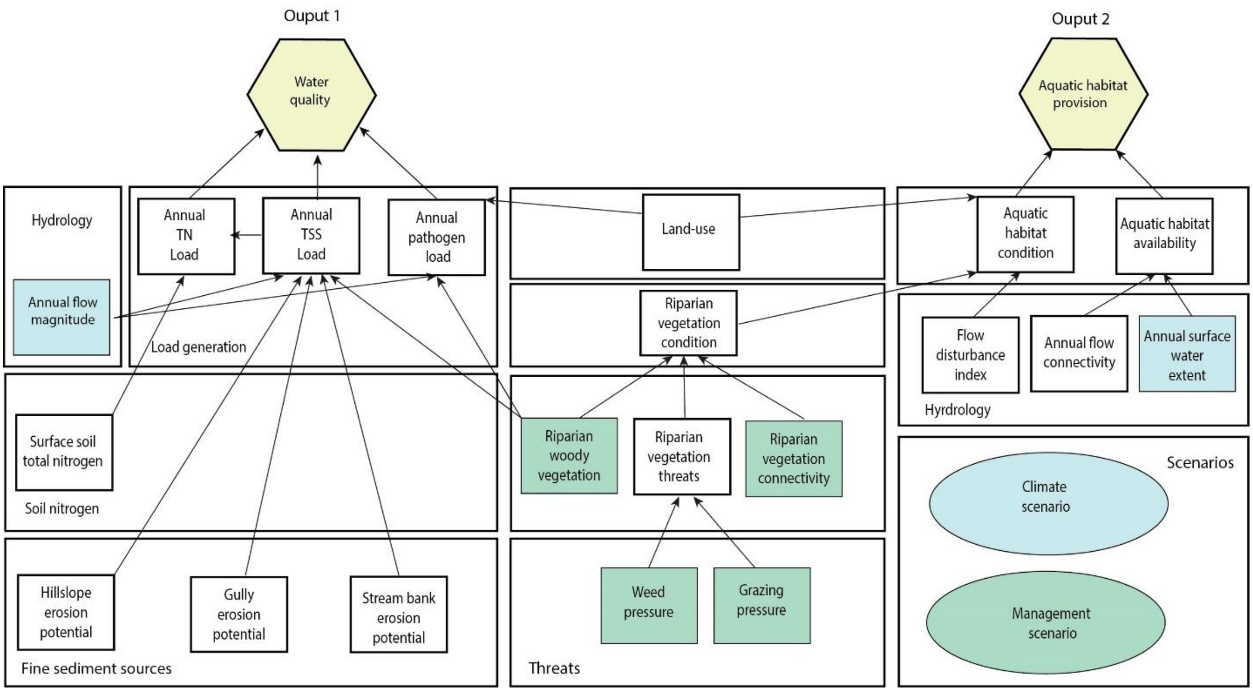

Figure 4: *Prototype Riparian Bayesian network (directed acyclic graph).*

5 Spatial data management

The power of the proof-of-concept workflow presented in this project stems from the ability of BN models to combine a wide range of data into a single model. Ironically, while BN models are statistically able to handle a wide variety of data, quantifying a model still requires significant data manipulation.

The final result of this stage of the project is a single, wide, spatial file with a range of factors aggregated to a sub catchment scale based on the Australian Geofabric dataset 'HydroID' (Bureau of Meteorology, 2024). The combination of such a wide range of Queensland-focused datasets relevant to riparian systems into a single layer represents a novel and significant contribution toward our primary priority of model improvement and integration and forms a core deliverable of the project (see **Appendix 3**).

5.1 Overview of datasets included

With a complex model, a wide variety of datasets were required to support model training and simulations. The datasets used in this iteration of model training are outlined in **Appendix 2**. The reference layer used to attribute spatial information was at the Australian Hydrological Geospatial Fabric sub catchments dataset (N = 358 sub catchments within 18 catchments). Datasets were sought for spatial context variables: any variables in the model that were not predicted by the conditional probability tables (i.e. had no parent nodes in the model) and were not scenario nodes (i.e. controlled by user input). Spatial context variables are identified in **Figure 5**, described in detail in **Appendix 2** and illustrated in **Appendix 4**.

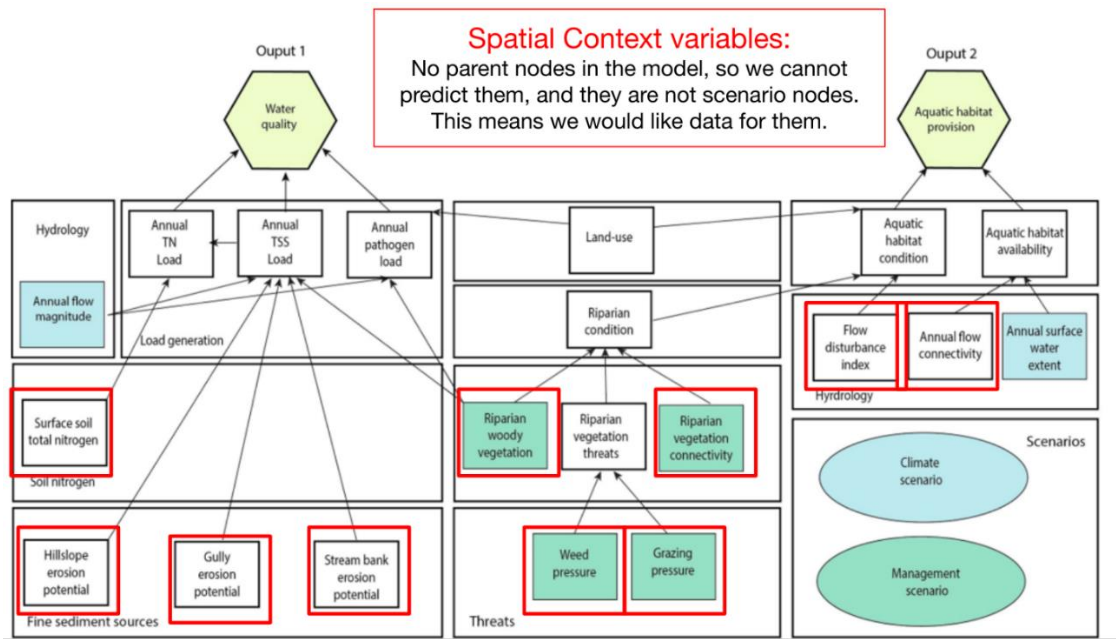

***Figure 5**: The spatial context variables, and their source data and transformations, are reported in **Appendix 2**.*

5.1.1 Summary of data transformations for baseline model

Baseline data were transformed to align with the Bayesian Network model. In most cases, this required a discretisation of the underlying continuous data into categories corresponding to the node states specified by the model. Specifics of the node states and transformations are presented in **Appendix 2**.

5.1.2 Missing data

We determined two types of data gaps in the datasets:

1. Data missing that should be interpreted as '0 occurrences'.
2. Data missing because the dataset had no information for that spatial area.

In the case of the first type, missing cells were recoded to 0. In the case of the second type, missing cells were recoded to 0.5, indicating 'no information'.

5.1.3 Spatial data management in python

The heterogeneity of the data types supporting each of the model nodes presented a significant data engineering challenge. We used Python3 to load, clean, manage, and standardise the spatial files into a dataset that can be used to train the BN model. The functions below can be used to combine a wide range of spatial files into a single reference dataset with a few lines of code. These Python functions and an example of their use is provided in **Appendix 3**.

5.2 Transformations for training the model

With all datasets standardised to the correct spatial units, the data was then aligned with the BN model developed by the experts. For example, land use was defined by the experts as having possible states of natural areas, agriculture, urban, and mining. However, the land use dataset available to the team does not make reference to the terms used by the experts to describe the node states in the model. To align this, we needed to transform the variable according to the available datasets. Due to the complexity of hydrological modelling, almost every dataset-node pairing required a bespoke mapping in order to complete the required alignment. Once this was achieved, we were able create the baseline set of predicted values for each spatial unit against which all simulations are calculated.

6 Model quantification

To estimate the model parameters in discrete Bayesian Networks (stored as conditional probability tables), there are several approaches available. Conditional probability tables can be estimated directly from data, or using expert opinion, literature, or other relevant sources of information to update the conditional probabilities.

In this project, we estimated the conditional probability tables for the nodes and links in the RIP-BN using a combination of data, literature, and expert opinion. First, published and available data on each node in the network was reviewed, and where possible, incorporated into the CPTs. Second, published research was assessed for any reported effect sizes, especially for moderator relationships included in the network structure. Third, where data and published research were not available, we used expert opinion to construct the CPTs. For the prototype network, conditional probabilities were estimated as a linear equal-weighted combination of the parent nodes, following the logic used in the Healthy Land & Water Report Card.

6.1 The GIS-linked Bayesian Network

The quantified Bayesian Network was used to produce sub catchment-level estimates of riparian quality, water quality, and aquatic biodiversity (**Figure 6**), using the following process. First, maps representing all input variables in the Bayesian Network were intersected using R and Python statistical software to form a single integrated data layer. The attribute table of this layer was used to create an evidence table with one row per sub catchment and node-state combination and an exact inference method was used to output probabilities for predicted riparian quality, water quality, and biodiversity for each sub catchment. The output probabilities were joined back to the sub catchment shapefile using reference IDs and mapped.

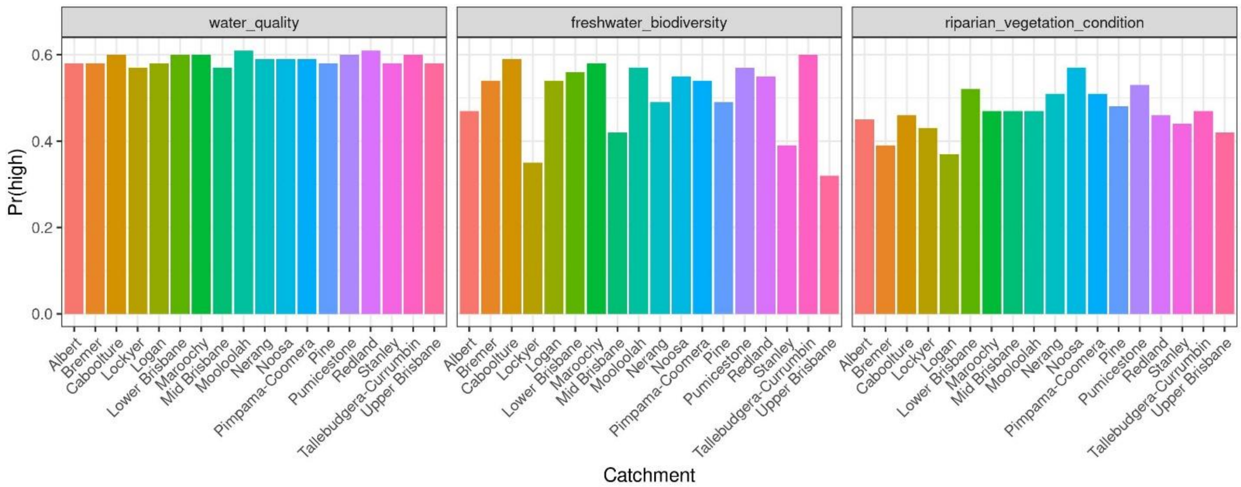

***Figure 6**: Baseline BN predictions.*

7 Model delivery

The model is delivered to users as an API hosted on cloud servers managed by Mirror Analytics. As a proof-of-concept stage product, the current API only has a single function allowing users to query the network with specific evidence. Serving the model as an API allows users to:

- Test scenarios based on their own needs.
- Incorporate the model into web-based and mobile applications.
- Include model outputs in future research articles.
- Make impact assessments based on the most recently trained model.

The API is accessed by a combination of *curl* and an *http* request.

7.1 Model automation

All required data are stored by Healthy Land & Water. The datasets used in this project were drawn from publicly available datasets, Healthy Land & Water or DESI. Code for this project was managed in a Google Cloud Source Repository managed by Mirror Analytics. The final state of the repository at the conclusion of the project is provided as supplementary material. Updates to the baseline datasets can be performed using the functions described in **Appendix 3**.

8 Interactive dashboard

The project includes delivery of an interactive dashboard as a key tool for users to access the datasets and model predictions relating riparian management to water quality and aquatic biodiversity (**Figure 7**, **Figure 8**, **Figure 9**, **Figure 10**, **Figure 11**). Following user consultation, the dashboard was designed to consolidate and present data on riparian management, allow users to simulate the impacts of management actions, and display sub catchment level variations in baseline and output variables. Users are invited to simulate increasing or decreasing the state of three model nodes – weed pressure, grazing pressure, and riparian woody vegetation.

The interactive dashboard was produced in R using the RShiny library with Bootstrap 5 elements for adjusting the look and feel elements.

Five sections of the interactive dashboard were developed.

