Development of Decision Support Tools for Water Energy Food Infrastructure Management of Sri Lanka

By

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To my father, Asison De Silva Manikkuwahandi (1947-2019)

Whose love, guide and encouragement day & night.….

Inspires me to go on adventures.

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LIST OF ACRONYMS

ADAPT-SL	Agricultural Decision making and Adaptation to Precipitation Trends of Sri Lanka
GDP	Gross Domestic Product
ENSO	El-Nino-Southern Oscillation
IOD	Indian Ocean Dipole
PDO	Pacific decadal oscillation
AMO	Atlantic multi-decadal mode oscillation
ITCZ	Intertropical convergence zone
NEM	Northeast monsoon
FIM	First inter-monsoon
SWM	South western monsoon
SIM	Second inter-monsoon
MEI	Multivariate ENSO Index
DMI	Dipole Mode Index
QDA	Quadratic discriminant analysis
MOEA	Multiobjective optimization evolutionary algorithms
MCDA	Multicriteria decision analysis
ELECTRE	Elimination and choice expressing reality
MAVT	Multi attribute value theory
DM	Decision makers
EIRR	Economic internal rate of return
CEB	Ceylon Electricity Board

MASL	Mahaweli Authority of Sri Lanka
WASP-IV	Wien Automatic System Planning version IV
PM	Particulate matters
ENS	Energy Not Served
LOLP	Loss of Load Probability
PVRR	Present value of the revenue requirement
RBR	Risk-benefit ratio
DSM	Demand Side Management
NG	Natural Gas
VRE	Variable Renewable Energy
RC	Reference case
EM	Energy mix case
EE	Energy efficiency case
IR	Maximum indigenous resource case
LE	Low emission case
ES	Energy security case
OFC	Other Food Crop

CHAPTER 1

Introduction

1.1 Overview

The energy and food sectors of the economy heavily rely on water resources. Agriculture accounts for 70% of global water withdrawal (FAO, 2017) and 90% of power generation technologies are water intensive (WWAP, 2014). Water, energy, and food security rely on infrastructure. Recognition of the relationship between water, energy, food sectors has led to new demands for infrastructure and technology solutions.

Population growth, urbanization, economic growth and other factors are projected to increase the demand for energy and food. Presently, 1.1 billion people do not have access to electricity (U.S. Energy Information Adminstration, 2018). Currently 15% of present fresh water withdrawal is used for electricity production (United Nations, 2018). Addition of new energy infrastructure will demand 85% more water by 2050. On the other hand, the predicted population of 9.1 billion by 2050 will increase food demand by 70% with a concomitant increase of 19% in demand for water (UN Water, 2012). The interdependence of water and energy infrastructure multiplies as demand for each sector increases (Rodriguez, Berg, & Mcmahon, 2013).

Facing the challenges of high demand for energy, water, and food is made more difficult by uncertainty of water availability. Climate change impacts water availability with shifts in precipitation patterns, increases in extreme events, and changes to evapotranspiration. All these climate factors can alter energy and food production as well. Water is necessary for hydropower generation and for the cooling of thermal power plants (Rodriguez et al., 2013). In addition, the El-Nino-Southern Oscillation (ENSO) phenomena and other modes of variability of the tropical ocean impacts global and regional weather patterns (Denise, Rogers, & Beringer, 2017; Seibert, Merz, & Apel, 2017). Uncertainty created by climate change and other factors is expected to lead to high competition for water and high demand for new and upgraded water and energy infrastructure.

Infrastructures for water resources management and energy systems are complex, requiring numerous resources, high capital investments, technical expertise, and a systematic approach to develop them. In order to optimize the resource use, understanding of the interactions between water resources and energy systems including both trade-offs and synergies is essential (Rodriguez et al., 2013). Both sectors depend on uncertain renewable resources (e.g. water, wind, and solar) and fossil fuels. Therefore, multidisciplinary technical experts on the resources, technology, economy, and the environment are required for infrastructure planning and management.

Both sectors must achieve multiple objectives and must be evaluated by multiple aspects, while including stakeholder preferences. Supplying reliable and affordable electricity to the people requires economic efficiency, technical reliability, and environmental sustainability. Similarly, water resources are managed to maximize the economic benefits, food security, assurance of clean water supply, generation of clean energy from hydropower, poverty reduction, and management of these systems with the minimum disturbance to the environment.

Construction of water and energy infrastructure systems is often delayed not only due to an initial high investment requirement, but also a lack of stakeholder consensus. Multiple stakeholders have diverse preferences and unique priorities when striving to achieve the multiple objectives of these infrastructure systems. Hence, efficient decisions for multipurpose water resources management are best achieved when taking into account the interrelationships among economic, social, and environmental systems with a clear recognition that stakeholders will value various aspects of any plan differently.

Optimized water-energy infrastructure development in developing countries is particularly difficult to achieve. High population growth rates, urbanization, and economic development fuel a high demand for infrastructure. Economies of these countries are strongly linked with the new infrastructure development, and high investments in new infrastructure are part of the national budgets. Over the last two decades, attention to power generation has been increased in multiple ways. One challenge is transition towards low carbon pathways in power generation along with emphasis of economic developments (Bazilian, Hobbs, Blyth, MacGill, & Howells, 2011). In addition to that, existing weak infrastructure in physical and institutional structures (Iizuka, 2015) add more challenge to infrastructure investments through multinational financing institutions (World Bank group, 2013). Lack of stakeholder consultation throughout the planning process is a big obstacle for the collaborative decisions of multi sector stakeholders.

Sri Lanka is a water rich developing country. Nevertheless, as the energy and food sectors compete for water, the pressure to develop new water and energy infrastructure stresses available resources. In 2016, the agricultural sector contributed 5.8% to the GDP, employing 27.1% of population (Central Bank of Sri Lanka, 2018). In 2008, 32% of agriculture relied upon irrigation water and the government is working on increasing the irrigation infrastructure (Ministry of Irrigation and Water Resources Management, 2013b). In the energy sector, hydropower is the main indigenous resource contributing 25% to electricity generation in 2016. Hydropower caters the ancillary-service of the power sector, where its importance has been increasing with the new additions of variable renewable energy sources. As a zero internal fossil fuel nation, the Sri Lankan government gives the highest priority to integrate renewable energy sources into the electricity sector which currently accounts for 48% in the present power generation capacity (Ceylon Electricity Board, 2016).

The water intensive economy of Sri Lanka faces multiple challenges in water resources management and energy systems infrastructure planning. As a small tropical island, the country is highly vulnerable to climate changes (Nurse, L.A., G. Sem, J.E. Hay, A.G. Suarez, P.P. Wong & Ragoonaden, 2001). Both uncertainty of water resource availability and high dependence have created serious national concerns for water resources management. Sri Lanka also faces several challenges in infrastructure expansion due to lack of resources and lack of decision makers' agreement.

1.2 Study Objectives

The complexity of the water-energy-food systems requires a more systematic approach to planning and management of the infrastructure than has occurred in the past. This research combines water, climate, energy and social data, and physics-based relationships of water and energy systems and diverse mathematical modelling capabilities to create decision support tools for water resources and power generation infrastructure planning and management. The decision tools are created by combining physics-based simulation models, optimization and data driven techniques, and decision analytics techniques that can incorporate stakeholder views in the planning process. The research objectives are as follows:

Objective 1: Explore teleconnections between rainfall and large climate patterns to determine whether seasonal forecasts to inform water use can be developed.

Objective 2: Achieve efficient water resource use by assessing the water allocation options of multipurpose reservoir systems in multiple measures.

Objective 3: Determine the operation policies for reservoir cascades that optimize multiple objectives under uncertain river flows.

Objective 4: Evaluate the expansion of water resources infrastructure using multiple criteria.

Objective 5: Support the choice of a future power generation pathway considering multiple objectives.

Uncertainty of spatial and temporal water availability is the major challenge of water-energy infrastructure planning. Hence, a season-ahead forecast of how monsoon rainfall could deviate from the average is highly important for planning adaptation measures to the power system as well as agriculture systems. In Chapter 2, we explore climate teleconnection to El Nino Southern Oscillation and the Indian Ocean Dipole to identify the dry and wet conditions of seasonal rainfall using data driven methods. Results suggest that season-ahead forecasts should be useful in identifying the likelihood of droughts. Identifying droughts ahead of the season would be really useful for water and energy planners to make the adaptation measures.

In Chapter 3, we concentrate on evaluating the water resource management decisions of a multipurpose reservoir cascade. Cascades are built and operated to overcome the spatial and temporal variability of natural water flows. To evaluate policies that seek to reduce risks and increase resilience of the cascade system, a system dynamics simulation of the complex cascade infrastructure, hydrology, water demands and operational rules is applied. The relatively simple model created in MATLAB/Simulink platform is used to evaluate the Mahaweli reservoir cascade hydropower and agriculture water users' performances. Study results expose the trade-offs among competitive water users, and how spatial variability of land properties and water availability interact with infrastructure to produce spatial and temporal distributions of reliability, resilience and vulnerability measures across the overall system being modeled.

In order to design robust management policies of large reservoir cascades for hydropower and agriculture, it is important to consider the effects of river flow variability (Julianne D Quinn et al., 2018). Multiobjective optimization evolutionary algorithms (MOEA) combined with simulation models facilitate the identification of desirable cascade operation policies for variable stream flows. However, these techniques also impose challenges of dimensionality. In Chapter 4, I identify the most important segments of the reservoir cascade, and divide the problem into two stages to avoid problems of dimensionality. The MOEA optimization method is applied to derive the Pareto optimal solution set which can be used to select operation rules by analyzing trade-offs between hydropower energy and agricultural yield.

Water and energy managers face challenges in infrastructure expansion of the hydropower and reservoir network; technical, economic, social, and environmental aspects related to infrastructure expansion must be considered in planning and implementation. The preferences of multiple stakeholders typically must be incorporated. In Chapter 5, using multicriteria decision analysis method (MCDA), we assess the infrastructure expansion alternatives to increase the water resources management capabilities of Mahaweli cascade, and the extension of benefits to many water users. Results suggest that an alternative that performs reasonably well across all criteria can balance the preferences of stakeholders representing water, energy, agriculture, hydrology, social, environment and economic sectors.

While competing for limited uncertain water for hydropower, energy managers have trouble selecting the future power generation pathways to satisfy increasing electricity demand. In Chapter 6, we deployed a planning method combining optimization and decision methods to help decision makers by identifying the strengths and weaknesses of power generation pathways considering multiple technologies, multiple objectives, and the variety of views held by different stakeholder groups. Results derived from testing the method using hypothetical decision makers suggested that a mix of renewable resources and fossil fuel constitutes an alternative that achieves energy security while satisfying multiple criteria associated with future power generation to a reasonable extent.

Chapter 7 synthesizes the findings from this dissertation, and discusses the broader impacts to the water-energy-food infrastructure planning of Sri Lanka and beyond.

CHAPTER 2

Identifying ENSO Influences on Rainfall with Classification Models: Implications for Water Resource Management of Sri Lanka

2.1 Introduction

The spatial and temporal uncertainty of water availability is one of the major challenges in water resource management of Sri Lanka. Out of several river basins, the majority of water infrastructure is associated with the Mahaweli and Kelani river basins which spread across several climate zones based on monsoon rainfall. Hence, understanding patterns and identifying trends in seasonal to annual precipitation are very important for water infrastructure management. In particular, forecasts that incorporate such information can be used to inform decisions about the operation of Mahaweli and Kelani multipurpose reservoir systems in the face of changing climate conditions.

Success in making useful forecasts often is achieved by considering climate teleconnections such as the El-Nino-Southern Oscillation (ENSO) as related to sea surface temperature variations and air pressure over the globe using empirical data (Amarasekera et.al., 1997; Denise et.al., 2017; Korecha and Sorteberg, 2013; Seibert et.al., 2017). Also, modes of variability of other tropical oceans can be related to regional precipitation (Dettinger and Diaz, 2000; Eden et al., 2015; Maity and Kumar, 2006; Malmgren et al., 2005; Ranatunge et al., 2003; Suppiah, 1996; Roplewski and Halpert, 1996). For example, the effect of the Indian Ocean Dipole (IOD) is identified as independent of the ENSO effect (Eden et al., 2015). Pacific decadal oscillation (PDO), Atlantic multi-decadal mode oscillation (AMO), ENSO, and IOD teleconnections to precipitation have been found by many studies over the globe. Variations of precipitation in the United States are explained by ENSO, PDO and AMO (Eden et al., 2015; National Oceanic and Atmospheric Administration, 2017; Ward et.al., 2014), in African countries by ENSO, AMO and IOD (Reason et.al., 2006), and in South east Asian countries by ENSO: Indonesia (Lee, 2015; Nur'utami and Hidayat, 2016), Thailand (Singhrattna et.al., 2005), China (Cao et al., 2017; Ouyang et al., 2014; Qiu et.al., 2014). Australia (Bureau of Meteorology, 2012; Verdon and Franks, 2005), and central and south Asia (Gerlitz et al., 2016).

The impact of ENSO and IOD on the position of the intertropical convergence zone (ITCZ) has been identified as a primary factor driving south Asian tropical climate variations. South Asian countries get precipitation from two monsoons from the movements of ITCZ in boreal summer (2^0 N) and boreal winter (8^0 S). The South western monsoon (summer monsoon) is during June-August months and the North eastern monsoon (winter monsoon) is during December – February months (Schneider et.al, 2014). Climate teleconnections have been studied for summer monsoons (Singhrattna et. al., 2005; Surendran et.al., 2015) and winter monsoons (Zubair and Ropelewski, 2006), A negative correlation of ENSO with Indian summer monsoon has been identified (Jha et al., 2016; Surendran et al., 2015).

The objective of this chapter is to explore the climate teleconnection to dual monsoons and inter monsoons. Water resource management decisions typically are based on precipitation throughout the year and it is extremely important to explore the possibility that rainfall might be related to teleconnection indices for which seasonal forecasts are available. Sri Lanka gets rainfall from two monsoons and two inter-monsoons. We explore ENSO and IOD climate teleconnection to Sri Lanka precipitation throughout the year. Past studies have identified climate teleconnection linking precipitation to climate indices for several months and monsoon seasons, and shown the importance of these for forecasting rainfall in river basins (Chandimala and Zubair, 2007; Chandrasekara et al., 2003). We extend these analyses across monsoon and inter-monsoon seasons. Although rainfall anomalies may be correlated strongly with teleconnection indices, the scatter in the data can be large, making predictions from regression models have high uncertainty. However, water managers may act on information about whether rainfall is expected to be abnormally low or high. Seasonal precipitation is generally forecasted in broad categories. For example, the US National Weather Service forecasts seasonal precipitation as above normal, below normal, and normal (National Oceanic and Atmospheric Administration, 2018). The International Research Institute for Climate and Society also forecasts seasonal precipitation as above, below and near normal (International Research Institute for Climate Society, 2018). We chose to follow a similar approach and investigate river basin rainfall teleconnections to climate indices with classification models. If reasonably accurate relationships can be developed, they will be useful for water resources management. For example, in Sri Lanka decisions about allocations of water for irrigation and hydropower could be improved with estimates of when low rainfall seasons are likely(De Silva M. & Hornberger, 2019a).

2.2 Hydrometeorology and Climatology of the Study Area

Sri Lanka is an island in the Indian Ocean (latitude 5° 55′ N - 9° 50′ N, longitudes 79° 40′ E – 81° 53′ E). Mean annual rainfall varies from 880 mm to 5500 mm across the island. The rainfall distribution is determined by the monsoon system of the Indian Ocean interacting with the elevated land mass in the interior of the country. The country is divided into three climatic zones according to the rainfall distribution: humid zone (wet zone) (annual rainfall > 2500 mm), intermediate zone (2500 mm < rainfall < 1750 mm) and arid zone (dry zone) (rainfall < 1750 mm) (Department of Agriculture Sri Lanka, 2017).

Sri Lanka, a water-rich country, has 103 river basins varying from 9 km^2 to 10448 km^2. A large fraction of the water resources management infrastructure of the country is associated with the Mahaweli and Kelani river basins. The catchment areas of the Mahaweli and Kelani are 10448 km^2 and 2292 km^2 respectively. The two rivers start from the central highlands. Mahaweli, the longest river, travels to the ocean 331 km in the eastern direction and the Kelani 145 km in the western direction. Average annual discharge volume for the Mahaweli and Kelani basins are 26368 10^6 m^3 and 8660 10^6 m^3 respectively (Manchanayake and Madduma Bandara, 1999). The Kelani river basin is totally inside the humid zone whereas the Mahaweli river basin migrates through all three climate zones (Figure 2.1).

The temporal pattern of rainfall in Sri Lanka can be divided into four seasons as follows.

(1) Generally low precipitation across the country from the Northeast monsoon (NEM), which gets most precipitation during January to February. The arid zone of the country gets significant precipitation from the NEM, while humid zone gets very little rainfall during this period.

(2) The whole country gets precipitation from the first inter-monsoon (FIM) during March to April months. However, rainfall during this period is not very high across the country.

(3) The highest precipitation for the country is from the South western monsoon (SWM) during May to September. However, only the humid zone gets high precipitation during this season.

(4) The whole country gets precipitation from the second inter-monsoon (SIM) during October to December. Generally, precipitation from SIM is higher than FIM.

The time period of NEM and SIM are generally considered as December to February and October to November respectively (Department of Meteorology Sri Lanka, 2017; Malmgren et.al, 2003; Ranatunge et al., 2003). However, considering the bulk amount of water received from the monsoon, we consider January and February as the period of NEM and October to December as the period of SIM.

Reflecting the rainfall seasons, the country has two agriculture seasons “Yala” (April - September) and “Maha” (October - March). Because the arid zone gets minimal precipitation during the SWM, the agricultural systems (165,000 ha) developed under the Mahaweli multipurpose project depend on irrigation water during the Yala season. The country depends on stored water to drive hydropower year-round. The Mahaweli and Kelani hydropower plants of 810 MW and 335 MW capacity serve as peaking and contingency reserve power to the power system (Ceylon Electricity Board, 2015). Management of reservoir systems is done to cater both to irrigation and hydropower requirements.

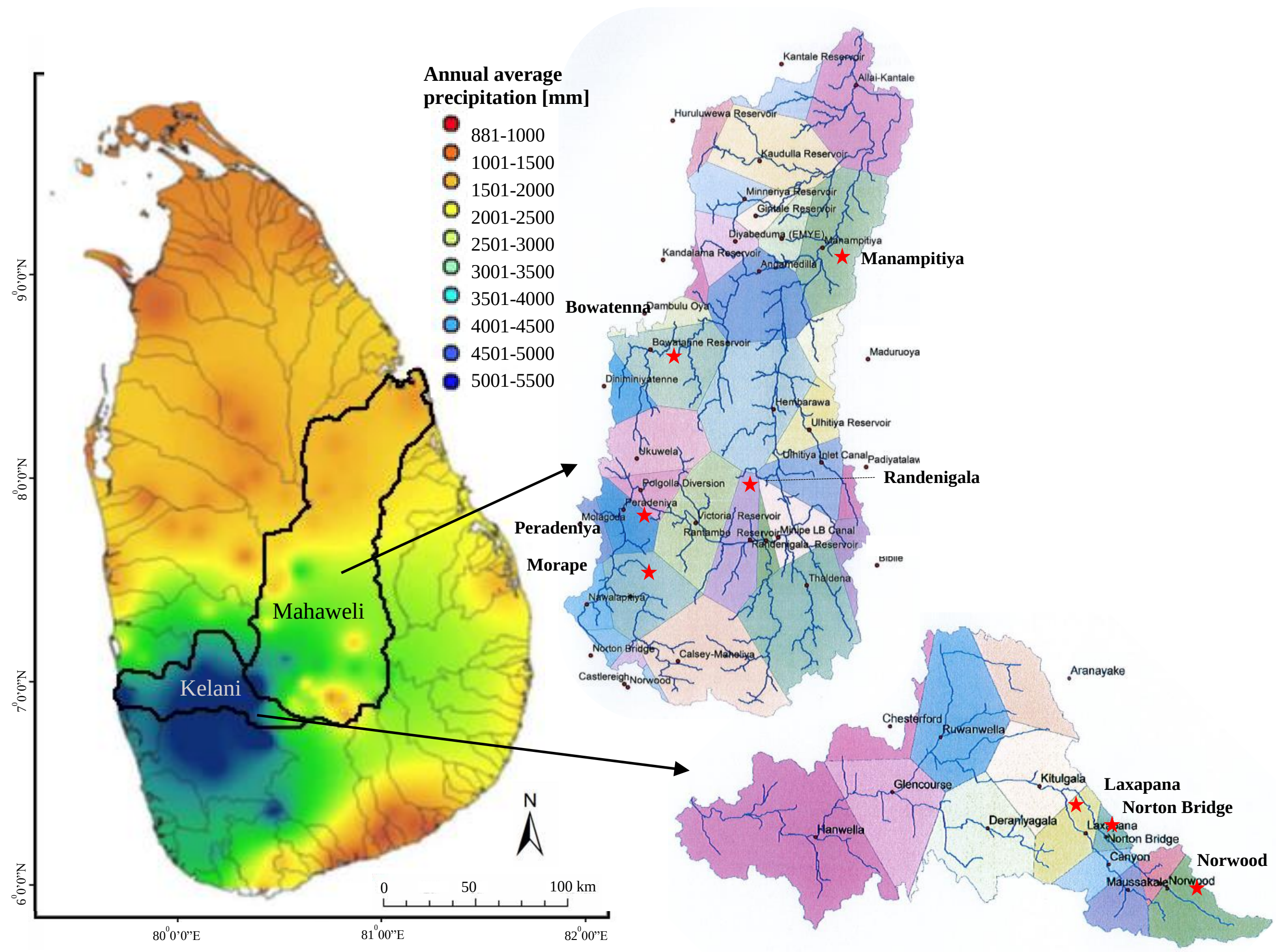

Figure 2.1 Mahaweli and Kelani river basins of Sri Lanka

2.3 Sub-basin Rainfall (Areal Rainfall)

Monthly rainfall data for years 1950 - 2013 are used for the study (Ceylon Electricity Board, 2017). River basin rainfall was calculated using the Thiessen polygon method (Viessman, 2002). The Mahaweli river basin is divided into 16 Thiessen polygons and the Kelani river basin is divided into 11 Thiessen polygons (Figure 2.1). Since this study does not aim to explore rainfall across sub-basins, we do not use digital elevation maps to define the sub-basins. Considering the importance of sub-basins for the reservoir catchment and for water use, eight sub-basins are selected for analysis. Morape, Randenigala, Peradeniya, Manampitiya and Bowatenna represent the Mahaweli major reservoir catchments and irrigation tanks, and Norton Bridge, Norwood and Laxapana represent the Kelani basin reservoir catchments. The catchment of the major Mahaweli river reservoir cascade (Kotmale, Victoria, Randenigala, Rantambe, Bowatenna) is represented by Morape and Peradeniya located in the humid zone and by Randenigala and Bowatenna located in the intermediate zone. The arid zone major irrigation catchments of the Mahaweli are represented by Manampitiya. The catchment of the Kelaniya reservoir cascade (Norton Bridge and Moussakele) in the humid zone is represented by Laxapana, Norton Bridge and Norwood.

We calculate the rainfall for the four seasons, NEM, FIM, SWM and SIM for 64 years of historical data. Rainfall anomalies are calculated by reducing the seasonal mean rainfall (2.1) and standardized anomalies are calculated by dividing the rainfall anomalies by the standard deviation (SD) (2.2).

$$X_{ANM} = (X - \bar{X}_t) \qquad (2.1)$$

$$X_{S\_ANM} = (X - \bar{X}_t)/SD_t \qquad (2.2)$$

Where, $\bar{X}_t$ is the average of seasonal rainfall, X_{ANM} is the rainfall anomaly and X_{S_ANM} is the standardized rainfall anomaly.

Standardized rainfall anomalies are divided into three classes as dry, average and wet (Table 2.1). A normality test for the rainfall data classes is done using the Shapiro-Wilk test. If the rainfall data are not normally distributed, log (e), square root or square functions are used to transform the data into normally distributed data sets (Figure A.1 in Appendix A). Extreme seasonal precipitation has been defined statistically in different ways using statistical thresholds (Easterling et al., 2000; Jentsch et.al., 2015; Smith, 2011). We use 0.5 as a threshold to define three classes, which results in fairly evenly distributed data across the three classes (Figure A. 2).

Table 2.1 Rainfall anomaly classification

Class	Range
dry	$X_{S\_ANM} < -0.5$
average	$-0.5 <= X_{S\_ANM} < 0.5$
wet	$0.5 <= X_{S\_ANM}$

2.4 ENSO & IOD Indices

The ENSO phenomenon is represented by MEI, NINO34, NINO3, NINO4 indices, and the Indian Ocean dipole phenomenon is represented by the DMI index. NINO34, NINO3, NINO4 indices are based on tropical sea surface temperature anomalies (National Center for Atmospheric Research, 2018) and the Multivariate ENSO Index (MEI) is based on sea-level pressure, zonal and meridional components of the surface wind, sea surface temperature, surface air temperature, and total cloudiness fraction of the sky (National Oceanic and Atmospheric Administration, 2017). The Indian Ocean Dipole (IOD) is an oscillation of sea surface temperature in the equatorial Indian ocean between Arabian sea and south of Indonesia (Bureau of Meteorology Australia, 2017). IOD is identified as relevant to the climate of Australia (Power et.al., 1999) and countries surrounded by the Indian ocean in southern Asia (Chaudhari et al., 2013; Maity and Nagesh Kumar, 2006; Qiu et al., 2014; Surendran et al., 2015). The Dipole Mode Index (DMI) is used to represent the IOD capturing the west and eastern equatorial sea surface temperature gradient.

Data used for the analyses are NINO34, NINO3, NINO4, MEI monthly data from years 1950 – 2013, (National Oceanic and Atmospheric Administration, 2017; National Center for Atmospheric Research, 2018), and the DMI monthly data from years 1950-2013 (HadISST dataset, Japan Agency for Marine-Earth Science and Technology 2017). Because we analyzed the data in rainfall seasons, values of the climate indices over the season are averaged. For example, for the NEM season, the MEI value is the average of January and February monthly values and for the SWM season, DMI is the average of May, June, July and September values.

2.5 Methods

Seasonal values of MEI and DMI were used as the predictors to classify seasons into the three rainfall classes. The total data set is divided into 75 % for training the model and 25 % for testing model performance. Quadratic discriminant analysis (QDA) and classification trees were selected for the analyses. A random forest model also was applied to investigate the reliability of a cross-validated statistical forecast tool based on an advance estimate of MEI and DMI. We used the R programming language to carry out the statistical analyses. R packages: caret, tree, randomForest, fitdistriplus, devtools and quantreg are used for the studies.

2.6 Quadratic Discriminant Analysis (QDA)

The mathematical formulation of QDA can be derived from Bayes theorem assuming that observations from each class are drawn from a Gaussian distribution (James et.al., 2013; Löwe et.al., 2016).

The prior probability π_k represents the randomly chosen observation coming from kth class with density function$f_k(x)$. Bayes theorem states that

$$Pr(Y = k|X = x) = -\frac{\pi_k f_k(x)}{\sum_{l=1}^{K} \pi_l f_l(x)} \qquad (2.3)$$

In (2.3), the posterior probability $Pr(Y = k|X = x)$ indicates that observation $X = x$ belongs to the kth class. For p predictors, the multivariate Gaussian distribution density function is defined for every class k (2.4).

$$f_k(x) = -\frac{1}{(2\pi)^{p/2}|\sum_k|^{1/2}} \, exp\left(-\frac{1}{2}(x-\mu_k)^T \textstyle\sum_k^{-1}(x-\mu_k\,)\right) \qquad (2.4)$$

In (2.4), $\sum_k$ is the covariance matrix and μ_x is the mean vector. The covariance matrix ($\sum_k$) and mean (μ_x) for each class are estimated from the training data set (2.5), (2.6).

$$\mu_k = -\frac{1}{N_k} \sum_{i:y_i=k} x_i \qquad (2.5)$$

$$\textstyle\sum_k = -\frac{1}{(N_k - 1)} \displaystyle\sum_{i:y_i=k} (x_i - \mu_k)^T (x_i - \mu_k) \qquad (2.6)$$

Substituting a Gaussian density function for the kth class (2.4) into Bayes theorem and taking the log values, the quadratic discriminant function is derived (2.7). Prior probabilities for class k (π_k) is calculated by the frequency of data points of class k in the training data (2.8). For a total number of N points in the training observations, N_k is the number of observations belong to kth class.

$$\delta_k(x) = -\frac{1}{2}\ (x-\mu_x)^T \Sigma_k^{-1}(x-\mu_x\ )\ + log\ \pi_k \tag{2.7}$$

$$\pi_k = -\frac{N_k}{N} \tag{2.8}$$

Covariance, mean and prior probability values are inserted into the discriminant function ($\delta_k(x)$) together with the state variables (2.5). The corresponding class is selected according to the largest value of the function. The number of parameters to be estimated for the QDA model for k classes and p predictors is $k.p.(p+1)\ /\ 2$. For this study, the QDA model output is the probability that an observation of a climate category will fall into each of the rainfall classes.

2.7 Classification Tree model

For the classification tree model the predictor space is divided into non-overlapping regions ($R_1..R_j$). A classification tree predicts each observation as belonging to the most commonly occurring class of the training data regions (James et.al., 2013). Recursive binary splitting is used to grow the classification tree.

