Drought and climate adaptation program

DCAP3

CREATING ALTERNATE INCOME STREAMS TO INCREASE FARM PROFITABILITY AND BENEFIT THE ENVIRONMENT (UNISQ)

MILESTONE 10A REPORT

Developing a tool to assess how climate risk affects the financial viability of converting marginal land to generate alternative income streams & inform farmers on the most beneficial/least risky time to adopt new practices

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Building on our earlier analyses and reports (Kath et al. 2023; Reardon-Smith et al., 2023; Thorpe et al., 2023; Kath et al., 2024a,b; Kath & Thorpe, 2024; Reardon-Smith & Mushtaq, 2024; Mushtaq & Reardon-Smith, 2024; Kath et al., 2024; Reardon-Smith et al., 2025), this current Milestone 10a (MS10a) report develops a prototype probabilistic decision-support tool, downscaled to farm level, to assess how climate risk affects the financial viability of converting marginal land to generate alternative income streams and inform farmers on the most beneficial/least risky time to adopt new practices. This decision support framework, once verified and if operationalised, might assist farmers in assessing and deciding whether income diversification options—specific environmental (carbon, biodiversity) benefit payment schemes—are feasible and likely to be beneficial, financially and environmentally, on their land. This and subsequent work on this project relate to the final, yet vital, stages in the overall 'logic' that informs this project (Figure 1)—a package of works to inform support packages for farmers around decisions about engaging in these income diversification opportunities. In this Milestone 10a report, we present this prototype probabilistic decision-support tool and provide some initial analysis of its logic and capacity for further development.

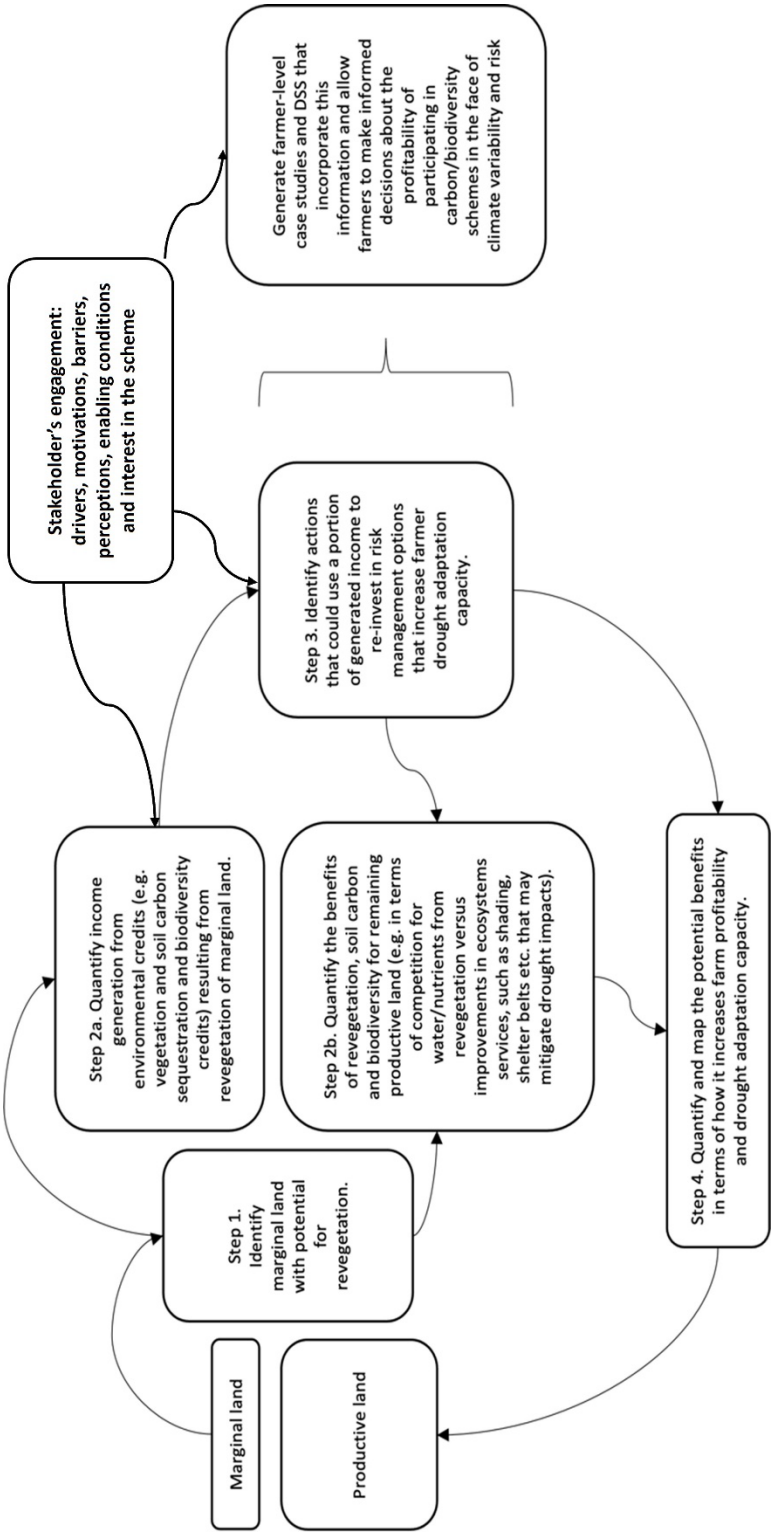

Figure 1. Schematic outlining the approaches and activities that are being undertaken in this project.

Environmental benefit scheme decisions

As indicated in earlier Milestone reports, environmental (carbon, biodiversity) benefit or 'natural capital' scheme investments are nominally expected to deliver improved financial gross margin outcomes for farming enterprises in Queensland's climatically marginal cropping areas (Kath et al., 2023; Kath & Thorpe, 2024). However, significant challenges exist in knowing not only which regions are effectively marginal (under both current and future levels of climate variability) in terms of long-term cropping productivity (i.e., which regions are potentially subject to 'hard' limits to adaptation where adoption of cropping practices and technologies may not adequately mitigate climate risk or enhance climate resilience), but also, at the finer farm scale, (i) which cropping systems within these regions are at risk; and (ii) what the 'soft' limits to adaptation are in terms of financial and personal capacity to adapt/transform production practices to accommodate increased climate risk within a cropping enterprise.

New environmental (carbon, biodiversity) income diversification projects offer additional options for consideration when making enterprise investment decisions aimed at building financial and environmental resilience into crop production systems (Kath et al., 2023; Thorpe et al., 2023; Kath et al., 2024; Kath & Thorpe, 2024). Alongside the range of investment options available to producers (Figure 2), financial incentives such as markets for ecosystem services—e.g., Queensland's Land Restoration Fund (LRF) and Reef Credits, and the Australian Government's Emissions Reduction Fund (ERF)—offer investment/income streams to participating agricultural producers who adopt certain sustainable on-farm practices (registered methodologies) designed to deliver enhanced environmental outcomes (Thorpe et al., 2023). However, any decision to participate/invest in a carbon or biodiversity benefits project should be made with access to the best available information. Such decision-making, in the context of dynamic and changing climatic conditions, is undoubtedly complex and the outcomes are not always easy to predict; hence the need for evidence-based decision-support that takes climate variability and risk into account.