Dashboard: Displays an overview of the model interactivity, including:

- A sidebar where users can:
    - Select their catchment and sub catchment(s) of interest, which then filters the data presented on the dashboard.
    - See the baseline parameter values.
    - Simulate interventions using slider bars and then see the results update in real time.
- Value boxes presenting the percentage of the selected area with high riparian quality, high water quality, and high biodiversity as predicted by the Bayesian Network model.
- Baseline graphs of the prior probabilities of each state of each input node of the Bayesian Network, based on the GIS values in the study area.
- An interactive map of the study area, presented as a choropleth divided into stream segments and coloured by the outcome, with three layers of outcome available: riparian quality, water quality, and biodiversity.

8.1 Application testing and solution refinement

The application development process supporting the presentation of the model results was heavily focused on user input, given that this was only the first iteration of the RIP-BN. Taking an iterative approach, the application is designed to be a 'minimum viable product' capable of demonstrating the usefulness of a riparian management decision support system.

The application development process used agile development principles to iteratively develop a set of visualisation and interaction modules that would best allow the model and data assembled in this product to be accessed and used in practice by practitioners.

The application was presented to a small group of identified potential users during and following the Queensland Water Monitoring Network 2024 showcase. Based on this feedback, the team prioritised development of the 'Analysis' tab, which provides users with the ability to compare the impact of actions across subcatchments, as well as defining the high-priority inputs for simulation in the proof-of-concept stage.

8.2 Hosting plan

The BN API and visualisation dashboard (**Figure 7, Figure 8, Figure 9, Figure 10** and **Figure 11**) is hosted by Mirror Analytics for 12 months following the delivery of the project, with the intention for Healthy Land & Water to take over hosting after 12 months. While being hosted by Mirror Analytics, the Dockerised BN and visualisation will be served on containers via the Google Cloud Run service, with specific processing requirements to be determined by the observed traffic load.

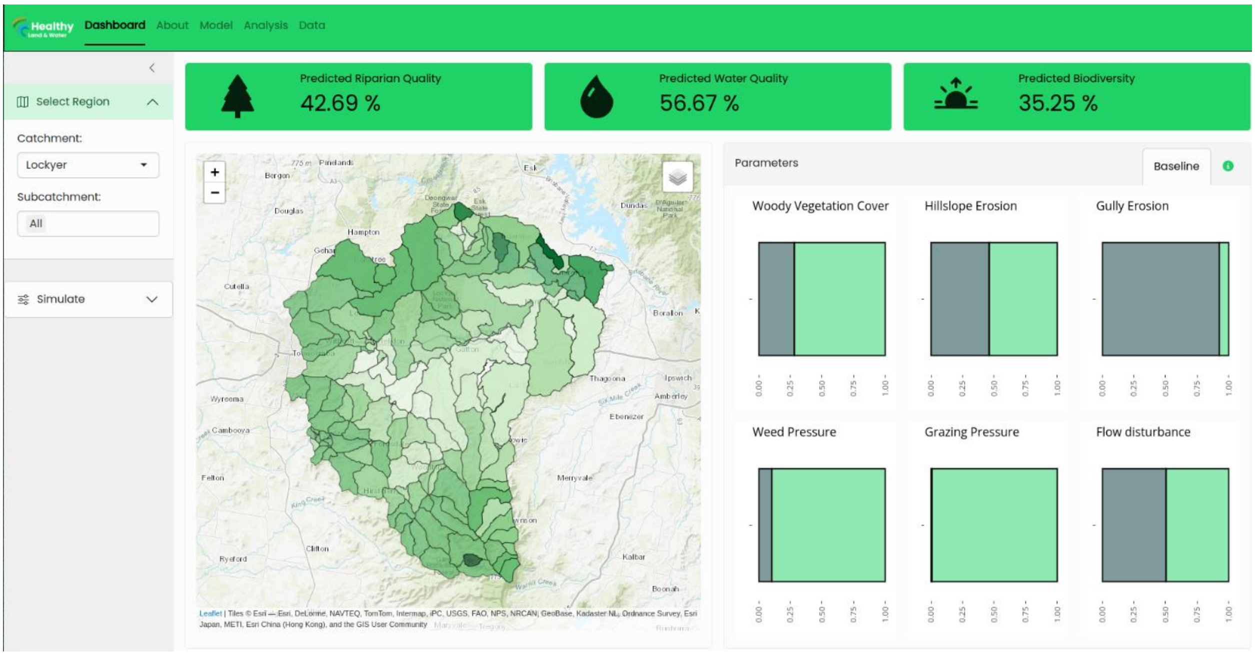

Figure 7: *Screenshot of the prototype interactive dashboard.*

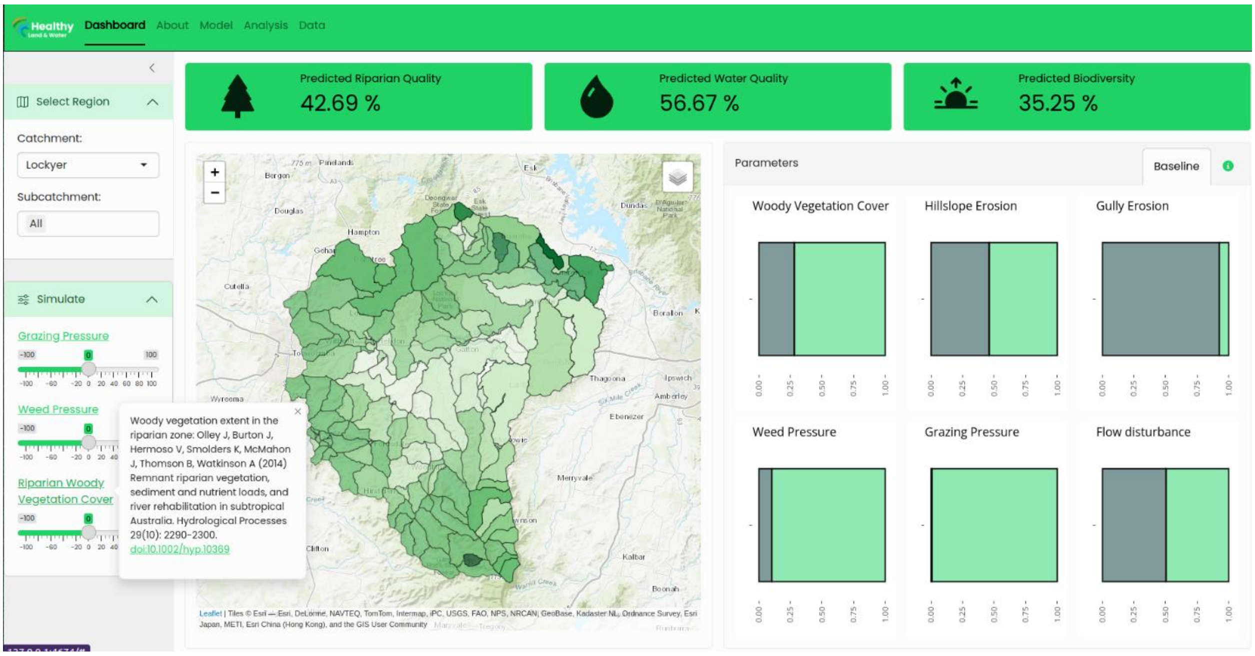

Figure 8: *The Simulate functions allow users to explore model prediction of the key outputs of riparian quality, water quality and freshwater biodiversity under different scenarios.*

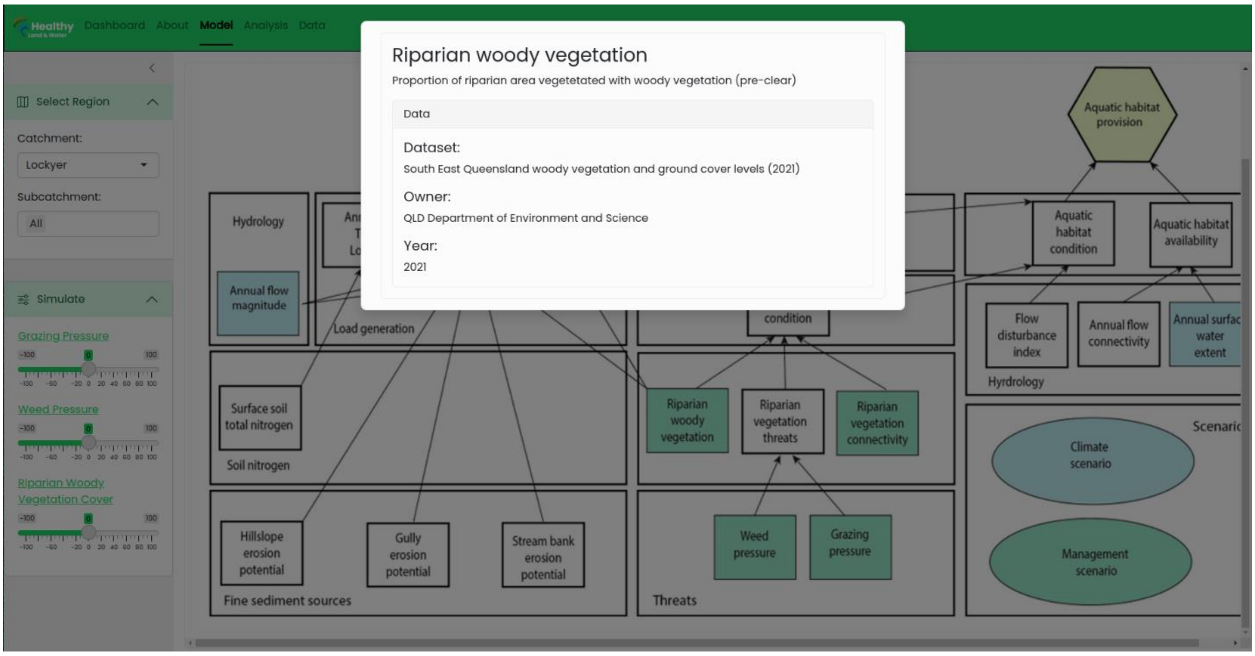

***Figure 9**: The Model tab presents an image of the Bayesian Network model that is clickable and gives information on each of the model parameters.*

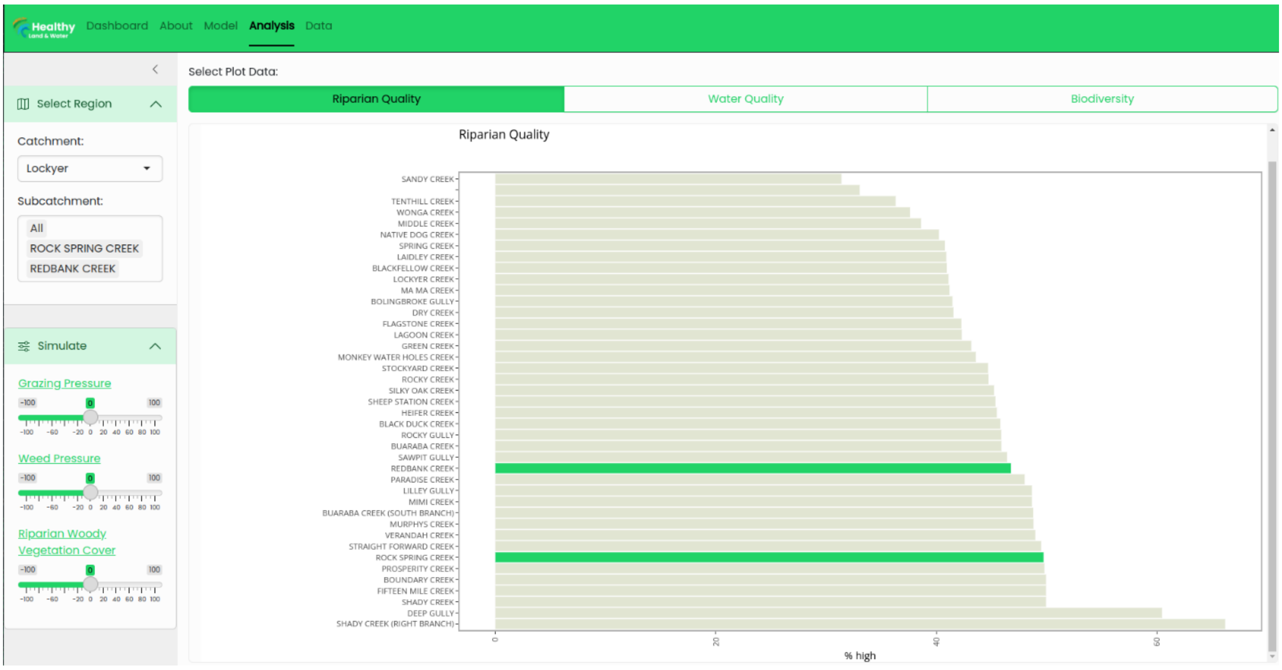

***Figure 10**: The Analysis tab allows the user to compare sub catchment results for different model outputs with simple graphs.*