Classification error rate, Gini index and cross-entropy are typically used to evaluate the quality of particular split (James et.al., 2013), and in our study we used the first two indices. Classification error rate (E) gives fraction of observation that do not belong to the most commonly occurring class of the training data regions (2.9). However, for the tree-growing, the Gini index (G) is considered as the criterion for splitting into regions (2.10)

$$E = 1 - max_k(\hat{p}_{mk}) \tag{2.9}$$

$$G = \sum_{k=1}^{K} \hat{p}_{mk}\ (1-\hat{p}_{mk}) \tag{2.10}$$

In (2.9) and (2.10), $\hat{p}_{mk}$ represents the fraction of observations in the mth class that belong to the kth class. The Gini index is considered as a measure of node purity of the tree model, since small values of the index indicate that node has a higher number of observations from a single class.

The complexity of the trees is adjusted using a pruning process to produce more interpretable results. Complex trees reduce training error by overfitting the training data. Simple trees can be interpreted well, however, selecting a model which can find the pattern of data is important. In order to achieve the low classification error (training error + testing error), a pruning technique is used. First, a very large tree is grown and then a sub tree is obtained by removing the weak links of the tree. Using a tuning parameter to examine the trade-off between complexity of tree and the training error, and defining minimum samples for a node, maximum depth of the tree, and maximum number of terminal nodes are pruning methods (Analytical Vidhya Team, 2016). For this study, we defined the maximum number of nodes to obtain the simple tree (pruned tree).

Tree models give the probability that an observation falls into each of the three rainfall classes. The predicted class is assigned based on the highest probability. Tree models handle ties of probability values by randomly assigning the class.

2.8 Random Forest

A random forest is an ensemble learning method used for classification and regression problems. The method is based on a multitude of decision trees based on training data with the final model as the mean of the ensemble (Breiman, 2001). Individual trees are built on a random sample of the training data with several predictors from the total number of predictors. Individual trees are built from the bootstrapped training data set.

There are some features that can be tuned to improve the performance of the random forest model. The maximum number of predictors from the total predictors for individual trees, maximum number of trees, maximum node size of the trees and minimum sample leaf size are some of these features (Analytical Vidhya Team, 2015). In our study, we use the maximum number of trees as the main tuning parameters.

In a random forest model the importance of the variable is measured as the decrease in node impurity from the splits over the variable. This value is calculated by averaging the Gini index over the multitude of trees with a larger value indicating high importance of the predictor (James et.al., 2013).

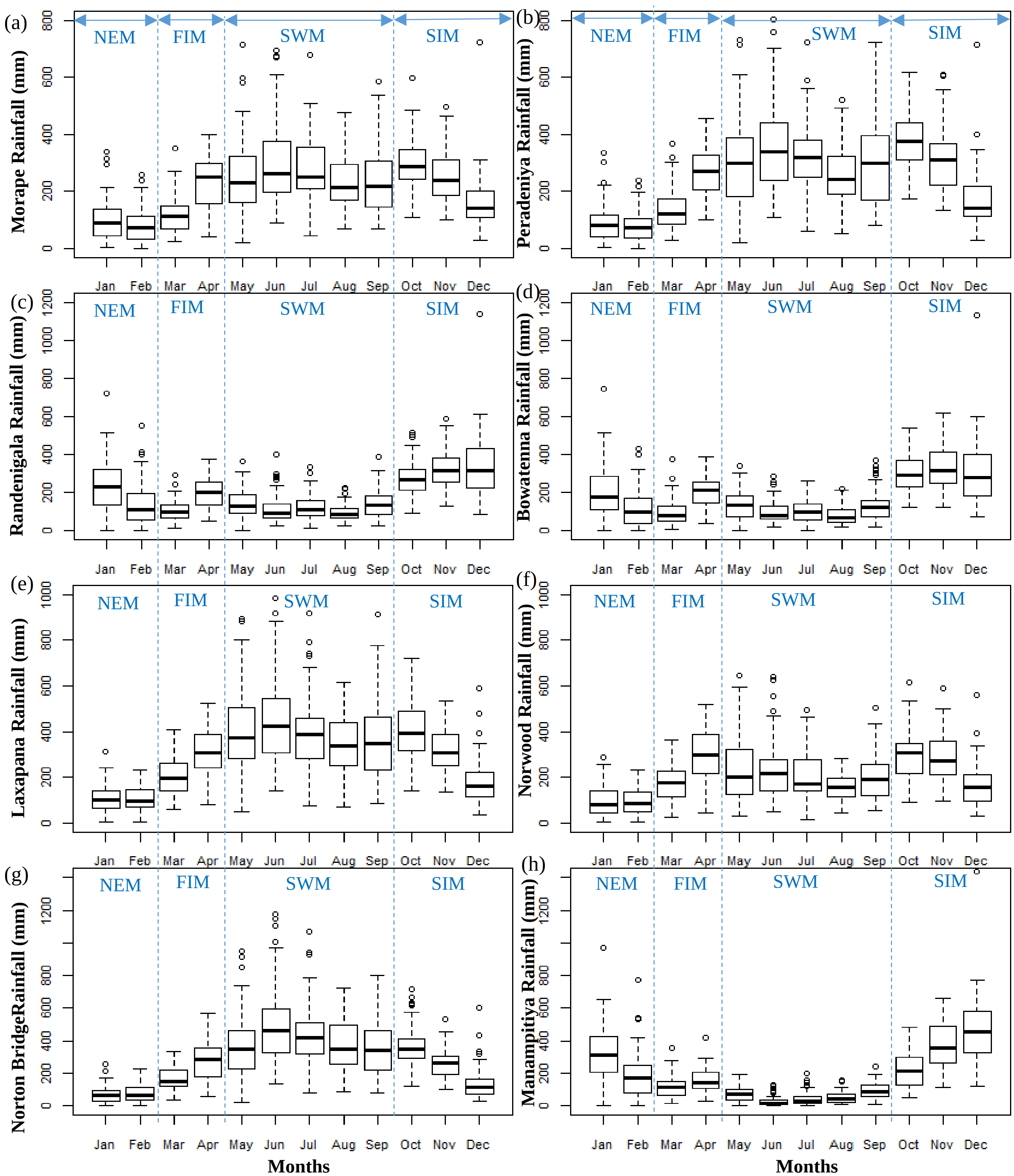

Figure 2.2 Sub basin Rainfall for (a) Morape (b) Peradeniya (c) Randenigala (d) Bowatenna (e) Laxapana (f) Norwood (g) Norton Bridge and (h) Manampitiya. Rainfall seasons are North East Monsoon (NEM), First Inter-Monsoon (FIM), South West Monsoon (SWM), and Second Inter-Monsoon (SIM)

2.9 Results

Monthly rainfall boxplots of eight sub basins over the year for 1950 - 2013 illustrate the seasonal and the spatial variation of rainfall patterns (Figure 2.2). The largest fraction of total rainfall in the arid zone occurs at the end of the SIM (December) and during the NEM (January - February) with correspondingly high variability whereas there is little rainfall in the arid zone during the SWM (May - September) with correspondingly little variability (Figure 2.2(h)). The intermediate zone receives approximately 60% of total rainfall from the SIM and NEM. Although the variability of the rainfall is low in the intermediate zone, high rainfall can occur in all seasons (Figure 2.2 (c) and (d)). In the humid zone, a large portion of rainfall occurs in SWM and early months of SIM (October-November). High variability of humid zone rainfall is observed at the end of FIM (April), in the SWM (May-September), and at the start of SIM (October) (Figure 2.2 (a), (b), (e), (f) and (g)).

Similar to other investigators, we observe several strong correlations between rainfall anomalies and the climate indices (Table A. 1, Table A. 2, and Appendix A). Higher correlation values between MEI and rainfall anomalies can be seen compared to the correlation with other ENSO indices (Table A. 1). In addition, rainfall in the SWM is very important for stations in the humid zone of the country which is the source of a large amount of water stored in reservoirs (Table A. 2). Correlation coefficients between SWM rainfall at Norton Bridge are negative and strong, -0.31 for MEI ($p = 0.01$) and -0.37 for DMI ($p < 0.01$). The strength of the correlation notwithstanding, the residuals from a regression model indicate that high uncertainty would attach to any forecast (Figure 2.3Figure 2.3). Thus, we are led to explore the efficacy of classification methods (Appendix A).

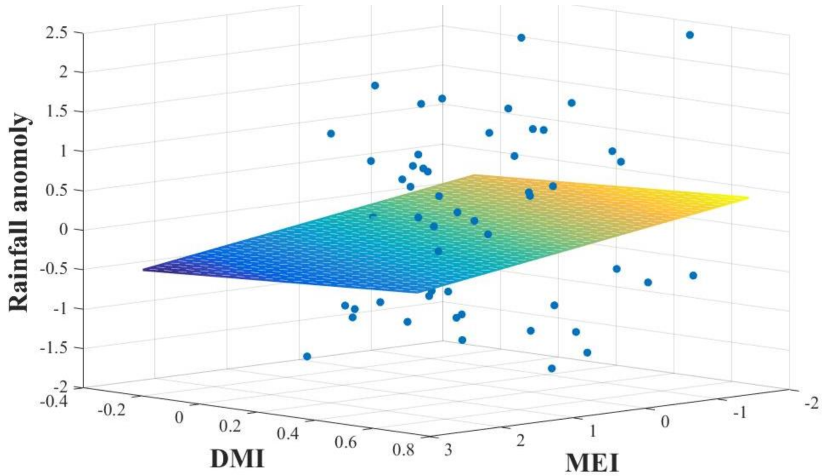

Figure 2.3 Linear regression of rainfall anomaly on MEI and DMI. High values of MEI and DMI are associated with low values of rainfall.

We present classification results for two sub-basins, one that has the highest rainfall during the NEM, Manampitiya, and one that has the highest rainfall for the SWM, Norton Bridge (Figure 2.4). Norton Bridge represents the areal rainfall of reservoir catchments in the wet zone and Manampitiya represents the rainfall that contributes to irrigation tanks in the dry zone. Results of other sub-basins are presented in the supplementary materials (Figure A. 4, Figure A. 5, Figure A. 6, Figure A. 7, Appendix A). Because MEI has higher correlation with rainfall anomalies than other ENSO indices, classification was done with only MEI and DMI.

The SWM is a season when the humid zone receives the bulk of rainfall. At Norton Bridge, the occurrences of the dry rainfall anomaly class in the SWM is seen to “clump” in the region of relatively high MEI and DMI. Both the classification tree and the QDA successfully identify the pattern (Figure 2.4 (a) and (c)) with an overall accuracy of 73 %, 19 and 16 correct out of 22 occurrences (Table 2.2). In the arid zone the NEM season is one of the most important for rainfall. At Manampitiya, the MEI provides the primary variable in the classification, with the dry anomaly class being correctly selected in 52 % by the tree model and 95 % by the QDA model. The results suggest that it may be possible to identify seasons when it is expected to be anomalously dry. The correct classification of “average” conditions likely has less importance for water managers. We explored classification using two classes, “Dry” and “Not Dry.” In this case, the classification model correctly classifies 86 % of the anonymously dry cases and gets more than 69 % of the “Not Dry” cases correct (Figure 2.5).

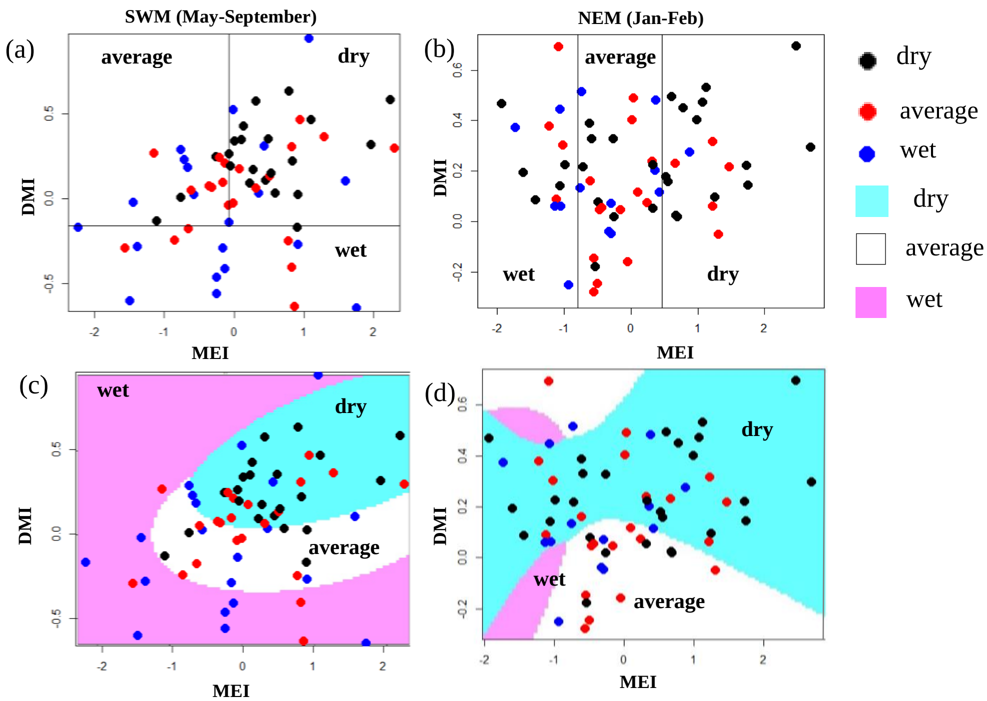

Figure 2.4 Norton Bridge and Manampitiya rainfall classes (dry, average, wet) identified by ENSO and IOD phenomena. (a) Norton Bridge SWM rainfall classification tree model (b) Manampitiya NEM rainfall classification tree model (c) Norton Bridge SWM rainfall QDA (d) Manampitiya NEM rainfall classification by QDA

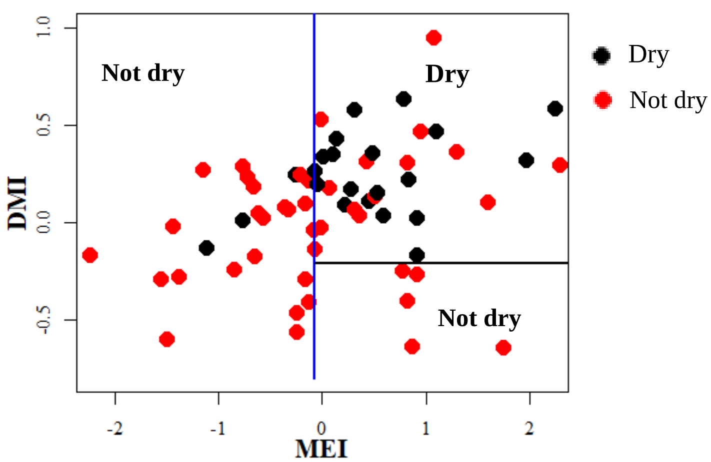

Figure 2.5 Classification tree for Norton Bridge SWM rainfall using two categories (dry and not dry)

Classification trees are known to be unstable. That is, small changes in the observations can lead to large changes in the decision tree. The random forest approach overcomes the issue by building a “bag” of trees from bootstrap samples. The robustness of the model can then be checked by considering the “out-of-bag” error. The results of the random forest indicate that predictions of three rainfall anomaly classes using MEI and DMI is not feasible (Table 2.3). The out-of-bag error rate is close to two thirds, which for three categories is equivalent to a random selection.

Table 2.2 Classification model results. Highlighted cells indicate where there may be information content with respect to forecasting either dry or wet anomaly classes as judged by a classification success rate of at least 2/3.

Season	**Manampitiya**			**Norton Bridge**		
	QDA Model			*QDA Model*		
	Dry	Normal	Wet	Dry	Normal	Wet
NEM	22/23	11/25	1/16	5/20	25/29	2/15
FIM	9/21	20/24	5/19	3/20	14/23	14/20
SWM	2/21	30/27	2/16	16/22	9/22	9/20
SIM	17/25	13/20	7/19	7/22	15/22	11/20
Season	*Tree Model*			*Tree Model*		
	Dry	Normal	Wet	Dry	Normal	Wet
NEM	12/23	9/25	11/16	11/20	18/29	8/15
FIM	9/21	19/24	8/19	13/21	6/23	15/20
SWM	6/21	25/27	7/16	19/22	8/22	9/20
SIM	20/25	0/20	17/19	19/22	5/22	14/20

Table 2.3 Results of random forest ensemble classification results

Season	**Norton Bridge**				**Manampitiya**			
	Dry	Normal	Wet	OOB Er	Dry	Normal	Wet	OOB Er
NEM	11/20	12/29	6/15	55%	14/23	10/25	5/16	55%
FIM	7/21	8/23	8/20	64%	10/21	11/24	6/19	58%
SWM	9/22	6/22	8/20	64%	6/21	17/27	5/16	56%
SIM	13/22	9/22	9/20	52%	15/25	8/20	7/19	53%

Table 2.4 Results of random forest ensemble classification results for two rainfall anomaly classes

Season	Norton Bridge			Manampitiya		
	Dry	Not dry	OOB Error	Dry	Not dry	OOB Error
NEM	9/20	36/44	30 %	13/23	33/41	28 %
FIM	5/21	35/43	38 %	8/21	35/43	33 %
SWM	9/22	32/42	36 %	5/16	34/43	39 %
SIM	10/22	36/42	28 %	16/25	34/39	22 %

However, the results of the random forest for a classification as either “Dry” or “Not Dry” suggests that there may be skill in such a prediction. The out-of-bag error rates for this case range from 22 % to 38 % for Norton Bridge and Manampitiya (Table 2.4) and from 20 % to 39 % across all stations (Table A. 7).

The QDA method produces results that are promising with respect to identification of extreme dry events as indicated by seasonal rainfall (Table 2.5).

Table 2.5 Classification results for extreme dry (very low rainfall) and wet (very high rainfall) seasons.

Class	Range	Norton Bridge SWM		Manampitiya NEM	
		tree	QDA	tree	QDA
Very dry	$X_{S\_ANM} < -1.0$	10/11	10/11	6/11	11/11
dry	$-1.0 <= X_{S\_ANM} < -0.5$	9/11	6/11	5/11	9/10
average	$-0.5 <= X_{S\_ANM} < 0.5$	8/22	9/22	9/25	11/25
wet	$0.5 <= X_{S\_ANM} <= 1.0$	5/11	5/11	1/5	0/5
Very wet	$1.0 <= X_{S\_ANM}$	6/11	6/11	7/11	1/11

2.10 Discussion

Understanding seasonal rainfall variability across the spatially diverse Mahaweli and Kelani river basins is important for irrigation and hydropower water planning. SWM and SIM are the key rainfall seasons for sub basins in the humid zone (Norton Bridge, Morape, Peradeniya and Laxapana), delivering 80 % of annual rainfall (Figure 2.2 (a), (b), (e), (f)). For the arid zone (Manampitiya) and intermediate zone (Randenigala, Bowatenna) sub basins, the major season is SIM, which delivers more than 40 % of annual rainfall (Figure 2.2 (c),(d),(h)). The arid zone also gets rainfall during the NEM (24 % of annual rainfall at Manampitiya) and the intermediate zone gets rainfall during the SWM (25 % - 30 % of annual rainfall at Randenigala and Bowatenna).

Climate teleconnection indices are related to rainfall anomalies observed during the two main growing seasons, Yala and Maha. The Maha agriculture season (October-March) depends on rain from SIM and NEM. During El Nino events rainfall increases for the first three months of the Maha season (SIM: October-December) (Figure A. 4, Figure A. 5, Figure A. 6, Figure A. 8) (Ropelewski and Halpert, 1995) and decreases during the last three months (NEM: January-March)(Figure 2.4 (b)). In Yala season (April-September), La-Nina events enhance the rainfall during SWM (Figure 2.4 (a), (c), Figure A. 4, Figure A. 5, Figure A. 6, Figure A. 8)(Whitaker et.al, 2001). During El Nino events the SWM rainfall is reduced (Figure 2.4 (a), (c), Figure A. 4, Figure A. 5, Figure A. 6, Figure A. 8) (Chandrasekara et.al, 2017; Chandimala and Zubair, 2007; Zubair, 2003). The El Nino impact during the SWM is not as significant as it is during the NEM season (International Research Institute, 2017a). We find, however, that there is an interaction between two teleconnection indices, MEI and IOD for SWM rainfall. During the Yala season there is a high probability of having a drought when both the IOD and MEI are positive (Figure 2.5). Also not having drought is probable when both the IOD and MEI are negative (Figure 2.5, Figure A. 8, Figure A. 9).

Classification of wet, average, and dry rainfall anomalies using the MEI and DMI indices is successful. For example, a dry SWM season for Norton Bridge (Table 2.2) and other humid-zone stations (Table A. 4) is classified correctly with greater than 70 % accuracy with QDA and tree models. However, a random forest approach demonstrates that there is little skill in identifying a full wet-average-dry classification. However, a random forest model using only two rainfall categories shows more than 60 % accuracy in identifying “dry” and “not dry” classes of key rainfall seasons of the humid zone (Table 2.4, Table A. 7). Similarly, for arid zone locations such as Manampitiya, the dry rainfall class identification for NEM and SIM seasons is about 60 % (Table 2.4, Table A. 7).

Our statistical classification models can be combined with MEI and DMI forecasts to indicate the season-ahead expectation for rainfall. ENSO forecasts are available from the International Research Institute for Climate and Society (International Research Institute, 2017b) and IOD forecasts are available in the Bureau of Meteorology (BOM), Australian Government (Bureau of Meteorology, 2017). ENSO and IOD predictions are also associated with the uncertainty. Therefore, final forecast accuracy is a combination of the MEI, DMI forecast uncertainties and model’s accuracy rate in each class. Although overall prediction accuracy is not extremely high, a forecast of an anomalously low rainfall season can have value for risk-averse farmers (Cabrera et.al., 2007) and can guide plans for hydropower management (Block and Goddard, 2012).

The electricity and agriculture sectors of Sri Lanka heavily rely on Mahaweli and Kelani river water resources so season ahead forecasts of abnormally low rainfall should be useful for decisions on adaptation measures. For example, water availability of the first three months of a growing season is important for crop selection and the extent of land to be cultivated. Hydropower planning and scheduling of maintenance of the power plants also can benefit from season-ahead forecasts. The damage that can occur due to incorrect rainfall forecasts in the agriculture and energy sectors can be minimized with emergency planning during the season, which is the usual practice.

Although the accuracy of predicting low or not low seasonal rainfall is not very high, decisions based on forecasts that are improvements over climate averages should be an improvement over current practices. The accuracy of statistical models can be improved with longer records, which are important to train the classification models. Also, models can be fine-tuned for important shorter periods such as crop planting months and harvesting months for irrigation water planning.

ENSO and IOD phenomena teleconnections with river basin rainfall provide potentially useful information for water resource management of multipurpose reservoir systems which is a challenging task. Relationships identified between teleconnection indices and river basin rainfall agree with other research findings. Prediction of seasonal rainfall classes from ENSO and IOD indices can inform water resources managers in reservoir operation planning for both hydropower and irrigation releases. However, allocation of variable water resources of multipurpose reservoir systems, between competitive users is still a challenging task. Reservoirs are built to manage the spatial and temporal variability of rainfall seasons; however, uncertainty of rainfall seasons due to many reasons such as climate teleconnections makes water resources management for many purposes complex. In such a case, systematic evaluation of water allocation alternatives of multipurpose reservoir cascades is required by planners.

CHAPTER 3

Assessing Water Management Alternatives in the Mahaweli Multipurpose Reservoir Cascade System

3.1 Introduction

Multipurpose reservoir cascades are managed to fulfill diverse and often conflicting water demands to as great an extent as possible. These projects are operated for hydropower generation, drinking water supply, tourism, irrigation, flood regulation, and navigation. The spatial and temporal diversity of water users and the limited availability of water in some seasons require that trade-offs be made in response to demands of the multiple water users. For example, if water managers keep reservoir water levels low during a wet period to meet flood protection goals, there may not be enough water to meet agricultural water demands in a subsequent dry period. One particularly important trade-off for developing countries is between hydropower and irrigation (Digna et al. 2018; Räsänen et al. 2015; Tilmant, Goor, and Pinte 2009). If water is transferred from upstream reservoirs for irrigation, downstream hydropower generation is penalized. On the other hand, if the water is taken from storage to run turbines to produce electricity during low irrigation water demand, water may not be available later to be used for irrigation.

The Mahaweli multipurpose water resources system of Sri Lanka furnishes water for irrigated agriculture and hydropower generation, supplying about 20% of the annual irrigation water demand and 20% of the electrical energy demand of the country. Water managers need to balance diversion of Mahaweli water to irrigation districts at the upstream end of the basin with downstream releases for hydropower generation and smaller irrigated agricultural systems. Specifically, Mahaweli water managers must consider spatial and temporal variability of hydrology across the cascade system, limitations of installed infrastructure, and trade-offs among competing demands of hydropower and agriculture.

Choices about how to operate the Mahaweli reservoir system will depend on how different aspects of performance are valued. The economic value of products such as hydropower generation and agricultural goods is a measure of system performance (Sakthivadivel & Molden, 1999). Evaluating trade-offs between hydropower and agriculture can involve non-economic preferences as well. For example, if agriculture is set as a priority, elevating the fraction of water delivered to agricultural fields may be a goal.

Maximizing system performance measures is the main operational goal for cascades, but minimizing risks of failure is also a management goal. Evaluation of water allocation options in a cascade system requires an assessment of the reliability, resilience, and vulnerability to variable and uncertain basin inflows (Huizar, Lansey, & Arnold, 2018; Jain & Bhunya, 2008; Mateus & Tullos, 2016; Saha, Roy, & Mazumdar, 2017; Srdjevic & Srdjevic, 2017; C. Zhang, Xu, Li, & Fu, 2017). Since Hashimoto et.al.(1982) proposed the use of reliability, resilience and vulnerability indices as performance measures of water resources systems, these indices have been used extensively for informing decisions in reservoir system planning and management (Ajami, Hornberger, & Sunding, 2008; Jain & Bhunya, 2008).

Water resources must be simulated to estimate the evaluation metrics for water management alternatives. Complex models (e.g. RIBASIM, WEAP, MIKE BASIN, MODSIM, WBalMo and HEC-ResSim) have been used in detailed studies of reservoir cascade systems (Loucks, 2005; Loucks & van Beek, 2017; US Army Corps of Engineers, 2013; Vieira & Sandoval-Solis, 2018) but these approaches may not be necessary for initial assessments. One powerful approach particularly useful at a screening level is a system dynamics approach (Jahandideh-Tehrani, Bozorg Haddad, & Mariño, 2014). A system dynamics simulation of reservoir cascade operation reflects a simplified flow diagram with water balance equations used to calculate the reservoir storages and releases under a set of operating rules (Sharifi, Kalin, & Tajrishy, 2013). Conceptual simulation models based on water balance relationships have been used for reservoir operation evaluation of multiple river basins (Kling, Stanzel, & Preishuber, 2014; Tinoco, Willems, Wyseure, & Cisneros, 2016).

The objective of this chapter is to develop a relatively simple model to evaluate the performance of various water resources allocations in meeting the hydropower and irrigation water demands for the Mahaweli multipurpose water resources system. We develop a modular simulation model based on water balance principles for the Mahaweli reservoir cascade, which can be used to screen water allocation alternatives through overall system performance judged by hydropower generated, paddy yield, the fraction of water delivered to agriculture, and a set of indices that describe the reliability, resilience and vulnerability of the system (De Silva M. & Hornberger, 2019b).

3.2 Description of Reservoir Cascade

The Mahaweli multipurpose project of Sri Lanka (Figure 3.1) is spread across 25500km^2 and is operated mainly for hydropower generation and irrigated agriculture. Seven major reservoirs of the Mahaweli project are associated with hydropower plants with 815MW capacity (Figure 3.2). Downstream of these major hydropower reservoirs water is delivered to four irrigation systems (A, B, C, and E). There are seven water distribution points where water allocations are managed. The main diversion at Polgolla currently is limited by rule to 875Mm^3 annually, although the diversion tunnel has the capacity to transfer 1400 Mm^3 per year. The diversion at Polgolla supports hydropower plants with 78MW and paddy farming with a capacity of 95,000 ha. Distribution points send water to ten agricultural systems. The agricultural systems are named using capital letters (Figure 3.1). Our overall system model includes the full complement of reservoirs, diversions, and distribution points (Figure 3.2). To provide clarity, we selected five representative irrigation systems to illustrate the results from our model for the Mahaweli complex. Two of the systems (B and C) are fed from the undiverted water used by upstream power plants of the Mahaweli (Figure 3.3). The other three systems (D1, D2 and H) represent areas fed by water diverted first at Polgolla and then at a set of distribution points. System D1 and H are served by a number of small local irrigation reservoirs (tanks) whereas System D2 is fed by one irrigation tank (Figure 3.2).

Mahaweli system irrigation water for agriculture systems in paddy production is planned considering the monsoon rainfall pattern (Figure 3.4). The crop water requirement for each system is varied throughout the two agricultural seasons: “Yala” (April-September) and “Maha” (October-March), which are based on the northeast monsoon (NEM) and the southwest monsoon (SWM) that bring rain to the country. Crop water requirements of Mahaweli agricultural systems vary spatially according to the soil type and soil moisture content (Mahaweli Authority of Sri Lanka, 2015). All the agricultural systems of the dry zone of the country benefit from the second intermonsoon (October-November) and the northeast monsoon (December-February) during the Maha season and irrigation water requirements are less for the Maha season than for the Yala season.