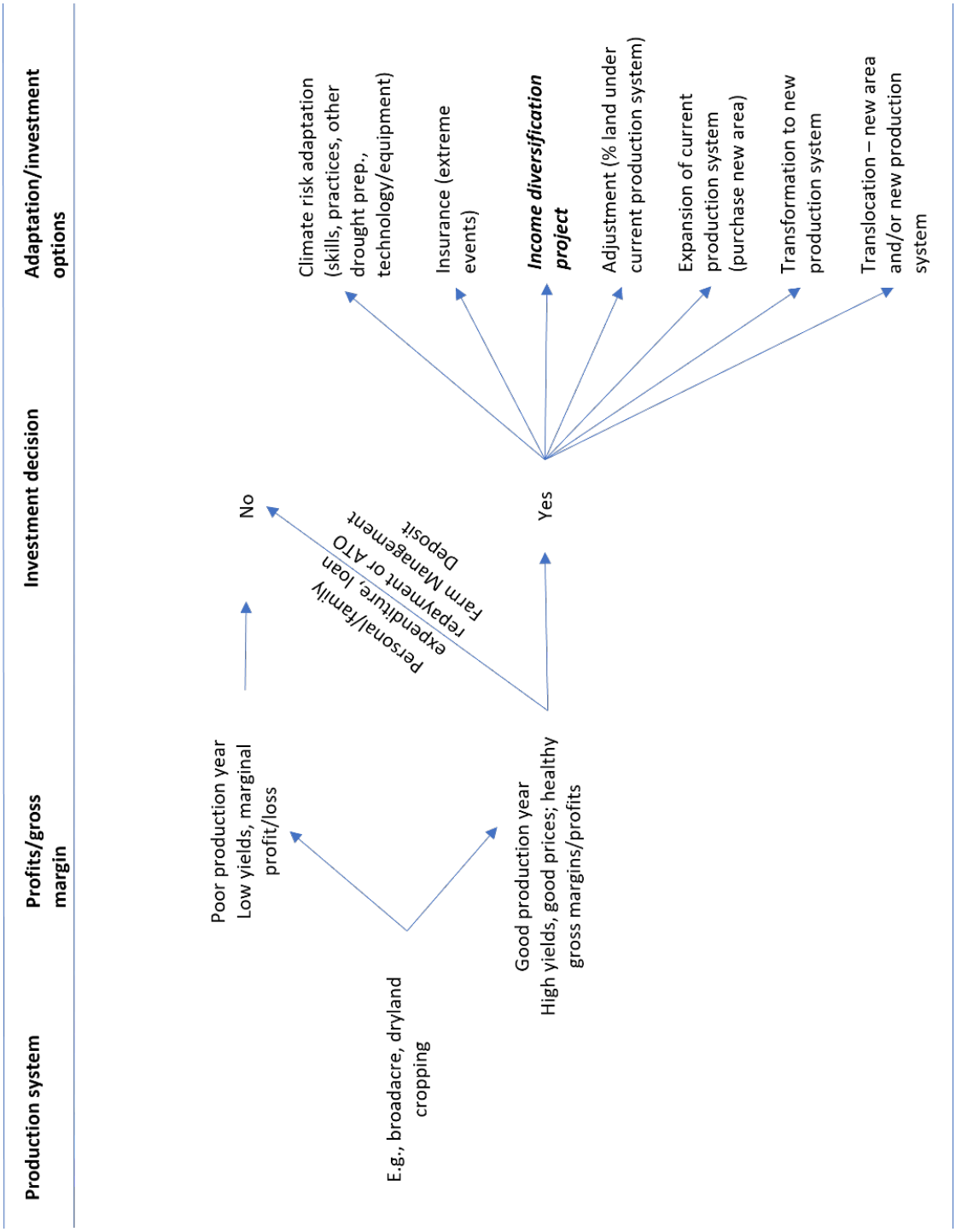

Figure 2. Potential investment options available for Australian broadacre crop production systems (Reardon-Smith et al., 2024).

Our earlier analyses have identified critical decision-points for diversification based on declining gross margins from crop production under climatically marginal conditions (Kath et al. 2024a; Kath & Thorpe, 2024). Such conditions may of course also play a role in the viability of the particular environmental projects on offer. Obtaining a sense of the financial implications of a decision to engage (or not) in such projects is an important first step in the decision-making process, especially where opportunity costs exist (e.g., when currently-profitable farming land is taken out of production). However, consideration of longer-term risks posed by climate change and increasing exposure to climate extremes (hence risks to current production values) may also be critical (Hughes and Gooday, 2021).

Risk implies uncertainty, which is inherent in complex dynamic interactive (e.g., environmental) systems. This is particularly the case in instances where our understanding of an issue is still evolving. Environmental management is often termed a 'wicked problem' (Parrott, 2017) as it involves complex, interconnected challenges that lack clear-cut solutions, making it difficult to gauge the effectiveness of management decisions. Such situations require explicit consideration and quantification of uncertainties (Williams and Johnson, 2017).

The ability to model and predict risks in complex dynamic ecosystems was, until quite recently, limited due to difficulties in (i) quantifying the causal relationships between multiple interacting factors and outcomes, and (ii) capturing uncertainty. Bayesian network (BN) tools—based on Bayes' theorem, which describes the likelihood or probability of an event given prior knowledge of the conditions related to the event—are increasingly used to understand and inform the management of such systems (Hart and Pollino, 2008; Merritt et al., 2010; Alvandi et al., 2023). This project adopts a Bayesian approach to developing a prototype decision support system, as described below.

Decision Support Tools (DST)

Decision support tools (DSTs) are resources that are designed to assist individuals in making informed choices, particularly in complex contexts such as healthcare and environmental (including agricultural) management. They do so by providing evidence-based information, outlining options, and helping individuals consider their preferences and values alongside potential benefits and risks. In agriculture, DSTs aim to help farmers make informed decisions by providing data analysis, insights, and recommendations. By integrating diverse information, often from technologies such as geographic information systems (GIS), remote sensing, and data analytics, they are designed to enable farmers to optimize farming practices, enhance productivity, reduce risks, and improve the profitability and increasingly the sustainability of their enterprise.

Key aspects of DSTs are/should be that they are evidence-based and user-friendly. In addition, they should help the decision-maker identify potential impacts, including risks. They can also play a role in facilitating informed discussions between programs and participants, and in helping individuals consider what is important to them when making decisions. Despite this, the uptake of DSTs has often been less than expected. As discussed in our previous MS9B report (Reardon-Smith et al, 2025), fifteen factors influence the uptake and usefulness, amongst farmers and their advisers, of decision support tools (Table 1). These provide a valuable checklist for the design and implementation of new DSTs.

Table 1. Checklist for the good design of DSTs (Rose et al., 2016)

1. Performance	Does the tool perform a useful function and work well?
2. Ease of use	Is the user interface easy to navigate?
3. Peer recommendation	Does it encourage peer-to-peer knowledge exchange?
4. Trust	Is the tool evidence-based and do we have the trust of users?
5. Cost	Is there a cost-benefit?
6. Habit	Does the tool match closely with existing habits of users?
7. Relevance to user	Can the tool say something useful about individual farms?
8. Farmer-advisor compatibility	Could the tool be targeted at advisors to encourage client uptake?
9. Age	Does the tool match the skills and habits of different age groups?
10. Scale of business	Is the tool applicable to different scales of farming?
11. Farming type	Is the tool applicable to different farming enterprises?
12. IT education	Does the tools require good IT skills to use?
13. Facilitating conditions	Can the tool be used effectively? Is there compatibility with existing devices? Is internet connectivity required?
14. Compliance	Does the tool help users satisfy legislative and compliance requirements?
15. Marketing	How do users find out about the tool?

In our previous MS9B report (Reardon-Smith et al, 2025), we presented a prototype decision tree (Figure 3) to support producers on marginal cropping land to source the critical information needed for them to make an informed decision about engaging (or not) in a registered environmental benefit payment project. The prototype decision tree clearly maps out choices, conditions, and outcomes, thereby providing clear guidance to assist the decision-making process by outlining the steps to be considered and information required to make such a decision. It asks key questions that highlight the information that should be considered at each step and points to the need to access advice/guidance where needed before proceeding on to the next step. Using a series of “YES/NO” logic-based questions, the decision tree enables the decision-maker to step through the series of considerations leading to an informed decision about proceeding to engage in the specific program/project under consideration. Using this tool, land managers will better understand the steps involved and further information/skills needed to implement a decision to undertake a registered environmental (carbon/biodiversity) benefits project; they will also be able to evaluate whether participation in an environmental benefits project is likely to be beneficial for them and other landholders with similar production systems in their region.

Coincidentally, we have since become aware of a recently published (May 2025) draft report by The Carbon Market Institute, entitled ‘Guidance for Landholders: a Checklist for Partnering on Carbon Farming Projects’, which includes a comparable decision tree (see p.5), along with a comprehensive list of questions that landholders should consider and links to additional information.