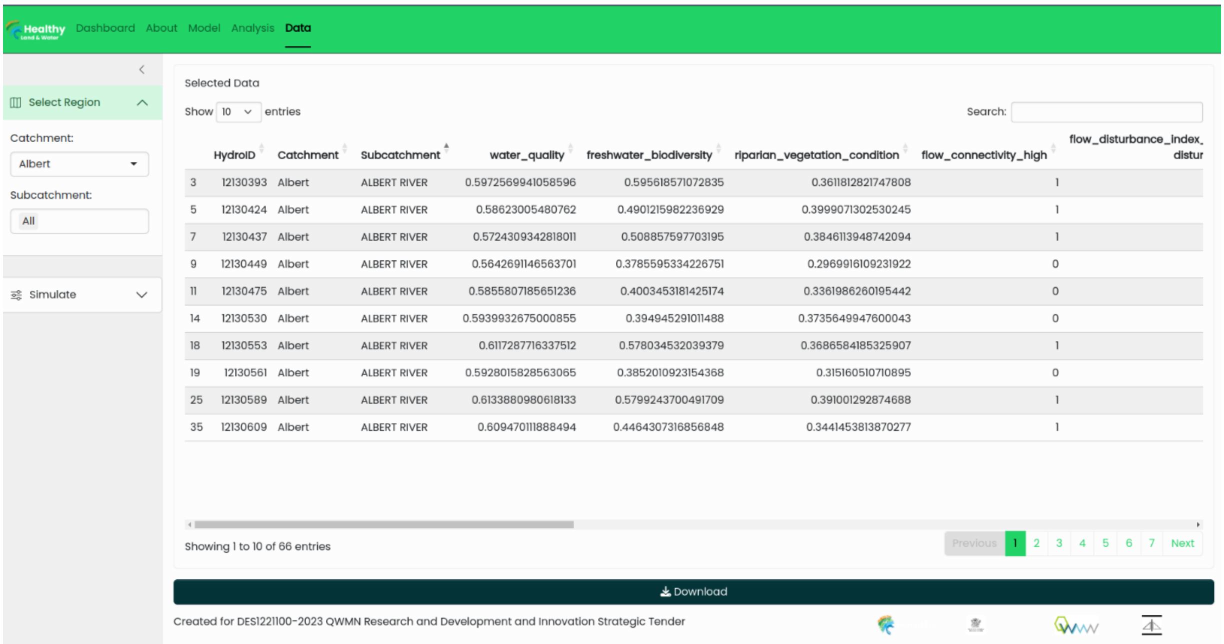

***Figure 11**: Data - presents a table of the dataset used to construct the visualisation, filtered according to the user's selections.*

9 Case studies

To demonstrate the usage and application of the workflow, we ran three case studies based on scenarios of interest to users. The results of these case studies are for demonstration purposes and should be validated further before they are used for determining optimal riparian management actions.

9.1 Simulating riparian management

Based on feedback from the advisory panel and potential users of the tool, we simulated the impact of two management actions, aimed at reducing grazing pressure and weed pressure respectively. Relevant management actions targeting these variables may include fencing for cattle, educational campaigns, or legislative changes. We also ran a scenario showing the impact of degradation of the riparian area, demonstrating how the model can be used to simulate impacts of decisions not directly intended to manage riparian areas.

The scenario analysis revealed that riparian management actions had, as expected, an effect on riparian vegetation condition, such that reduced threats from grazing and weeds were associated with higher riparian quality. Improved riparian quality was also associated with improved freshwater biodiversity, but this varied according to sub catchment characteristics, as expected. Water quality was less sensitive to changes in riparian management, as expected given that the model structure contained several other predictors that were closer in causal effect to the water quality output node.

Table 3: *Future management scenarios node state adjustments from baseline*.

Scenario	Grazing pressure	Weed pressure	Riparian woody vegetation
Rehabilitation	-50%	-50%	+25%
Decline	+20%	+20%	-25%

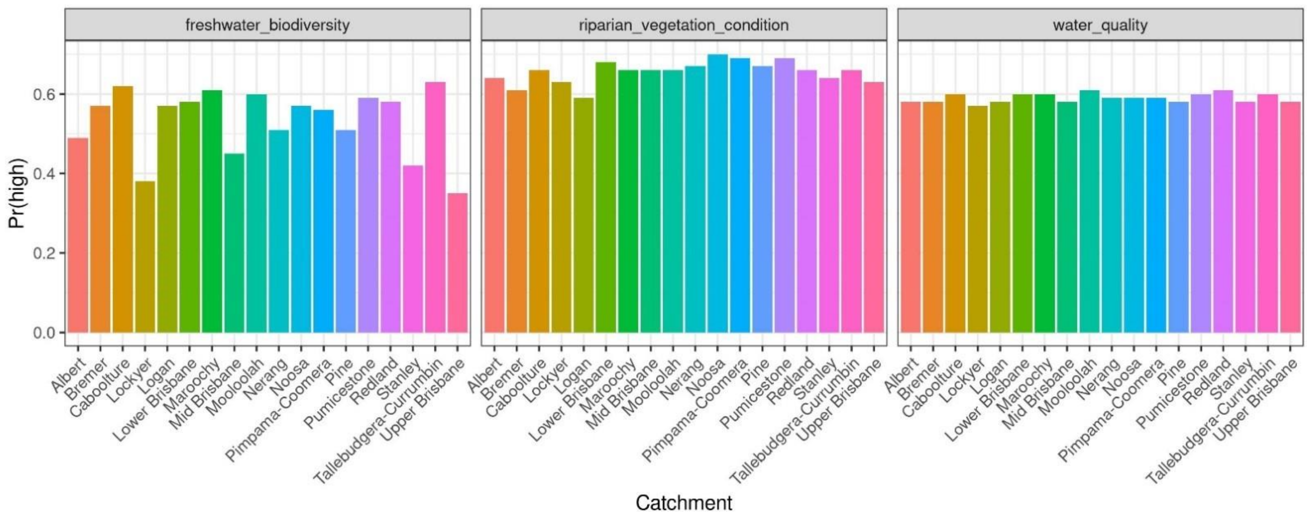

Figure 12: *Rehabilitation scenario marginal predictions by catchment.*

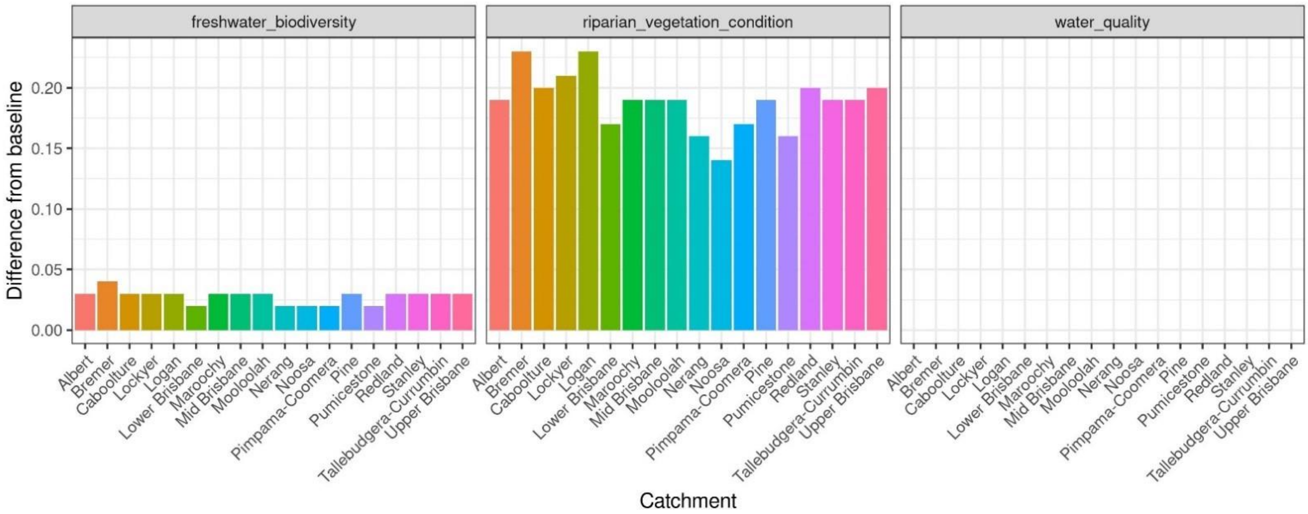

***Figure 13**: Rehabilitation scenario difference from baseline by catchment.*

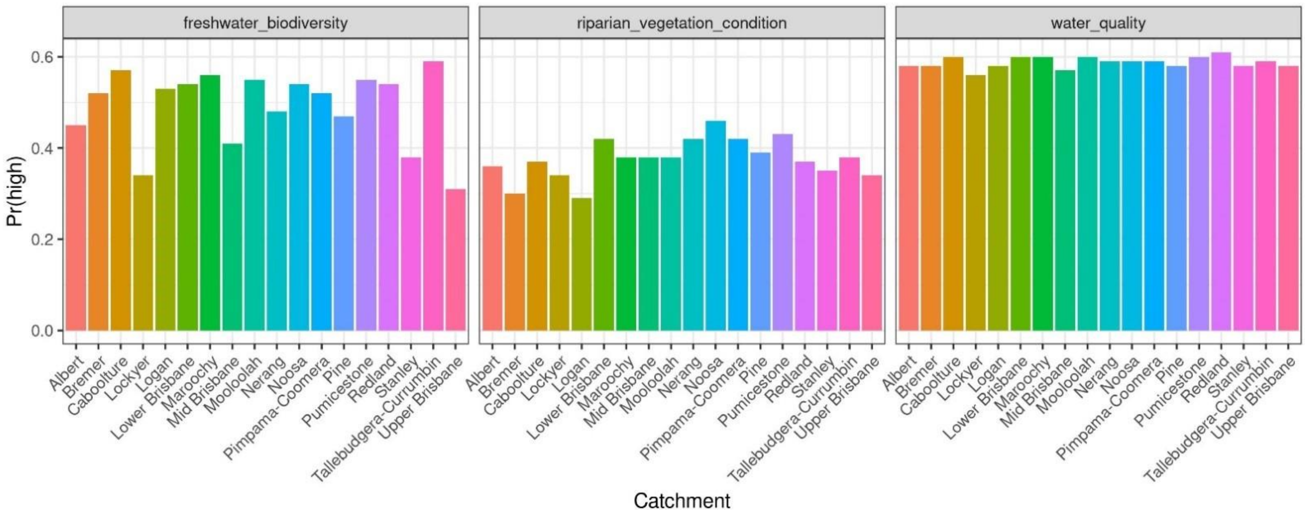

***Figure 14**: Decline scenario marginal predictions by catchment.*

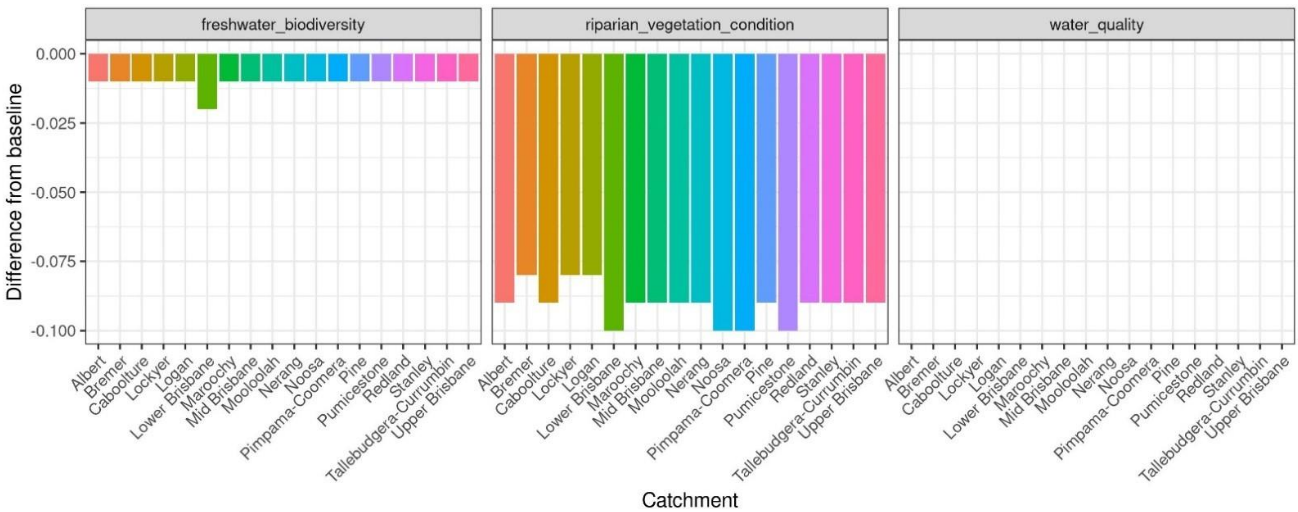

***Figure 15**: Decline scenario difference from baseline by catchment.*

9.2 High flow and low flow years

Here we simulate the influence of variability in annual flow magnitude on model outputs. The study area, South East Queensland, is a highly modified catchment with large areas of urban development. It is also subject to the risk of major flood events. Freshwater flows in the study area typically alternate between periods of major water flow or flood, and prolonged periods of no or low flow (Grinham et. al. 2024). During a flood, the increased stream power results in significant channel erosion, and therefore higher sediment loads (Grinham et. al. 2024). High and low flow years are simulated in the model by increasing streambank and gully erosion, as well as increasing flow magnitude and decreasing flow connectivity (**Tabel 4**).