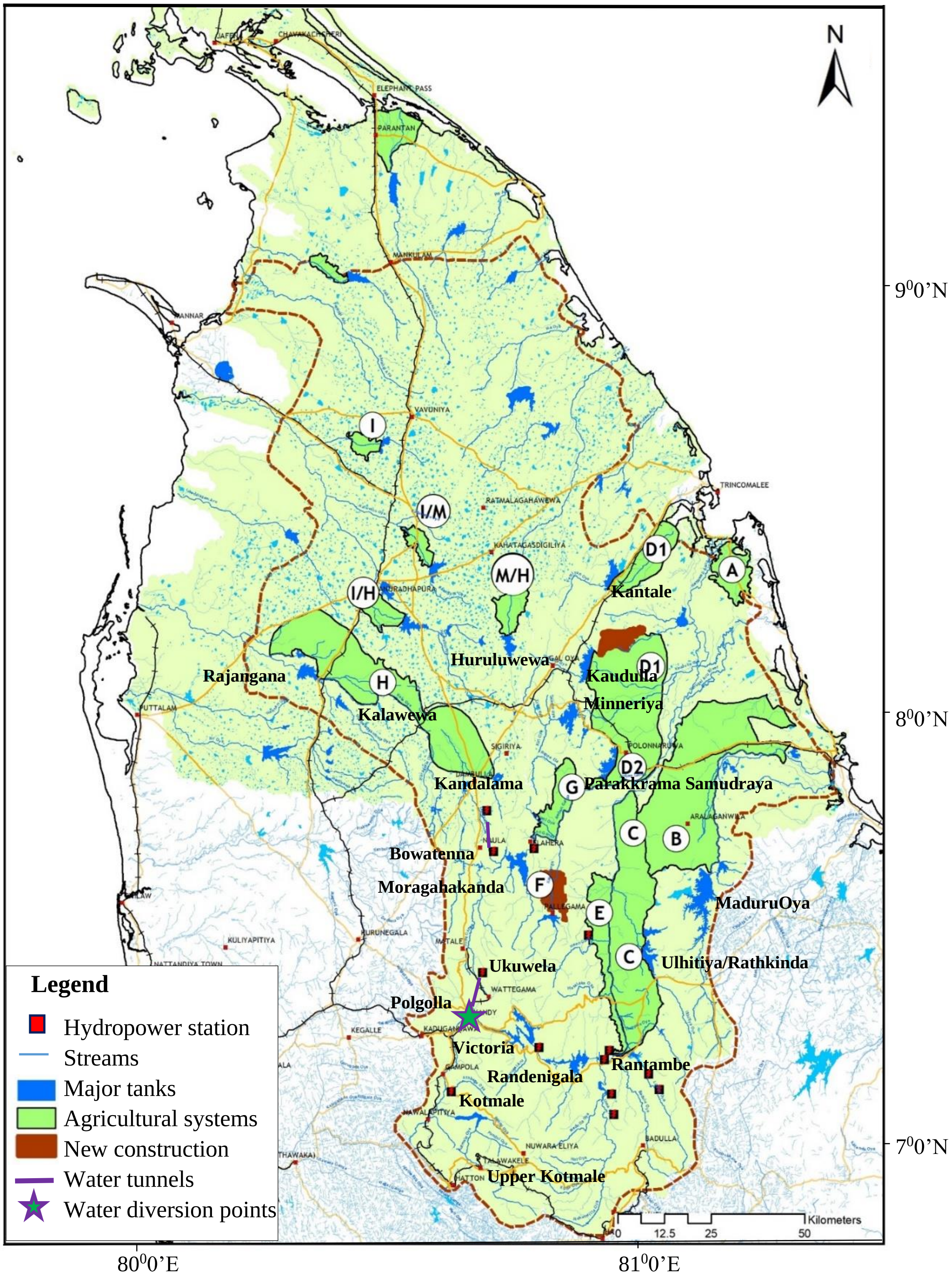

Figure 3.1 Mahaweli multipurpose project reservoirs, stream network and irrigated agricultural systems (A,B,C,D1,D2,E,G,H,I/H and MH).

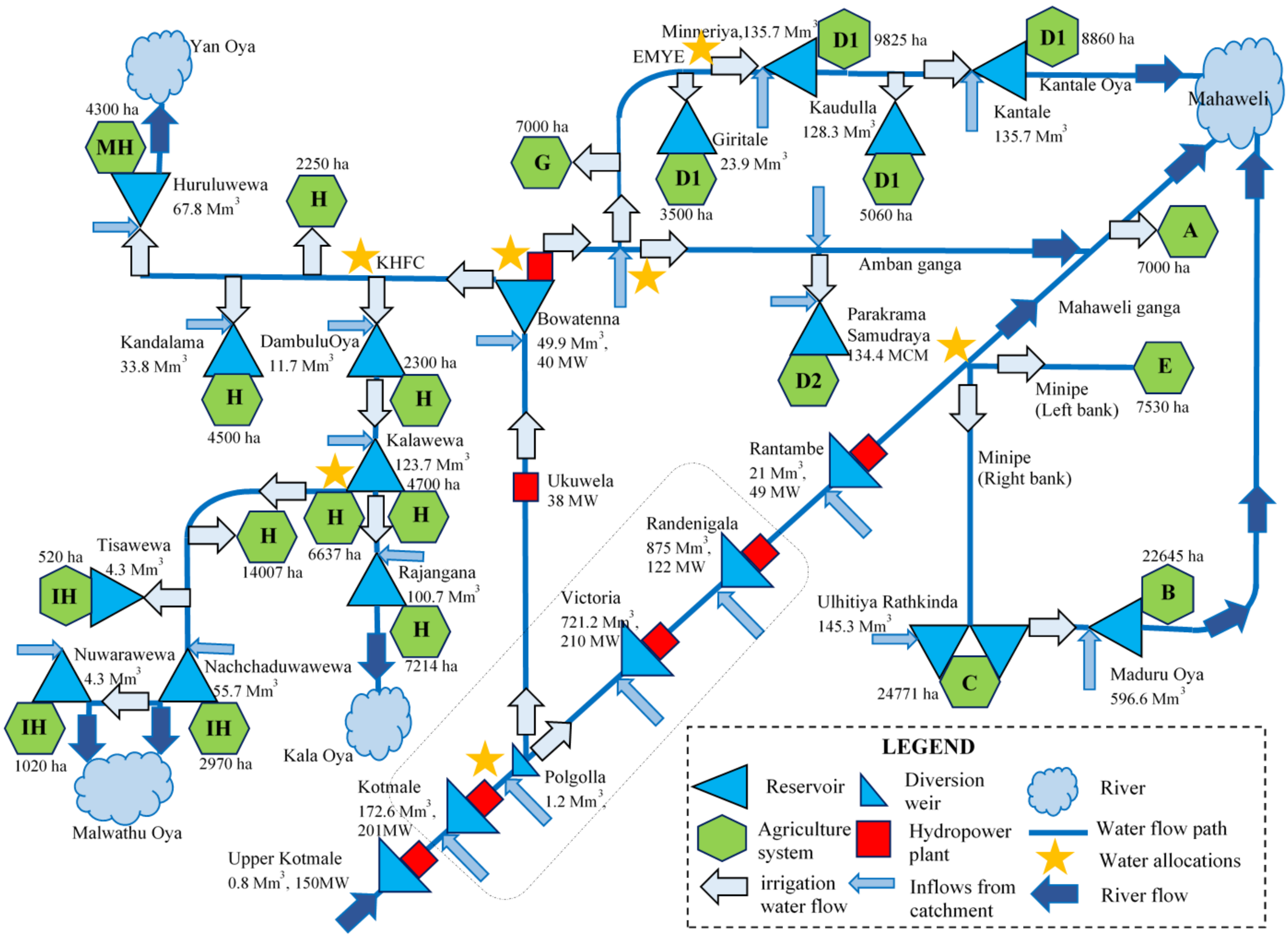

Figure 3.2 Schematic diagram of Mahaweli multipurpose water resources project

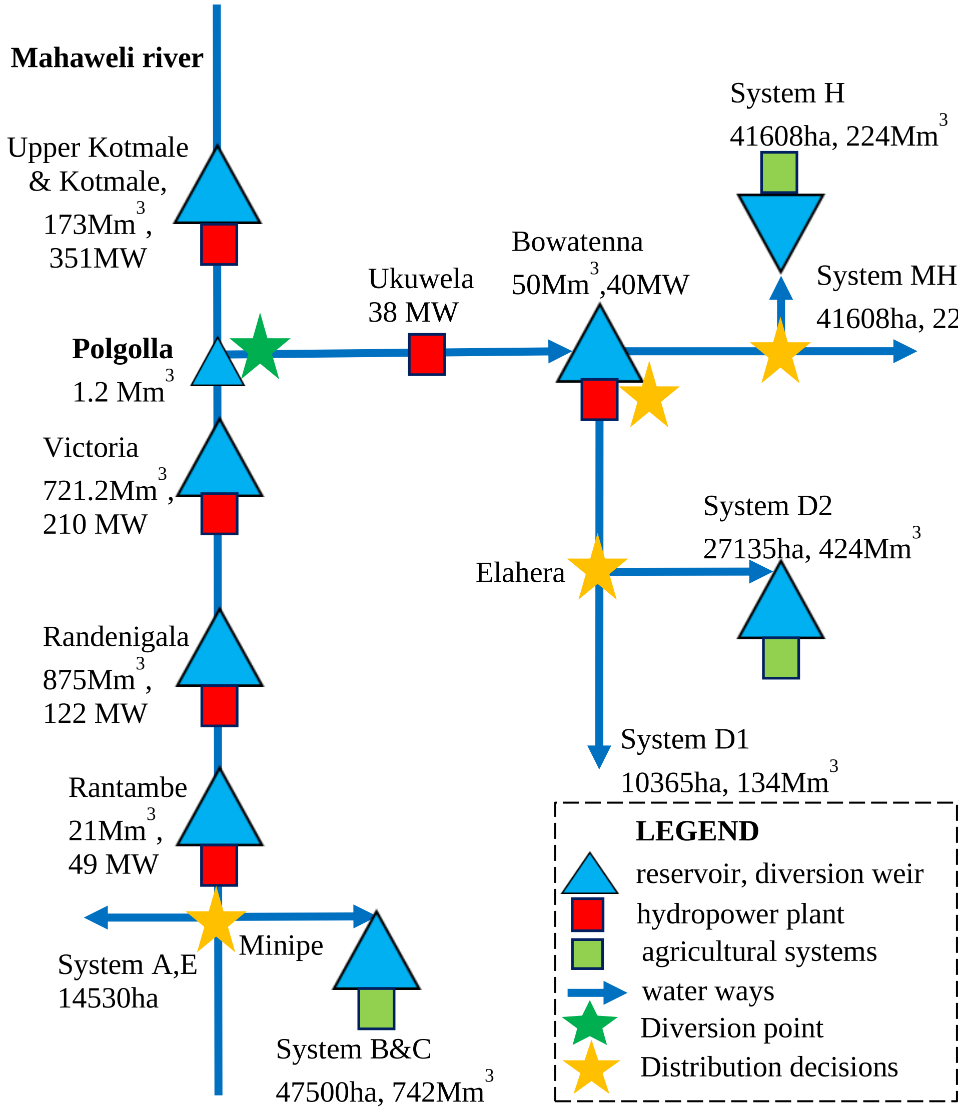

Figure 3.3 Schematic diagram of Mahaweli hydropower plants and agriculture systems B, C, D2 and H

We use data on power production for each dam, information about water requirements for agriculture systems (Figure 3.4), and 63 years of data on the system hydrology (i.e., inflows to the reservoirs) to calculate the hydropower and paddy production. There are two growing seasons in each year so there are 126 seasons in the historical record to explore how the hydropower and irrigation systems perform for various water allocation options.

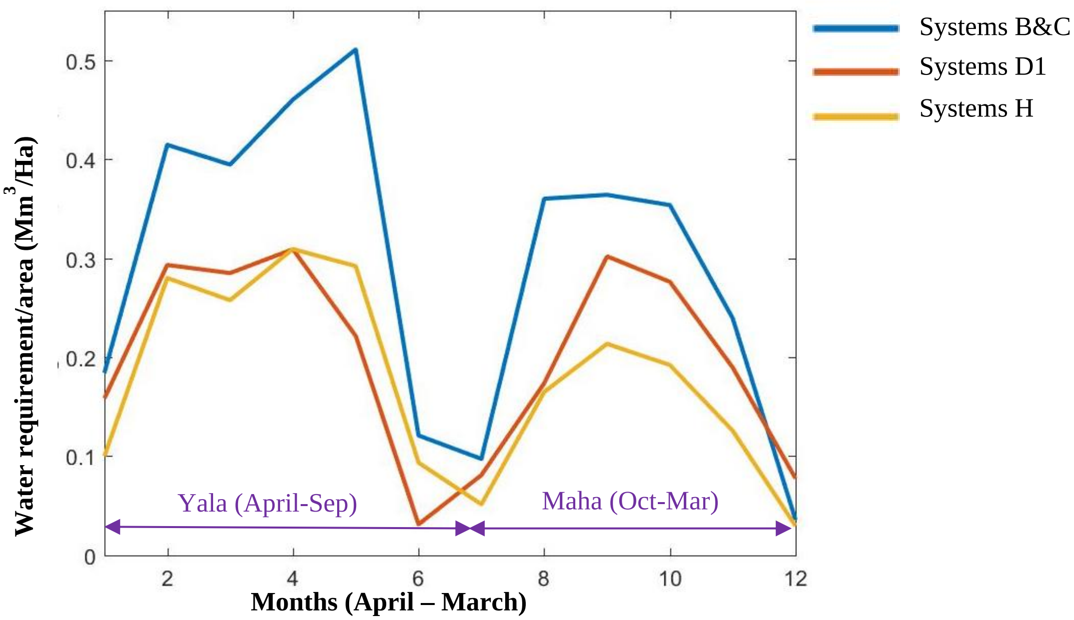

Figure 3.4 Crop water duty cycle for system B&C, D1, H for two agriculture seasons 'Yala' and 'Maha'

3.3 Methods

We develop a simulation model for the Mahaweli multipurpose project of Sri Lanka to evaluate water resource management alternatives to supply irrigation and hydropower demands. The simulation model represents the major components of the system -- reservoirs, agricultural systems, and hydropower plants. Operational rules for reservoir water releases and water diversions are incorporated.

3.4 Simulation Model

The reservoir simulation model is developed in the MATLAB/ SIMULINK platform.

3.4.1 Reservoir

Consider N reservoirs in the cascade system. Reservoir operation for the ith reservoir is represented through the water mass balance equation (3.11).

$$S_i(t) = S_i(t-1) + LI_i(t) + Q_{i-1}(t) - E_i(t) - Q_i(t) - Sp_i(t) \qquad (3.11)$$

Reservoir storage ($S_i(t)$) is calculated by adding local inflows ($LI_i(t)$) and upstream reservoir discharges ($Q_{i-1}(t)$) and by subtracting evaporation ($E_i(t)$), spill ($Sp_i(t)$), and reservoir discharge ($Q_i(t)$) ((3.11)). Reservoir spill ($Sp_i(t)$) is a positive value when the total water ($T_i(t)$) in a reservoir is greater than the reservoir capacity (S_{max}) and otherwise is zero (Figure 3.5). Reservoir area ($A_i(t)$) and elevation ($H_i(t)$) are calculated from the reservoir characteristics curves. Reservoir discharge ($Q_i(t)$) at each time step is determined according to the reservoir operation rules.

Reservoir discharge ($Q_i(t)$) is determined from: (1) a reservoir guide curve ($RC_i(t)$), (2) the water requirements ($R_{Mi}(t)$) for hydropower and/or agricultural purposes (reservoirs are operated for both purposes or one purpose), (3) the current reservoir storage, and (4) the minimum reservoir operating level (S_{min}) using (3.12), (3.13), (3.14), and (3.15). Division by six in equation (3.13) is to reflect the need to supply water for the entire agricultural season, which lasts for six months.

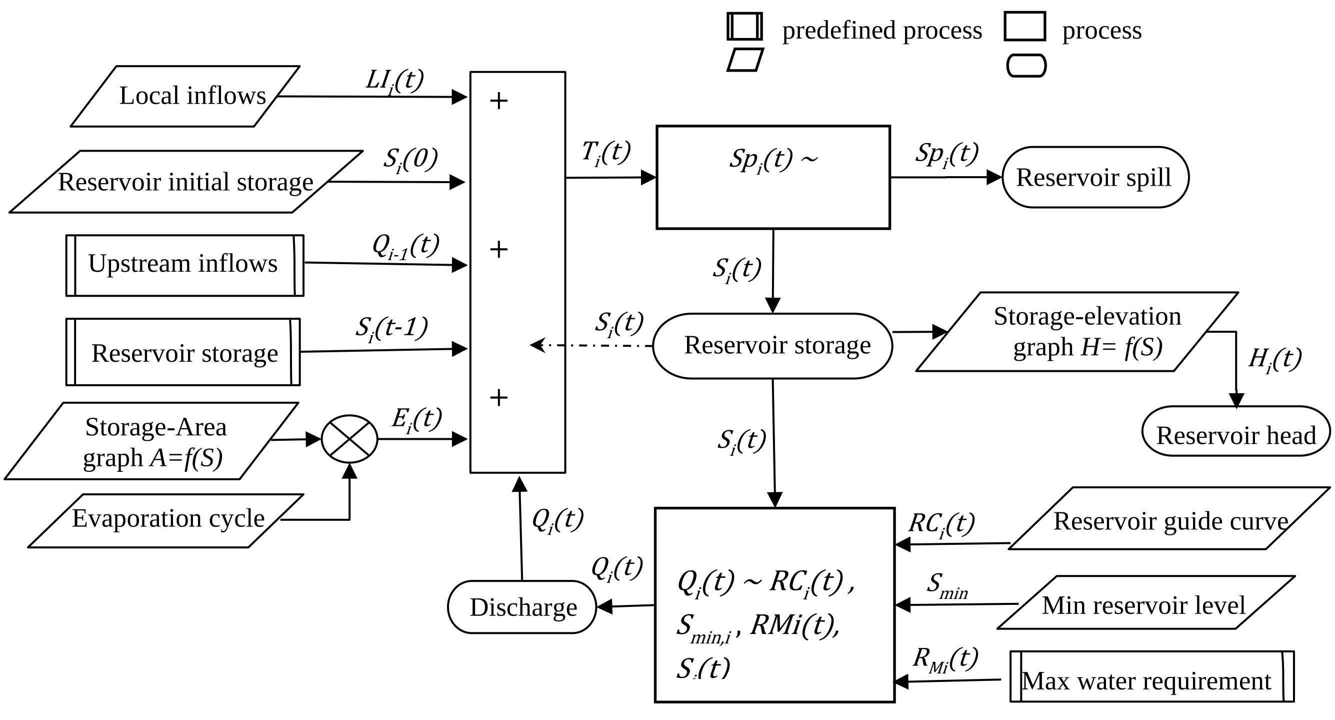

Figure 3.5 Reservoir operation simulation

$$S_i(t) < S_{min},\ Q_i(t) = 0 \tag{3.12}$$

$$S_{min} < S_i(t) < RC_i(t),\ Q_i(t) = (S_i(t) - S_{min})/6 \tag{3.13}$$

$$S_i(t) > RC_i(t) \text{ but } R_{Mi}(t) > \left(S_i(t) - RC_i(t)\right),\ Q_i(t) = S_i(t) - RC_i(t) \tag{3.14}$$

$$R_{Mi}(t) < \left(S_i(t) - RC_i(t)\right),\ Q_i(t) = R_{Mi}(t) \tag{3.15}$$

Managing the reservoir cascade according to the composite storage volumes in all reservoirs to develop rule curves for individual reservoir releases is a way to achieve an overall optimal policy. However, due to calculation complexities and spatial differences in hydrometeorology and irrigation demands, Mahaweli system reservoir cascade rule curves have been developed individually. The reservoir rule curves are based on the rainfall pattern of the catchment, temporal variation of irrigation water demands, and individual reservoir parameters.

3.4.2 Hydropower Plant

Hydropower production is a function of efficiency ($\eta_i(t)$), density of water (ρ), acceleration due to gravity (g), effective head ($H_i(t)$) and discharge ($Q_i(t)$) (3.16). Reservoir head varies according to the reservoir water level. Efficiency($\eta_i(t)$) is a function of both effective head and discharge (Figure 3.6).

$$P_i(t) = \eta_i(t)\rho\, g\, H_i(t)Q_i(t) \tag{3.16}$$

Hydropower energy production is the product of power and time. The maximum value of energy is constrained by the total power plant capacity. At each time step, the plant factor is calculated. If the plant factor is less than one, energy is calculated using (3.16). Otherwise energy is calculated from the total plant capacity.

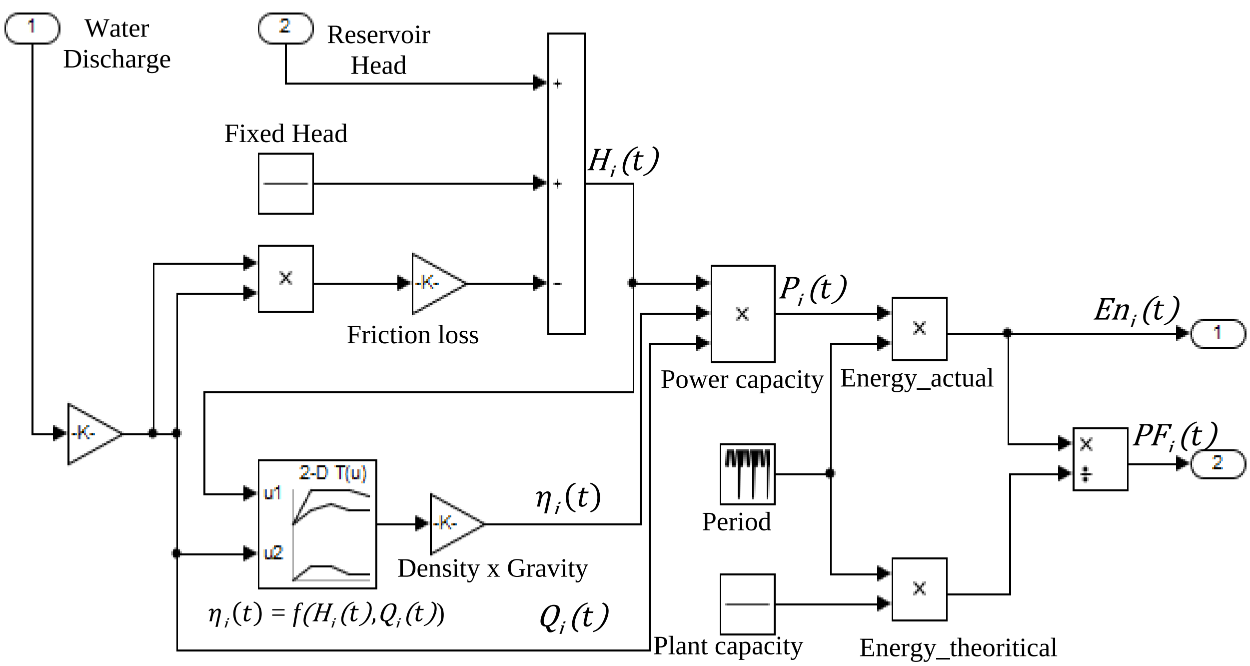

Figure 3.6 Hydropower plant simulation

3.4.3 Agricultural Systems

Water is distributed to a number (n) of agricultural systems. The success of meeting agricultural water demands in the ith agricultural system is measured by comparing irrigation water availability ($Ir_i(t)$) and the water requirement for agricultural crops ($Dt_i(t)$) (Figure 3.7). Crop water requirement or water duty ($D_i(t)$) varies during the cycle from land preparation to harvesting. In addition, the crop water requirement varies spatially according to the soil type and soil moisture content (Rivera, Gunda, & Hornberger, 2018). The total water requirement ($Dt_i(t)$) is a product of water duty ($D_i(t)$), water requirement per unit area (Mm^3/Ha) (Figure 3.4), and harvested land ($A_i(t)$) from the total land available in the system. We calculate the fraction ($U_i(t)$) where total water demand ($Dt_i(t)$) is met from available irrigation water ($Ir_i(t)$). A water demand threshold $MT_i(t)$ = x% of total arable land is specified and used to decide the success or failure of the agricultural season. If $U_i(t) >= MT_i(t)$, the season is taken to be successful. Water managers can specify the water demand threshold taking into account water thresholds of irrigation systems, in essence defining success by cutting back on the area irrigated when water is scarce. For this study we specify the threshold as 90% for each time period.

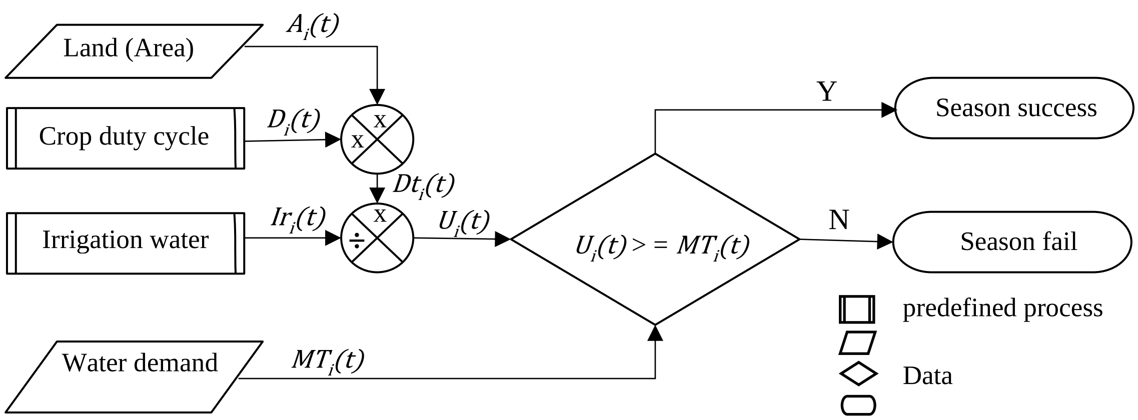

Figure 3.7 Agriculture system simulation

3.4.4 Water Distribution Decision

Irrigation water from upstream reservoirs is distributed in two steps to the smaller irrigation tanks (Figure 3.8). First, maximum possible quantities ($Ir1_i(t)$) are distributed among the systems, considering the total irrigation water ($I(t)$) availability and the water requirement ($Dt_i(t)$) of each agricultural system (3.17). Then, if the remaining water in upstream reservoirs is higher than the upstream reservoir capacity (S_{max}), additional water ($Ir2_i(t)$) is distributed among the downstream irrigation tanks according to the availability of space in each tank ($C_i(t)$)(3.18). If there is no space in the downstream irrigation tanks, additional water is spilled (3.11). Some agricultural systems have a dedicated irrigation tank to serve the local system while some others do not. For these systems irrigation water requirement ($Dt_i(t)$) from upstream reservoirs is the deficit not served by local tanks. For other systems, it is the total water requirement for cultivation. In (3.17) and (3.18), n is the number of agricultural systems served by the upstream reservoirs.

$$Ir1_i(t) = \begin{cases} I(t)\dfrac{Dt_i(t)}{\sum_{i=1}^{n} Dt_i(t)}, & I(t) \le \sum_{i=1}^{n} Dt_i(t) \\ Dt_i(t), & I(t) > \sum_{i=1}^{n} Dt_i(t) \end{cases} \tag{3.17}$$

$$Ir2_i(t) = \begin{cases} \left[I(t) - \sum_{i=1}^{n} IR1_i(t)\right]\dfrac{C_i(t)}{\sum_{i=1}^{n} C_i(t)}, & I(t) > \sum_{i=1}^{n} IR1_i(t) \text{ and } I(t) - \sum_{i=1}^{n} IR1_i(t) \le \sum_{i=1}^{n} C_i(t) \\ C_i(t), & I(t) > \sum_{i=1}^{n} IR1_i(t) \text{ and } I(t) - \sum_{i=1}^{n} IR1_i(t) > \sum_{i=1}^{n} C_i(t) \\ 0, & I(t) \le \sum_{i=1}^{n} IR1_i(t) \end{cases} \tag{3.18}$$

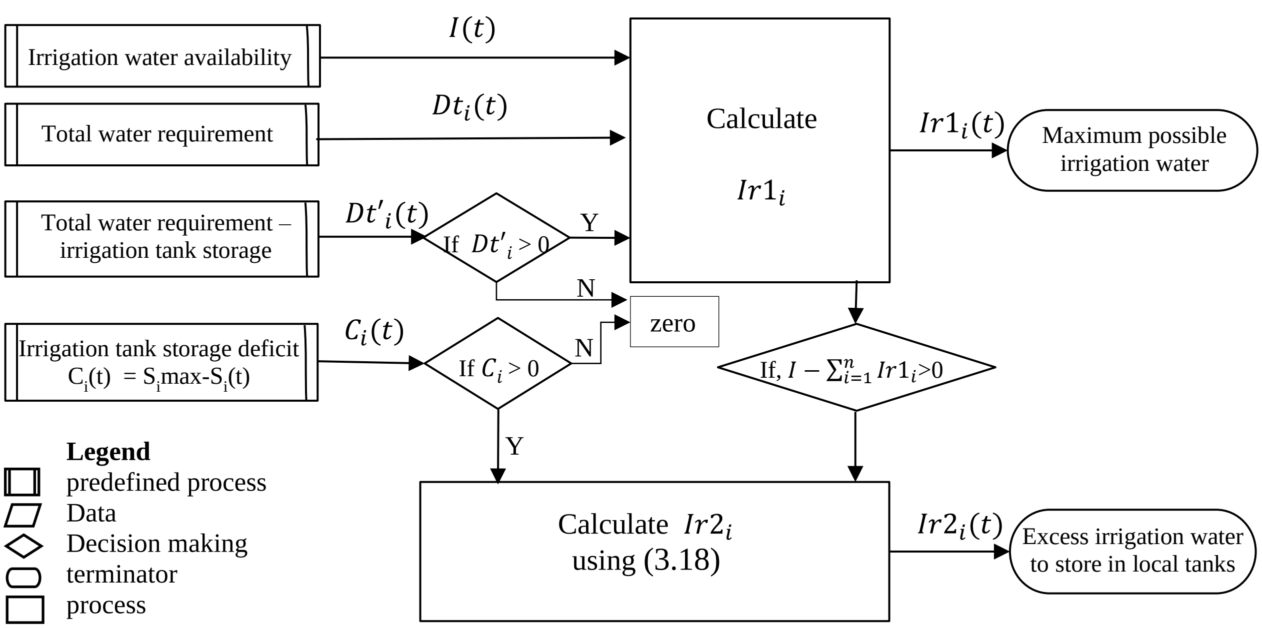

Figure 3.8 Irrigation water distribution decision

3.5 Project Performance Measurements

The performance of water management decisions is assessed using three measures: (1) products (agricultural products and electricity generated); (2) reliability, resilience, and vulnerability indices; and (3) the fraction of water delivered to irrigated fields.