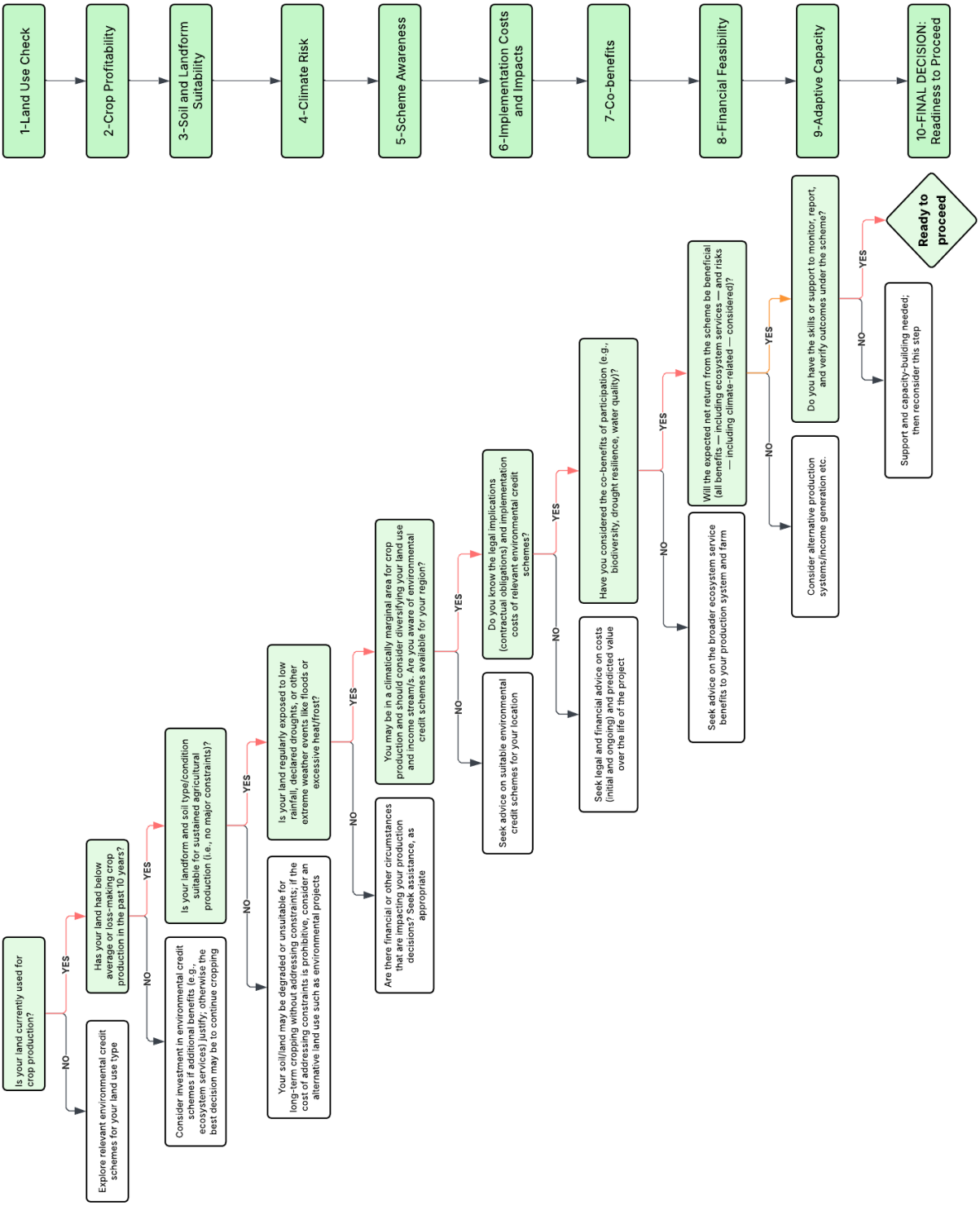

Figure 3. Prototype decision tree depicting the sequence of steps involved in identifying whether to invest in an environmental benefit (carbon/biodiversity) project on climatically-marginal cropping land.

This simple visual structure captures the logic and sequence of the decision-making processes (without requiring immediate data input) and provides end-users with a clear and consistent roadmap for the decision-making process. It will also be of value in facilitating stakeholder engagement in registered environmental benefit programs.

Developing a prototype decision support tool

This current Milestone 10a report documents the development of a prototype predictive environmental (including projected climate) model to better inform this decision-making process, specifically addressing Step 8 in the Decision Tree developed earlier and described in Figure 3 above. Based on the decision-making context of an individual cropping enterprise, our prototype DST takes a Bayesian network (BN) modelling approach to predict the probability of improved (and also less than beneficial) financial outcomes likely to result from a decision to invest in an environmental (in this case, carbon) benefit project.

Bayesian network models

Bayesian modelling frameworks such as Bayesian Networks (BNs) are increasingly used to conceptualise and analyse complex management systems (Pollino et al., 2006; Liedloff and Smith, 2010) and are particularly useful in NRM contexts. They allow the integration of a range of data types—including expert opinion—where data is limiting; facilitate identification of key knowledge/data gaps; enable explicit analysis of uncertainty associated with potential management and/or environmental scenarios (Pollino et al., 2006; Pollino and Henderson, 2010). All data in a BN is represented in terms of its probability; hence, uncertainty is propagated throughout the model. This enables the likelihood of particular outcomes to be predicted, given the condition or state of each constituent factor in the model, and thereby allows the risk associated with a management decision to be assessed (and understood) prior to implementation.

BN model development

Bayesian Networks (BNs) are probabilistic graphical system models that capture cause and effect (i.e., ‘if this, then that’) relationships between key variables that influence particular outcomes. This type of model integrates key factors (variables) and the

relationships between these—represented by boxes and arrows, respectively—to graphically describe the systems of concern (Figure 4). They provide explicit and transparent representation of (present understanding of) the system of interest (Stow and Borsuk, 2003). Critically, BNs also enable explicit treatment of uncertainty (Pollino and Henderson, 2010). The simplicity of the BN structure also allows a large number of state variables to be included, often without greatly increasing the complexity of the model or the computational power required to run it (Letcher et al. 2004), although Pollino and Henderson (2010) argue for model parsimony, where possible.

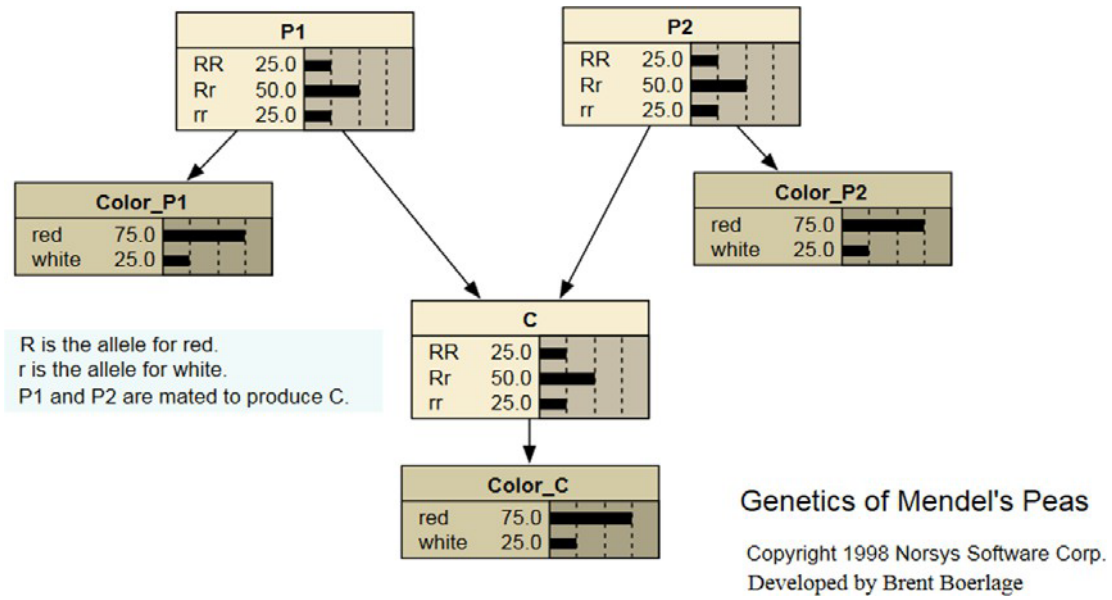

Figure 4. Simple BN model example (Source: Norsys Software Corp, 1992–2023)

Application of BNs

BNs are used to explore relationships between factors and system outcomes associated with particular objectives, and can be used to predict the probable outcome/effectiveness of particular management decisions and system changes (e.g. those predicted for climate change) (Pollino and Henderson, 2010). Unlike many other modelling approaches, BNs use probabilistic, rather than deterministic, expressions to characterise the strength of

relationships between variables (Borsuk et al., 2004). This means that BNs can incorporate both quantitative and qualitative information, as well as information of variable quality—such as subjective assessments (e.g. expert opinion) of the probability that a particular outcome will occur—where data may be limiting. Uncertainty is reflected in the model as the likelihood of the system being within a set of defined states for each variable. A further advantage of using probability is that models can be easily updated as new knowledge or data becomes available (Pollino and Henderson, 2010).

BN model outcomes are testable through structured review processes. Sensitivity analysis tools can be used to identify key causal factors within the model; this can also highlight specific knowledge gaps. Further, because information rapidly propagates through the network, the effect of particular management interventions or changed conditions can easily be examined, through scenario analysis, within the modelling framework, facilitating the examination of alternative decisions to optimise a particular outcome (Pollino et al. 2008; Pollino and Henderson, 2010).

A significant advantage of BNs over other modelling approaches in decision-making contexts is their relative simplicity. They are graphically based, readily interpreted and allow explicit documentation of assumptions and uncertainties, making them easier to understand and use than most modelling frameworks. This also makes them particularly useful as a communication tool for engaging with stakeholders (e.g. policy makers), where they can be used to develop a broader understanding of the modelled system (Pollino and Henderson, 2010).

Limitations of BNs

Despite their significant advantages, BNs do have certain limitations. Of relevance to this project, while BNs are able to incorporate qualitative (and possibly subjective) information, there are risks and limitations associated with different types of information and the sources of information used in creating a model need to be transparently documented. For example, expert judgement may be subject to cognitive and knowledge-based bias (Anderson, 1998; Baddeley et al., 2004; Burgman, 2005), hence caution

should be exercised when this is used in the absence of the necessary science (Drescher et al., 2013) to create BNs for use in decision making. Models based on expert judgment should not been seen as a substitute for data or research (Drescher et al., 2013).

So, in summary, while Bayesian networks can support decisions in complex and uncertain domains by assembling disparate information in a consistent and coherent framework and incorporating the uncertainties inherent in natural systems and decision making, where possible they should be informed by process-based understanding and verified against comprehensive datasets.

Model development

In this study, we developed a Bayesian Network (BN) model to assess how climate risk affects the financial viability of converting marginal land to generate alternative income streams using Norsys Netica™ software (Norsys Software Corp, 1992– 2023).