***Table 4**: High and low flow year scenarios node adjustments from baseline.*

Scenario	Annual flow magnitude	Gully erosion	Stream bank erosion	Flow connectivity
High flow year	+50%	+50%	+50%	+50%
Low flow year	-50%	-50%	-50%	-50%

The simulation showed that wet season flows predicted declines in both water quality, but increases in freshwater biodiversity across catchments, with the magnitude of the changes depending on spatial characteristics of each catchment. Conversely, dry seasons saw an opposite pattern, with improvements in water quality and decreases in freshwater biodiversity.

Riparian vegetation condition was not affected by wet/dry season in the scenario simulation, which is as expected given that the model represents a short time snapshot in which season would not be expected to influence riparian vegetation.

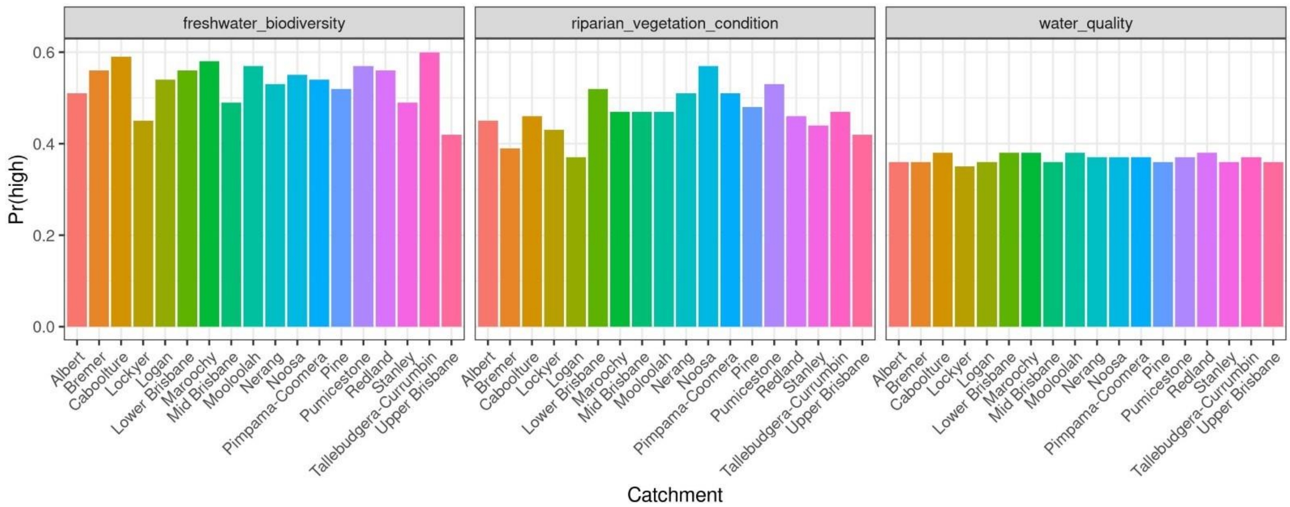

***Figure 16:** Extreme wet scenario marginal outcomes by catchment.*

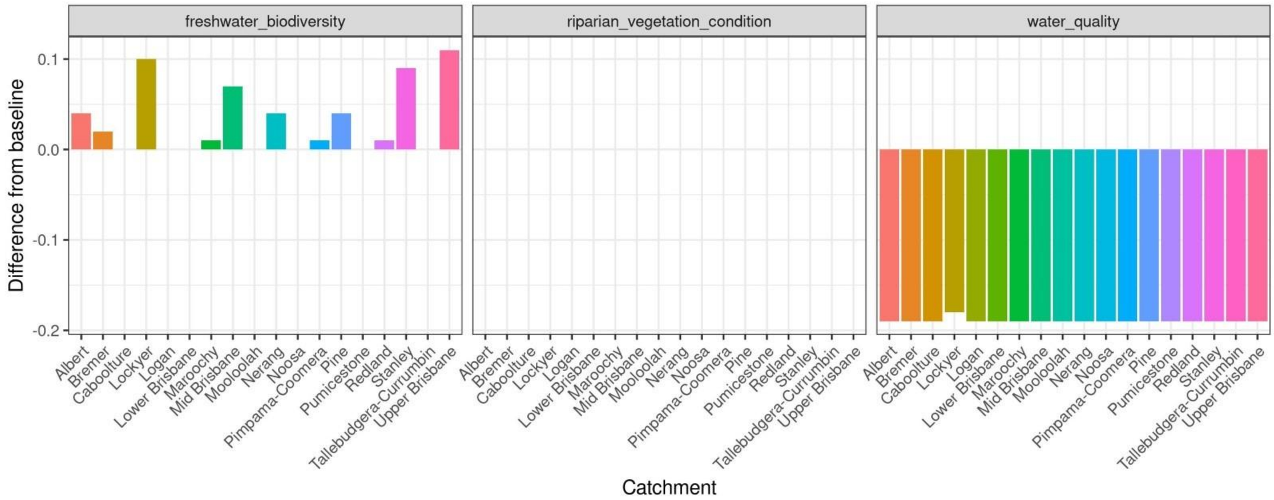

***Figure 17**: Extreme wet scenario difference from baseline by catchment.*

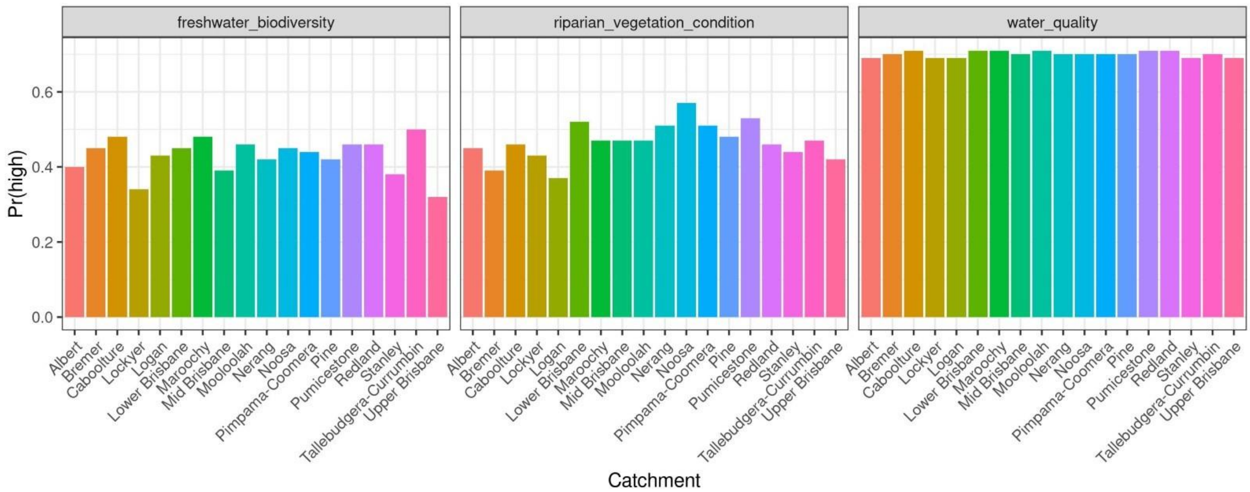

***Figure 18**: Extreme dry scenario difference marginal outcomes by catchment.*

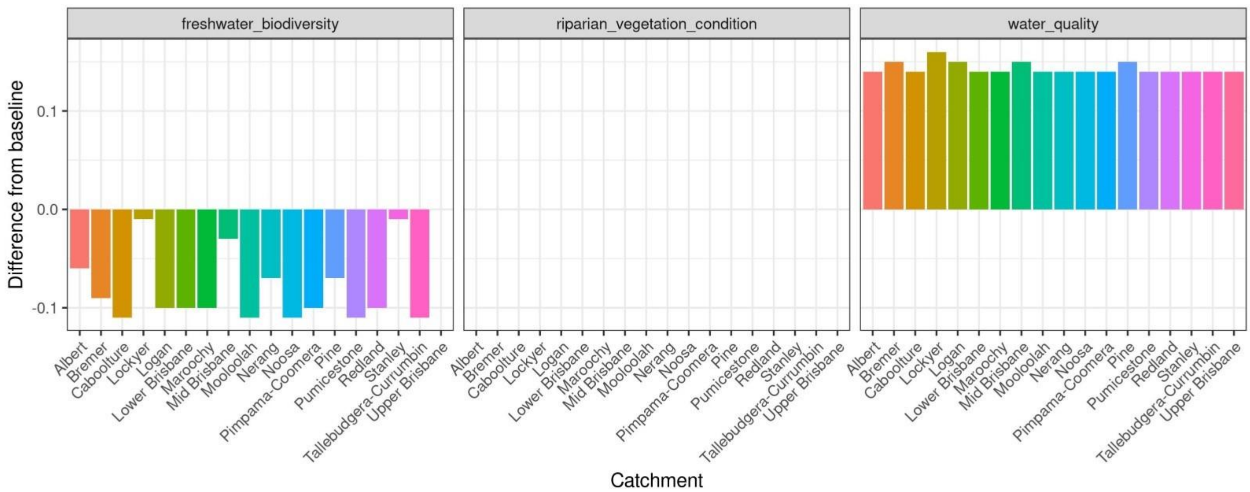

***Figure 19**: Extreme dry scenario difference from baseline by catchment.*

10 Limitations

Although we conducted a thorough data and literature search, we were not able to locate suitable training data for the full Bayesian Network. Therefore, the conditional probability table parameters were assembled using best estimates. A strength of the Bayesian Network is its ability to incorporate existing data from a range of sources, thereby providing an efficient way to iterate and test new research questions without having to collect new data.

The RIP-BN is a snapshot of a point in time, and it is not a process model. It therefore has limitations when considering processes that are time dependent. In future versions of the model, causally important time parameters could be added to address this limitation. For example, the causal effect of land use on water-borne pathogens could be different in summer than in winter, due to warmer temperatures having an accelerating effect on microbe growth (Ferguson & Kay, 2012). This time parameter could be included in the present RIP-BN model by adding a node labelled "Season" with two states (winter/summer) and adjusting the conditional probability tables accordingly.

In the long term, the Bayesian Network could be made dynamic. Dynamic Bayesian Networks are a potential way of including changes over time, even for complex natural systems (Wu et al. 2018).

The current implementation of the RIP-BN does not consider the spatial dependencies of user-input simulations. That is, if the user simulates an action in one sub catchment that may have an effect downstream, that downstream effect is not currently captured in the simulation of the RIP-BN. Future versions of the model and software could include the functionality to update the model predictions accounting for hydrological connectivity, and this would require additional specification of the changes in conditional probabilities caused by spatial dependencies, and specification of the timeframe to be considered for the flow-on effects.

Much of the policy discussion regarding riparian management focuses on specific management actions, such as, "fencing stock to exclude them from stream banks". In the current implementation of the RIP-BN, this granularity of detail is not explicitly included. The RIP-BN requires the user to abstract their input to the level presented in the model, for example, "taking some action to lower the impact of grazing pressure on riparian vegetation". Scientifically, it is difficult to provide any more specific levers due to the uncertainties and contradictions in empirical datasets on the impacts of specific management actions. This problem is present for many types of water management models.

At this stage the tool should only be used to aid general discussion. It's application as an effective decision support tool is currently limited by;

- Limited spatial data on river and catchment attributes of South East Queensland
- The science behind the conceptual model on the Bayesian Network, including the degree to which model assumptions can be generalised across the study area (South East Queensland catchments).
- The surety of the casual relationships
- Detailed critical review of literature across all model components, and scientific consensus on model nodes and their relationships.

11 Observations and conclusions

The RIP-BN is an end-to-end system that relies on the Bayesian Network modelling approach described in this report to determine the likely state of the riparian system in any given sub catchment in South East Queensland under a range of simulated conditions. This project adopted a research synthesis approach starting with building a conceptual understanding of how the characteristics of riparian zones influence water quality and aquatic habitat provision, identifying available data and expert knowledge. These data sources are combined using a model that encodes the relationships between the important variables in the system in probabilistic terms. The web interface then provides a way for users to query the trained model with scenarios based on proposed projects or desired outcomes.

Several observations were possible over the course of this project.

1. The causal processes at work in riparian systems are not a matter of scientific consensus.

   The Bayesian Network model went through several rounds of revision. Each time it was revised, the model changed substantially. The number of changes suggests that the causal structure of riparian systems is not yet a matter of scientific consensus, and there is substantial scope to further test and understand the relationships between variables in waterway management in South East Queensland. This observation makes it even more important to ensure that the present model, and future models, can be easily and frequently updated as more scientific research becomes available.

2. The datasets available for riparian modelling are variable.

   Upgrading the conceptual model to simulate riparian management changes required the assembly of an adequate spatial dataset. Various datasets were available for spatial variables, but these datasets had been created for various purposes and therefore were available in varying formats, at varying resolutions, and with varying levels of documentation. A standardised data repository catchment and river attributes of the region would be an asset for future research in this area. In the meantime, our project has created a reference dataset that can be accessed and used for other models.