3.5.1 Products of Water Users

Crop yield for agriculture and electricity produced from hydropower are taken as measures of production. Although the monetary value of electricity typically is higher than the monetary value of crops, agricultural systems are associated with high employment opportunities and the social value is very high.

3.5.2 Reliability, Resilience, and Vulnerability

Reliability, resilience, and vulnerability indices are used to evaluate the performances of hydropower plants and agricultural systems (Ajami et al., 2008; Hashimoto et al., 1982; Loucks & van Beek, 2017). Reliability is a measure of success of meeting water demands and resilience is a measure of recovering from a failure. Vulnerability measures the severity of failure (Jain & Bhunya, 2008; Sandoval-solis, Mckinney, & Loucks, 2011; C. Zhang et al., 2017). The indices are calculated for each agricultural season in recognition of the way decisions for water allocation are made. For this study, the system is simulated using a monthly time step. Success or failure is identified by setting a threshold for the partial fulfillment of the demands for hydropower and agricultural systems for the seasons (Table 3.1). In section 3.1.3 (Figure 3.7), we estimate the success or failure of agricultural systems for each month and convert this data into the success of the six month season using the threshold. We use satisfaction of a minimum of four months water requirement as a season success (S_t). Since we haven’t taken into account all the local inflows to the agricultural systems, and studying past seasonal data for 2002-2017 (Mahaweli Authority of Sri Lanka & Secreatariat, 2015) we assume partial fulfillment as a success of season rather than requiring fulfillment of all six months water demands from irrigation water. We use the 2002-2017 average as our threshold measure for hydropower (Table 3.1) since data for hydropower production are not available for all 63 years of the record. To be consistent, we use only energy data for hydropower plants operated throughout the 15 years for calculating the average value. Although there is no absolute reason for selecting the average as a threshold, we consider it useful for comparison of hydropower reliability, resilience and vulnerability values for different water allocation options.

Table 3.1. Measure of success for hydropower and irrigation performance

Water user	Success measure
Hydropower	Power production for the season equals or exceeds the 15-year (2002-2017) average for the season
Irrigation	90% of the crop water requirement for 4 months of the season is provided for 90% of land available for irrigation

The success or failure of a season ($V(t)$) is measured as $X(t)$, where the state is set as one for success and zero for failure (3.19)(Hashimoto et al., 1982; Mondal & Wasimi, 2007; C. Zhang et al., 2017).

$$X(t) = \begin{cases} 1, & if\ V(t)\ success \\ 0, & if\ \ V(t)\ fail \end{cases} \qquad (3.19)$$

Reliability is a measure of the number of successful seasons over the total number of seasons (T) considered for the simulation (3.20) (Hashimoto et al., 1982; Mondal & Wasimi, 2007; C. Zhang et al., 2017).

$$Reliability = \frac{\sum_{t=1}^{T} X(t)}{T} \qquad (3.20)$$

Transition from failure to the next state is measured by $W(t)$, where success is set as one and failure is set as zero (3.21).

$$W(t) = \begin{cases} 1, & if\ X(t) = 0\ and\ X(t-1) = 1 \\ 0, & if\ \ X(t) = 0\ and\ X(t-1) = 0 \end{cases} \qquad (3.21)$$

Resilience is a measure of how quickly a system is likely to recover after a failure (Chanda, 2014; Hashimoto et al., 1982; Mondal & Wasimi, 2007; Simonovic & Arunkumar, 2016). We estimate the ratio of total recoveries from failure to success from the total number of failures during the simulation (3.22).

$$Resilience = \frac{\sum_{t=1}^{T} W(t)}{T - \sum_{t=1}^{T} X(t)} \qquad (3.22)$$

Vulnerability is a measure of the severity of the failure (Ajami et al., 2008; Asefa, Wanakule, Adams, Shelby, & Clayton, 2014; Fowler, Kilsby, & O'Connell, 2003; Moy, Cohon, & ReVelle, 1986), which is measured as the maximum number of successive seasonal failures in this study (3.23), (3.24).

$$Y(t) = \begin{cases} 1 - X(t), & t = 1 \\ Y(t-1) + (1 - X(t)), & t > 1 \; and \; X(t) = 0 \\ 0, & t > 1 \; and \; X(t) = 1 \end{cases} \tag{3.23}$$

$$Vulnerability = \max_{t \in (1,..T)} Y(t) \tag{3.24}$$

3.5.3 Fraction of Water Utilization for Irrigation

The beneficial utilization of water for agriculture in the total system is estimated from total water inflows to the reservoirs, water releases for irrigation, and losses. Total water inflow (I) to the system is consumed by agricultural systems (Ir), is evaporated from the reservoir or tank (E), or is spilled (Sp) (3.25). Hydropower plants do not consume water so all water used for hydropower is available for irrigation in downstream areas. Water losses in waterways by evaporation and seepage, and water losses in the reservoirs by seepage are not considered for the water balance model. The share of water to the agricultural systems from the total is considered as the cascade's fractional agricultural utilization (Ef) in our study. We use cascade's fractional agricultural utilization as an indicator to measure the different water allocation options at the main water diversions of the water resources management. In our study, Polgolla is the main water diversion location and fractional utilization is considered only as a metric to compare options for this diversion.

$$\sum_{t=1}^{T}\sum_{i=1}^{N} I(t,i) = \sum_{t=1}^{T}\sum_{i=1}^{M} Ir(t,i) + \sum_{t=1}^{T}\sum_{i=1}^{N} [E(t,i) + Sp(t,i)]$$
$$Ef = \frac{\sum_{t=1}^{T}\sum_{i=1}^{M} Ir(t,i)}{\sum_{t=1}^{T}\sum_{i=1}^{N} I(t,i)} \tag{3.25}$$

3.6 Evaluation of Water Allocation Alternatives of Mahaweli Project

Several water allocation scenarios of Mahaweli reservoir cascade are analyzed using the simulation model. We examine two objectives associated with the agricultural systems: (1) risk indices for each system according to water management decisions and (2) fraction of land from the total arable lands that have 100% reliability according to the given water management decisions. Because one agricultural adaptation mechanism for seasons with very limited irrigation water available is to cultivate only a fraction of the arable land available, we also explore how performance varies considering planting decisions between 50% and 100% of the available land.

We explore performance relative to management options of maintaining the current maximum diversion at Polgolla and of increasing the maximum diversion in steps up to 140% of the current value. Performance is measured in terms of: (1) reliability, resilience, and vulnerability (2) fraction of water used by irrigation systems, and (3) total agricultural crop yield and hydropower generation.

3.7 Results

For the present Polgolla water diversion policy, the irrigation systems show variable performance measures. System D2 shows the best reliability, resilience and vulnerability values. Systems B&C have higher reliability values than does system H, while system H shows higher resilience and lower vulnerability (Table 3.2). The 15-year average hydropower production is met in 89 of the 126 seasons in the historical record.

Table 3.2. Performance measures of irrigation and hydropower systems

Systems	Reliability	Resilience	Vulnerability	Land fraction meeting 100% reliability
System B&C	0.61	0.66	18	0.56
System D1	0.53	0.60	32	0.49
System D2	1.0	1.0	0	1.0
System H	0.57	0.71	13	0.45
Hydropower	0.71	0.57	8	

The relative performance of the agricultural systems changes as the fraction of land cultivated decreases from 100% to 50% (Figure 3.9). In particular, system H achieves the best performance indicators as the fraction of land irrigated decreases. Because water used for hydropower is available for irrigation downstream, hydropower does not affect results for irrigation in systems below the diversion at Polgolla; there is no influence for hydropower generation with variation of land fraction.

Reducing yields by decreasing the fraction of arable land cultivated from 100% to 50% results in improvements in risk performance measures (Figure 3.10). In systems B&C reducing yield from 400 kT to 300 kT increases reliability from 0.6 to 0.74 and increases resilience from 0.66 to 0.76. Patterns are similar for other systems, although in system H resilience improvements are minimal after yield is reduced by one third. (Note that the large yield values of system H and B&C compared to system D1 simply reflect a difference in total land area in each.)

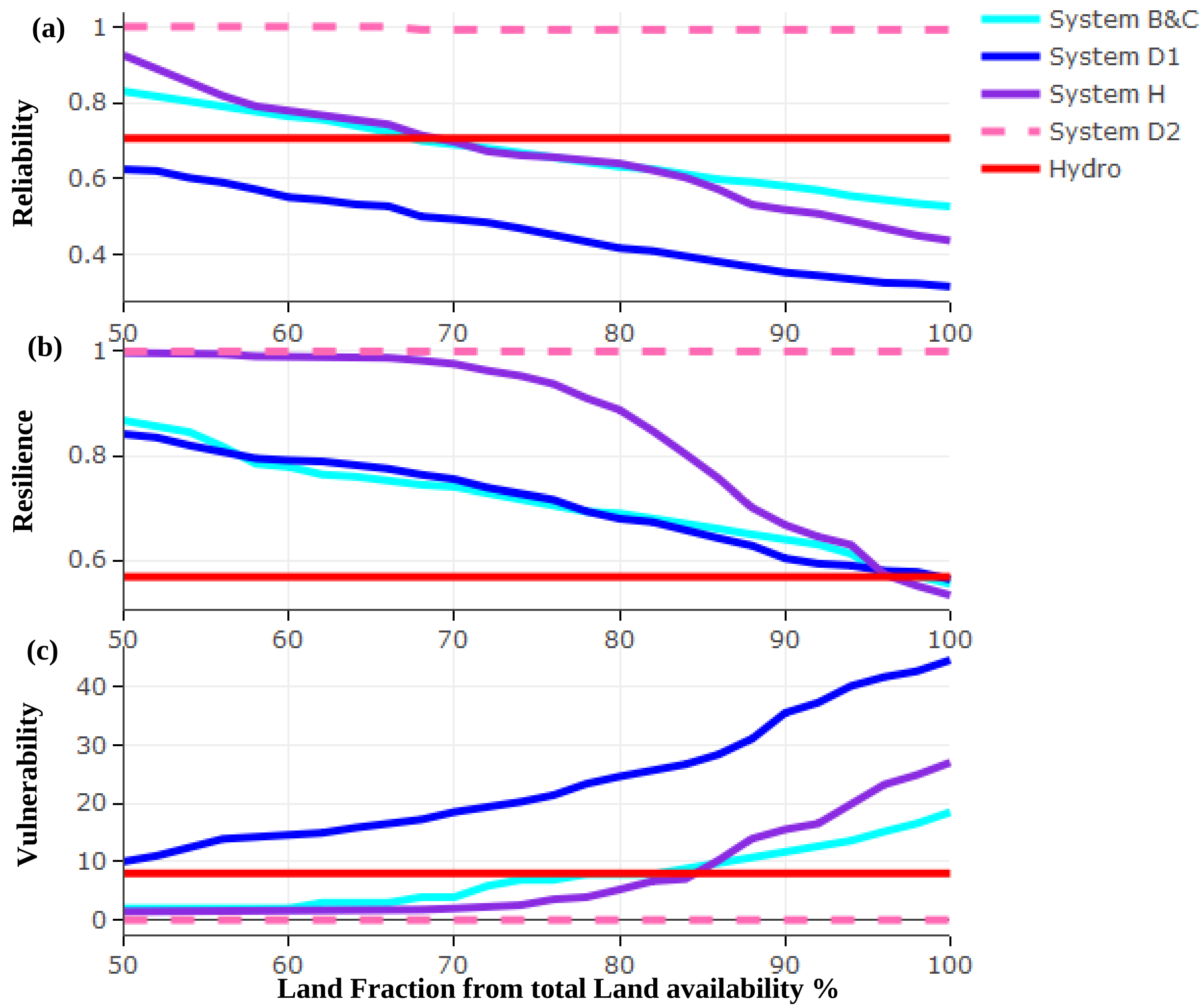

Figure 3.9 Performances of agricultural systems and hydropower plants for the present water diversion policy for variable fraction of land cultivated in reliability, resilience and vulnerability measures. Note that hydropower is not affected because the diversion

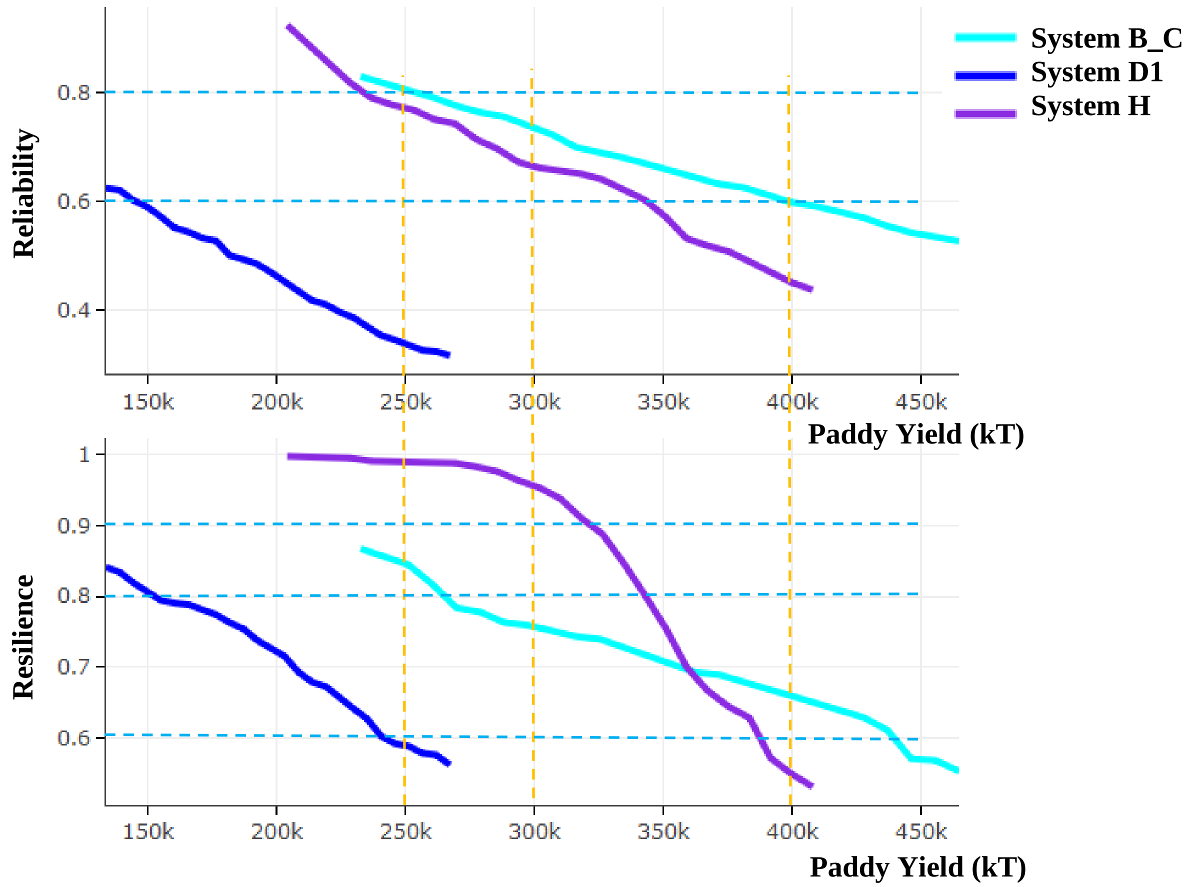

Figure 3.10 Trade-offs between expected agricultural yield and reliability, resilience indices.

Changing the water diversion policy at Polgolla has both positive and negative impacts (Figure 3.11, Figure 3.12). Performance of the system of hydropower plants and of irrigation systems B and C, which are on the main stem of the Mahaweli River below the diversion at Polgolla, become weaker with diversion of additional water to the northern area of the country and the performance of the irrigation systems supplied from the Polgolla diversion, D1 and H, become stronger (Figure 3.12). As diversions at Polgolla increase, spills from the reservoirs off the main stem of the Mahaweli river increase, evaporation losses decrease, and the fraction of water supplied to irrigate lands first increases and then decreases (Figure 3.12 (a)). Diverting water from upstream to the north reduces the natural Mahaweli river flow; diversion has an essentially non-measurable impact on evaporation losses of downstream main reservoirs (Figure 3.12 (b)).

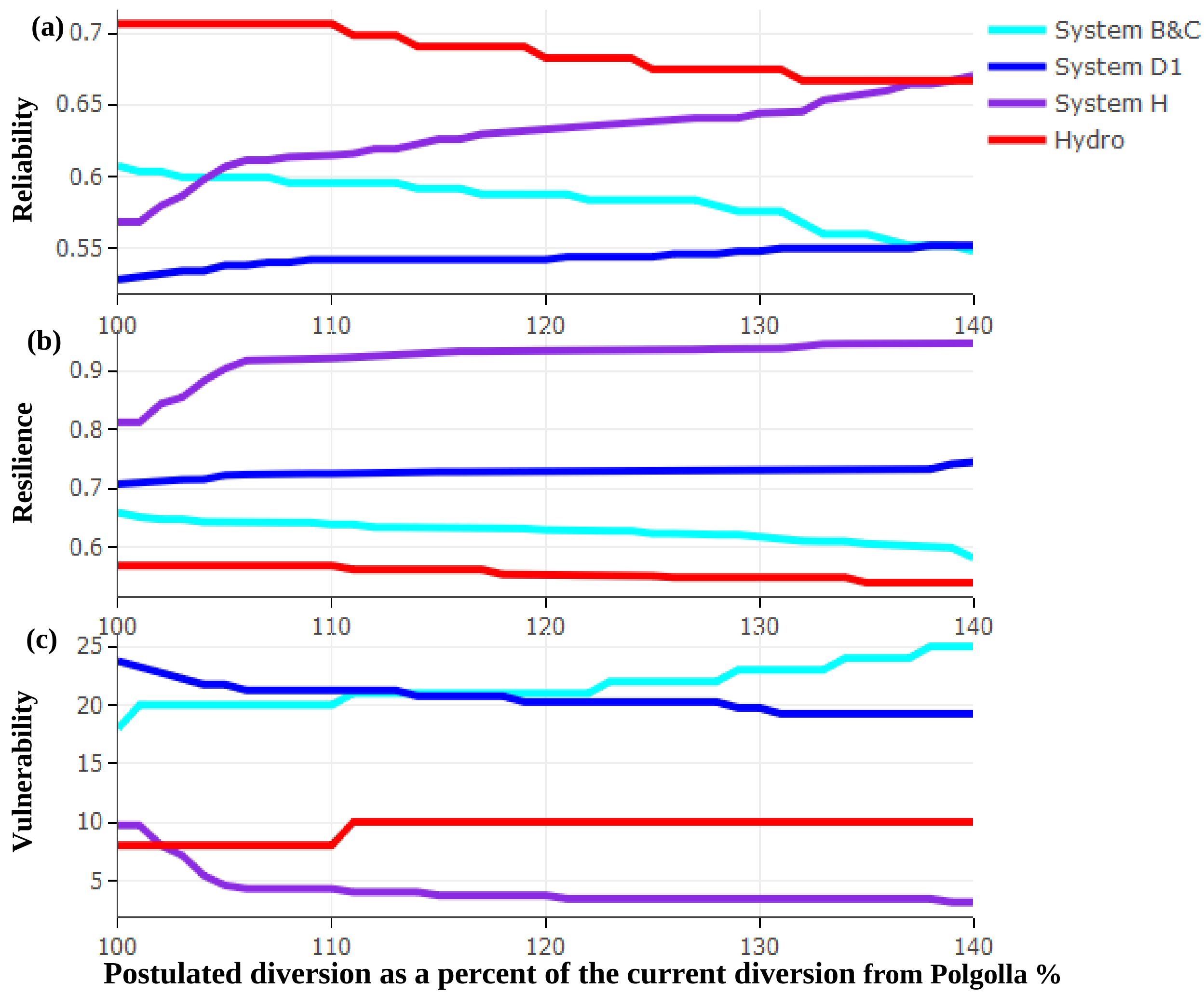

Figure 3.11 Performances of agricultural systems and hydropower plants for increasing water diversion to the north from the Polgolla diversion weir

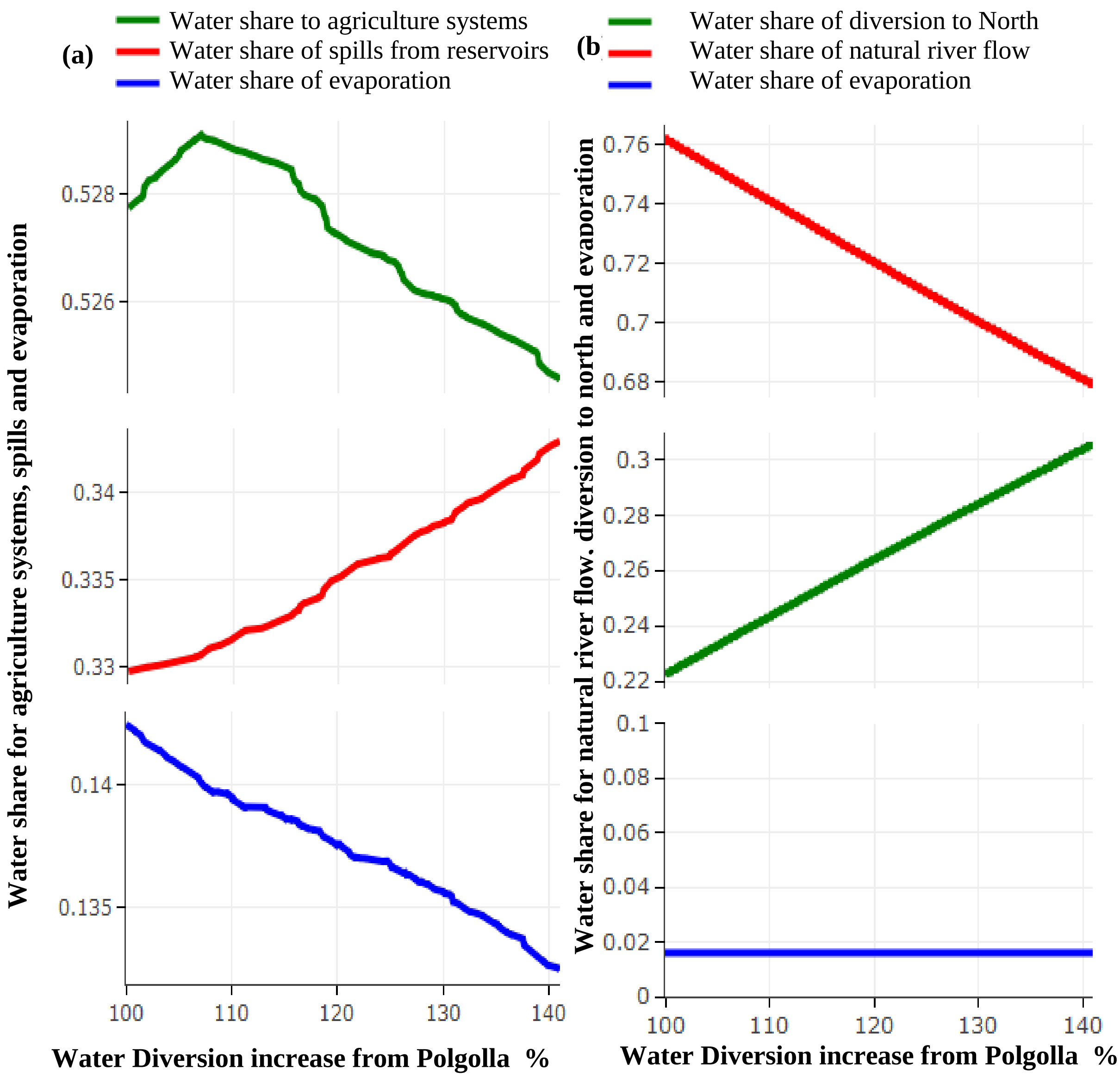

Figure 3.12 (a) Water balance among agricultural systems, evaporation loss and spilling from reservoirs (b) Mahaweli river flow and evaporation from downstream reservoirs

Water diversion at Polgolla involves a trade-off between irrigated agriculture and hydropower generation. Beyond a 16%, increase of the present water diversion at Polgolla there is no enhancement of either the paddy yield or energy production (Figure 3.13). In fact, beyond a 16% increase, paddy yield actually decreases because systems on the main stem of the Mahaweli (e.g., B and C) receive less water and thus are less productive while at the same time systems to the north that receive water diverted at Polgolla (e.g., D1 and H) do not have the capacity to store the additional water and so agricultural production remains flat and spill losses increase. A trade-off frontier curve between hydropower and paddy yield for different increases in diversion shows that the feasible region for decisions about the tradeoff is between an average annual range of 1012- 1034 Mtonnes of paddy and 2186-2229 GWh of hydropower generation ((Figure 3.13(b)).

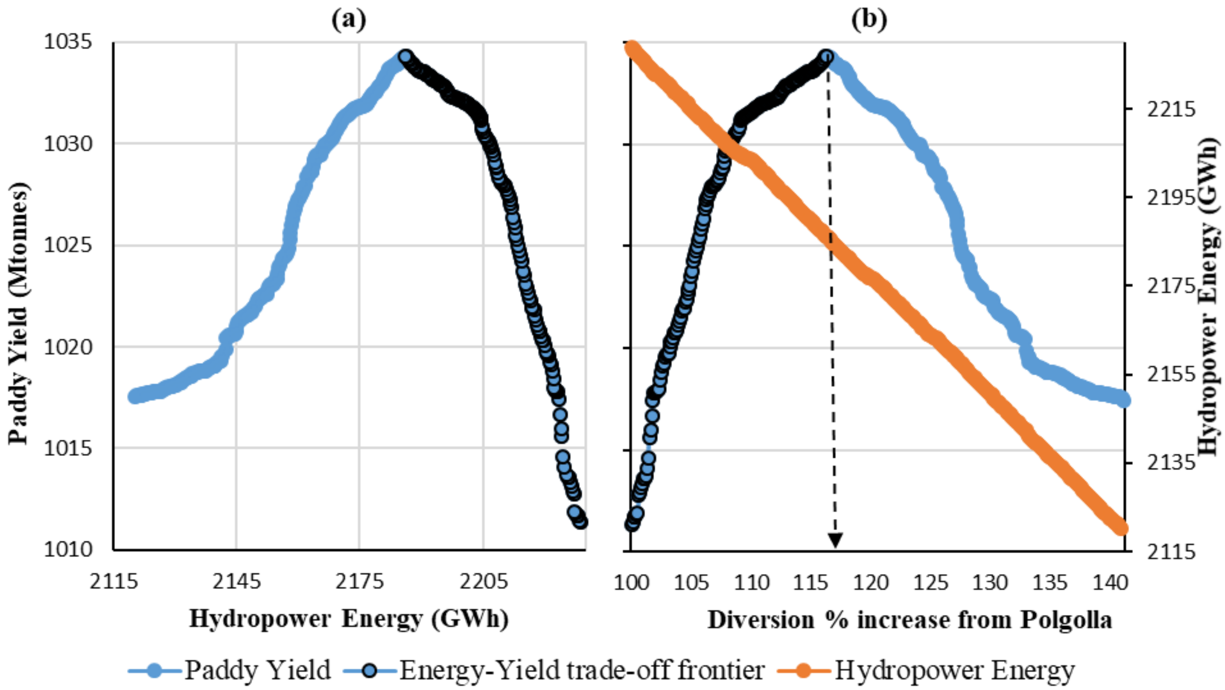

Figure 3.13 Agriculture and energy performance according to increasing Polgolla water diversion to the dry northern area (a) Variation of paddy yield (blue) and hydropower generation (orange) (b) Trade-off between paddy yield and hydropower generation.

3.8 Discussion

Under the present policy for water diversion at Polgolla, the reliability, resilience and vulnerability values show how different issues can affect different systems (Table 3.2). Hydropower exceeds the recent 15-year average more than 70% of time using hydropower generation of the recent past years (2002-2017) for comparison. However, the low resilience (0.57) and comparatively high vulnerability (8/126) values demonstrate the uncertainty of hydropower generation. Limitations of infrastructure and spatial variability of available water constrain agricultural system performance. For example, system H has a poor reliability value because about 42,000 ha of arable land is supported by only 224 Mm^3 of local water storage capacity. However, a large local storage capacity does not improve risk measures if water is not available to supply the reservoirs and tanks. For example, systems B&C (about 48,000 ha) show relatively weak performance despite being supported by a large water storage capacity of 742 Mm^3 (Figure 3.9,

Figure 3.11) System D2, which has the best performance measures, is a good example for high local storage capacity and an abundant supply of water. Although D1 is adjacent to D2, its risk measures are much worse due to a lack of infrastructure to distribute water.