The prototype model structure captures the key elements, and interactions between these, that are relevant to a farmer's decision-making context, based on the knowledge and expertise of the research team. As such, the model captures the current process-based understanding of the issues associated with a decision to engage in a registered environmental benefits project on marginal cropping land, informed by the work the project team has completed and reported in earlier MS reports. Discussion with industry experts and decision makers may further inform the model structure and future data collection, which will further improve the model and enable validation. Full operationalisation of the model as a DST would require development of a user interface and ongoing improvements to the model as data accumulate.

Developing the conceptual framework/BN structure

The BN model was constructed using 'nature' (or 'chance') nodes (i.e., variables), which then enable the potential empirical states and range of values likely to be exhibited by

each of these model elements to be described. Variables were integrated (i.e., links between these were defined) according to current process-based understanding to create a graphical representation of the system and a single 'financial benefit' endpoint.

Environmental management issues are inherently both multivariate and multidimensional. Pollino and Henderson (2010) discuss the tension between model complexity or 'truthfulness' and the need for model parsimony to ensure that models do not exceed the 'power' of the data or incorporate so much detail that model accuracy is compromised. The number of parameters and interactions included in the BN model framework was therefore kept to a minimum to limit its complexity. While user feedback and its incorporation into the model will inform further refinement of the model, this overarching constraint must be observed.

Model parameterisation

Behind each variable in the model sits a Conditional Probability Table (CPT), which specifies the likelihood of the system being within each of the states defined for each variable. CPTs for the BN model are currently parameterised based on the understanding (i.e. expert opinion) of the model developers, who collectively have prior experience in climate risk and adaptation, rural finance, and agricultural and environmental management. At present, the probability values applied represent an educated first guess and the BN model is a base working model which can be further developed and refined over time with the incorporation of available data (e.g., regional historical climate data and crop gross margins), further data collection, and feedback from industry.

Model validation is yet to be conducted.

Model sensitivity testing

The sensitivity of the model response to variation in each of the model terms across the observed range within the prototype model dataset (with CPTs derived from expert judgement) was tested in NeticaTM. This analysis checks the relative strength of

relationships between variables (Pollino and Henderson, 2010) and quantifies the level of influence of each variable on model outcomes, expressed as a percentage reduction in variance (Norsys Software Corp, 1992– 2023). Given the model is not yet validated or populated with actual data, sensitivity analysis was conducted to test the logic of the expert derived model relationships in the model.

Results and Discussion

The BN framework

The final working model consists of a total of 14 variables, as listed in Table 2, along with the number of states defined in the model and the rationale for their inclusion. These are incorporated into the working BN model, as shown in Figure 5. Table 3 describes the dependencies (i.e., links between variable) in the model.

Table 2. Nodes and states included in the BN model

#	Node	States	Rationale
1	Region	Balonne-Maranoa, Central QLD, and Burnett-Mary	Regions previously identified (Kath et al., 2024a) as climatically marginal for cropping (Appendix A)
2	Rainfall Anomaly	Extremely Positive, Positive, Neutral, Negative, Extremely Negative	Extremely positive and extremely negative states represent the likelihood of extreme rainfall conditions (severe flooding and drought, respectively) associated with climatic variability
3	Temperature Anomaly	Extremely Positive, Positive, Neutral, Negative, Extremely Negative	Extremely positive and extremely negative states represent the likelihood of extreme temperature conditions (heatwaves and cold snaps/frost, respectively) associated with climatic variability
4	Crop Type	Cotton, Wheat, Sorghum, Chickpeas	Example crops grown in the regions
5	Irrigation	Yes, No	Irrigation is a form of climate risk adaptation that mitigates the risk of reduced crop yields due to rainfall deficits
6	Crop Gross Margin	High, Medium, Low	Crop gross margins represent the financial difference between the gross income from a crop (yield x price) and the variable costs associated with production.
7	Carbon Method	Soil Carbon, Tree Planting, Grazing Management	Selected methodologies relevant to crop production systems
8	Carbon Sequestration Potential	High, Medium, Low	Based on modelled or empirical data (documented in the academic literature)

#	Node	States	Rationale
9	Ecosystem Service Benefit	High, Low	Benefits to crop production systems from ecosystem services (e.g., nutrient availability; pest control; pollination) associated with enhanced carbon sequestration
10	Implementation Cost	High, Moderate, Low	Cost of implementing a selected carbon sequestration methodology
11	Carbon price	High, Medium, Low	Contract price for delivery of improved carbon outcomes ($/tonne)
12	Carbon Credit Value	High, Medium, Low	Sequestered carbon (tonnes/ha) x carbon price ($/tonne)
13	Input Cost Reduction	High, Medium, Low	Estimated economic benefit in terms of reduced input costs for crop production (e.g., use of artificial fertiliser and pest control technologies) where these are provided by ecosystem services through improved ecological function.
14	Financial Benefit	High, Medium, Low	Financial outcome resulting from the integration of carbon payments and crop production with higher ES benefits, hence reduced input costs.

Table 3. Dependencies in the BN model

Node	Depends on
Rainfall anomaly	Region
Temperature anomaly	Region
Crop gross margin	Crop type, Rainfall anomaly, Temperature anomaly, and Irrigation,
Carbon sequestration potential	Rainfall anomaly, Temperature anomaly, and Carbon method
Farm input cost reduction	Ecosystem service benefit
Carbon credit value	Carbon sequestration potential, Implementation cost, and Carbon price
Financial benefit	Crop gross margin, Farm input cost reduction, and Carbon credit value

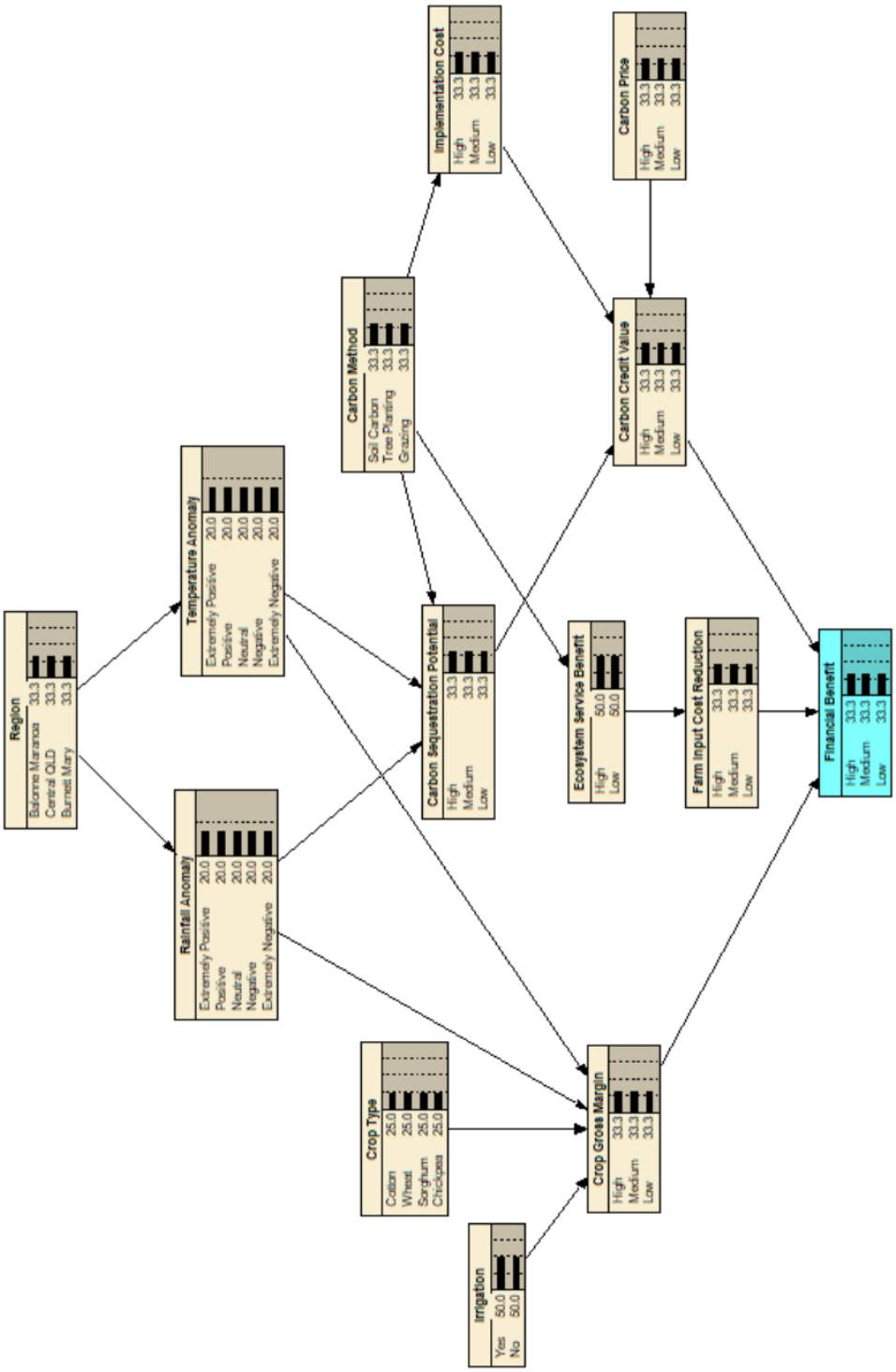

Figure 5. Prototype Bayesian network (BN) model for farm-level decision support

Model sensitivity

Sensitivity analysis was conducted to identify the most influential variables in the BN model on the query node, which in this case is 'Financial benefit'. The results from a sensitivity analysis show how much the beliefs, mean values, and other metrics of the query node are affected by a single finding at each of the other nodes in the network. Each of these is referred to as a finding node.