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Appendix 1 End-user survey responses

	Yes, I use it regularly	Yes, I've used it once or twice	No, but I've heard of it	No, and I
Local Knowledge	92.3%	7.7%	0%	
The Whole of System, Values Base...	23.1%	30.8%	38.5%	
Queensland River Rehabilitatio...	3.8%	34.6%	50%	
Catchment Action Plans	34.6%	38.5%	23.1%	
Multi-Criteria Analysis	26.9%	30.8%	38.5%	
Purpose Built Decision Support...	30.8%	30.8%	30.8%	
Rule of Thumb	28%	36%	32%	
Queensland Environmental Values and...	32%	32%	36%	
AquaBAMM	0%	15.4%	57.7%	
South East Queensland Catchment...	0%	7.7%	53.8%	
Healthy Land & Water Report Card	23.1%	38.5%	26.9%	
Queensland River Classificatio...	15.4%	26.9%	42.3%	
Rapid Appraisal of Riparian...	11.5%	11.5%	50%	

***Figure 20**: End-user survey responses on the frequency that they use available decision support tools or approaches.*

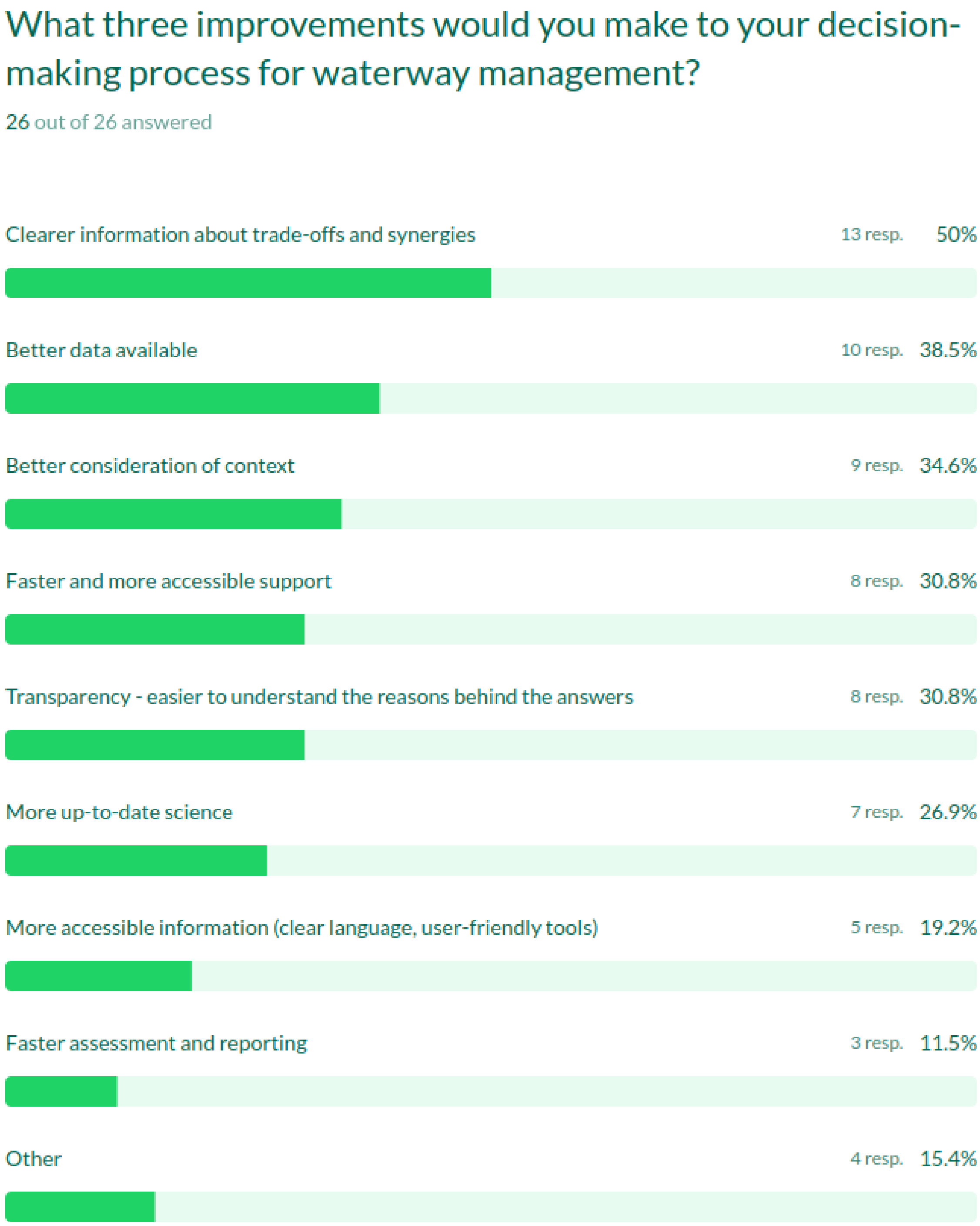

Figure 21: *End-user survey responses when asked, "What three improvements would you make to your decision-making process for waterway management"?*

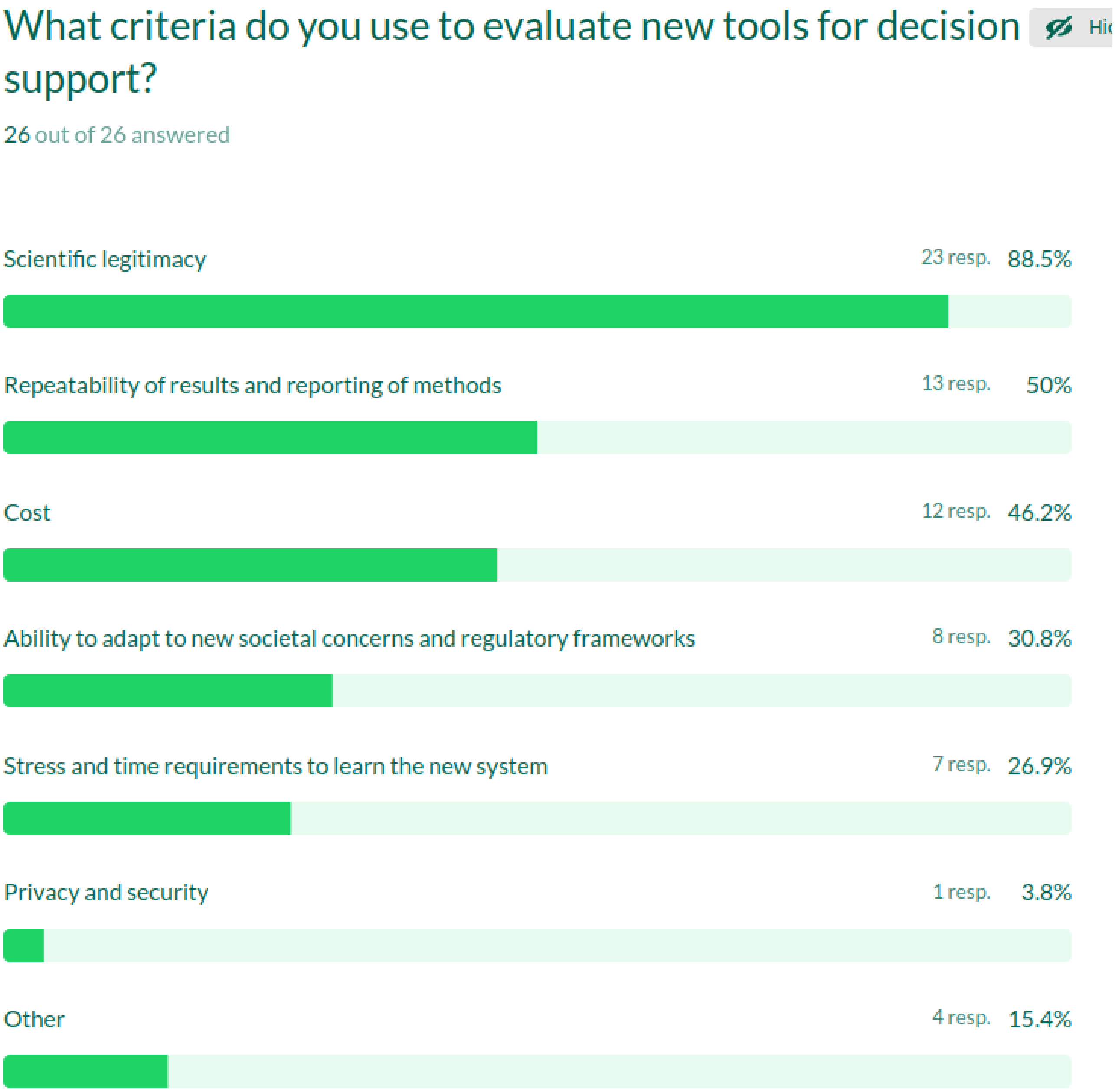

Figure 22*: End-user survey responses when asked, "What criteria do you use to evaluate new tools for decision support"?*

Appendix 2 Bayesian Network documentation

***Table 5**: Prototype BN nodes and definitions.*

Node	Definition
Riparian woody vegetation	Proportion of riparian area vegetated with woody vegetation (pre-clear)
Riparian vegetation connectivity	Proportion of riparian with high remnant and woody vegetation connectivity (proportion with value >200)
Riparian vegetation condition	The condition of riparian vegetation within the catchment (0-100)
Weed pressure	Riparian area impacted by high weed pressure (large trees, shrubs, vines, grasses)
Grazing pressure	Proportion of drainage network impacted by grazing and direct access to stock
Riparian vegetation threats	Overall threat index -riparian vegetation
Annual flow magnitude	The magnitude of annual flow observed within a catchment
Hillslope erosion potential	Proportion of catchment area presenting moderate to high hillslope erosion risk (RUSLE del ratio > 2.8)
Streambank erosion potential	Proportion of the drainage network presenting moderate to high stream bank erosion risk (potential)
Gully erosion potential	Gully density (length of active gullies within sub catchment area)
Surface soil total nitrogen	Average concentration of total nitrogen within catchment soils
Annual TSS load	Annual load of total suspended sediment mobilised to waterways
Annual TN load (soil-derived)	Annual load of soil-derived total nitrogen mobilised to waterways
Annual pathogen load	Annual load of pathogens mobilised to waterways (Faecal bacteria load in surface water load of run-off)
Water quality	Quality of water within receiving waters of the catchment
Land use	Dominant primary land use of the catchment area
Flow disturbance index	The level of flow disturbance within the catchment - Segment Flow Regime Disturbance Index
Annual flow connectivity (time)	Annual proportion of zero flows - zero flow proportion (ZFP)

Node	Definition
Annual surface water extent (climate scenarios 2050)	Annual mean surface water extent (% of stream segment) under wet future climate scenario 2040-2059
Aquatic habitat condition	The condition of aquatic environs within the drainage network
Aquatic habitat availability	The level of aquatic habitat availability
Aquatic habitat provision	The level of provision of habitat for aquatic habitat

Table 6: *Prototype BN node links and supporting literature.*

From	to	Reference
Hillslope erosion potential	Annual TSS load	Hancock, G., Caitcheon, G. (2010). Sediment sources and transport to the Logan–Albert River estuary during the January 2008 flood event. Water for a Healthy Country National Research Flagship.
Streambank erosion potential	Annual TSS load	Olley, J.M., Burton, J., Smolders, K., Pantus, F., and Pietsch, T. (2013) The application of fallout radionuclides to determine the dominant erosion process in water supply catchments of subtropical South-East Queensland, Australia. Hydrological Processes, 27(6), 885-895.
Gully erosion potential	Annual TSS load	Saxton N., Olley, J.M., Smith, S., Ward, D., Rose, C. (2012) Gully erosion in sub-tropical southeast Queensland, Australia. Geomorphology 173, 80–87.
Annual TSS load	Annual TPN load	Beusen, A.H.W., Dekkers, A.L.M., Bouwman. A.F. Ludwig, W., Harrison, J. (2005) Estimation of global river transport of sediment and associated particulate C, N, and P. Global biogeochemical cycles, 19 (4).
Annual TSS load	Water quality	Grinham, A.; Gibbes, B.; Gale, D.; Watkinson, A.; Bartkow, M., Extreme rainfall and drinking water quality: A regional perspective. In WIT Transactions on Ecology and the Environment, WIT Press: Chilworth, UK, 2012; Vol. 164, pp. 183–194.
Surface soil total nitrogen	Annual TN load (soil-derived)	Garzon-Garcia, A., Laceby, P., Olley, J., Bun, S. (2017) Differentiating the sources of fine sediment organic matter and nitrogen in a sub-tropical Australian catchment. Science of the Total Environment 575, 1384-1394.
Annual TN load	Water quality	Grinham, A., Costantini, T., Deering, N., Jackson, C., Klein, C., Lovelock, C., Pandolfi, J., Eyal, G., Linde, M., Dunbabin, M., Duncan, B., Hutley, N., Byrne, I., Wilson, C., Albert, S. (2024). Nitrogen loading resulting from major floods and sediment resuspension to a large coastal embayment. Science of the Total Environment (918) 170646.
Land use	Annual pathogen load	Ferguson, C.; Kay, D. Transport of microbial pollution in catchment systems. In Animal Waste, Water Quality and Human Health; Dufour, A., Bartram, J., Bos, R., Gannon, V., Eds.; IWA Publishing: London, UK, 2012; pp. 157–193.