One drought adaptation measure is to reduce the amount of cultivated land. Improvement of performances of agriculture systems under this adaptation measure varies across systems. For example, system H shows large improvements in resilience at 80% of land cultivated whereas systems D1, B and C show much more modest improvement (Figure 3.9 (b)). Due to advantageous climate and soil properties system H has a lower crop water requirement compared to other systems (Figure 3.4) and improves at a high rate in terms of resilience as the extent of arable land cultivated decreases. This also is the reason for the marked improvement shown in System H as increased diversion at Polgolla provides additional irrigation water (Figure 3.11).

Reducing the extent of irrigated lands involves trade-offs between improving risk performance measures and reducing the yield and hence economic return of agricultural systems (Figure 3.10). The trade-offs are not the same for different agricultural systems due to water availability and infrastructure for water storage. Notably, the resilience improvement in system H is approximately double that in system B&C (Figure 3.11). Hence, individual system performance can inform water management decisions.

Performance measures downstream of the diversion at Polgolla are sensitive to the water allocation policy (Figure 3.11). As expected, performance of irrigation systems to the north is improved for higher diversions at Polgolla. Beyond about a 16% increase in the diversion, however, water spilling from northern local reservoirs is increased (Figure 3.12 (a)) and overall paddy production decreases because water is taken away from systems on the main stem of the Mahaweli leading to decreased production there, while the additional water diverted north cannot be stored and used efficiently so paddy production there remains flat (Figure 3.13).That is, the fractional agricultural utilization (Ef) decreases because spilling increases. In addition, although we have not accounted for environmental impacts in our analysis, significant decreases in flow in the main Mahaweli River will negatively impact social and natural capital downstream.

Our results indicate that a simulation model based on a system dynamics approach can provide information to assist in analyzing consequences of water allocation decisions. A relatively simple model such as we propose can be useful for a screening analysis of the impacts of proposed water allocation policies using a modest amount of data about the water resources project. Our case study of the Mahaweli system shows that it is possible to develop a simulation model for a complex reservoir cascade using basic simulation blocks; reservoir, hydropower plant, agriculture system and water distribution decision. The Simulink platform (MathWorks Simulink, 2018) is easy to understand and can be used by those with modest programming skills. Components of the reservoir cascade can be visualized and the model can be modified easily according to new infrastructure additions and parameter changes. The relatively simple simulation model developed in the MATLAB/Simulink platform can be used for studying similar reservoir systems.

The performance of reservoir cascade systems in terms of economic products as well as in risk measures provide information to inform decisions about the operation and planning for future alternatives. Analysis of the performance of components of the overall system indicates limitations imposed by existing infrastructure and also changes that would result from proposed new infrastructure. Overall cascade performance measures in terms of economic products expose the energy-yield trade-offs of water sharing between hydropower and irrigated agriculture. Reliability, resilience and vulnerability indices of agricultural systems vary according to the spatial variability of land properties, water availability, and infrastructure facilities. Knowledge about these variabilities across the systems can be used to fine tune system level decisions about the tradeoffs between increasing yields and increasing RRV metrics. Reducing the extent of cultivated land or changing of water allocations at one location provide only marginal improvement of RRV measures of most of the systems. Because changing the operation policy of one major location can marginally increase agricultural production but substantially decrease hydropower generation. Hence, we further explore the combination of important components in the reservoir cascade operation rules that enhance the cascade performance and enable to make informed decisions of water resources management by analyzing trade-offs between hydropower energy and agricultural yield. Specifically, optimizing hydropower and agricultural yield without losing a substantial amount of either objective values can inform the balance decision of reservoir cascade operation rules.

CHAPTER 4

Deriving Reservoir Cascade Operation Rules for Variable Stream Flows by Optimizing Hydropower Generation and Irrigation Water Delivery for the Mahaweli Project in Sri Lanka

4.1 Introduction

The importance of hydropower for the Sri Lankan power grid is increasing in many aspects similar to the other parts of the world. Hydropower is a renewable energy source, relatively less expensive and stable compared to other variable renewable energy sources (Stoll et al., 2017). Hydropower supplies grid ancillary services such as frequency control, contingency reserves, and spinning reserves. The quick start and stop time and ramping rates of hydropower plants support the power system in many ways. Because of these features hydropower is identified as a promising way to integrate variable renewable sources such as wind and solar power (Gebretsadik, Fant, Strzepek, & Arndt, 2016; Hirth, 2016; Jurasz, Mikulik, Krzywda, Ciapała, & Janowski, 2018; F. Li, Shoemaker, Qiu, & Wei, 2015; Ming et al., 2017).

Managing reservoir cascades to harness maximum hydropower while satisfying other water uses such as flood protection, navigation, irrigation and potable water use is challenging. Rule curves, which are a function of reservoir characteristics, geography, hydrology and water demands, guide the effective management of reservoirs by prescribing storage vs. water releases (Kangrang, Prasanchum, & Hormwichian, 2018; Lin, Wu, & Chen, 2005). Water allocations among competing water users is another important element in reservoir cascade management. For example, consistent water releases can benefit hydropower production whereas storage of water until needed for irrigation is a goal for agriculture. Hence, the development of optimal reservoir operation policies requires analysis of values associated with the multiple, competing uses of the water in the face of annual and seasonal variability in river inflows to the reservoir system (Gaudard, Avanzi, & De Michele, 2018).

Although optimization methods such as multiobjective evolutionary algorithms (MOEA) have been successfully applied for exploring optimal operation policies for reservoir cascades that balance conflicting objectives (Giuliani, Castelletti, Pianosi, Mason, & Reed, 2016a; Giuliani, Quinn, Herman, Castelletti, & Reed, 2018a; F. F. Li, Shoemaker, Qiu, & Wei, 2015; Zhou, Guo, Chang, Liu, & Chen, 2018), the “curse of dimensionality” makes the problem difficult or even intractable for more than a small number of reservoirs (Chu, Zhang, Fu, Li, & Zhou, 2015; Zhou, Guo, Chang, Liu, et al., 2018). Although optimization of reservoir cascades can be accomplished using advanced computing technology (J. D. Quinn, Reed, Giuliani, & Castelletti, 2017; J. D. Quinn et al., 2018), approximations are necessary when only modest computational resources, e.g., personal computers, are available. Evolutionary algorithms can be used with successive approximations (Zhou, Guo, Chang, Liu, et al., 2018) to reduce the dimensions of the optimization problems. In such methods the n-dimensional problem is divided into a smaller number of individual problems to overcome the calculation burden (Zhou, Guo, Chang, & Xu, 2018). In this chapter we illustrate how the MOEA optimization method, judiciously applied to a small number of segments of the Mahaweli reservoir cascade to avoid problems of dimensionality, can be used to derive operating rules that balance conflicting objectives. The computation is carried out in two stages focusing on the Polgolla, major diversion that allocates water preferentially to favor either hydropower generation or agricultural production and on the operating rules for three reservoirs with the largest generation capacities – Kotmale, Victoria, Randenigala - in the system (Figure 3.2). The resulting computationally efficient method yields improvements in performance compared to existing operating rules and allocation rules and exposes trade-offs of achieving objective values for Pareto optimal solution sets.

4.2 Methods

As described in the previous chapters, the Mahaweli reservoir cascade system, which is comprised of 21 reservoirs, 21 agricultural regions, and seven hydropower plants (Figure 3.2), is operated mainly for hydropower generation and irrigated agriculture. Inflows to the reservoirs reflect the dual monsoon seasons, referred to as Maha and Yala, that characterize Sri Lanka's climate. The key water allocation point in the system is at Polgolla, where water diverted away from the main stem of the river is used primarily for irrigation while water that is not diverted is used primarily for hydropower generation. Kotmale reservoir, just upstream of Polgolla, is a large hydropower generator, as are two other large reservoirs, Victoria and Randenigala, immediately downstream of the diversion at Polgolla. The allocation rule for the one diversion point and the operating rule curves for the three major reservoirs (outlined with a dashed line in Figure 3.2 and isolated in Figure 4.1) are currently based on experience, i.e., they do not result from any formal analysis.

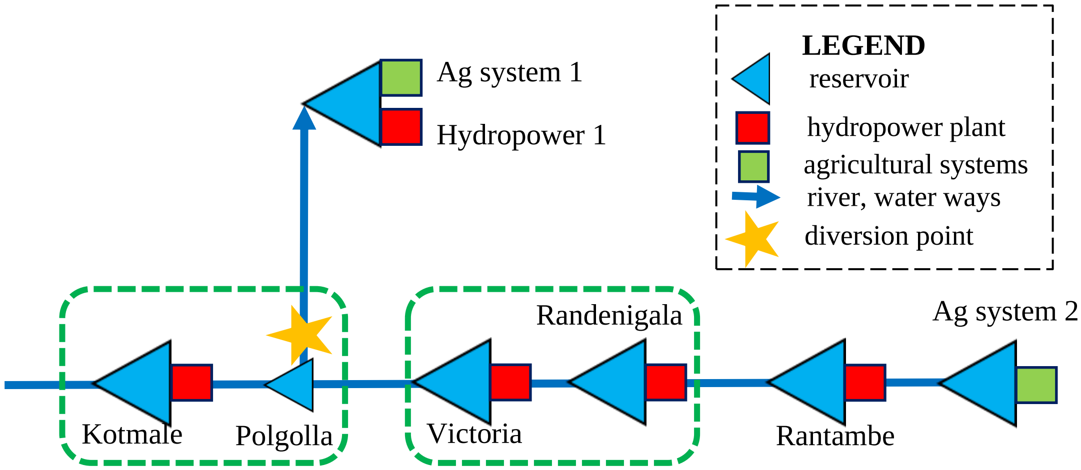

Figure 4.1 Simplified schematic diagram of Mahaweli cascade for the study, stage 1: Kotmale and Polgolla operation policies and stage 2: Victoria and Randenigala operation policies

We derive optimal operation rules of three reservoirs and one diversion and the optimization is done in two stages. First the rules for Kotmale and for Polgolla are jointly optimized, holding all else fixed at the existing rules. Subsequently, the rules for Victoria and Randenigala are jointly optimized, holding the optimized rules from the first stage for Polgolla and Kotmale (and all other reservoirs and diversions in the system) fixed. Agriculture is planned for two six-month seasons, from April-September (Yala season) and from October-March (Maha season) according to the monsoon rainfall. The Yala season is dry for the agricultural systems compared to the Maha season because of differing rainfall patterns so allocation and releases are necessarily different for the two seasons. The optimization study is carried out in the following steps.

1) Yala season, stage 1: Kotmale, Polgolla
2) Yala season, stage 2: Victoria, Randenigala
3) Maha season, stage 1: Kotmale, Polgolla
4) Maha season, stage 2: Victoria, Randenigala

A simulation-based multiobjective optimization using the evolutionary algorithm (Deb, Pratab, Agarwal, & Meyarivan, 2002; MathWorks, 2019) is used to derive the optimal reservoir operation policies by optimizing hydropower and agricultural yield for a 1000-year synthetically generated inflow series. The optimization exercise is carried out focusing on both the extreme and average inflow conditions (Figure 4.2).

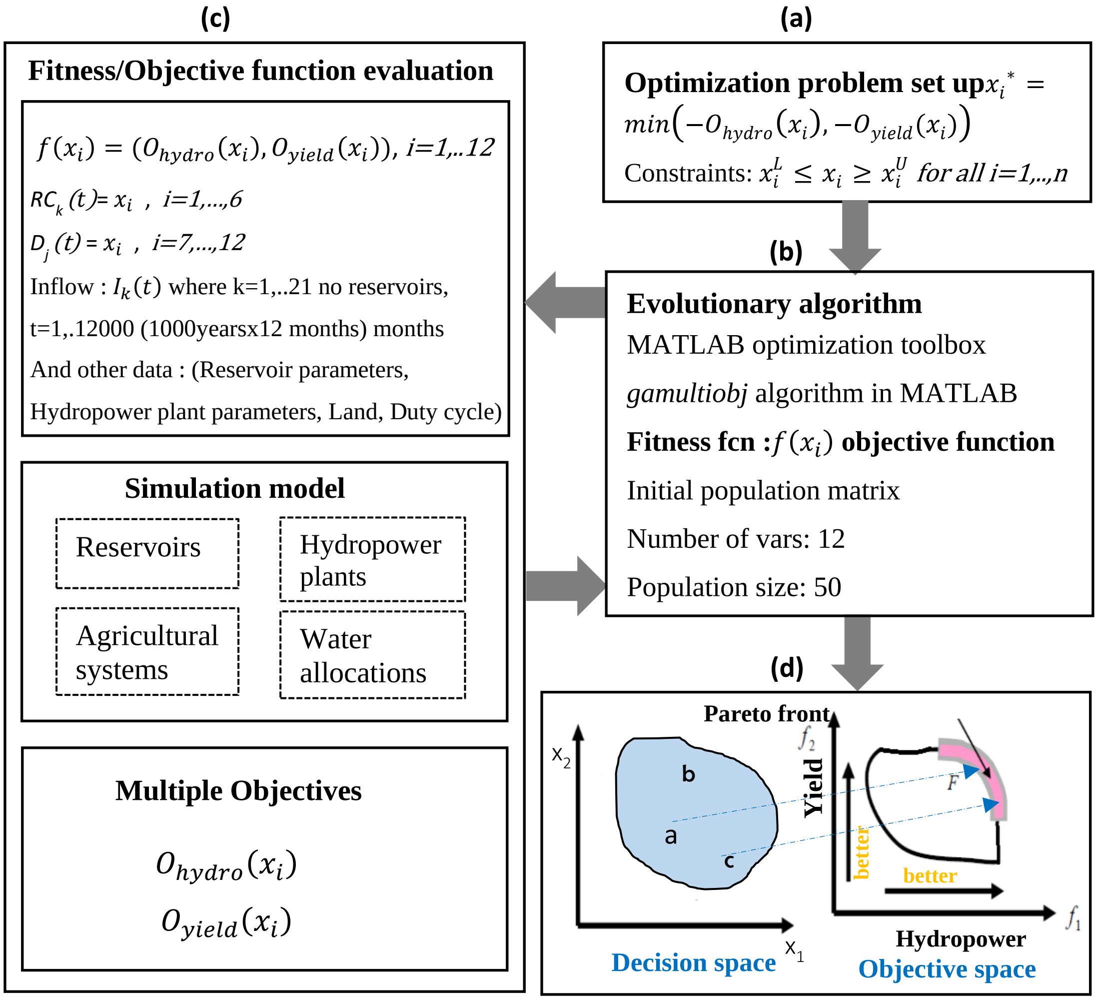

Figure 4.2. Steps of deriving the Pareto frontier for maximizing hydropower energy and agriculture yield and reservoir cascade operation rules. (a) Identify multiple objectives and decision variable boundaries. (b) Invoke evolutionary algorithm, MATLAB optimization (c) Evaluate the fitness function; assemble hydropower and yield for the lowest 10%/average for 1000 years of simulated inflow data and system simulation model. (d) Complete the calculations using the gamultiobj evolutionary algorithm

4.3 Synthetic Stream Flow Generation

Accounting for the variability of monsoon rainfall over the Mahaweli cascade is essential in water resources planning for hydropower and agriculture. We use records of monthly reservoir inflows for 63 years to characterize the seasonal and annual variability in the system. We generate synthetic stream flows considering the statistical properties of the historical data. Synthetic stream flows are generated that preserve the temporal and spatial correlations of stream flows assuming stationarity of the hydrology. We used mathematical codes developed by Quinn, J.D. (2018) based on Cholesky decomposition (Kirsch, Characklis, & Zeff, 2013; Julianne D Quinn, 2017).

We use N_H (63 years) of historical data to generate N_S (1000 years) of synthetic data (I_S) in several steps. First, historical data (I_H) is transformed to a log scale (A_H) to obtain an approximately normally distributed data set and then standardized using (4.26), where is μ_j the mean value and σ_j is the standard deviation of jth month.

$$B_{H_{(i,j)}} = \frac{A_{H_{(i,j)}} - \mu_j}{\sigma_j} \tag{4.26}$$

$$Z_S = \gamma_S \alpha \tag{4.27}$$

$$I_S = \exp\left(Z_S"\right) \tag{4.28}$$

A synthetic data series ($\gamma_{S_{(Ns\, x\, 12)}}$) is generated from the randomly sampled historical standardized data, by first creating a temporary matrix ($M_{(Ns\, x\, 12)}$). Each column of the M is generated from randomly sampled integers (1,…,N_H), which is the number of rows of matrix B_H (standardized log scale historical data). Elements for the matrix $\gamma_{S_{(i\, x\, j)}}$ are assigned from B_H according to the matrix M. To preserve the spatial correlation among the 21 reservoir sites the same temporary matrix M is used to generate synthetic streamflow for each site. Autocorrelation of the synthetic data set (I_S) is preserved by carrying out two further steps. From the correlation of the historical data between different months, which is a correlation of matrix B_H columns ($\beta = corr(B_H)$), an upper triangular matrix α is generated from the Cholesky decomposition ($\beta = \alpha\alpha^T$). First, the standardized autocorrelated synthetic data series (Z_S)is calculated (4.27), and then converted to flow data using mean (μ_j) and standard deviation (σ_j).

A further step is carried out to preserve the autocorrelation of data from the last month of the previous year to the first month of the next year (Kirsch et al., 2013). The same procedure carried out to generate the standardized autocorrelated synthetic data series (Z_S) is repeated by creating a new matrix ($I_H{}'$) from historical data (I_H). The new matrix ($I_H{}'$) is for data for the 7th to 12th months of the previous year and for the 1st to 6th months of the present year as one row and a new standardized autocorrelated synthetic data series ($Z_S{}'$) is generated. By linking the first row, last 6 columns (months 1-6) of the $Z_S{}'$ with the last 6 columns of the second row, last 6 columns (months 7-12) of the Z_S a continuous autocorrelated data series (Z_S") is generated. Finally the data are transformed from the logarithmic scale back to the measured discharge scale to generate the synthetic data set (4.28)(Figure B. 1).

4.4 Reservoir Cascade Operation Policy Optimization

We use the Mahaweli reservoir cascade system model of Chapter 3 (De Silva M. & Hornberger, 2019b) to simulate performance given various operation rules. Reservoirs of the cascade are simulated according to the water balance equation (29.4). Reservoir storages ($S_k(t)$) are dynamically updated using a monthly time step from the addition of stream flows ($I_k(t)$) to the reservoir, discharges ($Q_{k-1}(t)$) and spills ($Sp_{k-1}(t)$) from the upstream reservoirs and subtraction of evaporation loss ($E_k(t)$) and water releases ($Q_k(t)$). Reservoir physical parameters such as storage-area and storage-elevation data, and evaporation cycle are used to calculate evaporation loss ($E_k(t)$).

$$S_k(t) = S_k(t-1) + I_k(t) + Q_{k-1}(t) + Sp_{k-1}(t) - E_k(t) - Q_k(t) \quad (29.4)$$

Water releases ($Q_k(t)$) from a reservoir are set according to the target storage specified by the rule curve ($RC_k(t)$), the reservoir storage ($S_k(t)$), the minimum reservoir capacity (S_{kmin}) and the maximum water requirement (Q_{kmax}) of the hydropower plant. If the reservoir storage is less than the minimum, water release is zero (4.30), and if the storage is between the minimum and targeted value, water releases are pro-rated (4.31). In (4.31), the value of *'a'* is the number of months of the water release plan; for this study we use the value as six since water releases are planned for two six-month seasons during a year. If the reservoir storage is greater than the target value, the difference between storage and target is released (4.32). If the difference is greater than the maximum hydropower plant capacity, the maximum water requirement is released (4.33). Operation of reservoirs except Kotmale, Victoria and Randenigala follow the rule curves of current practices (Chapter 3).

$$S_k(t) < S_{kmin}, \; Q_k(t) = 0 \quad (4.30)$$

$$S_{kmin} < S_k(t) < RC_k(t), \; Q_k(t) = (S_k(t) - S_{kmin})/a) \quad (4.31)$$

$$S_k(t) > RC_k(t), \text{ but } Q_{kmax} > \left(S_k(t) - RC_k(t)\right), Q_k(t) = S_k(t) - RC_k(t) \quad (4.32)$$

$$Q_{kmax} < \left(S_k(t) - RC_k(t)\right), Q_k(t) = Q_{kmax} \quad (4.33)$$

The water allocation rules for Polgolla define the fraction of water allocated between diversion to the dry zone (for Ag system 1 and Hydropower 1; Figure 4.1) and pass through to the downstream (Ag system 2 and downstream hydropower plants; Figure 4.1). The total water available at the diversion point at each time step is the addition of releases from upstream hydropower power plants ($Q_k(t)$), spill from the upstream reservoir Kotmale ($Sp_k(t)$) and local inflows ($I_p(t)$) from the sub-catchment (4.34). Water diversion at Polgolla ($D_1(t)$) is constrained by the physical capacity (V) of the tunnel that can transfer the maximum amount of water each month ((4.35) ,(4.36). Water allocation rules of the other six points for different agriculture systems are specified as a function of time according to the irrigation water requirement of the agricultural systems.

$$T_p(t)=Q_k(t)+Sp_k(t)+I_p(t) \quad (4.34)$$

$$D_1(t)*T_p(t)=(1-D_2(t))*T_p(t) \quad (4.35)$$

$$0<D_1(t)*T_p(t)<V \quad (4.36)$$

4.5 Multiple Objectives in Optimization

The objectives for the optimization of the reservoir cascade are maximizing hydropower energy and agricultural yield. We simulate the reservoir cascade operation for N_S = 1000 years to calculate the multiple objective values for each year.

4.5.1 Hydropower Energy

Hydropower generation of each power plant is calculated using the hydropower equation (4.37). Hydropower head ($H_k(t)$) consists of a fixed head (height difference between water intake point of the reservoir and turbine of the power plant) and a variable head. Variable head refers to the reservoir water level which varies with reservoir releases ($Q_k(t)$), evaporation losses ($E_k(t)$), and inflows ($I_k(t)$) to the reservoir at each time step. The maximum power capacity of the power plant is generator and turbine capacity of the power plant (C).

$$P^k(t)=\begin{cases} \eta_k\rho\, g\, H_k(t)Q_k(t), & C>\eta_k\rho\, g\, H_k(t)Q_k(t) \\ C, & C\le\eta_k\rho\, g\, H_k(t)Q_k(t) \end{cases} \quad (4.37)$$

4.5.2 Agricultural Yield

Agricultural yield from 21 agricultural system for 1000 years is calculated using the Mahaweli reservoir cascade simulation model (Chapter 3), with adjustment to calculate the yield values for a monthly time step. Each agricultural season is six months. The simulation model calculates the yield for a predefined land extent considering the satisfaction of the water demand from the irrigation water supply. Historical records are used to derive the duty curves (i.e., water requirements) for the agriculture systems (Figure 4.3).

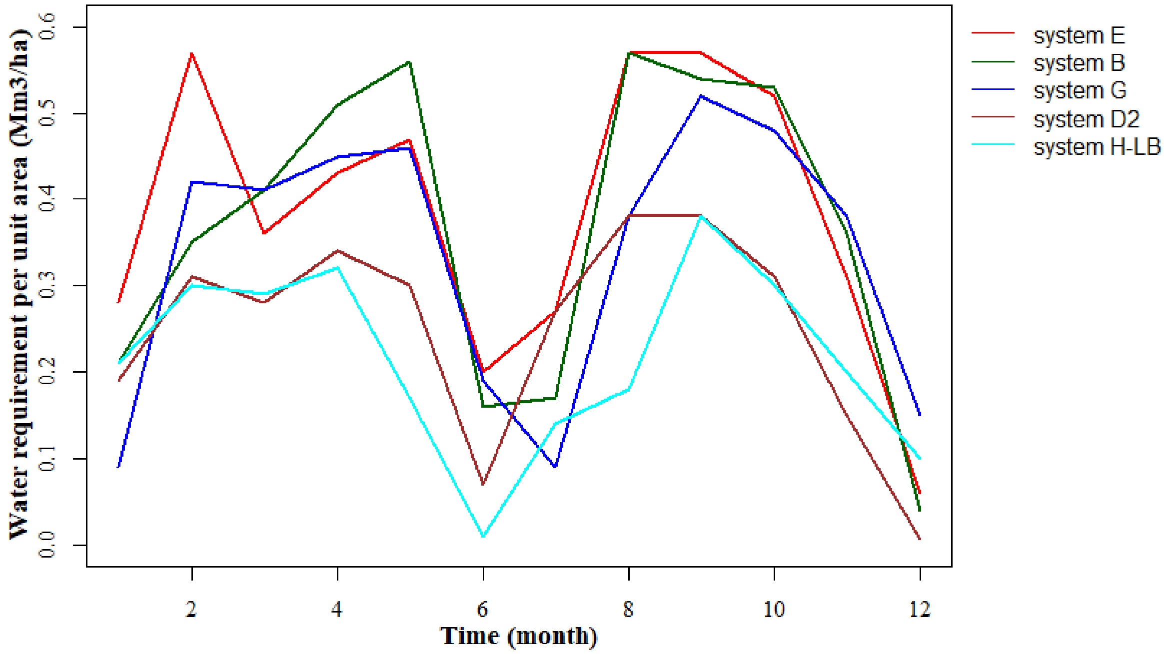

Figure 4.3: Crop duty cycle of the agricultural system that describes water requirement (Mm^3) per unit area of land (ha) derived from past records (2001-2015)

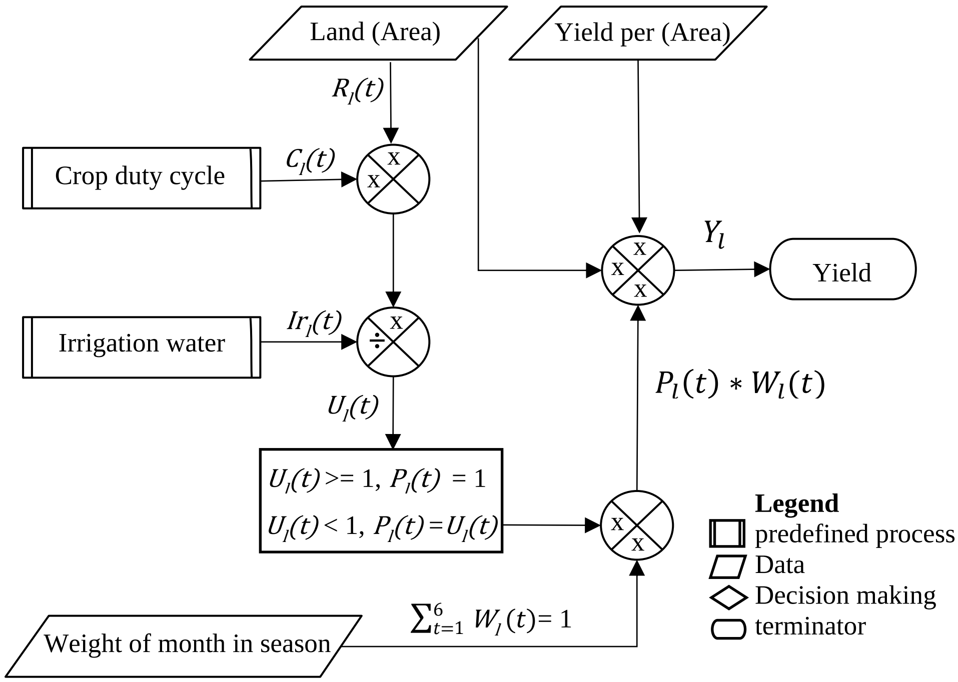

Figure 4.4. Agricultural system simulation

Agricultural yield is calculated for the two six-month seasons (Figure 4.4) "Yala" and "Maha". Water demand for the agricultural systems is changed according to the crop duty cycle ($D_l(t)$), water demand per unit land area (Figure 4.3). The ratio ($U_l(t)$) calculated as the available irrigation water ($Ir_l(t)$) divided by the total water requirement ($C_l(t)$ x $R_l(t)$) gives the fraction of success (P) for each month. The water requirements of the critical months of the season are determined by multiplying the success fraction (P) by a weight ($W_l(t)$) which derives from the crop duty cycle (Figure 4.3). During agricultural seasons crop water requirements are higher during the 2nd, 3rd, 4th and 5th months than during the 1st and 6th months. Hence, we use weights of 0.09, 0.22, 0.22, 0.22, 0.2, 0.05 for the first to sixth months sequentially.

4.5.3 Formulating Objectives in Optimization

The goal of the optimization is to find operation rules (x_i) of the reservoir cascade for maximizing of hydropower and agricultural yield (4.38). We carry out optimization for two formulations of the performance criteria for 1000 years (N), 6 power plants (K), and 21 agricultural systems (L). First, we optimize the lowest 10th percentile of the two objectives to determine operation rules that focus on performance during dry years using (4.38),(4.39) and (4.40). In other words, the result is a 90% probability of attaining hydropower energy and agricultural yield at least equal to the values for the lowest 10th percentile of optimal solutions. Second, we formulate the problem to optimize the average values of two objectives for 1000 years stream flows using (4.38),(4.41) and (4.42).