Below is an example of the sensitivity analysis results from the BBN for the marginal land model, in which the query node is "Financial Benefits" and the remaining nodes in the network serve as finding nodes. Figure 6 presents the sensitivity of Financial Benefits to each finding node, along with a column that ranks all nodes based on their level of influence on the Financial Benefits node.

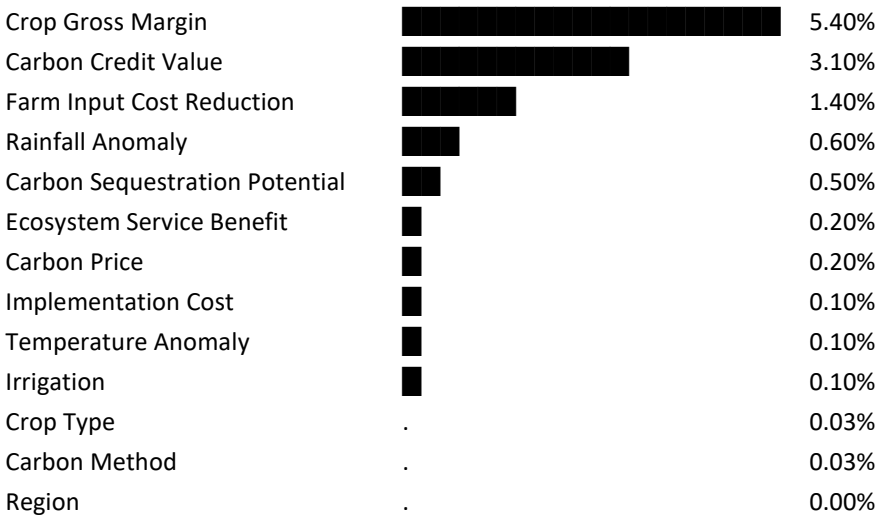

Figure 6. Sensitivity of the 'Financial Benefit' output variable (query node)

As can be seen in the sensitivity analysis results of the prototype BN model (Figure 6), Crop Gross Margin was found to be the most important driver of Financial Benefit results contributing over 5% to the model's total explanation of variance. Secondary drivers include Carbon Credit Value (3%) and Farm Input Cost Reduction (1.4%). Currently,

climatic and environmental factors, including Rainfall anomalies, Temperature anomalies, Carbon Sequestration Potential, Ecosystem Service Benefits, explain less than 2% of the overall sensitivity; however, given the model is not currently populated with empirical data and the values incorporated in the model are indicative only, these results are not yet reliable.

Training of the model based on a comprehensive dataset, and validation against strategic data collection on real world outcomes, will eventually facilitate this. Given the model is not currently data-informed or validated, results of the sensitivity analysis should not be used to support decision making without further industry review.

Milestone outcomes

The BN model developed in this project is a prototype and not currently presented as a robust evidence-based decision support tool. It does however have significant value as a learning and discussion tool. This project has highlighted the need for verification—and, where possible, incorporation of comprehensive robust farm level data—by farmers who have adopted registered carbon benefit projects. Such input is critical to further development of the model as an effective decision-support tool.

As it stands, the model is valuable as an industry engagement and communication tool to enhance understanding of risk and the potential value of engaging in these programs as a risk mitigation measure, and also as evidence of the need for investment in a targeted data collection/verification campaign.

This project has developed an initial risk-based predictive framework which captures current understandings of the potential financial outcomes associated with engagement in registered carbon sequestration projects on cropping land in Queensland's climatically-marginal broadacre cropping regions. It has potential, once verified and trained using empirical data, to increase industry understanding of the likely financial value of these programs, particularly where climatic marginality is likely to impact both cropping and carbon outcomes. It also has potential, when fully developed, to contribute to improved farm-level adaptive decision making and management by providing a consistent, reliable and informed approach to determining whether investment in a carbon benefit project is likely to be financially beneficial.

Next steps

Our next Milestone (MS11) activity will investigate how integrated re-investment of funds generated from carbon/biodiversity credits into climate risk management/adaption options (e.g., practices to improve soil condition, pasture improvement) can be optimised to enhance farm profitability while minimising risk (e.g., due to climate variability, carbon market volatility) to further increase farmer drought adaptation capacity, thereby generating a positive feedback loop that continually increases farmers' climate resilience over time.

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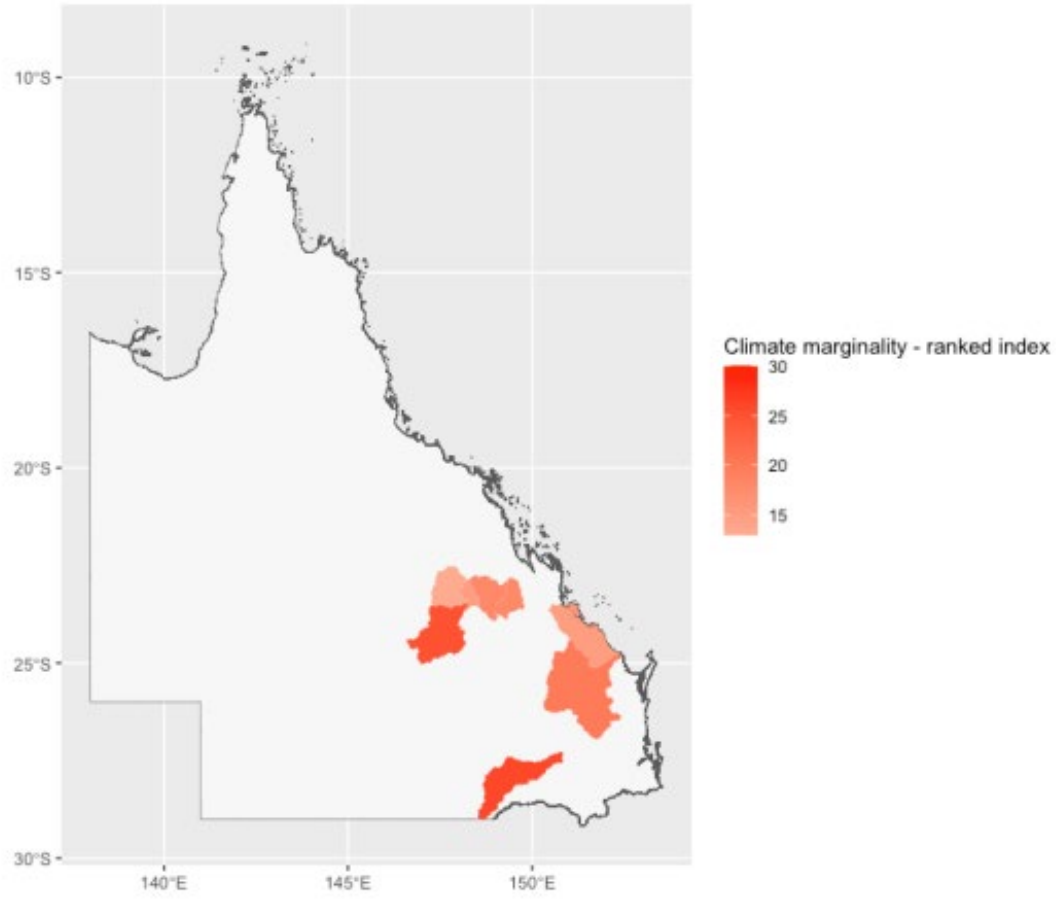
Appendices

Appendix A

Queensland's climatically-marginal cropping regions (from Kath et al., 2024a)



Appendix B

1. Conditional Probability Table (CPT)

The following CPTs are hypothetical, trend-consistent priors to initialise Netica. They reflect the DCAP3 evidence on climate marginality and profitability but are not empirical estimates; they are intended as defensible starting points that can be updated.

1.1. Region

State	Prior
Balonne-Maranoa	0.33
Central Queensland	0.33
Burnett-Mary	0.33

1.2. Irrigation

State	Prior
Yes	0.5
No	0.5

1.3. Carbon Method

State	Prior
Soil Carbon	0.33
Tree Planting	0.33
Grazing Management	0.33

1.4. Crop Type

State	Prior
Cotton	0.25
Wheat	0.25
Sorghum	0.25
Chickpea	0.25

1.5. Carbon Price

State	AUD/tonne CO_2e	Prior
Low	< $30	0.20
Medium	$30 - $40	0.60
High	>$40	0.20

1.6. Rainfall Anomaly | Region - priors

Region	ExPos	Pos	Neutral	Neg	ExNeg
Balonne-Maranoa	0.1	0.2	0.4	0.2	0.1
Central Queensland	0.1	0.2	0.4	0.2	0.1
Burnett-Mary	0.1	0.2	0.4	0.2	0.1

Remark: ExPos=extremely positive (Flooding), Pos=positive, Neg=negative, ExNeg=extremely negative (drought).