From	to	Reference
Annual flow magnitude	Annual pathogen load	Collender, P.A., Cooke, O.C., Bryant, L.D., Kjeldsen, T.R., Remais, J.V. (2017) Estimating the microbial risks associated with inland flood events: bridging theory and models of pathogen transport. Critical reviews in Environmental science and technology 46(23-24), 1787-1833.
Annual flow magnitude	Annual TSS load	Kroon, F.J.; Kuhnert, P.M.; Henderson, B.L.; Wilkinson, S.N.; Kinsey-Henderson, A.; Abbott, B.; Brodie, J.E.; Turner, R.D. River loads of suspended solids, nitrogen, phosphorus and herbicides delivered to the Great Barrier Reef lagoon. Mar. Pollut. Bull. 2012, 65, 167–181.
Riparian woody vegetation cover	Annual TSS load	Olley, J., Burton, J., Hermoso, V., Smolders, K., McMahon, J., Thomson, B., and Watkinson, A. (2015) Remnant riparian vegetation, sediment and nutrient loads, and river rehabilitation in subtropical Australia, Hydrological Processes 29(10), 2290-2300.
Riparian woody vegetation cover	Annual pathogen load	Kay, D.; Crowther, J.; Kay, C.; McDonald, A.; Ferguson, C.; Stapleton, C.; Wyer, M. Effectiveness of best management practices for attenuating the transport of livestock-derived pathogens within catchments. In Animal Waste, Water Quality and Human Health; Dufour, A., Bartram, J., Bos, R., Gannon, V., Eds.; IWA Publishing: London, UK, 2012; pp. 195–255.
Riparian woody vegetation cover	Riparian vegetation condition	Jansen, A, Robertson, A, Thompson, L & Wilson, A., (2005), Rapid appraisal of riparian condition, version 2', River Management Technical Guideline No. 4A. [online], Land & Water Australia, Canberra.
Weed pressure	Riparian vegetation threats	Richardson, D.M., Holmes, P.M., Esler, K.J., Galatowitsch, S.M., Stromberg, J.C., Kirkman, S.P., Pysek, P., Hobbs, R.J. (2007) Riparian vegetation: degradation, alien plant invasions, and restoration prospects. Diversity and distribution 13, 126-139.
Grazing pressure	Riparian vegetation threats	Jansen, A., Robertson, A. (2001) Relationships between livestock management and the ecological condition of riparian habitats along an Australian floodplain river. Journal of Applied Ecology 38, 63-75.
Riparian vegetation threats	Riparian vegetation condition	Naiman, R.J., Decamps, H, McClain, M.E. (2005) Riparian: ecology, conservation and management of streamside communities. New York: Academic Press.
Riparian remnant vegetation connectivity	Riparian vegetation condition	Bennet, A.F., Nimmo, D.G., Radford, J. (2014) Riparian vegetation has disproportionate benefits for landscape-scale conversation of woodland birds in highly modified environments. Journal of Applied Ecology 51(2), 514-523/.
Riparian vegetation condition	Aquatic ecosystem condition	Sheldon, F., Petersen, E., Boone, E., Sippel, S., Bunn, S., and Harch, B. (2012) Identifying the spatial scale of land use that most strongly influences overall river ecosystem health score. Ecological Applications 22(8), 2188-2203.
Flow disturbance index	Aquatic ecosystem condition	Ward, J.V. Stanford, J.A. (1995) Ecological connectivity in alluvial river ecosystems and its disruption by flow regulation. Regulated Rivers: Research and Management 11 (1), 105-119.
Land use	Aquatic ecosystem condition	Lake, P.S., Bond., N. (2007) Australian futures: freshwater ecosystems and human water usage. Futures 39(2-3) 288-305.

From	to	Reference
Annual flow connectivity	Aquatic habitat availability	Yu, S., Rose, P.M., Bond, N., Bunn, S., Kennard, M.J. (2022) Identifying priority aquatic refuges to sustain freshwater biodiversity in intermittent streams in eastern Australia. Aquatic Conservation: Marine and freshwater ecosystems, 32 (10), 1584-1595.
Annual surface water extent	Aquatic habitat availability	Yu, S., Bond, N., Bunn, S. Kennard, M. (2019) Development and application of predictive models of surface water extent to identify aquatic refuges in Eastern Australian temporary stream networks. Water Resources Research 55 (11), 9639-9655.
Aquatic habitat condition	Aquatic habitat provision	Dalal, E.L.H., Tomscha, S.A., Dallaire, C.O., Bennet, E.M. (2017) A review of riverine ecosystems service quantification: research gaps and recommendations. Journal of Applied Ecology 55 (3) 1299-1311.
Aquatic habitat availability	Aquatic habitat provision	Boulton, A., Ekebom, J., Gislason, G.M. (2016) Integrating ecosystem services into conservation strategies for freshwater and marine habitats: a review. Aquatic conservation: Marine and Freshwater Ecosystems 26 (5) 963-985.

Table 7: *Nodes and node connection justifications.*

Node	Parent nodes	Node connection summary justifications
Water quality	*Annual TN Load* *Annual TSS load Annual* *Pathogen load*	Diffuse fine sediments and particulate nutrients originating from non-urbanised catchments impact the quality of water within fresh, estuarine and marine receiving waters (Grinham et. al. 2012; Grinham et. al. 2024). The safety of water for drinking is also influenced by the level of pathogens, which are also transported to waterways from diffuse catchment sources. Water quality is defined in the model as the annual load of total suspended sediments, total nitrogen and pathogens delivered to receiving waters
Aquatic habitat provision	*Aquatic habitat condition Aquatic habitat availability*	The condition and extent or availability of aquatic habitat are key determinants of aquatic habitat provision. The characteristics of riparian zones have a substantial influence on in-stream biophysical components and processes, and the condition of aquatic habitats (Sheldon et. al. 2012; Tockner, 1999)
Riparian vegetation condition	Riparian woody vegetation cover Riparian vegetation threats Riparian vegetation connectivity	The characteristics of vegetation in the riparian have a substantial influence on key indicators of aquatic ecosystem health and fine sediment and nitrogen loads of catchments (Sheldon et. al. 2012; Olley et. al. 2015). Key factors that influence the condition of riparian vegetation in South East Queensland, including riparian vegetation connectivity, threats to riparian vegetation and the level of cover of riparian woody vegetation
Aquatic habitat availability	Surface water extent Annual flow connectivity	The distribution and abundance of aquatic species are dependent on surface water distribution within catchments, and temporal connectivity of flows. Many streams in South East Queensland are ephemeral and aquatic species are adapted to this high flow variability (Yu et. al. 2019).
Aquatic habitat condition	Flow disturbance Land-use Riparian vegetation condition	The condition of aquatic habitats including structural and process components are influenced by catchment land use, the condition of riparian ecosystems and flow disturbance. An analysis of the Ecological Health Monitoring Program dataset determined that land use was a predictor of aquatic ecosystem condition (Sheldon, 2012). Specifically, urban land use within the riparian buffer of the waterway had a negative effect on aquatic habitat condition (Sheldon, 2012).
Total suspended sediment (annual)	Annual flow Gully erosion potential Hillslope erosion potential Stream bank erosion potential Riparian woody vegetation	The total suspended sediment load of a catchment is dependent on the annual run-off of a catchment and subsequent mobilisation of fine sediment from gully erosion, hillslope and stream bank erosion processes. Riparian woody vegetation also has a strong influence on sub catchment total suspended sediment yield (Olley et. al. 2023).

Node	Parent nodes	Node connection summary justifications
Total nitrogen (soil-derived) load	Annual flow magnitude Annual TSS load	The total particulate nitrogen load from eroded soil of a catchment area for a given year is dependent on the concentration of nitrogen within the soils, the volume of catchment run-off and the total mass of soil mobilised (total suspended sediment load).
Annual pathogen load	Annual flow magnitude Land-use Riparian woody vegetation cover	Studies are sparse and problem-focused, making it difficult to assess the relative contributions of different types of land use (e.g., urban, farming, natural) to pathogen levels in drinking water. Different land uses contribute to potential sources of pathogens in water (Ferguson & Kay, 2012). The annual load of pathogens delivered to waterways is dependent on run-off volume and inputs from different sources within the catchment.
Riparian vegetation threats	Weed pressure Grazing pressure	Beyond land-clearing and other direct disturbances, invasive weeds and grazing pressure are key threats to riparian vegetation in South East Queensland (Jansen and Robertson, 2001; Richarson et. al. 2007).

***Table 8**: Node states, thresholds, units and description.*

Node	States	Threshold	Unit	Description
Riparian woody vegetation	High Low	70%	%area	Proportion of riparian area vegetated with woody vegetation (pre-clear)
Riparian vegetation connectivity	High Low	50%	%area	Proportion of riparian with high remnant and woody vegetation connectivity (proportion with value >200)
Riparian vegetation condition	High Medium Low	<50, 50-75-75-100	%area	The condition of riparian vegetation within the catchment (0-100)

Node	States	Threshold	Unit	Description
Weed pressure	High Low	0 (any=high)	% area	Riparian area impacted by weed pressure
Grazing pressure	High/Low	0 (any=high)	% area	Proportion of drainage network impacted by grazing and direct access of stock
Riparian vegetation threats	High Low	0.5	Probability index (0-1)	Overall threat index - riparian vegetation
Annual flow magnitude	High (2022) Medium (2020) Low(2021)	5	ML/yr/Ha	The magnitude of annual flow observed within a catchment
Hillslope erosion potential	High Low	50%	%area	Proportion of catchment area presenting moderate to high hillslope erosion risk (RUSLE del ratio > 2.8)
Streambank erosion potential	High Low	50%	%length	Proportion of the drainage network presenting moderate to high stream bank erosion risk (potential)
Gully erosion potential	High Low	0.2km	Km/Km2	Gully density (length of active gullies within sub catchment area)
Surface soil total nitrogen	High Low	0.5	%mass	Average concentration of total nitrogen within catchment soils
Annual TSS load	High Low	500	kg/ha	Annual load of total suspended sediment mobilised to waterways
Annual TPN load	High Low	1	kg/ha	Annual load of soil-derived total nitrogen mobilised to waterways
Annual pathogen load	High Low	0.5	CFU/100ml/ha/yr	Annual load of pathogens mobilised to waterways (Faecal bacteria load in surface water load of run-off)
Water quality	High	0.5	Probability index (0-1)	Quality of water within receiving waters of the catchment

Node	States	Threshold	Unit	Description
	Medium Low			
Land use	Natural Agriculture Urban Mining	Dominant	%area	Dominant primary land use of the catchment area
Flow disturbance index	Not disturbed Disturbed	0 (any=high)	Proportion of stream segment (0-1)	The level of flow disturbance within the catchment - Segment Flow Regime Disturbance Index
Annual Flow connectivity (time)	High Low	50%	Proportion of stream segment (0-1)	Annual proportion of zero flows - zero flow proportion (ZFP)
Annual surface water extent (climate scenarios 2050)	High Medium Low	50%	Proportion of stream segment (0-1)	Annual mean surface water extent (% of stream segment) under wet future climate scenario 2040-2059
Aquatic habitat condition	High Low	0.5	Probability index (0-1)	The condition of aquatic environs within the drainage network
Aquatic habitat availability	High Low	0.5	Probability index (0-1)	The level of aquatic habitat availability
Aquatic habitat provision	High Medium Low	0.5	Probability index (0-1)	The level of provision of habitat for aquatic habitat

***Table 9**: Spatial context variables and associated spatial data.*

Node	Dataset	Producer	Year	Geometry	Projection/ coordinate system	Scale	Reference
Flow disturbance index	National Environmental Stream Attributes v1.1.5	Australian Government Geoscience Australia	2015	Polygon		AHGF stream segments	Stein, J.L. Mutchison, M. Stein, J.A. (2012): National Environmental Stream Attributes v1.1.5. dataset. https://pid.geoscience.gov.au/dataset/ga/75066
Land use Grazing pressure	Queensland Land Use Mapping Program	Department of Science, Information Technology, Innovation and the Arts	2013	Polygon	Albers Conical Equal Area	1:50,000	State of Queensland (Department of Environment, Science and Innovation) website: https://qldspatial.information.qld.gov.au/catalogue/custom/detail.page?fid={C3CD23AD-7101-4765-8BED-AFC2C5DF1F5F}
Gully erosion potential	Integrated Sediment Assessment (2018) Gullies	Healthy Land & Water, Seqwater and Alluvium	2017	Polygon	GDA 1994	5m	Alluvium, Healthy Land & Water, Seqwater (2018). Integrated Sediment Assessment Project – Final Report. Report P416053_ISA_R01 by Alluvium Consulting Australia, Healthy Land & Water and Seqwater.
Hillslope erosion potential	Integrated Sediment Assessment (2018) Hillslope erosion risk	Healthy Land & Water, Seqwater and Alluvium	2017	Raster	GDA 1994	30m	Alluvium, Healthy Land & Water, Seqwater (2018). Integrated Sediment Assessment Project – Final Report. Report P416053_ISA_R01 by Alluvium Consulting Australia, Healthy Land & Water and Seqwater.
Streambank erosion potential	Integrated Sediment Assessment (2018) Stream bank erosion risk	Healthy Land & Water, Seqwater and Alluvium	2017	Linestring	GDA 1994	Stream order ≥3	Alluvium, Healthy Land & Water, Seqwater (2018). Integrated Sediment Assessment Project – Final Report. Report P416053_ISA_R01 by Alluvium Consulting Australia, Healthy Land & Water and Seqwater.