4.5.4 Multi-Objective Evolutionary Algorithm

Multi-objective optimization provides a range of solutions, which are "best" according to the priorities among the objectives. For our case study, either hydropower or agricultural yield can be maximized while keeping constraints to satisfy the minimum requirements of the other objective using single objective optimization algorithms such as dynamic programming (Bogardi & Nandalal, 2007; Feng, Niu, Cheng, & Liao, 2017; Heidari, Chow, & Kokotovi, 1971), genetic algorithms (Cai, McKinney, & Lasdon, 2001; Tayebiyan & Mohammad, 2016), linear programming (Sreenivasan & Vedula, 1996), nonlinear programming (Niu, Feng, & Cheng, 2018) and extensions (J. Wang, Chen, & Liu, 2018; J. Wang, Guo, & Liu, 2018). In contrast to that, multi-objective optimization finds a set of solutions, referred to as a Pareto-front or trade-off front (Figure 4.2). Among the wide range of heuristic optimization algorithms (Ming, Chang, Huang, Wang, & Huang, 2015; Nagesh Kumar & Janga Reddy, 2007; Zhou et al., 2019), the multiobjective evolutionary algorithms (MOEA) have been successfully applied for discovering

$$x_i^{*} = max\left(O_{hydro}(x_i), O_{yield}(x_i)\right) \qquad (4.38)$$

$$O_{hydro}(x_i) = quantile_N \left\{\left(\sum_{t=1}^{12}\sum_{k=1}^{K} P_{(t,j)}^{k}\right), 0.90\right\} \qquad (4.39)$$

$$O_{yield}(x_i) = quantile_N \left\{\left(\sum_{t=1}^{12}\sum_{l=1}^{L} Y_{(t,j)}^{l}\right), 0.90\right\} \qquad (4.40)$$

$$O_{hydro}(x_i) = average_N \left(\sum_{t=1}^{12}\sum_{k=1}^{K} P_{(t,j)}^{k}\right) \qquad (4.41)$$

$$O_{yield}(x_i) = average_N \left(\sum_{t=1}^{12}\sum_{l=1}^{L} Y_{(t,j)}^{l}\right) \qquad (4.42)$$

reservoir cascade operation policies for balancing of conflicting objectives (Giuliani et al., 2016a, 2018b; F. Li et al., 2015; Zhou, Guo, Chang, Liu, et al., 2018).

For this study we use the gamultiobj algorithm of the MATLAB global optimization toolbox, which uses a controlled, elitist genetic algorithm to create the trade-off frontier (Deb et al., 2002;

MathWorks, 2019). Objective values for hydropower and yield corresponding to the individual months (12 variables) are calculated using (4.38), (4.39), (4.40) or (4.41), (4.42) using the simulation model of the Mahaweli cascade (Chapter 3). Several population values ranging from 40-300 were tested; 50 populations were deemed adequate for the search. The evolutionary algorithm searches solutions in the feasible region of the variable space; in our study the feasible region is defined by upper and lower boundaries. Boundaries for the Polgolla water diversion are one and zero, and for the reservoir boundaries are maximum and minimum reservoir operating capacity.

4.6 Results

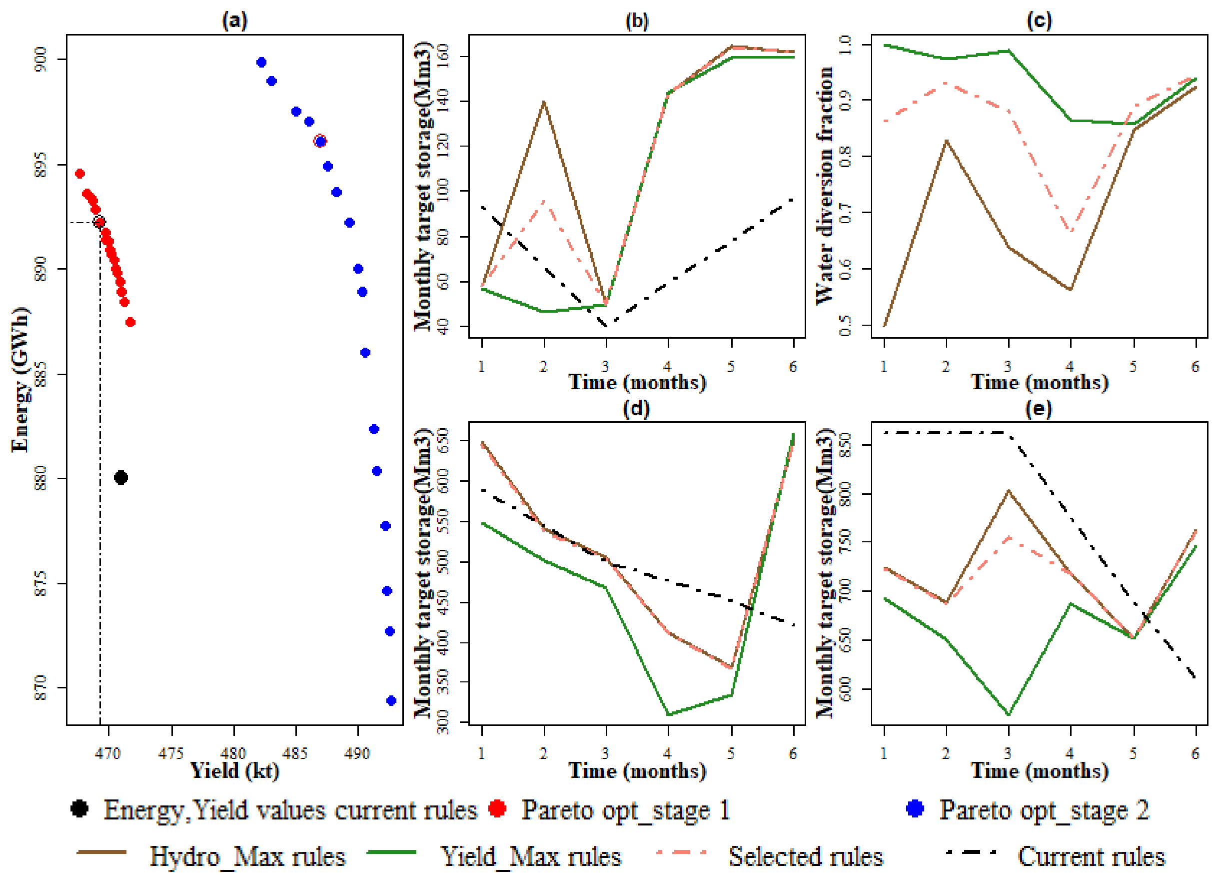

Figure 4.5. Trade-off curves and operation rules for minimum 10th percentile optimization of Yala (a) Pareto front for stage 1 & 2, and objective values for current rules, and operation rules corresponding to maximum hydropower, maximum yield, current operation rules and an example intermediate point on the Pareto front (the red-circled blue dot in (a)) of (b) Kotmale target storage for each month (c) Polgolla water diversion fraction of total inflow to the north for each month (d) Victoria target storage for each month (e) Randenigala target storage for each month

The Pareto optimal solution sets (18 solutions) for the Mahaweli reservoir cascade in the Yala season illustrate the trade-offs between energy and yield (Figure 4.5 (a)). The optimal solution sets show imporvements relative to the current operation rules for either or both hydropower and yield. For example, for the point on the Pareto front indicated by the red-circled blue dot in Figure 4.5(a), there would be a 1.8% increase in hydropower production and a 3.4% increase in agricultural yield relative to results using current rules. The second stage values depend on the Kotmale reservoir's and Polgolla water distribution operation rules selected in the first stage, for which we used the Pareto solution that gave an energy of 892.5 GWh (dotted line in Figure 4.5 (a)). In the trade-off analysis maximum hydropower is achieved with high storage in reservoirs and low water diversion rules (Hydro_Max rules) and the maximum yield is achieved with the lowest storage in reservoirs and high-water diversion at Polgolla (Yield_Max rules). The operating rules for intermediate values of hydropower and yield are between the Hydro_Max and Yield_Max rules. For example, the rule curves for the point on the Pareto front indicated by the red-circled blue dot in Figure 4.5 (a) are indicated by the "selected rules" in Figure 4.5 (b-e). The Kotmale reservoir rules are consistently greater than the current rules (Figure 4.5 (b)), while Victoria and Randenigala rules are lower than current rules in the majority of the months (Figure 4.5 (d),(e)).

Similar to the lowest 10% multiobjective optimization, the average objective optimization indicates improvement in the objectives relative to the result for current operation rules (Figure 4.6 (a)). Kotmale operation rules are again consistently higher than those used currently (Figure 4.6 (b)). Victoria and Randenigala rules corresponding to the highest energy value solution are similar to current operation rules (Figure 4.6 (d), (e)).

The optimization results of Maha seasons also indicate similar improvements of Pareto solutions relative to current operation rules. However, the improvement of agricultural yield corresponding to the Polgolla water allocation is smaller in the Maha season than in the Yala season. Hydropower production of the Maha season is about 500 GWh lower than the Yala season, but both seasons have a similar range of yield values.

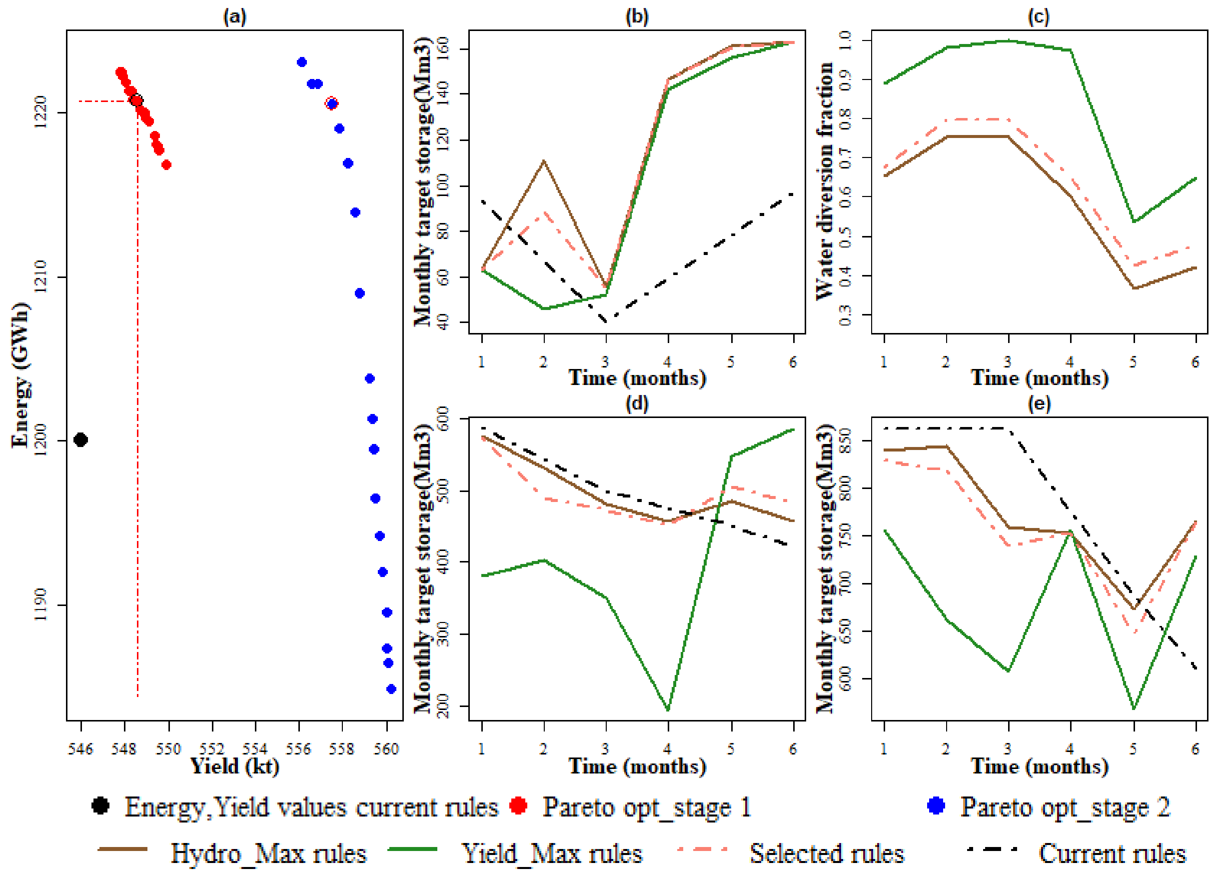

Figure 4.6. Trade-off curves and operation rules for average objective optimization of Yala (a) Pareto front for stage 1 & 2, and objective values for current rules, and operation rules corresponding to maximum hydropower, maximum yield, current operation rules, and an example intermediate point on the Pareto front (the red-circled blue dot in (a)) of (b) Kotmale target storage for each month (c) Polgolla water diversion fraction of total inflow to the north for each month (d) Victoria target storage for each month (e) Randenigala target storage for each month

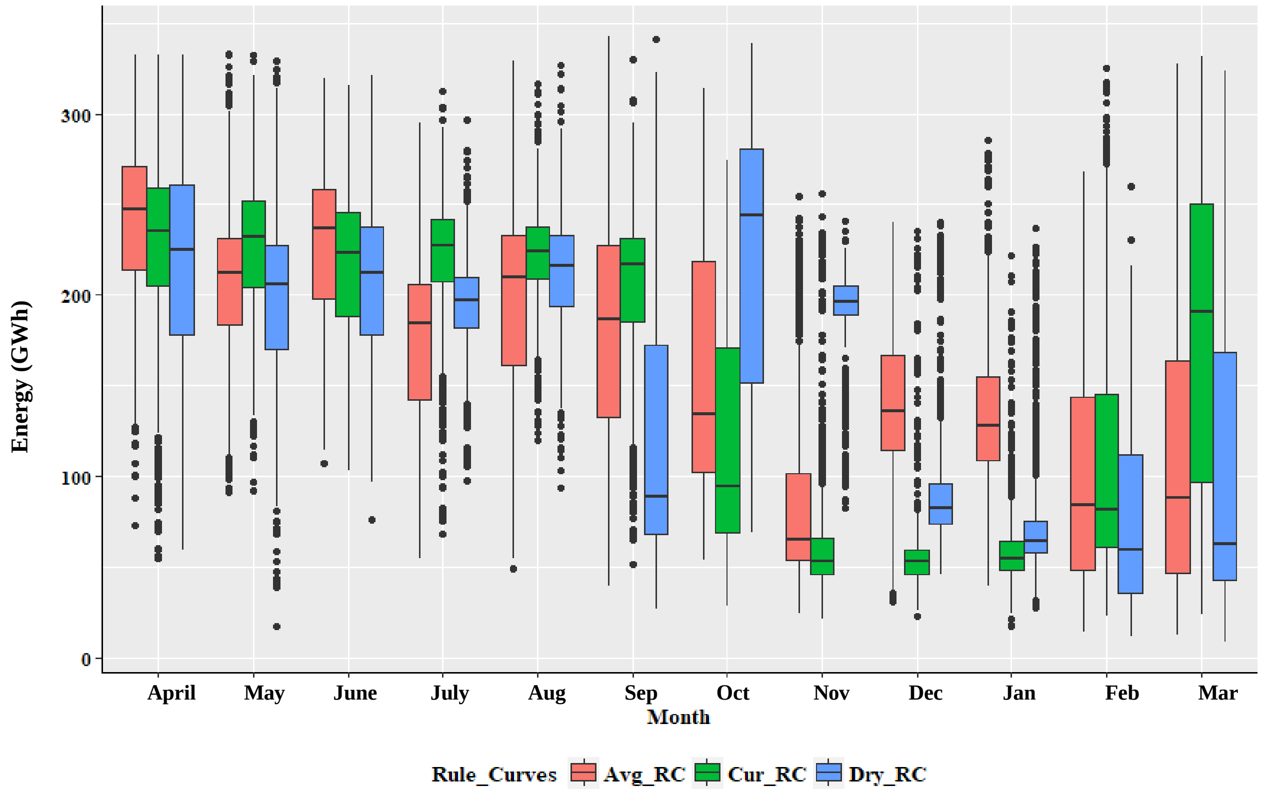

Figure 4.7. Hydropower generation variability in each month for the 1000 year sequence by applying the example set of reservoir cascade operation rules derived for average and dry objective optimization marked in the Figure 4.5, Figure 4.6, Figure B. 2, Figure B. 3; Yala season (April-September) and Maha season (October-March)

Monthly variation of hydropower generation from six power plants across the 1000-year sequence of river basin inflows is conditioned by the set of rule curves applied. To illustrate, we use the rule curves for the average and dry objective optimizations corresponding to the selected solution from the Pareto front which is circled red in the blue dots (Figure 4.5 (a), Figure 4.6 (a), and Figure B. 2 (a), Figure B. 3(a) in Appendix B). Although the annual hydropower generation and agricultural yield is greater for the optimized cases than for the current case, the median monthly hydropower values for the current operating rules exceed those for the optimization rule curves for some months (Figure 4.7). The optimization rule curves are consistently better than the current RC from October through January and the current RC is better than the dry RC for February through September and better than the average RC for 5 of those 7 months.

4.7 Discussion

Reservoir cascade operation rules derived from the multiobjective optimization in two stages can enhance the Mahaweli project hydropower generation and agricultural yield (Figure 4.5, Figure 4.6, Figure B. 2, Figure B. 3). Chapter 3 showed that changing only the water allocation policy at Polgolla can enhance agricultural yield to a limited extent but decrease hydropower substantially due to infrastructure limitations. Multiobjective optimization achieves a set of solutions for alternative operation rules of the main three reservoirs and the diversion rules at Polgolla that enhances agricultural yield and increases hydropower as well by taking into account infrastructure limitations and hydrological variability. Results from two problem formulations -- the lowest 10% objectives optimization and the average objectives optimization -- provide information that could be used to adapt water management practices for different hydrological conditions considering the trade-off between energy and yield.

Pareto optimal solution set exposes trade-offs between energy and yield that correlate to the reservoir operation and water allocation rules. As results indicated, high hydropower values are corresponding to Polgolla low water allocation for the north and high reservoir storage levels of Victoria and Randenigala reservoirs (Figure 4.5 (a), Figure 4.6 (a)) On the other hand, high water diversion from Polgolla improves the agricultural schemes of northern area, meanwhile high-water releases of Victoria and Randenigala lowering the storage levels improves the downstream agricultural schemes. Generally, variation of reservoir storage level can be impacted to the hydropower generation in two ways. Lowering of reservoir levels allows capturing of monsoon rainfall, which increases the water releases through turbines ($Q_k(t)$). Meanwhile high storage levels correspond to the high head ($H_k(t)$) for the hydropower generation (4.37). Analyzing trade-offs, our results confirm that high hydropower generation of Mahaweli generators correspond to the high heads and high agricultural yield corresponding to the lowering storage levels and water releases.

Optimization for two seasons Yala and Maha for two problem formulations suggested variable water allocation rules for Pollgolla corresponding to the Pareto optimal solutions. For example, for the Yala average objective value optimization, the Polgolla water diversion is comparatively lower than the lowest 10% objective optimization (Figure B. 2(c), Figure B. 3(c)). In addition, during the Maha season, although there is large range for the Polgolla water allocation for the Pareto optimal solution set, the corresponding agricultural yield range is very small (Figure

B. 2(a), Figure B. 3(a)). Meanwhile, a small gain of yield reduces the amount of hydropower significantly. During the Maha season, northern agricultural systems benefit from NEM rainfall, hence, water diversion from Polgolla can improve the system only marginally. Further, results indicate that the Polgolla water diversion patterns for Yala average optimization and Maha lowest 10% optimization follow the pattern of crop water duty cycle. Operating to have high diversion during Yala low inflows, a diversion pattern similar to crop duty cycle for Yala average inflow and Maha low inflows, and a low diversion for Maha average inflows could give a reasonably balanced solution for the hydropower generation irrigation water delivery objectives.

In contrast to single objective optimization, multiobjective optimization provides a set of optimal solutions where water managers can make decisions considering the trade-offs among the two objectives, hydropower and agriculture yield. Furthermore, if one objective is considered to be of greater importance than the other, even better solutions than the ones we report are achievable. That is, in our two-stage optimization one set of rule curves for Kotmale reservoir and for the Polgolla diversion from the stage 1 optimization must be selected for use in stage 2. Although in our study, we selected an intermediate point on the Pareto front as an example, water managers could select other values, in particular either the maximum hydropower or the maximum yield values as the solution to move forward from stage 1 to stage 2. For example, using the stage 1 Pareto solution corresponding to maximum hydropower and minimum yield that meets the annual yield target to define the rule curves for Kotmale and Polgolla in stage 2, it is possible to further increase hydropower energy in the second stage.

Understanding of hydropower production variability is essential for power grid operation planning. Pareto optimal solutions show the 1000-year average hydropower values; however, hydropower generation for any set of operation rules has large variability for 1000 years (Figure 4.7). The variability of hydropower across the months is related to the monsoon rainfall and water releases for agricultural systems (Figure 4.7). Specifically, in the Yala season agricultural systems depend strongly on irrigation water because the majority of the agricultural systems are located in the dry zone and do not get rainfall during May-August. On the other hand, hydropower reservoirs get substantially high rainfall during the Yala season (Figure B. 1) which results in higher hydropower. However, during the Maha season (September-March) hydropower reservoirs get relatively low inflows. The current rule curves result in relatively low hydropower generation during this season; the rule curve sets from the two-stage optimization improves hydropower generation during the Maha season.

A multiobjective optimization method enables the computation of operation rules for Mahaweli reservoir cascade that improves both hydropower production and agricultural yield. The stage-wise optimization method can be used without sophisticated advanced computation facilities. Water managers can select the solution from the Pareto optimal solutions that shows trade-offs among the objectives. The approach could be further developed to examine economic policies relevant to water-energy-food interconnections, power generation planning considering the uncertainty of hydropower generation, and water management of food crops. The methodology can be applied to similar complex multipurpose reservoir cascade studies.

Optimization methods enable decisions to be made about efficient use of limited water within a given system. However, a requirement of new infrastructure for increasing water demand is inevitable. Hence, Sri Lankan water managers are looking to add new infrastructure for water resources management. Water resources infrastructure development is complex since it impacts multiple sectors and various stakeholders. Therefore, new infrastructure alternatives are best planned systematically by evaluating technical, economic, environmental and social aspects while considering diverse stakeholder views.

CHAPTER 5

Decision Analysis for the Expansion of the Mahaweli Multi-Purpose Reservoir System in Sri Lanka

5.1 Introduction

Water is a key driver of socio-economic development of Sri Lanka similar to other parts of the world (FAO 2017; WWAP, United Nations World Water Assessment Programme 2014; USEPA 2013). Specifically, decisions surrounding choices about the development of Mahaweli water resources infrastructure are often very important with respect to sustainable development goals. Such decisions must account for all major water uses and consider economic, social, and environmental goals. Irrigated agriculture, various industries, municipal water supplies, and electrical power generation all depend on water infrastructure and all these sectors will have different goals. In addition, environmental values related to water are important to many who are impacted by water resources infrastructure.

Reservoir cascade systems on major rivers are of great importance to many countries (Räsänen et al., 2015; Yang, Ringler, Brown, & Mondal, 2016). Increasing demand for water resources for multiple purposes such as energy, agriculture, and potable water supply within a variable hydrological regime makes development of new infrastructure essential. The objectives of infrastructure expansion of a multi-purpose reservoir system include, but are not limited to, (1) maximizing economic development, (2) maximizing food production and self-sufficiency, (3) ensuring adequate potable water supply, (4) maximizing hydropower generation, (5) improving water quality, (6) alleviating poverty by creating employment opportunities, and (7) minimizing project cost of implementation and maintenance.

The various entities (stakeholders hereafter) that hold a strong interest in water resource management (politicians, utility companies, government entities, non-governmental agencies (NGO), among others) have different interests and seek different benefits, which can create conflict among these parties (Afshar, Mariño, Saadatpour, & Afshar, 2011). Cultural diversity – the life style, traditions, and beliefs of water use in different groups – impact stakeholder's participation in water resource management (Cai, Lasdon, & Michelsen, 2004; Calizaya, Meixner, Bengtsson, & Berndtsson, 2010). Plans for meeting water demands address multiple objectives that are valued differently by different stakeholders making the evaluation of alternatives for infrastructure development complex (T. H. Y. Li, Ng, & Skitmore, 2016). Decision analysis tools can be used to assess the values placed by different stakeholders on the multiple objectives and thereby assist decision makers to choose among a set of alternative development proposals to address the competing objectives (Flug, Seitz, & Scott, 2005).

Multi-criteria decision analysis (MCDA) techniques have been used in a wide range of applications and, in particular, they are commonly applied to inform decision making for water resources planning in developing countries (Abrishamchi, Ebrahimian, Tajrishi, & Mariño, 2005; Giupponi & Sgobbi, 2013; Opricovic, 2009). MCDA constitutes a body of techniques capable of improving the transparency and auditability of decisions using mathematical modelling (Cole et al., 2018; Hajkowicz & Collins, 2007; Kim, Fontane, Julien, & Lee, 2018). The model structure facilitates assessment of multiple attributes (economic, social, and environmental) measured in incommensurable units and incorporation of stakeholders' preferences.

In this chapter, we analyse plans for infrastructure expansion in the Mahaweli multipurpose reservoir cascade system using a MCDA method. Government policies give a high priority to the economic and social development of the northern dry area of the country, and improvement of Mahaweli water resource management is a major goal. New infrastructure is to be developed to allow a larger capacity of water storage in the river basin, and two new routes are planned to divert additional water towards the northern area to serve new irrigation lands (Figure 3.1, Figure 5.1). The current infrastructure of the project is capable of managing 2400 Mm^3 of water in the basin while the upgraded Mahaweli water resource management project with the new infrastructure will increase its capacity to 4000 Mm^3 (Ministry of Irrigation and Water Resources Management, 2013a, 2014). As explained in the previous chapters the largest sectors that use water in the Mahaweli are agriculture and hydroelectric power generation, and so water and energy are especially tightly linked in Sri Lanka (Manthrithilake & Liyanagama, 2012; Perrone & Hornberger, 2016). The integration of water resources planning with power generation planning is not routinely done, and, in particular, the issue has not been studied for the Mahaweli expansion project. We consider water for irrigation, hydropower and potable water supply. Objectives considered include the economic viability of the massive investment, the environmental sustainability of the project, and enhancement of the country's stability through supplying the water needs of different ethnic groups. Stakeholders' preferences for economic, social and environmental objectives are incorporated in the decision process (De Silva Manikkuwahandi, Hornberger, & Baroud, 2019).

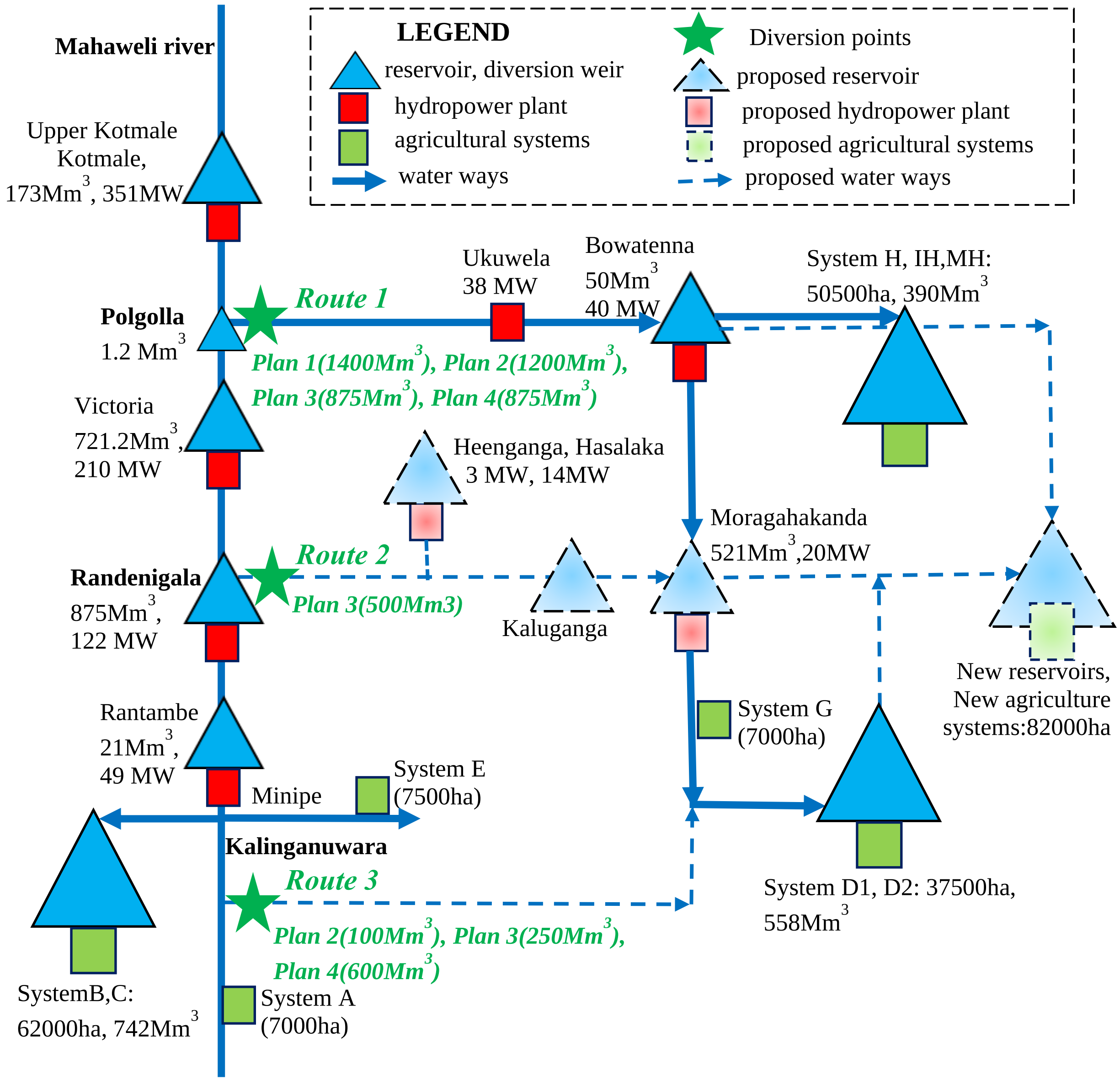

Figure 5.1 The schematic diagram of Mahaweli reservoir network with proposed infrastructure additions under four alternative plans develop through three water transferring routes.