1.7. Temperature Anomaly | Region - priors

Region	ExPos	Pos	Neutral	Neg	ExNeg
Balonne-Maranoa	0.1	0.2	0.4	0.2	0.1
Central Queensland	0.1	0.2	0.4	0.2	0.1
Burnett-Mary	0.1	0.2	0.4	0.2	0.1

Remark: ExPos=extremely positive (extremely hot/heatwave), Pos=positive, Neg=negative, ExNeg=extremely negative (very cold/frost).

1.8. Implementation Cost | Carbon Method

Carbon Method	High	Moderate	Low
Soil Carbon	0.25	0.45	0.30
Tree Planting	0.25	0.45	0.30
Grazing	0.25	0.45	0.30

1.9. Ecosystem Service Benefit | Carbon Sequestration Potential

Higher vegetation/cover → stronger co-benefits

Sequestration Potential	High	Low
High	0.50	0.50
Medium	0.50	0.50
Low	0.50	0.50

1.10. Farm Input Cost Reduction | Ecosystem Service Benefit

Ecosystem Service Benefit	High	Low
High	0.7	0.3
Medium	0.5	0.5
Low	0.3	0.7

1.11. Crop Gross Margin | (Crop Type, Rainfall Anomaly, Irrigation, Temperature Anomaly)

Assumptions:

- Best-case scenario: Average-high rainfall anomaly + irrigation + mild temperatures → high gross margins
- Worst-case scenario: Severe drought + no irrigation + extreme heat → low gross margins.

Crop Type	Rainfall Anomaly	Irrigation	Temperature Anomaly	High	Medium	Low
Cotton	Positive	Yes	Neutral	0.65	0.25	0.10
Cotton	Positive	Yes	Positive	0.60	0.25	0.15
Cotton	Positive	Yes	Negative	0.70	0.25	0.05
Cotton	Neutral	Yes	Negative	0.60	0.35	0.05
Cotton	Positive	Yes	Extremely Positive	0.55	0.25	0.20
Cotton	Positive	Yes	Extremely Negative	0.55	0.25	0.20
Cotton	Positive	No	Negative	0.55	0.40	0.05
Cotton	Neutral	Yes	Neutral	0.55	0.35	0.10
Cotton	Positive	No	Neutral	0.50	0.40	0.10
Cotton	Neutral	Yes	Positive	0.50	0.35	0.15
Cotton	Positive	No	Positive	0.45	0.40	0.15
Cotton	Neutral	Yes	Extremely Positive	0.45	0.35	0.20
Cotton	Neutral	Yes	Extremely Negative	0.45	0.35	0.20
Cotton	Neutral	No	Negative	0.45	0.40	0.15
Cotton	Extremely Positive	Yes	Negative	0.40	0.35	0.25
Cotton	Positive	No	Extremely Positive	0.40	0.40	0.20
Cotton	Positive	No	Extremely Negative	0.40	0.40	0.20
Cotton	Neutral	No	Neutral	0.40	0.40	0.20
Cotton	Negative	Yes	Negative	0.40	0.40	0.20
Cotton	Extremely Positive	Yes	Neutral	0.35	0.35	0.30
Cotton	Extremely Positive	No	Negative	0.35	0.35	0.30
Cotton	Neutral	No	Positive	0.35	0.40	0.25
Cotton	Negative	Yes	Neutral	0.35	0.40	0.25
Cotton	Extremely Positive	Yes	Positive	0.30	0.35	0.35
Cotton	Extremely Positive	No	Neutral	0.30	0.35	0.35
Cotton	Neutral	No	Extremely Positive	0.30	0.40	0.30
Cotton	Neutral	No	Extremely Negative	0.30	0.40	0.30
Cotton	Negative	Yes	Positive	0.30	0.40	0.30
Cotton	Negative	No	Negative	0.30	0.40	0.30
Cotton	Extremely Negative	Yes	Negative	0.30	0.40	0.30
Cotton	Extremely Positive	Yes	Extremely Positive	0.25	0.35	0.40
Cotton	Extremely Positive	Yes	Extremely Negative	0.25	0.35	0.40
Cotton	Extremely Positive	No	Positive	0.25	0.35	0.40
Cotton	Negative	Yes	Extremely Positive	0.25	0.40	0.35
Cotton	Negative	Yes	Extremely Negative	0.25	0.40	0.35
Cotton	Negative	No	Neutral	0.25	0.40	0.35
Cotton	Extremely Negative	Yes	Neutral	0.25	0.40	0.35

Crop Type	Rainfall Anomaly	Irrigation	Temperature Anomaly	High	Medium	Low
Cotton	Extremely Positive	No	Extremely Positive	0.20	0.35	0.45
Cotton	Extremely Positive	No	Extremely Negative	0.20	0.35	0.45
Cotton	Negative	No	Positive	0.20	0.40	0.40
Cotton	Extremely Negative	Yes	Positive	0.20	0.40	0.40
Cotton	Negative	No	Extremely Positive	0.15	0.40	0.45
Cotton	Negative	No	Extremely Negative	0.15	0.40	0.45
Cotton	Extremely Negative	Yes	Extremely Positive	0.15	0.40	0.45
Cotton	Extremely Negative	Yes	Extremely Negative	0.15	0.40	0.45
Cotton	Extremely Negative	No	Negative	0.15	0.25	0.60
Cotton	Extremely Negative	No	Neutral	0.10	0.25	0.65
Cotton	Extremely Negative	No	Positive	0.05	0.25	0.70
Cotton	Extremely Negative	No	Extremely Positive	-	0.25	0.75
Cotton	Extremely Negative	No	Extremely Negative	-	0.25	0.75
Wheat	Positive	Yes	Neutral	0.60	0.30	0.10
Wheat	Positive	Yes	Positive	0.55	0.30	0.15
Wheat	Positive	Yes	Negative	0.65	0.30	0.05
Wheat	Positive	No	Negative	0.55	0.35	0.10
Wheat	Neutral	Yes	Negative	0.55	0.35	0.10
Wheat	Positive	Yes	Extremely Positive	0.50	0.30	0.20
Wheat	Positive	Yes	Extremely Negative	0.50	0.30	0.20
Wheat	Positive	No	Neutral	0.50	0.35	0.15
Wheat	Neutral	Yes	Neutral	0.50	0.35	0.15
Wheat	Positive	No	Positive	0.45	0.35	0.20
Wheat	Neutral	Yes	Positive	0.45	0.35	0.20
Wheat	Extremely Positive	Yes	Negative	0.40	0.35	0.25
Wheat	Positive	No	Extremely Positive	0.40	0.35	0.25
Wheat	Positive	No	Extremely Negative	0.40	0.35	0.25
Wheat	Neutral	Yes	Extremely Positive	0.40	0.35	0.25
Wheat	Neutral	Yes	Extremely Negative	0.40	0.35	0.25
Wheat	Neutral	No	Negative	0.40	0.40	0.20
Wheat	Negative	Yes	Negative	0.40	0.40	0.20
Wheat	Extremely Positive	Yes	Neutral	0.35	0.35	0.30
Wheat	Extremely Positive	No	Negative	0.35	0.35	0.30
Wheat	Neutral	No	Neutral	0.35	0.40	0.25
Wheat	Negative	Yes	Neutral	0.35	0.40	0.25
Wheat	Extremely Positive	Yes	Positive	0.30	0.35	0.35
Wheat	Extremely Positive	No	Neutral	0.30	0.35	0.35
Wheat	Neutral	No	Positive	0.30	0.40	0.30
Wheat	Negative	Yes	Positive	0.30	0.40	0.30
Wheat	Extremely Negative	Yes	Negative	0.30	0.40	0.30
Wheat	Extremely Positive	Yes	Extremely Positive	0.25	0.35	0.40
Wheat	Extremely Positive	Yes	Extremely Negative	0.25	0.35	0.40
Wheat	Extremely Positive	No	Positive	0.25	0.35	0.40
Wheat	Neutral	No	Extremely Positive	0.25	0.40	0.35