Node	Dataset	Producer	Year	Geometry	Projection/ coordinate system	Scale	Reference
Weed pressure	Queensland weed distribution current	Department of Agriculture and Fisheries	2023	Point	EPSG:4283	18km	State of Queensland (Department of Agriculture and Fisheries) website https://qldspatial.information.qld.gov.au/catalogue/custom/detail.page?fid={20F76BD3-970B-4EBD-A690-BA51BC081F57}
Annual flow connectivity (time)	Research paper supplementary material	Griffith University	2022	Linestring		AHGF stream segments	Yu S, 2022. Flow indices to support freshwater Environmental Health Monitoring Program. ARI Report No. 2022/008 to Healthy Land & Water. Australian Rivers Institute, Griffith University, Brisbane.
Annual surface water extent	Research paper supplementary material	Griffith University	2022	Linestring		AHGF stream segments	Yu et. al. et al2022 Modelling surface water availability to inform water security for freshwater biodiversity.
Riparian vegetation connectivity	Riparian remnant and woody vegetation connectivity (2017)	Healthy Land & Water	2017	Raster	GDA 1994 Australia Albers	30m	Healthy Land & Water, 2017.
Annual flow magnitude	SEQ SOURCE hydrological modelling (annual flow volume)	Healthy Land & Water and Alluvium	2022	Raster	WGS 1984 web mercator	SEQ Sub catchments	Alluvium, 2022. SEQ Source catchment modelling. Report to Healthy Land & Water.
Annual TSS load	SEQ Source pollutant load modelling	Healthy Land & Water and Alluvium	2022	Raster	WGS 1984 web mercator	SEQ Sub catchments	Alluvium, 2022. SEQ Source catchment modelling. Report to Healthy Land & Water.

Node	Dataset	Producer	Year	Geometry	Projection/ coordinate system	Scale	Reference
Annual TN load	SEQ Source pollutant load modelling	Healthy Land and Water & Alluvium	2022	Raster	WGS 1984 web mercator	SEQ Sub catchments	Alluvium, 2022. SEQ Source catchment modelling. Report to Healthy Land & Water.
Surface soil total nitrogen	Soil and Landscape Grid National Soil Attribute Maps - Total Nitrogen	CSIRO	2023	Raster	WGS 1984	30m	Malone, Brendan; Searle, Ross (2023): Soil and Landscape Grid National Soil Attribute Maps - Total Nitrogen (3" resolution) - Release 2. v1. CSIRO. Data Collection. https://doi.org/10.25919/pm2n-ww12
Riparian woody vegetation	South East Queensland woody vegetation and ground cover levels (2021)	QLD Department of Environment Science and Innovation	2021	Polygon	GDA 1994	10m	Healy, A. 2022. Riparian Forest and Ground Cover Levels in South East Queensland Catchments. Brisbane: Department of Environment, Science and Innovation, Queensland Government.

Appendix 3 Spatial data management in Python

These functions used to aggregate spatial data into the standard spatial unit (sub catchments) are provided in code as part of the project deliverables.

aggregate_categorical(intersection, ref, cat_col): Aggregate a categorical variable to the reference shape area.

aggregate_continuous(intersection, ref, con_col): Aggregate the values of a continuous variable to the reference shape area.

aggregate_values(intersection, ref, mycols): Combine all values in areas smaller than the reference into the reference shapes.

create_reference_shapefile(reference_filename, ref): Generate a shapefile with a unique id for each shape, equivalent to the reference shapes.

drop_variables(spatial, used_cols): Reduce the pandas data table to only the features being used in the model.

fix_geometry_projection(spatial): Convert the shapefile to Web Mercator projection, fix any broken polygons, and remove the unfixable ones.

intersect_linestrings(reference, overlay, ref_id, reference_cols, overlay_cols): Overlay a linestring spatial file onto a reference polygon spatial file, and slice the lines based on the reference shapes.

intersect_polygons(reference, overlay, ref_id, reference_cols, overlay_cols): Overlay two polygons, and slice the overlay shapes into the reference shapes, recording the area.

load_spatialfile(spatialfile): Load a spatial file, choose the correct layers and standardise the metadata.

A user can easily standardise any polygon or line-based spatial file to a reference spatial file using the following Python3 code snippet:

```
import spatial_functions as sf

# Load the spatial files, clean them, and standardise their projections

reference = sf.load_spatialfile(reference_filename)

line_overlay = sf.load_spatialfile(line_overlay_filename)

# Combine the two spatial files

intersection = sf.intersect_linestrings(reference, line_overlay, reference_column,
[reference_columns_to_keep], [overlay_columns _to_keep])

# Aggregate the columns of the overlay dataset to the reference shapes

df = sf.aggregate_values(intersection, reference_column, [overlay_columns])
```