5.2 Multicriteria Decision Analysis (MCDA) Method

MCDA aims to rank options of alternatives based on selected evaluation criteria. Criteria are measured by attributes, and their importance judged by assigned weights. A performance matrix contains values of the attributes and a preference matrix contains values of the associated weights. Both matrices may have ordinal and cardinal data. Different MCDA techniques rank the alternatives according to specified algorithms of combining performance matrix and preference matrix (Hajkowicz & Higgins, 2008).

The sequence of developing an MCDA model is identified as follows (Abrishamchi et al., 2005; Cole et al., 2018; Mutikanga, Sharma, & Vairavamoorthy, 2011):

- structuring the problem (objectives, constraints),
- identifying the alternatives,
- assigning alternative performance measures,
- eliciting decision makers' preferences,
- evaluating alternatives through MCDA techniques,
- analyzing the results (sensitivity and robustness), and
- reporting information to allow decision makers to select a preferred alternative.

There are various techniques of MCDA that have been used in water resource management. Multi attribute utility theory (MAUT), multi attribute value theory (MAVT), analytic hierarchy process (AHP), fuzzy set theory, compromise programming (CP) and outranking methods; elimination and choice expressing reality (ELECTRE) and preference ranking organization method for enrichment of evaluations (PROMETHEE) are generally popular tools of MCDA applied in water resource studies (Ahmadi, Arabi, Fontane, & Engel, 2015; Govindan & Jepsen, 2016; Hajkowicz & Collins, 2007; Hajkowicz & Higgins, 2008; Huang, Keisler, & Linkov, 2011; Kang, Lee, Chung, Kim, & Kim, 2013).

The selection of appropriate MCDAs in water resource planning is based on a number of considerations such as practicality, user familiarity, availability of information, effect on group dynamics, and likelihood of user acceptance of the results. This study applied two MCDA techniques, based on information availability and applicability in water resources management studies: the single synthesizing approach MAVT (Cole et al., 2018) and the outranking method ELECTRE (Cunha & Morais, 2012; Govindan & Jepsen, 2016; Raj & Nagesh Kumar, 1996). The structure of MAVT with multiple decision makers' participation helps in understanding the important details in policy negotiations, while ELECTRE guarantees robustness of the ranking of alternatives.

5.3 MAVT with Multiple Decision Makers

This method calculates a single value that represents the performance of each alternative through several steps (Fishburn, 1968; Keeney & Raiffa, 1976). A weighted sum is used to calculate a single value for MAVT (van Herwijnen, 2010). Weights for each attribute of an alternative plan are calculated from the preference elicited from the decision makers. Similar to Cai et al. (2004), multiple decision makers' preferences for the criteria are incorporated to calculate the total score for alternative plans.

The MCDA calculations produce a performance matrix, $G(i,j)$, of the alternative plans populated with the values of their respective indicators. The first step of MAVT consists of transforming the attribute performances of each plan, $g(i,j)$, to commensurate units through the value function or standardization. For this study, we use interval standardization, using (5.43) for criteria to be maximized and (5.44) for criteria to be minimized (Clemen, Robert T., Reilly, 2001; T. H. Y. Li et al., 2016).

These two equations compute the elements of the evaluation matrix E, $e(i,j)$; $g(j,i)$ is the target value of attribute j in plan i, max $g(j)$ is the maximum target value of value of criterion j, min $g(j)$ is the minimum target value of criterion j, and $e(j,i)$ is the standardized performance of plan i on criterion j. Value path is a graphical representation of the standardized alternatives' performance over the attributes, which facilitates the evaluation of alternatives (Cai et al., 2004; B. Hobbs & Meier, 2000).

$$e(i,j) = \frac{g(j,i) - min\ g(j)}{max\ g(j) - min\ g(j)} \tag{5.43}$$

$$e(i,j) = \frac{\max g\,(j) - g(j,i)}{\max\ g(j) - \min\ g(j)} \tag{5.44}$$

The method can be extended to account for multiple decision makers (DMs). Mathematically this is represented in (5.45) and (5.46) (Cai et al., 2004).

$$S(i,k) = E(i,j).\, C(j,k) \tag{5.45}$$

$$U(i) = \sum_{k=1}^{K} s(i,k) \tag{5.46}$$

In these equations, i - 1,..,I refers to the alternative index, j - 1, …, J is the criterion index, k - 1,…, K is the index representing each DM, E is the criterion evaluation matrix in which each entry, $e(i,j)$, is the performance of plan i on criterion j (standardised), C is the DM's preference matrix in which each entry, $c(j,k)$, calculates how important attribute j is for DM k (weight trade-off), S is the support plan matrix, $s(i,k)$ is the degree of approval of DM k for plan i, U is the vector representing the multi-attribute value function of each alternative, $U(i)$ is the degree of approval of plan i by all decision makers.

The MAVT method helps in structuring the problem and understanding policy problems. Simplicity and transparency of the method with cardinal weights provides a means for communication and negotiation and for the incorporation of diverse views in selecting criteria and value functions (De Montis, Toro, Droste-Franke, Omann, & Stagl, 2000). However, the main weakness of the method is that criteria are considered to be compensatory where a high value of any criterion can compensate for a correspondingly low value of another criterion. In addition, the calculation of the utility value as an additive function and using linear transformations for the criteria can lead to inaccurate results (Hajkowicz & Higgins, 2008).

5.4 ELECTRE III

The development of the outranking methods started in France in the late 1960s by Bernard Roy and his team (Benayoun, Roy, & Sussman, 1966; Roy, 1991). The method involves comparing two alternatives across a full range of criteria using an outranking relationship (Figueira, Greco, Roy, & Słowiński, 2013). As such, I decision alternatives result in I^2-I pairwise comparisons to test the strength of hypothesis 'at least as good as' and opposition to the hypothesis. Three matrices populated with concordance indices, discordance indices and credibility indices are calculated to rank the alternatives.

The ELECTRE method can handle four types of preferences considering three threshold values: preference threshold (p_j), indifference threshold (q_j) and veto threshold (v_j) (Roy, 1991). The modelling of four types of preferences is done through outranking, which is associated with two main concepts, pseudo-criteria and binary relationships (Figueira et al., 2013). In (5.47), simulation of weak preference, indifference and strict preference, and incomparability (hesitating between the indifference and the opposition) are represented.

$$\begin{aligned} &c_j(i,i') = 0; && if g(i',j) - g(i,j) > p_j[g(i,j)] \\ &c_j(i,i') = 1; && if g(i',j) - g(i,j) < q_j[g(i,j)] \\ &0 < c_j(i,i') < 1; && if\ p_j[g(i,j)] < g(i',j) - g(i,j) < q_j[g(i,j)] \end{aligned} \quad (5.47)$$

The concordance index is a measure of the degree of dominance of alternative i over alternative i' given by the outranking relation given in (5.48).

$$c(i,i') = \sum_{j \in C^S(ii')} w_j + \sum_{j \in C^Q(ii')} w_j\, \Psi_j \quad (5.48)$$

In (5.48) and (5.49) $c_{ii'}$ is the concordance index, w_j represents the total weight associated with criteria $g(j)$, $C^S(ii')$ contains attributes (j) where i is at least as good as i' with no reservation (indifference and strict preference), $C^Q(ii')$ contains attributes (j) hesitating between the indifference and the opposition that i is at least as good as i'. ψ – set of criteria agree about preference alternative i with respect to i'.

$$\phi_j = \frac{g(i',j) - g(i,j) + p_j[g(i,j)]}{p_j[g(i,j)] - q_j[g(i,j)]} \quad (5.49)$$

The discordance index is a measure of the degree of opposition to the hypothesis that i is as good as i'. The discordance is measured with respect to the veto threshold as well. A veto threshold is associated with the most important criterion or with all the criteria instead of preference threshold to differentiate the weak performance of alternatives' attributes.

The credibility index provides a value for outranking relation of alternative i over alternative i' by combining the concordance index and the discordance index. If there is a criterion with discordance index greater than the overall concordance index, the concordance index is modified to a lower value according to (5.50) (Figueira et al., 2013).

$$\sigma(i,i') = c(i,i') \prod T(i,i') \quad (5.50)$$

$T(i,i') = (1 - d_j(i,i'))/(1 - c(i,i'))$, if $d_j(i,j) > c(i,j)$, otherwise $T(i,i') = 1$

The relative values of the three thresholds have the relationship of $v > p > q$ (Rogers & Bruen, 1998) and for this study we select the ratio between thresholds as 2 and q of 2%, p of 5%, and v of 10% for all criteria. Assigning values to the threshold are highly subjective in the decision making process and sometimes values are elicited from the decision makers. In practice, choosing values and doing sensitivity analyses are very common due to imperfect knowledge (Figueira, Mousseau, & Roy, 2005; Rogers & Bruen, 1998; Roy & Bouyssou, 1986).

Ranking of alternatives is based on two pre-orders, ascending distillation and descending distillation. Ascending and descending pre-orders are based on credibility indices, and cut-off level and distillation threshold that are decided according to how strongly alternatives are outranked by each other (Marzouk, 2011; Rogers & Bruen, 2000). We selected 0.2 for both cut-off level and distillation thresholds.

ELECTRE is a family of methods with comprehensive characteristics that can handle real time decision problems (Figueira et al., 2013). The main strength of the method is the ability to deal with quantitative and qualitative data and with non-compensatory effects (avoiding the choice of alternatives with a very low value for the criterion that is compensated by higher values for the rest of the criteria). The parameters have threshold values to avoid the compensation of the weak performance of certain criteria by improving the performance of other criteria. However, due to the complex analysis, communicating the results to stakeholders may be difficult.

5.5 Application of MCDA Method to Case Study

The influence diagram of the decision problem in the Mahaweli multipurpose water resource management (Figure 5.2) illustrates the fundamental objective (societal benefit) and means objectives (e.g., economic benefit from agriculture, amount of water shared with northern dry zone, etc.). Means objectives are clustered under four criteria: economic benefits, economic viability, societal aspects and environmental stewardship.

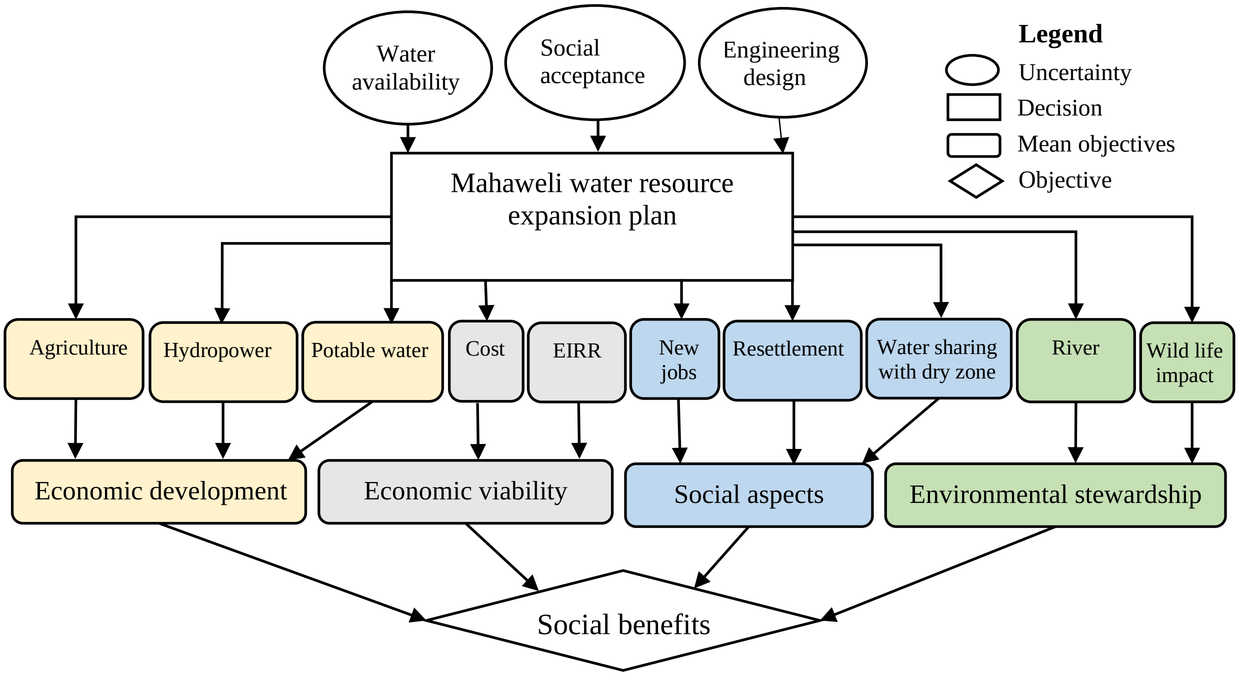

Figure 5.2 Influence diagram for multipurpose water resource planning and management decision

5.5.1 Alternatives

Four alternative plans are identified to improve the water management in this study (Figure 5.1**,** Figure C. 1). New plans are developed to send different amounts of water captured from monsoons upstream to dry northern areas via three water diversion routes. Route 1 is the existing underground tunnel from Polgolla, which has a capacity of 1400Mm^3, which is 525Mm^3 higher than the present water diversion. Route 2 is a new underground tunnel from Randenigala reservoir, and route 3 involves pumping of water from downstream in the river at Kalinganuwara to agricultural reservoirs.

Plan 1: 1400Mm^3 water is diverted through route 1. Kotmale dam height will be increased to store an additional 175 Mm^3 water to improve the system operation by having a larger water storage capacity (Ministry of Irrigation and Water Resources Management, 2013a; Ministry of Mahaweli Development and Environment, 2016).

Plan 2: 1250Mm^3 water is diverted through route 1 and 100 Mm^3 is pumped through route 3. In addition to the Kotmale reservoir capacity increase, pumping water from Kalinganuwara allows for more hydropower generation (Ministry of Irrigation and Water Resources Management, 2013a).

Plan 3: 875 Mm^3 water is diverted through route 1 as is the present practice. An additional 500 Mm^3 is diverted through route 2 and 250 Mm^3 is diverted through route 3. Construction of a new water diversion route from Randenigala reduces flexibility of operation because high water levels must be maintained in the Randenigala reservoir. Pumping additional water from Kalinganuwara relative to Plan 2 compensates for potential loss of hydropower due to operational restrictions at Randenigala (Ministry of Irrigation and Water Resources Management, 2013a, 2014; Ministry of Mahaweli Development and Environment, 2016).

Plan 4: 875 Mm^3 of water is diverted through route 1 as is the present practice and an additional 600 Mm^3 is diverted through route 3 by pumping. Diversion of water from upstream of Polgolla or Randenigala significantly affects hydropower generation. Pumping the water from downstream of the Rantambe power plant allows use of the water for maximum hydropower generation. Avoiding electricity peak demand period for pumping allows use of energy at lower cost. Irrigation tanks of system D1 will be used for the storage of pumped water to send to the northern areas.

5.5.2 Evaluation of Criteria

We assess the four alternative plans outlined above to achieve the ten means objectives that contribute to the fundamental objective. The ten objectives are clustered under four criteria (economic benefits, economic viability, societal aspects and environmental stewardship) and attributes are identified for each criterion for quantification.

Economic development is measured using agriculture development, hydropower generation, and potable water supply for domestic and industrial use. *Agriculture benefits* are the economic benefits resulting from the paddy and other food crops (OFC) and the improvement of cropping intensity of existing agricultural lands as well as newly developed lands with high water availability (Table C. 1 in Appendix C). *Hydropower benefit* is the reservoir based hydropower capacity and energy benefit increase, and the replacement of fossil fuel-fired thermal power with more sustainable renewable energy sources (Table C. 2**,** Table C. 3). *Potable water* supply is an estimate of the benefits of drinking water and industrial water supply; the main infrastructure provides part of the indirect cost associated with potable water supply (Table C. 4).

The project is financed through long-term loans from international funding agencies; hence economic viability of the new infrastructure development is important. The *project cost* is based on past construction of Sri Lankan infrastructure and similar projects of neighboring countries

(Ministry of Irrigation and Water Resources Management, 2013a) (Table C. 5). The value of *economic internal rate of return* (*EIRR)* is based on a 30-year return of a 4-year single investment accounting for annual operations and maintenance cost for irrigation, hydropower, and potable water (Table C. 6).

To evaluate the social objectives of the project, social development is assessed through (i) new *employments* in agriculture, energy, transportation and construction sectors (Table C. 7), (ii) disturbance to the society by *resettlement* of people in areas providing water routes and reservoirs (Ministry of Irrigation and Water Resources Management, 2013a), and (iii) *water diversion to northern post conflict areas* (Table C. 8).

Environmental impacts of the project are measured through natural *river flow violation* and disturbance to the *wildlife.* *Natural river flow* will be reduced by diversions to the northern irrigation tanks with an impact on the downstream water users and aquatic habitats (Ministry of Irrigation and Water Resources Management, 2013a). Disturbance to *wildlife (*Table C. 9*)* in new water conveying routes and reservoirs are assessed.

Values associated with each attribute for each plan were assembled from a variety of sources (Ministry of Irrigation and Water Resources Management, 2013a, 2014; Ministry of Mahaweli Development and Environment, 2016); detailed calculations are presented in the supplementary data (Table C. 1-C.9).

5.5.3 Eliciting the Decision Makers' Preferences (Weights)

Multiple organizations represent the different sectors of the project. Presently, the Mahaweli Authority of Sri Lanka (MASL) operates major reservoirs and the Irrigation Department (ID) operates several irrigation reservoirs. The National Water Supply Board and local authorities manage potable water supplies. The Ceylon Electricity Board (CEB) manages all the hydropower generation stations. Water distribution decisions are made jointly by stakeholder agencies led by MASL.

The stakeholders are agriculture experts, energy experts, environmentalists, social service sector experts, hydrologists, and a mixed group of stakeholders without a specific expertise. The Ministry of Mahaweli Development and Environment of Sri Lanka conducted meetings with participation of 98 stakeholders representing the various interest groups. In addition to government agencies, representatives included people from water resource management consulting companies, from funding agencies, and from non-government organizations (NGOs). The stakeholders self-identified themselves according to the six groups listed above and scored the importance of 41 attributes that define the quantification of the multiple criteria considered (Ministry of Mahaweli Development and Environment, 2016). We obtained and used the results of the meeting conducted by the Ministry of Mahaweli Development and Environment and grouped them into the relevant attributes of this study. The preferences of experts, who are referred to as decision makers (DMs) below, were elicited on a scale from 1 to 10. These values were standardized using (5.43).

5.5.4 Sensitivity Analysis

The model result is sensitive to the uncertainties of alternative performances due to natural variability such as climate variability for hydrology, economic parameters such as discount rates, agriculture and electricity market prices, decision maker priorities for the multiple criteria and parameters of decision models (Hyde, Maier, & Colby, 2004). The robustness of the MCDA results is tested for uncertainties of both attribute performances and decision makers' weights. One thousand Monte Carlo simulation runs are carried out for ±20% sensitivity of attribute performance values and ±20% of decision makers' weights.

In addition to the general sensitivity analysis, we examine important elements of the Mahaweli water resources policy decisions. Economic and environmental aspects of the water resources management projects are two main elements of water policy. Therefore, economic and environmental aspects of the alternative plans are examined through the sensitivity in DMs' weights for attributes categorized under the two categories by using MAVT method. Economic benefits from hydropower, agriculture, potable water, EIRR, project cost attributes are categorized under the economic category. Social attributes such as new employment, resettlement, water sharing with the northern area and environmental stewardship attributes such as river flow violation and impact to the wild life are categorized under the environmental category. Sensitivities of plan scores are calculated using DM's $(u(i)$ in (5.46). We modify the average DM weights for the economic and environmental categories from 0 to 1 in 0.01 steps.

Finally, a stylized analysis was done to explore the sensitivity of the rankings to variations of the commodity market. In Case 1, the original assumption that electricity price for pumping was 50% of the base price because pumping was considered to be done at off-peak times; the sensitivity to this assumption was evaluated through an analysis assuming that electricity cost is constant in time. In Case 2, we considered sensitivity to a 50% increase of agriculture benefit of each alternative. Sensitivity of rankings to the decision parameters of the ELECTRE III model was explored by selecting high threshold values for the indifference threshold *q*, preference threshold *p*, and veto threshold *v* from the original values of 2%, 5% and 10% using three cases (Cases 3, 4, and 5): p = 10%, q = 3%, v = 15%; p = 15%, q = 3%, v = 20%; p = 25%, q = 4%, v = 30%.

5.6 Results

The ten attributes fall into four criteria classes that express (1) economic development, (2) economic viability, (3) social development, and (4) environmental sustainability broken out in the performance matrix of the attributes (Table 5.1). The standardized values of the attributes illustrate the differences among the four alternative plans meeting multiple objectives represented by attributes (Figure 5.3 (a)). Plan 2 does not have minimum performances for any attributes while the performances of other plans vary between maximum and minimum values.

Decision makers’ preferences show consistency with regard to a few attributes (e.g., potable water) but varied widely on several others (e.g., resettlement) (Table 5.1). The standardized stakeholder preferences calculated using interval standardization, illustrate how the various decision makers evaluate their relative preferences for the attributes (Figure 5.3 (b)). The weights of the power utility decision makers show large variation across the attributes, while the weights of the mixed (other) group vary over a smaller range. The mean value of weight per attribute is 0.1 and the standard deviation (SD) is 0.016. The maximum score value any attribute can achieve is 60 (6x10). EIRR has a total score of 49.6, the highest among the 10 attributes. Total project investment, water diversion to northern post-conflict areas, and drinking water also have high utility values (Table 5.1).

Both MAVT and ELECTRE III methods results rank Plan 2 the highest, with small differences in other rankings (Figure 5.4). In the MAVT method, all decision makers rank the alternative plans from highest to lowest as Plan 2, Plan 4, Plan 3 and Plan 1 (Table C. 10). In the ELECTRE III, the decision makers rank plans from highest to lowest as Plan 2, Plan 4, Plan 1 and Plan 3, with Plan 4 and Plan 1 ranking equivalently. ELECTRE III ranks the alternatives (Figure 5.4, Figure C. 3) according to credibility indices (Table C. 13), which are calculated using concordance (Table C. 11) and discordance indices (Table C. 12).

Table 5.1. Attribute performance matrix and decision makers' preferences in 1-10 scale. DM1: Agricultural experts, DM2: Power experts, DM3: Environmental experts, DM4: Social experts, DM5: Hydrology experts, DM6: Other mixed stakeholder group

Criteria	Alternatives				Decision Makers					
	Plan 1	Plan 2	Plan 3	Plan 4	DM1	DM2	DM3	DM4	DM5	DM6
C1:Economic development										
Agricultural annual benefits[a] ($M) (maximize)	39.9	47.5	47.8	39.9	8.5	5.3	5.5	8.7	6.7	5.9
Hydropower annual benefits[b] ($M) (maximize)	-0.6	30.9	26.6	43.2	6.4	10	7.3	6.2	6.5	5.4
Potable water annual benefits[c] ($M) (maximize)	7.18	9.02	9.02	9.02	7.4	7	6.9	7.9	7.9	7.2
C2:Economic viability										
Total investment[d] ($B) (minimize)	0.8	1.16	1.91	1.45	8.4	10	7.7	7.9	6.8	7.6
Economic Internal Rate of Return[e] (%)(maximize)	3.6	5.1	3.5	7.8	8.5	10	7.9	8.4	6.9	7.9
C3:Social development										
New employment[f] (1000 person days) (maximize)	31016	34846	38055	31016	7.8	5.3	4.8	8.4	5.2	6.3
Resettlement (Number of People) (minimize)	3475	7880	8114	4910	6.2	4.3	6.8	8.9	5.1	6.4
Water sharing with Northern area[g] (Mm^3) (maximize)	830	1030	1050	930	9.4	6.6	7.9	7.3	9.2	7.3
C4:Environmental steward.										
River flow violation(%)(minimize)	22.63	25.79	29.5	25.79	5.9	7.7	8.7	7.1	5.7	6.1
Impact to wildlife[h] (1-10 scale) (minimize)	3	6	10	5	5.6	6.6	9.2	7.8	6.2	6.4

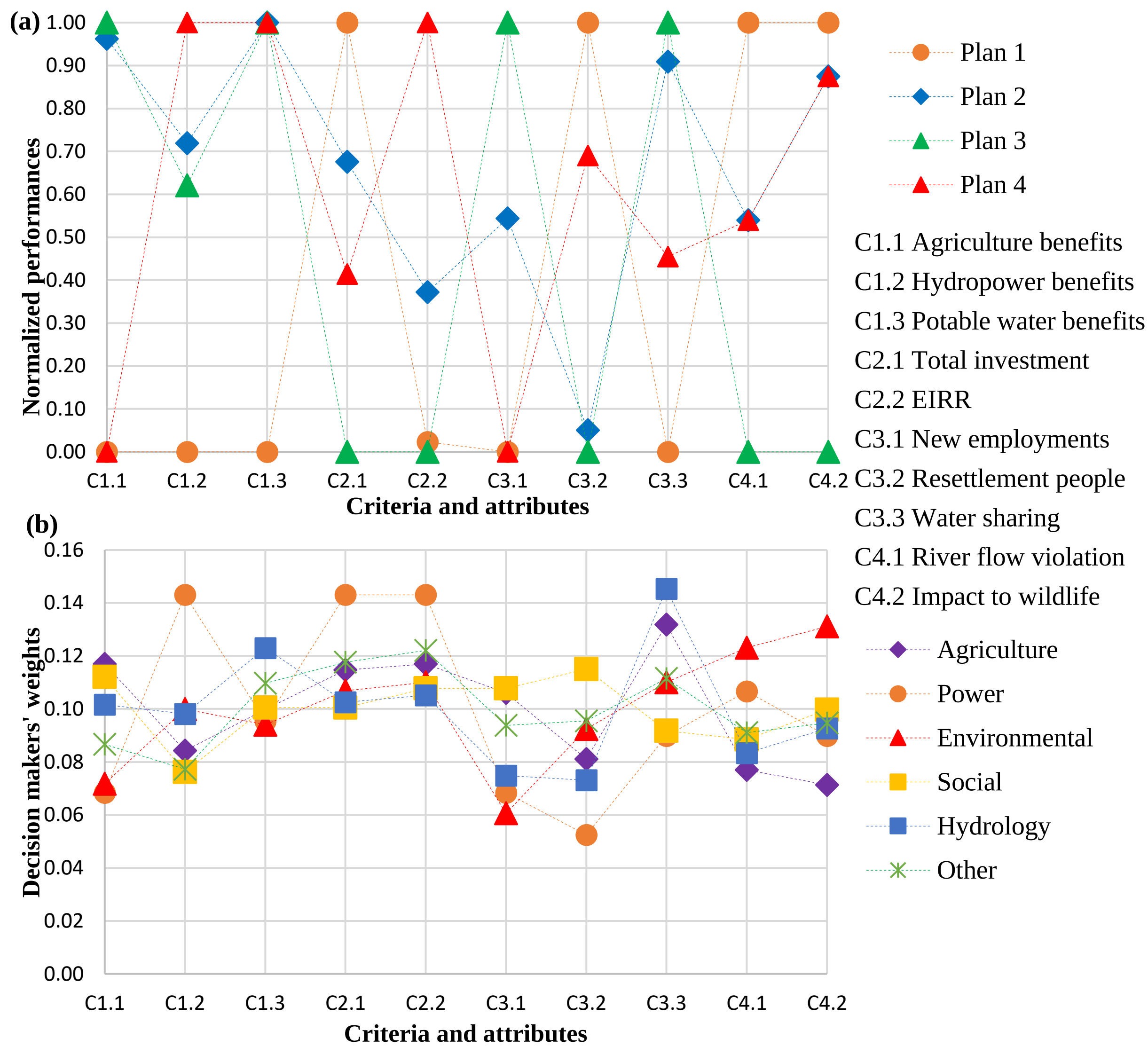

Figure 5.3. Performances of four alternative plans and decision makers' weight over ten attributes (a) Value path of trade-off between attributes of alternative plans (b) Standardized six decision makers' weight trade-off between attributes

Sensitivity analysis confirms the ranking order from best to least of alternatives as Plan 2, Plan 4, Plan 1 and Plan 3 respectively (Figure 5.5). Monte Carlo simulation indicates Plan 2 as the best plan according to six decision makers' weights with both MAVT and ELECTRE III methods. Although, Plan 1 and Plan 4 have high uncertainty with respect to their relative ranking order, the majority of simulations have Plan 4 as higher than Plan 1.

The ranking of alternatives across a wide range of variation in economic criteria and environmental and social criteria, which have the original weight ratio of 0.52:0.48, is robust, i.e., insensitive to changes in weights of attributes (Figure 5.6). The Plan 1 score varies substantially with changes in weights of economics and environmental attributes, while the scores of Plans 2 and 3 are stable. Nevertheless, the rankings are unchanged for modest changes in weights with changes in rank occurring only for very low (high) weights of economic (environmental) attributes (Figure 5.6).