Crop Type	Rainfall Anomaly	Irrigation	Temperature Anomaly	High	Medium	Low
Wheat	Neutral	No	Extremely Negative	0.25	0.40	0.35
Wheat	Negative	Yes	Extremely Positive	0.25	0.40	0.35
Wheat	Negative	Yes	Extremely Negative	0.25	0.40	0.35
Wheat	Negative	No	Negative	0.25	0.40	0.35
Wheat	Extremely Negative	Yes	Neutral	0.25	0.40	0.35
Wheat	Extremely Positive	No	Extremely Positive	0.20	0.35	0.45
Wheat	Extremely Positive	No	Extremely Negative	0.20	0.35	0.45
Wheat	Negative	No	Neutral	0.20	0.40	0.40
Wheat	Extremely Negative	Yes	Positive	0.20	0.40	0.40
Wheat	Extremely Negative	No	Negative	0.20	0.25	0.55
Wheat	Negative	No	Positive	0.15	0.40	0.45
Wheat	Extremely Negative	Yes	Extremely Positive	0.15	0.40	0.45
Wheat	Extremely Negative	Yes	Extremely Negative	0.15	0.40	0.45
Wheat	Extremely Negative	No	Neutral	0.15	0.25	0.60
Wheat	Negative	No	Extremely Positive	0.10	0.40	0.50
Wheat	Negative	No	Extremely Negative	0.10	0.40	0.50
Wheat	Extremely Negative	No	Positive	0.10	0.25	0.65
Wheat	Extremely Negative	No	Extremely Positive	0.05	0.25	0.70
Wheat	Extremely Negative	No	Extremely Negative	0.05	0.25	0.70
Sorghum	Positive	Yes	Neutral	0.65	0.30	0.05
Sorghum	Positive	Yes	Positive	0.60	0.30	0.10
Sorghum	Positive	Yes	Negative	0.65	0.30	0.05
Sorghum	Positive	No	Negative	0.60	0.35	0.05
Sorghum	Neutral	Yes	Negative	0.60	0.35	0.05
Sorghum	Positive	Yes	Extremely Positive	0.55	0.30	0.15
Sorghum	Positive	Yes	Extremely Negative	0.55	0.30	0.15
Sorghum	Positive	No	Neutral	0.55	0.35	0.10
Sorghum	Neutral	Yes	Neutral	0.55	0.35	0.10
Sorghum	Positive	No	Positive	0.50	0.35	0.15
Sorghum	Neutral	Yes	Positive	0.50	0.35	0.15
Sorghum	Neutral	No	Negative	0.50	0.35	0.15
Sorghum	Negative	Yes	Negative	0.50	0.40	0.10
Sorghum	Extremely Positive	Yes	Negative	0.45	0.35	0.20
Sorghum	Positive	No	Extremely Positive	0.45	0.35	0.20
Sorghum	Positive	No	Extremely Negative	0.45	0.35	0.20
Sorghum	Neutral	Yes	Extremely Positive	0.45	0.35	0.20
Sorghum	Neutral	Yes	Extremely Negative	0.45	0.35	0.20
Sorghum	Neutral	No	Neutral	0.45	0.35	0.20
Sorghum	Negative	Yes	Neutral	0.45	0.40	0.15
Sorghum	Extremely Positive	Yes	Neutral	0.40	0.35	0.25
Sorghum	Extremely Positive	No	Negative	0.40	0.35	0.25
Sorghum	Neutral	No	Positive	0.40	0.35	0.25
Sorghum	Negative	Yes	Positive	0.40	0.40	0.20
Sorghum	Extremely Negative	Yes	Negative	0.40	0.40	0.20

Crop Type	Rainfall Anomaly	Irrigation	Temperature Anomaly	High	Medium	Low
Sorghum	Extremely Positive	Yes	Positive	0.35	0.35	0.30
Sorghum	Extremely Positive	No	Neutral	0.35	0.35	0.30
Sorghum	Neutral	No	Extremely Positive	0.35	0.35	0.30
Sorghum	Neutral	No	Extremely Negative	0.35	0.35	0.30
Sorghum	Negative	Yes	Extremely Positive	0.35	0.40	0.25
Sorghum	Negative	Yes	Extremely Negative	0.35	0.40	0.25
Sorghum	Negative	No	Negative	0.35	0.40	0.25
Sorghum	Extremely Negative	Yes	Neutral	0.35	0.40	0.25
Sorghum	Extremely Positive	Yes	Extremely Positive	0.30	0.35	0.35
Sorghum	Extremely Positive	Yes	Extremely Negative	0.30	0.35	0.35
Sorghum	Extremely Positive	No	Positive	0.30	0.35	0.35
Sorghum	Negative	No	Neutral	0.30	0.40	0.30
Sorghum	Extremely Negative	Yes	Positive	0.30	0.40	0.30
Sorghum	Extremely Positive	No	Extremely Positive	0.25	0.35	0.40
Sorghum	Extremely Positive	No	Extremely Negative	0.25	0.35	0.40
Sorghum	Negative	No	Positive	0.25	0.40	0.35
Sorghum	Extremely Negative	Yes	Extremely Positive	0.25	0.40	0.35
Sorghum	Extremely Negative	Yes	Extremely Negative	0.25	0.40	0.35
Sorghum	Extremely Negative	No	Negative	0.25	0.30	0.45
Sorghum	Negative	No	Extremely Positive	0.20	0.40	0.40
Sorghum	Negative	No	Extremely Negative	0.20	0.40	0.40
Sorghum	Extremely Negative	No	Neutral	0.20	0.30	0.50
Sorghum	Extremely Negative	No	Positive	0.15	0.30	0.55
Sorghum	Extremely Negative	No	Extremely Positive	0.10	0.30	0.60
Sorghum	Extremely Negative	No	Extremely Negative	0.10	0.30	0.60
Chickpea	Positive	Yes	Neutral	0.60	0.30	0.10
Chickpea	Positive	Yes	Positive	0.55	0.30	0.15
Chickpea	Positive	Yes	Negative	0.65	0.30	0.05
Chickpea	Positive	No	Negative	0.55	0.35	0.10
Chickpea	Neutral	Yes	Negative	0.55	0.35	0.10
Chickpea	Positive	Yes	Extremely Positive	0.50	0.30	0.20
Chickpea	Positive	Yes	Extremely Negative	0.50	0.30	0.20
Chickpea	Positive	No	Neutral	0.50	0.35	0.15
Chickpea	Neutral	Yes	Neutral	0.50	0.35	0.15
Chickpea	Positive	No	Positive	0.45	0.35	0.20
Chickpea	Neutral	Yes	Positive	0.45	0.35	0.20
Chickpea	Positive	No	Extremely Positive	0.40	0.35	0.25
Chickpea	Positive	No	Extremely Negative	0.40	0.35	0.25
Chickpea	Neutral	Yes	Extremely Positive	0.40	0.35	0.25
Chickpea	Neutral	Yes	Extremely Negative	0.40	0.35	0.25
Chickpea	Neutral	No	Negative	0.40	0.40	0.20
Chickpea	Extremely Positive	Yes	Negative	0.35	0.35	0.30
Chickpea	Neutral	No	Neutral	0.35	0.40	0.25
Chickpea	Negative	Yes	Negative	0.35	0.40	0.25

Crop Type	Rainfall Anomaly	Irrigation	Temperature Anomaly	High	Medium	Low
Chickpea	Extremely Positive	Yes	Neutral	0.30	0.35	0.35
Chickpea	Extremely Positive	No	Negative	0.30	0.35	0.35
Chickpea	Neutral	No	Positive	0.30	0.40	0.30
Chickpea	Negative	Yes	Neutral	0.30	0.40	0.30
Chickpea	Extremely Positive	Yes	Positive	0.25	0.35	0.40
Chickpea	Extremely Positive	No	Neutral	0.25	0.35	0.40
Chickpea	Neutral	No	Extremely Positive	0.25	0.40	0.35
Chickpea	Neutral	No	Extremely Negative	0.25	0.40	0.35
Chickpea	Negative	Yes	Positive	0.25	0.40	0.35
Chickpea	Negative	No	Negative	0.25	0.35	0.40
Chickpea	Extremely Negative	Yes	Negative	0.25	0.40	0.35
Chickpea	Extremely Positive	Yes	Extremely Positive	0.20	0.35	0.45
Chickpea	Extremely Positive	Yes	Extremely Negative	0.20	0.35	0.45
Chickpea	Extremely Positive	No	Positive	0.20	0.35	0.45
Chickpea	Negative	Yes	Extremely Positive	0.20	0.40	0.40
Chickpea	Negative	Yes	Extremely Negative	0.20	0.40	0.40
Chickpea	Negative	No	Neutral	0.20	0.35	0.45
Chickpea	Extremely Negative	Yes	Neutral	0.20	0.40	0.40
Chickpea	Extremely Positive	No	Extremely Positive	0.15	0.35	0.50
Chickpea	Extremely Positive	No	Extremely Negative	0.15	0.35	0.50
Chickpea	Negative	No	Positive	0.15	0.35	0.50
Chickpea	Extremely Negative	Yes	Positive	0.15	0.40	0.45
Chickpea	Extremely Negative	No	Negative	0.15	0.20	0.65
Chickpea	Negative	No	Extremely Positive	0.10	0.35	0.55
Chickpea	Negative	No	Extremely Negative	0.10	0.35	0.55
Chickpea	Extremely Negative	Yes	Extremely Positive	0.10	0.40	0.50
Chickpea	Extremely Negative	Yes	Extremely Negative	0.10	0.40	0.50
Chickpea	Extremely Negative	No	Neutral	0.10	0.20	0.70
Chickpea	Extremely Negative	No	Positive	0.05	0.20	0.75
Chickpea	Extremely Negative	No	Extremely Positive	-	0.20	0.80
Chickpea	Extremely Negative	No	Extremely Negative	-	0.20	0.80