Appendix 4 Spatial context variables

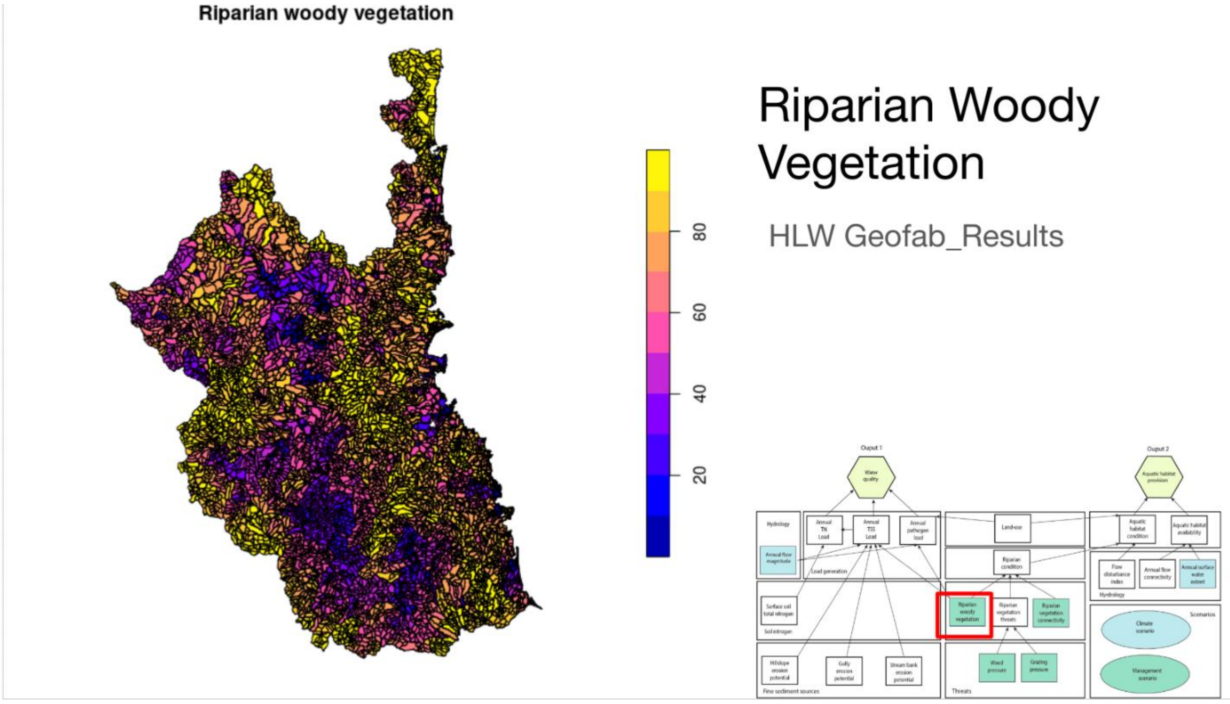

Figure 23: *South East Queensland riparian woody vegetation cover.*

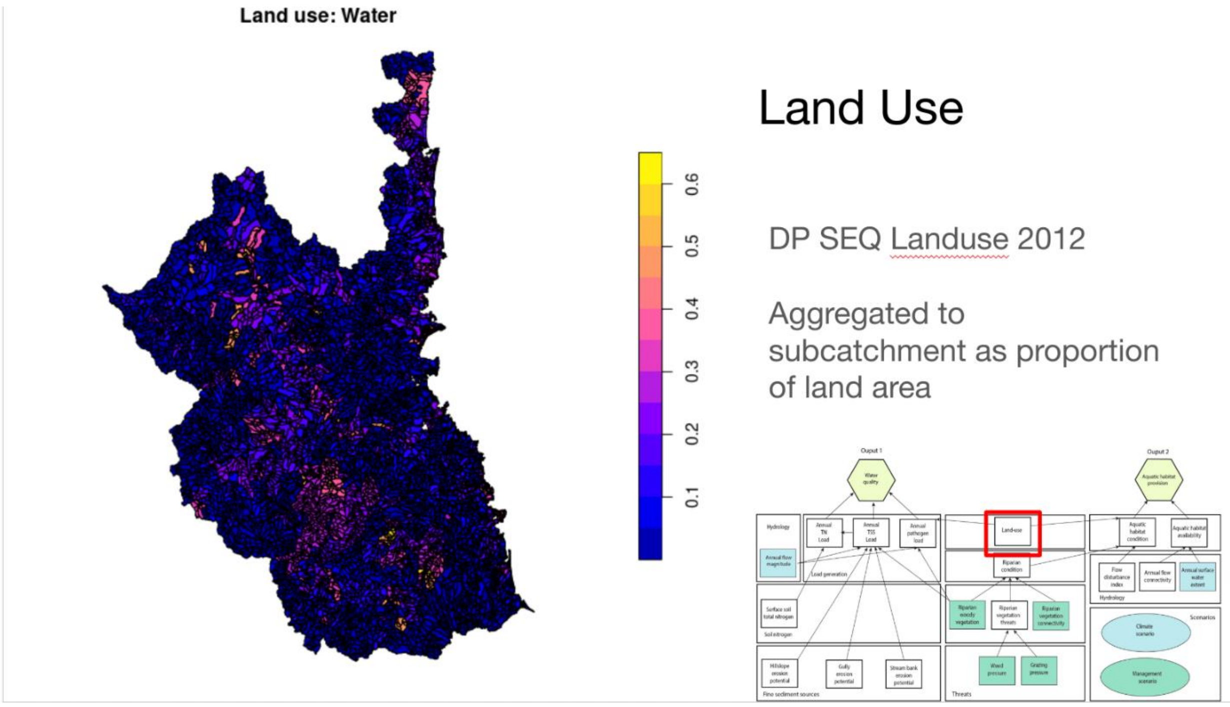

Figure 24: *South East Queensland land use.*

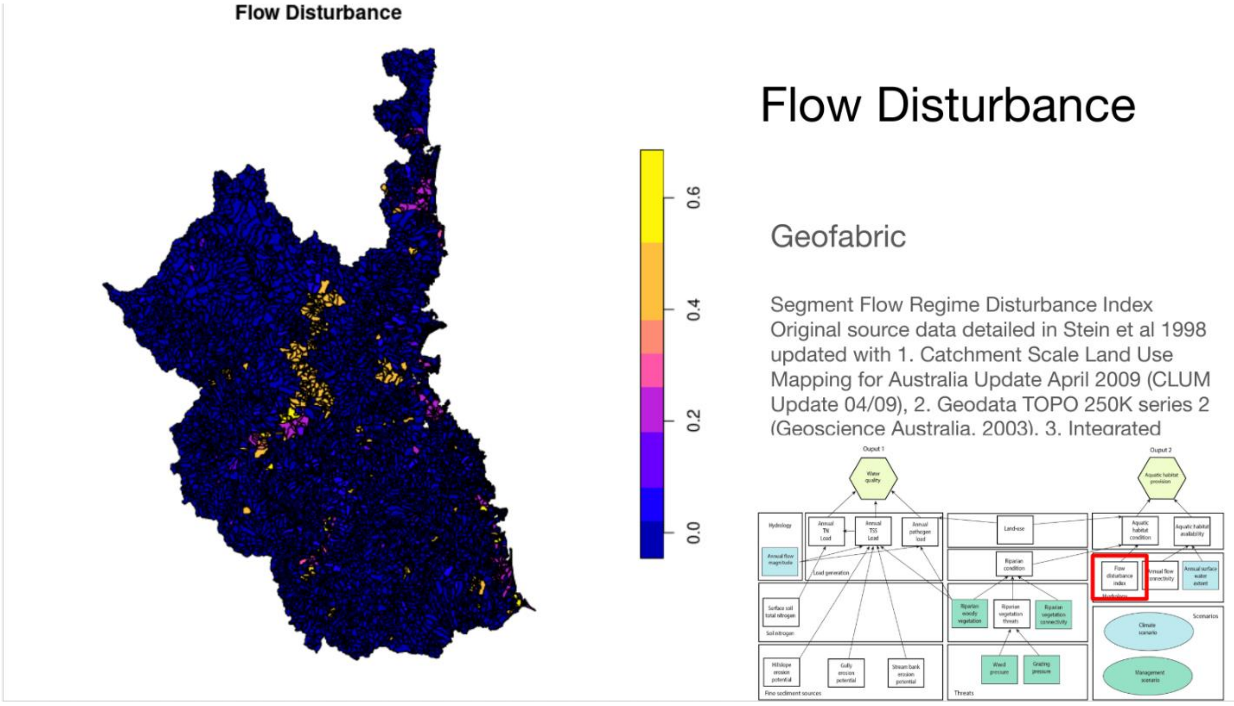

***Figure 25**: South East Queensland flow disturbance.*

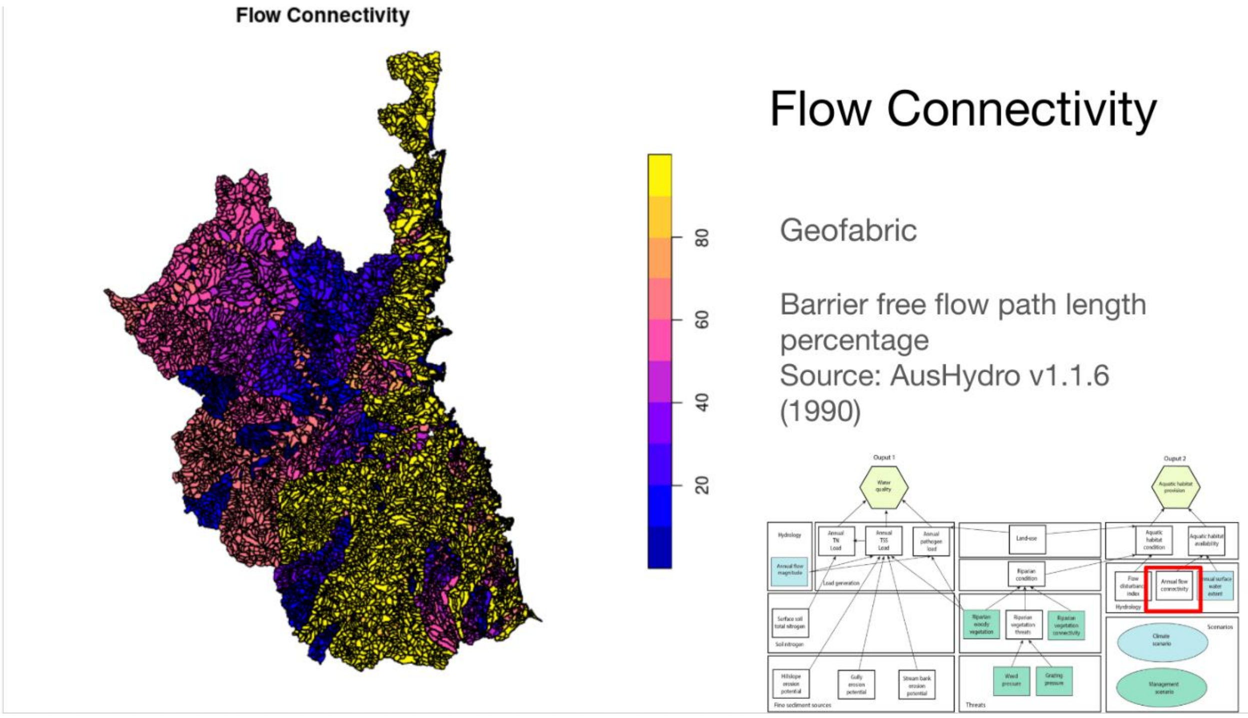

***Figure 26**: South East Queensland flow connectivity.*

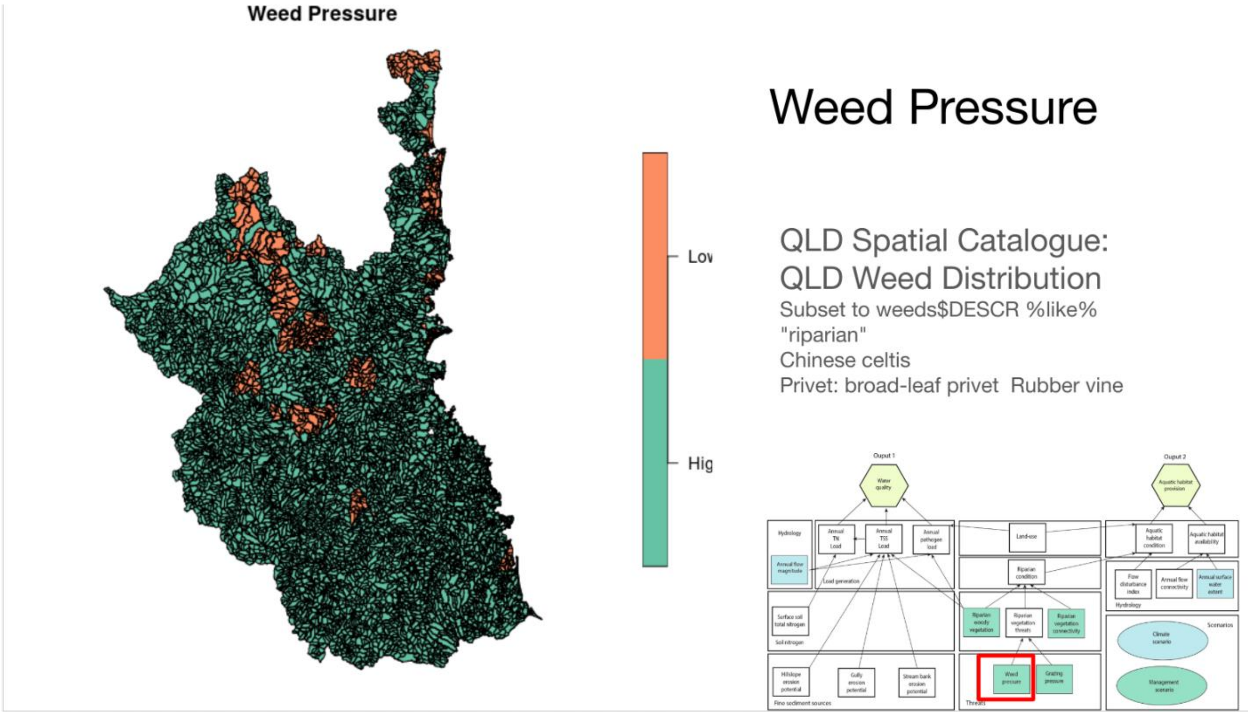

***Figure 27**: South East Queensland weed pressure.*

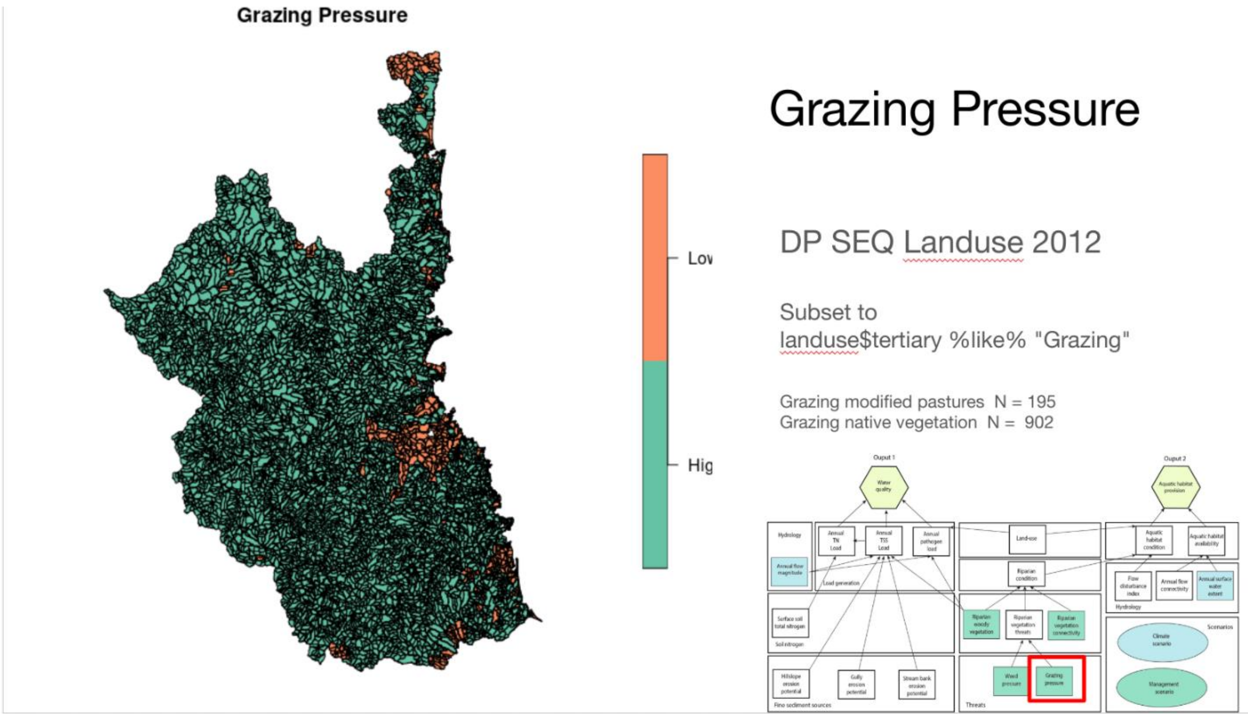

***Figure 28**: South East Queensland grazing pressure.*

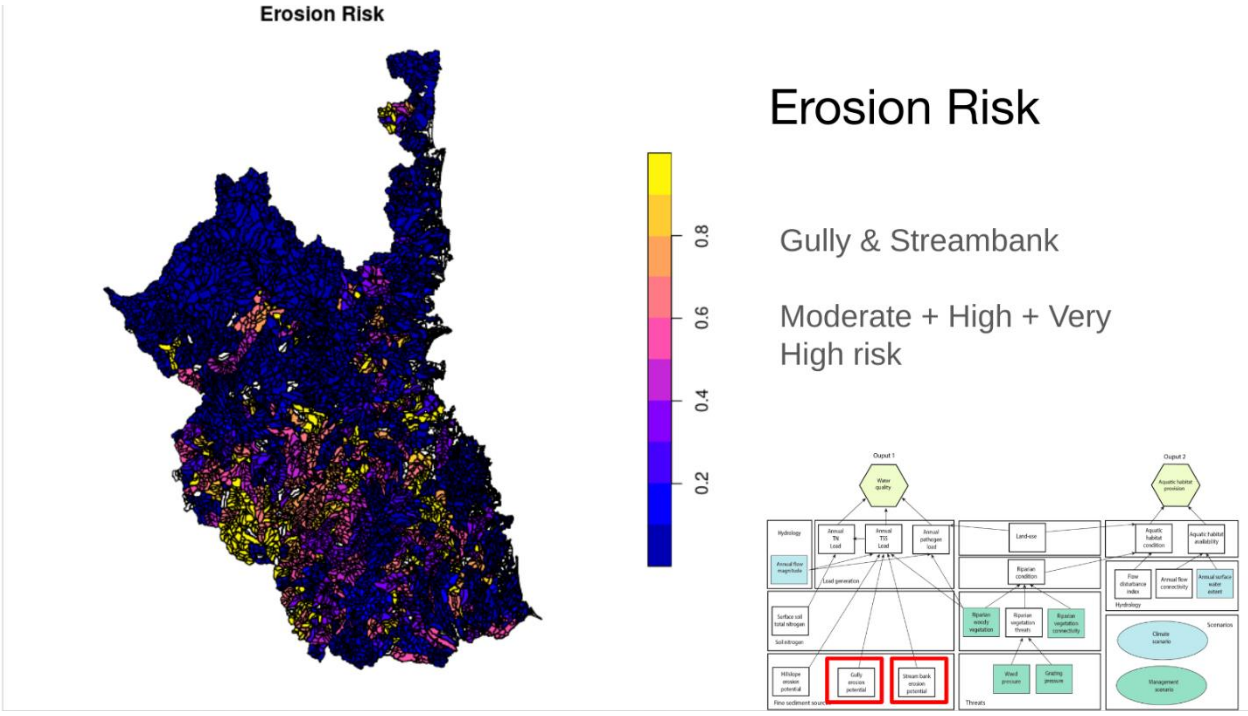

***Figure 29**: South East Queensland erosion risk.*

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