1.12. ***Carbon Sequestration Potential | (Carbon method, Rainfall anomaly, Temperature anomaly)***

Carbon Method	Rainfall Anomaly	Temperature Anomaly	High	Medium	Low
Soil Carbon	Positive	Neutral	0.45	0.40	0.15
Soil Carbon	Positive	Negative	0.50	0.40	0.10
Soil Carbon	Neutral	Negative	0.45	0.45	0.10
Soil Carbon	Positive	Positive	0.40	0.40	0.20
Soil Carbon	Neutral	Neutral	0.40	0.45	0.15
Soil Carbon	Positive	Extremely Positive	0.35	0.40	0.25
Soil Carbon	Positive	Extremely Negative	0.35	0.40	0.25
Soil Carbon	Neutral	Positive	0.35	0.45	0.20
Soil Carbon	Extremely Positive	Negative	0.30	0.45	0.25
Soil Carbon	Neutral	Extremely Positive	0.30	0.45	0.25
Soil Carbon	Neutral	Extremely Negative	0.30	0.45	0.25
Soil Carbon	Negative	Negative	0.30	0.45	0.25
Soil Carbon	Extremely Positive	Neutral	0.25	0.45	0.30
Soil Carbon	Negative	Neutral	0.25	0.45	0.30
Soil Carbon	Extremely Positive	Positive	0.20	0.45	0.35
Soil Carbon	Negative	Positive	0.20	0.45	0.35
Soil Carbon	Extremely Negative	Negative	0.20	0.40	0.40
Soil Carbon	Extremely Positive	Extremely Positive	0.15	0.45	0.40
Soil Carbon	Extremely Positive	Extremely Negative	0.15	0.45	0.40
Soil Carbon	Negative	Extremely Positive	0.15	0.45	0.40
Soil Carbon	Negative	Extremely Negative	0.15	0.45	0.40
Soil Carbon	Extremely Negative	Neutral	0.15	0.40	0.45
Soil Carbon	Extremely Negative	Positive	0.10	0.40	0.50
Soil Carbon	Extremely Negative	Extremely Positive	0.05	0.40	0.55
Soil Carbon	Extremely Negative	Extremely Negative	0.05	0.40	0.55
Tree Planting	Positive	Neutral	0.70	0.25	0.05
Tree Planting	Positive	Positive	0.65	0.25	0.10
Tree Planting	Positive	Negative	0.75	0.25	-
Tree Planting	Neutral	Negative	0.65	0.30	0.05
Tree Planting	Neutral	Neutral	0.60	0.30	0.10
Tree Planting	Positive	Extremely Positive	0.60	0.25	0.15
Tree Planting	Positive	Extremely Negative	0.60	0.25	0.15
Tree Planting	Neutral	Positive	0.55	0.30	0.15
Tree Planting	Neutral	Extremely Positive	0.50	0.30	0.20
Tree Planting	Neutral	Extremely Negative	0.50	0.30	0.20
Tree Planting	Extremely Positive	Negative	0.40	0.40	0.20
Tree Planting	Negative	Negative	0.40	0.40	0.20

Carbon Method	Rainfall Anomaly	Temperature Anomaly	High	Medium	Low
Tree Planting	Extremely Positive	Neutral	0.35	0.40	0.25
Tree Planting	Negative	Neutral	0.35	0.40	0.25
Tree Planting	Extremely Positive	Positive	0.30	0.40	0.30
Tree Planting	Negative	Positive	0.30	0.40	0.30
Tree Planting	Extremely Positive	Extremely Positive	0.25	0.40	0.35
Tree Planting	Extremely Positive	Extremely Negative	0.25	0.40	0.35
Tree Planting	Negative	Extremely Positive	0.25	0.40	0.35
Tree Planting	Negative	Extremely Negative	0.25	0.40	0.35
Tree Planting	Extremely Negative	Negative	0.15	0.40	0.45
Tree Planting	Extremely Negative	Neutral	0.15	0.40	0.45
Tree Planting	Extremely Negative	Positive	0.15	0.40	0.45
Tree Planting	Extremely Negative	Extremely Positive	0.10	0.40	0.50
Tree Planting	Extremely Negative	Extremely Negative	0.10	0.40	0.50
Grazing	Positive	Positive	0.20	0.40	0.40
Grazing	Neutral	Neutral	0.20	0.40	0.40
Grazing	Positive	Negative	0.30	0.40	0.30
Grazing	Positive	Neutral	0.25	0.40	0.35
Grazing	Neutral	Negative	0.25	0.40	0.35
Grazing	Extremely Positive	Negative	0.20	0.40	0.40
Grazing	Extremely Positive	Neutral	0.15	0.40	0.45
Grazing	Positive	Extremely Positive	0.15	0.40	0.45
Grazing	Positive	Extremely Negative	0.15	0.40	0.45
Grazing	Neutral	Positive	0.15	0.40	0.45
Grazing	Negative	Negative	0.15	0.35	0.50
Grazing	Extremely Positive	Positive	0.10	0.40	0.50
Grazing	Neutral	Extremely Positive	0.10	0.40	0.50
Grazing	Neutral	Extremely Negative	0.10	0.40	0.50
Grazing	Negative	Neutral	0.10	0.35	0.55
Grazing	Extremely Negative	Negative	0.10	0.30	0.60
Grazing	Extremely Positive	Extremely Positive	0.05	0.40	0.55
Grazing	Extremely Positive	Extremely Negative	0.05	0.40	0.55
Grazing	Negative	Positive	0.05	0.35	0.60
Grazing	Negative	Extremely Positive	-	0.35	0.65
Grazing	Negative	Extremely Negative	-	0.35	0.65
Grazing	Extremely negative	Neutral	0.05	0.30	0.65
Grazing	Extremely Negative	Extremely Positive	-	0.25	0.75
Grazing	Extremely Negative	Positive	-	0.30	0.70
Grazing	Extremely Negative	Extremely Negative	-	0.25	0.75

1.13. Carbon Credit

Carbon Sequestration Potential	Implementation Cost	Carbon Price	High	Medium	Low
High	Low	High	0.85	0.12	0.03
High	Medium	High	0.75	0.2	0.05
High	Low	Medium	0.7	0.25	0.05
Medium	Low	High	0.7	0.25	0.05
High	High	High	0.6	0.3	0.1
Medium	Medium	High	0.6	0.3	0.1
High	Medium	Medium	0.55	0.35	0.1
Medium	Low	Medium	0.55	0.35	0.1
High	Low	Low	0.5	0.35	0.15
Low	Low	High	0.5	0.35	0.15
Medium	High	High	0.45	0.35	0.2
High	High	Medium	0.4	0.45	0.15
Medium	Medium	Medium	0.4	0.45	0.15
Low	Medium	High	0.4	0.4	0.2
High	Medium	Low	0.35	0.4	0.25
Medium	Low	Low	0.35	0.4	0.25
Low	Low	Medium	0.35	0.4	0.25
Medium	High	Medium	0.25	0.45	0.3
Low	High	High	0.25	0.4	0.35
Low	Medium	Medium	0.2	0.45	0.35
High	High	Low	0.2	0.4	0.4
Medium	Medium	Low	0.2	0.4	0.4
Low	Low	Low	0.15	0.4	0.45
Medium	High	Low	0.1	0.35	0.55
Low	High	Medium	0.1	0.35	0.55
Low	Medium	Low	0.05	0.35	0.6
Low	High	Low	0.05	0.2	0.75

1.14. Financial Benefit

Crop Gross Margin	Farm Input Cost Reduction	Carbon Credit Value	High	Medium	Low
High	High	High	0.9	0.09	0.01
High	Medium	High	0.8	0.15	0.05
High	High	Medium	0.75	0.2	0.05
Medium	High	High	0.75	0.2	0.05
High	Low	High	0.7	0.2	0.1
High	Medium	Medium	0.65	0.25	0.1
Medium	Medium	High	0.65	0.25	0.1
Medium	High	Medium	0.6	0.3	0.1
High	High	Low	0.6	0.25	0.15
High	Low	Medium	0.55	0.3	0.15
Medium	Low	High	0.55	0.3	0.15
Medium	Medium	Medium	0.5	0.35	0.15
Low	High	High	0.5	0.35	0.15
High	Medium	Low	0.5	0.3	0.2
Medium	High	Low	0.45	0.35	0.2
Medium	Low	Medium	0.4	0.4	0.2
Low	Medium	High	0.4	0.4	0.2
High	Low	Low	0.4	0.35	0.25
Medium	Medium	Low	0.35	0.4	0.25
Low	High	Medium	0.35	0.4	0.25
Low	Low	High	0.3	0.4	0.3
Medium	Low	Low	0.25	0.45	0.3
Low	Medium	Medium	0.25	0.45	0.3
Low	High	Low	0.2	0.45	0.35
Low	Medium	Low	0.15	0.4	0.45
Low	Low	Medium	0.15	0.4	0.45
Low	Low	Low	0.05	0.25	0.7