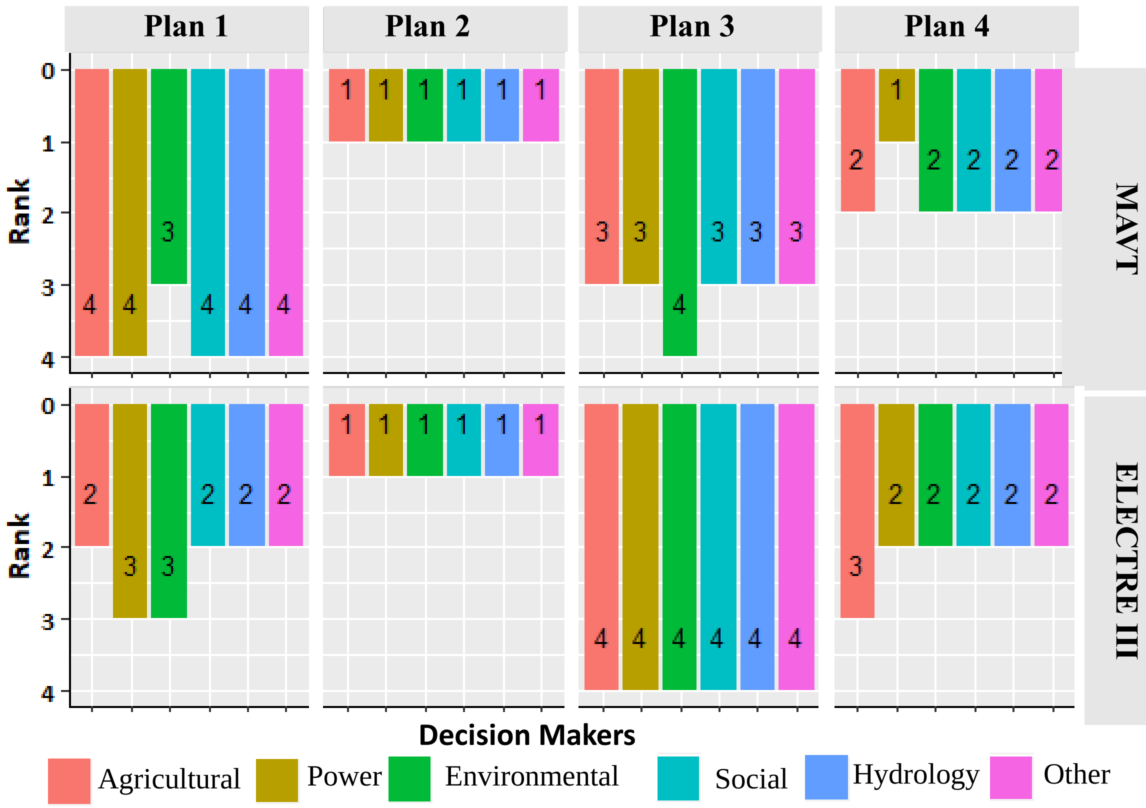

Figure 5.4. Ranking of alternatives by MAVT and ELECTRE-III methods. The rank obtained by each plan according to six decision makers' weight shown inside the bar graphs.

Our stylized sensitivity analysis also confirms Plan 2 as the highest ranked. The ranks of other Plans change for extreme values of variables. For example, removing the difference in electricity price between peak and off-peak times or making moderate changes in the decision threshold values in the ELECTRE III method do not affect the ranking of alternatives. However, a drastic change, such as a as 50% increase in agriculture benefit, reorders the alternative rankings as Plan 2, 1, 4, 3. In addition, for large changes in threshold values in ELECTRE III (p = 25%, q = 4%, v = 30%), Plan 4 is elevated to be co-equal with Plan 2.

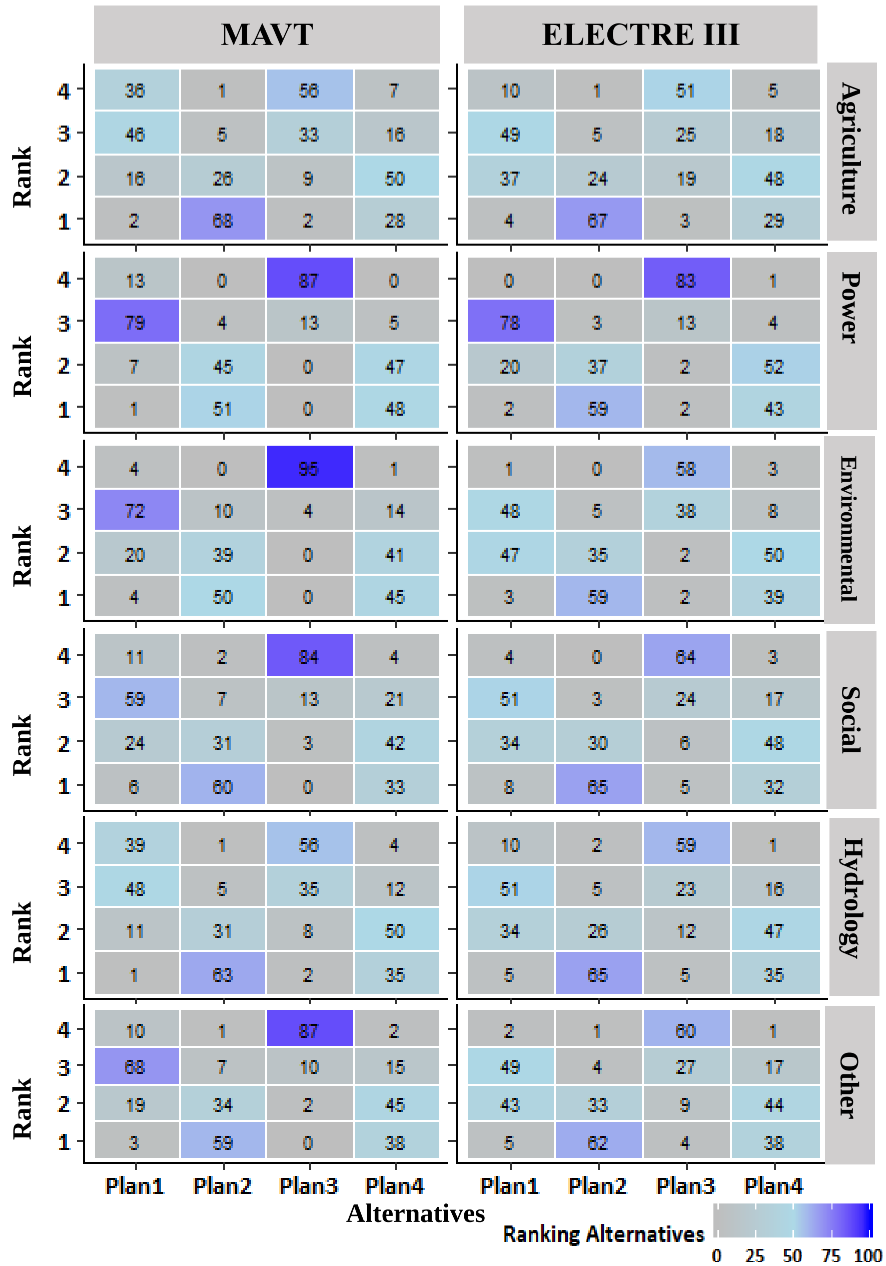

Figure 5.5. Sensitivity analysis of ranking order considering uncertainty of attribute performances and decision makers' weight in ±20% range. Percentage of ranks obtained by each plan is shown in the corresponding box for each plan to method and decision

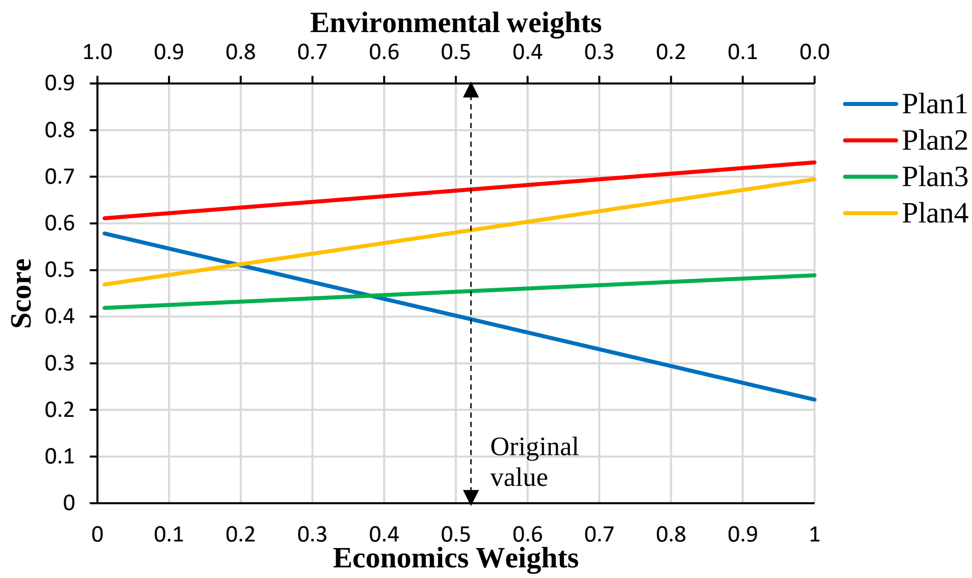

Figure 5.6. Sensitivity of Plan score according to economics and environmental criteria weight

5.7 Discussion

The four alternative plans for the extension of the Mahaweli project that we considered cover a range of values of associated attributes in our multicriteria decision analysis (Figure 5.3). Plan 1 and Plan 3 are two extreme alternatives in which the best performance is observed in a few categories and the worst performance is observed in several others. Plan 1 is the least expensive option, using existing infrastructure extensively while providing the least disturbance to the social and biological environment. Plan 3 is associated with the highest capital cost and the lowest EIRR; the plan heavily relies on new infrastructure to facilitate the best water management of the river basin, resulting in higher disturbance to the social and biological environment than other plans. Plan 3 is focused on agriculture, water sharing, and employment generation, with very low performance measured by the other attributes. Plan 4 is associated with the highest economic performance; the plan prioritizes the optimal utilization of reservoir-based hydropower. Agriculture development and agriculture employment generation associated with Plan 4 are low compared to other alternative plans. Plan 2 is the least extreme alternative with no particular focus on any sector.

The standardized values of DMs preferences are largely consistent with the respective organizational goals and constraints but also reflect the DMs' broad understanding of common objectives of the project (Table 5.1). As expected, DMs representing the agriculture and social sectors give higher preference to the agriculture benefits while the DM from the power sector prioritizes hydropower. Agriculture and hydrology DMs give a higher preference to water sharing and amount of water diverted to the north, while environmentalists are mostly concerned with environmental sustainability. Resettlement of people is the highest and hydropower is the lowest priority attribute for the social DMs. For the power DM, hydropower is the highest and resettlement of people is the lowest priority. Even though DMs have their own priorities and preferences, they still acknowledge the importance of other less preferred attributes and their impact on social welfare overall; therefore, they do not overly penalize the attributes that are not highly ranked (weight mean 0.1and SD 0.016). All the DM groups have identified common goals associated with the project. All DM groups gave high preference values (>6.6) for these attributes. Therefore, common goals of the project such as potable water supply and water sharing with the northern conflict areas in an economically sound manner achieve the maximum score values (Table 5.1).

The multi-attribute value function indicates that all the DMs have the highest utility value for Plan 2 and second highest utility value for Plan 4 (Table C. 10, Score column). Plan 4 has high economic development due to high hydropower development and high economic viability by low project cost and better EIRR. However, Plan 2 is associated with agriculture development and has less impact on the social and biological environment. The overall favoured ranking of plan 2 reflects the combined valuation of different attributes by different stakeholders. Sensitivity analysis for attribute weights variation demonstrates that Plan 2 has high scores throughout the weight range, while Plan 4 gets high scores only for high *hydropower* benefit and *EIRR* attribute weights.

The empirical data are not perfect and can certainly be further refined with more detailed studies and additional surveys. This study assumes risk neutrality of decision makers, without consideration of uncertainties of future water availability, engineering designs, and acceptance of the solution by society (including political preferences). However, the robustness of the best alternative selected by the MCDA framework with MAVT and ELECTRE is supported by the sensitivity analyses, which show that the rankings of the alternatives are stable to changes in assumptions.

With the consideration of multiple competing objectives as well as the preference of multiple stakeholders from different water use sectors, an MCDA analysis is a good fit for decision problems involving water resources trade-offs. The decision analysis methods that we use to explore planning alternatives in the Mahaweli basin in Sri Lanka highlight their usefulness for including preferences of stakeholders. The trade-off weights elicited from multiple decision makers reflect priorities of the institutions that they represent, with the highest weights assigned to criteria most closely associated with organizational goals (e.g., agricultural decision makers' prioritized irrigation). Nevertheless, the various assigned weights also demonstrated an appreciation among all stakeholders of the importance of all of the criteria considered. The results indicate that an alternative that performs well across all the criteria considered, although it is not uniformly the "best" in any criterion, has broad support from stakeholders. This case study shows that MCDA models can be used as a platform for deriving a collective decision from stakeholders with diverse interests and thus serve as a guide to inform the decision regarding the development of water resources infrastructure, the extension of the Mahaweli multipurpose project.

Moving from 100% hydropower to renewable thermal power mix to meet the increasing energy demand, energy managers face challenges to expand the infrastructure considering multiple objectives. Similar to the water resources infrastructure development, energy infrastructure is associated with many sectors. Stakeholders have diverse views about future power generation pathways. There are many conflicts that arise in expansion of power generation in Sri Lanka as a developing country with one aim being a transfer to low carbon pathways but at the same time securing the energy economically and in a technically efficient way. As with water resources, proper power generation expansion planning requires consideration of technical, economic, environmental and social aspects as well as considering diverse stakeholder views.

CHAPTER 6

Decision Analysis to Support the Choice of a Future Power Generation Pathway for Sri Lanka

6.1 Introduction

Power planning in Sri Lanka is important due to the expected high growth in demand (U.S. Energy Information Adminstration, 2017), and heavy attention from stakeholders. The economy in the country relies heavily on the electricity supply (Wolfram, Shelef, & Gertler, 2012) and achieving sustainable objectives of power generation (Yi, Xu, & Fan, 2019; S. Zhang, Zhao, & Xie, 2018) is challenging. The country enjoys significant clean hydropower, which catered the full electricity demand until the early 1990s. The country presently has no commercially proven fossil fuel resources and no grid connection to the neighboring countries. Electricity demand is expected to continue to increase over the next several decades, and plans have been developed to expand the generation system, i.e., appropriately construct new power plants over time as needed (Ceylon Electricity Board, 2015). Realization of power generation capacity plans of adding thermal power and renewable power other than hydropower to the system is constrained by both capital investments and stakeholder consultation (Chen et al., 2015).

Power generation planning is a complex task under supply and demand uncertainties and investment challenges (Jin, 2009). The selection of power technologies should reflect the expected long-term electricity demand increases as well as changes in the pattern of demand from daily to seasonal time scales. Power generation planning must be done in the face of fluctuations and uncertainties in the price of fossil fuel and in the availability of renewable resources (Vithayasrichareon, Riesz, & MacGill, 2017). Capital investments in power generation are conditioned by long lead times and long-term payback periods. Investment additions for power grid expansion according to the locations of power generation is another consideration (Motamedi, Zareipour, Buygi, & Rosehart, 2010; Samarakoon, Shrestha, & Fujiwara, 2001). In addition, impacts to the natural and social environment from power generation add further complexity to the planning. Hence, planning of power generation expansion for time horizon of 20 years or longer must consider the engineering, economic, physical science, and social science aspects of the process.

The goal of power planning is supplying a reliable and affordable power supply to consumers in an environmentally friendly manner for multiple decades. To achieve this goal, power planning seeks to (1) maximize economic benefits of power generation as a business, (2) maximize the reliability of the power system, (3) minimize environmental impacts from power generation, and (4) minimize negative impacts and maximize positive impacts to society from power generation. Plans must be implementable in a timely manner to achieve a reliable outcome.

Despite the multi-faceted nature of power generation planning, traditional planning by power utilities primarily focuses on meeting the forecasted electricity demand in an economically favorable manner (B. F. Hobbs, 1995) by centralized power capacity expansion (Kagiannas, Askounis, & Psarras, 2004). The process is to minimize cost (single objective optimization) under a few constraints for technical and environmental regulations (Afful-Dadzie, Afful-Dadzie, Awudu, & Banuro, 2017). Since planning is mostly handled by utilities, energy policy analysis does not adapt a thorough process, rather it considers a few alternatives and sensitivity analyses done within a narrow bound around the “business-as-usual” plan. Comparison of alternative plans often highlights the technical and economic aspects with limited consideration of information on environmental and social aspects (Mai et al., 2015).

Over the past two decades, the power generation planning process has evolved to consider multiple objectives with the participation of diverse stakeholders. The increase in environmental awareness and advances in technological innovations have put pressure on power generation planners to address sustainability objectives (Pfenninger, Hawkes, & Keirstead, 2014). Integrated resource planning, which considers both supply side and demand side options to meet power demand, is one initiative that helps facilitate the process (Greacen, Greacen, von Hippel, & Bill, 2013; Tennessee Valley Authority, 2015; Wilson & Biewald, 2013). Increasing renewable energy share in a portfolio (Sharifzadeh, Hien, & Shah, 2019; Zappa, Junginger, & van den Broek, 2019), developing of carbon capture storage (Koelbl et al., 2016) constructing efficient fossil fuel plants (Pettinau, Ferrara, Tola, & Cau, 2017), instituting demand side management (Behboodi, Chassin, Crawford, & Djilali, 2016) and switching to different fuels for efficiency gains (Lewandowska-Bernat & Desideri, 2018) are methods employed to achieve sustainability objectives. Several mathematical algorithms including linear programming (Clímaco, Henggeler Antunes, Gomes Martins, & Traça Almeida, 1995), mixed integer programming (Guerra, Tejada, & Reklaitis, 2016), dynamic programming (Parpas & Webster, 2014), evolutionary programming (S.Kannan, S.Mary Raja Slochanal, 2005) among other algorithms (Flores, Montagna, & Vecchietti, 2014), are used for energy policy analysis. Other power planning tools (Connolly, Lund, Mathiesen, & Leahy, 2010; Gacitua et al., 2018) such as TIMES (Pina, Silva, & Ferrão, 2013), OPTGEN, MESSAGE (Aliyu, Ramli, & Saleh, 2013; International Atomic Energy Agency, 2016), OSeMOSYS (Howells et al., 2011), LEAP (Heaps, 2016), EGEAS, PLEXOS and WASP-IV(International Atomic Energy Agency, 2001) have also been used (Koltsaklis & Dagoumas, 2018). However, multiple objectives can be conflicting and multiple stakeholders will have diverse views on the technical, economic, and environmental aspects associated with power planning, weighing the importance of various objectives differently. As a result, the importance of incorporating diverse concerns of stakeholders and building trust and confidence in the power generation planning process has become widely recognized (Grafakos, Flamos, & Enseñado, 2015).

A multicriteria decision analysis (MCDA) model provides a path to evaluate power generation alternatives (Løken, 2007).by analyzing both quantitative and qualitative data associated with multiple aspects of the plans (Pohekar & Ramachandran, 2004). MCDA also provides a platform for collaborative decision making considering diverse views of the decision makers on conflicting objectives (B. Hobbs & Meier, 2000). MCDA has been used for power generation planning in developed countries such as Portugal(Ribeiro, Ferreira, & Araújo, 2013) and other EU countries (Baležentis & Streimikiene, 2017) as well as developing countries Bangladesh (Rahman, Paatero, Lahdelma, & Wahid, 2016) and Mexico (Martinez, Lambert, & Karvetski, 2011). The method has been used for individual technology assessment such as solar PV (Al Garni & Awasthi, 2017), hydropower (Vučijak, Kupusović, MidŽić-Kurtagić, & Ćerić, 2013), energy storage (Murrant & Radcliffe, 2018) and power technology comparison (Shaaban, Scheffran, Böhner, & Elsobki, 2018). It has also used to incorporate social aspects of technologies (Chatzimouratidis & Pilavachi, 2008). Specifically, in energy policy analysis, power generation pathway assessments have been carried out with a focus on specific targets for energy mix and a specific set of objectives. For example, decarbonization energy pathways for Bosnia and Herzegovina were studied using WASP-IV optimization with several attributes to measure economic, environment and technical criteria (Kazagic, Merzic, Redzic, & Music, 2014). In another example, a pathway analysis in Bangladesh was used to identify renewable investment opportunities (Shiraishi, Shirley, & Kammen, 2019). The diversification of a power generation mix to achieve energy security for Tunisia (Brand & Missaoui, 2014), Jordan (Malkawi, Al-Nimr, & Azizi, 2017) and Australia (Hong, Bradshaw, & Brook, 2014) has been studied. These power investment portfolios were evaluated under uncertainty using multiple resource options as criteria (Martinez et al., 2011), using macro and micro economic attributes (Hernandez-Perdomo, Mun, & Rocco, 2017), conducting sensitivity analysis (Georgopoulou, Lalas, & Papagiannakis, 1997), and considering uncertainty of technologies and decision-maker preferences (Heinrich, Basson, Cohen, Howells, & Petrie, 2007). In addition, MCDA has been used to incorporate social concerns into the decisions of power generation planning (P. Ferreira, M. Ara´ujo, 2010).

This chapter illustrates the use of MCDA to support decision making of generation capacity expansion planning in Sri Lanka to meet future electricity demands. The power generation plans have been controversial at least in part because of a lack of transparency for the public (Jayasuriya & Avanthi, 2017; Ratnasingham, 2017) and environmental issues of the energy choices (Economic Consulting Associates, Consultants, & ERM, 2010; Meier & Munasinghe, 1994). Sri Lanka would benefit by having a transparent planning process where stakeholders' diverse views can be accommodated rather than a closed evaluation process by a power utility that has a monopoly over the power sector. Although, energy policy analysis with MCDA has been used for certain developing countries, comprehensive analysis considering stakeholder views has not been conducted for the Sri Lanka.

The objective of this study is to apply a planning method using optimization and decision methods to help decision makers by identifying the strengths and weaknesses of power generation pathways for Sri Lanka considering multiple technologies, multiple objectives, and the variety of views held by groups of different stakeholders. We first construct various hypothetical alternatives of energy mixes that reflect emphasis on different strategic elements of energy policy put forward by Sri Lanka (Ministry of Power and Energy, 2008). We next find the least-cost implementation pathway for each alternative using an optimization model; these optimized versions (the pathways) provide the economic, technical, environmental and social aspects of each proposed plan. Finally, MCDA incorporates stakeholder preferences using a number of metrics in addition to economic costs and benefits to explore how various pathways are valued. These results are interpreted to suggest a possible preferred pathway (De Silva M., Hornberger, & Baroud, 2019).

6.2 Background

The total power capacity of Sri Lanka is comprised of oil-fired thermal power (1233 MW), coal-fired thermal power (900 MW), large hydropower with reservoir storage (1384 MW), run-of-the- river small hydropower (354 MW), wind power (131 MW) and other renewable power (45 MW) plants. The total electricity generation in 2017 was 14671 GWh, which was 31% from renewable energy and 69% from fossil fuel fired power plants (Ceylon Electricity Board, 2016). The average power generation growth and peak demand growth for the last 20 years are 5.1% and 4.7%, respectively (Ceylon Electricity Board, 2016) and continued growth in demand is expected.

The national energy policy for Sri Lanka determined specific targets, milestones and implementation strategies for the energy sector (Ministry of Power and Energy, 2008). Supplying basic energy needs of the nation, ensuring energy security, protecting consumers, providing high-quality power supply, promoting indigenous resources, increasing energy efficiency, and implementing transparent tariff policy are key elements of the national energy policy. In addition, special attention is given to increase the share of renewable energy. These elements provide the basis for formulating alternatives to consider for power generation expansion in Sri Lanka.

In Sri Lanka, as elsewhere, planning involves the evaluation of different pathways to meet anticipated demand. A pathway is a scheduling plan detailing the timeline for the addition of power plants to the system over the course of the planning period, which we take to be 20 years. Different alternatives of mixes of types of power generation plants lead to different pathways. This study provides a mechanism to evaluate the pathways using criteria that account for stakeholders' preferences.

6.3 Methods

Our approach consists of four components, (1) identification of alternatives, (2) formulation of an implementation pathway for each alternative, (3) identification of criteria and attributes, and (4) evaluation of the pathways (Figure 6.1).

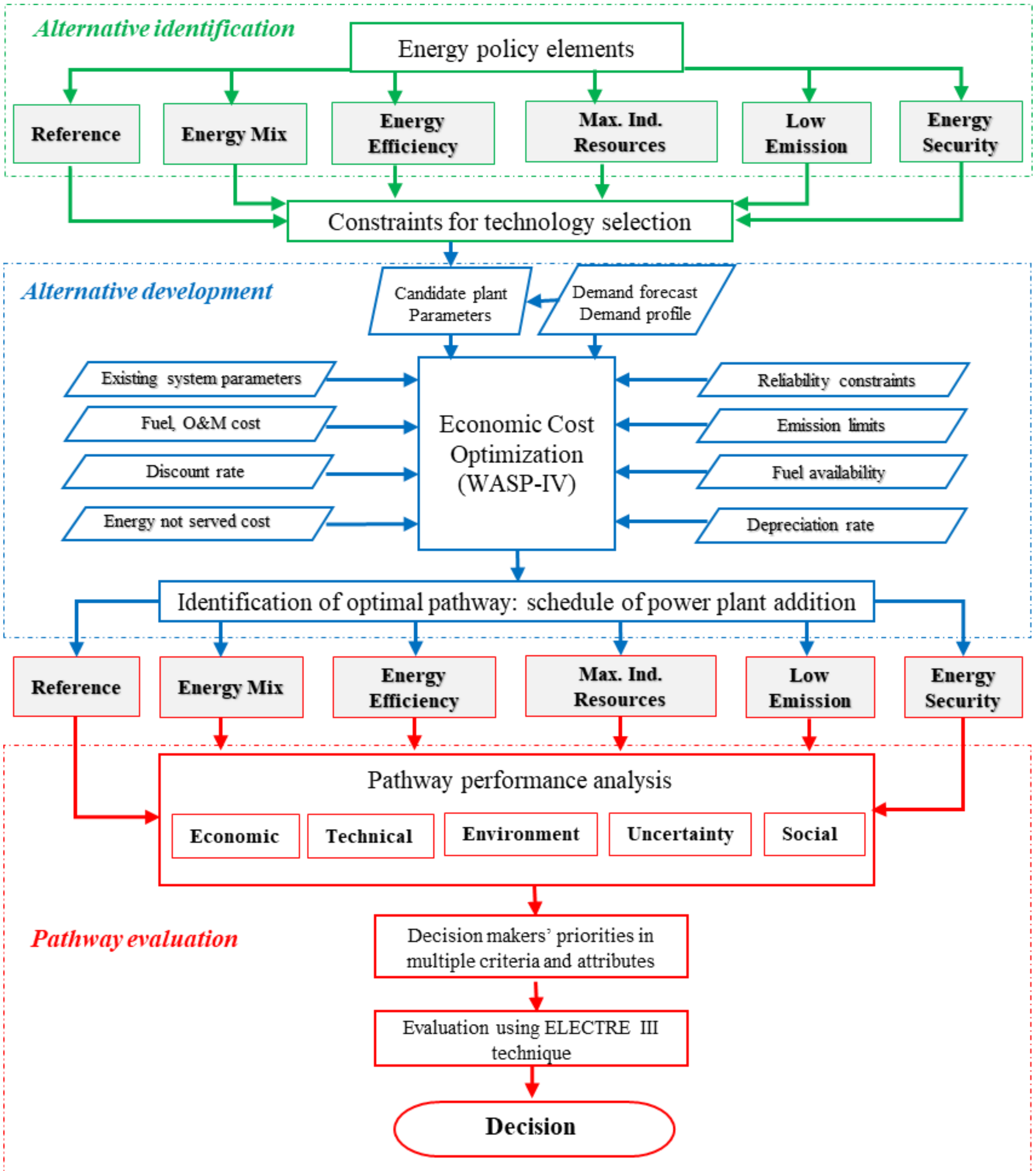

Figure 6.1 Methodology for power generation pathway selection by developing the details of each alternative (the best way to implement each alternative) through optimization followed by evaluation using MCDA.

6.4 Identification of Alternatives

Six alternatives are proposed. The alternatives are based on elements of the national energy policy (Ministry of Power and Energy, 2008), current power generation plans of the country (Ceylon Electricity Board, 2015), communication between the Ceylon Electricity Board (CEB), the power utility responsible for the preparation of power generation expansion plan for the country, and the Public Utility Commission (PUCSL), the regulatory authority on power planning matters (Public Utility Commision of Sri Lanka, 2017, 2018), stakeholder views gleaned from media coverage (Jayasuriya & Avanthi, 2017; Ratnasingham, 2017), and power plans prepared by utilities of other countries such as the United States (Tennessee Valley Authority, 2015), Korea (MOTIE KPX (Korea Power Exchange), 2015) and Thailand (Ministry of Energy Thailand, 2015) (Table 6.1).

Table 6.1. Alternative plans for power generation pathways in Sri Lanka

Alternatives	Description
1. Reference case (RC).	Traditional planning concepts are used; the total power capacity is planned with conventional power plant options (large hydro and thermal) with the least cost plant combination selected. Power capacity contribution from variable renewable energy (VRE) sources (wind, solar, small hydro, and biomass) is not considered.
2. Energy mix case (EM):	The total power capacity is planned with conventional power plants, with an emphasis on diverse technology and fuel mix. Power capacity contribution from variable renewable sources is not considered.
3. *Energy efficiency case (EE)*	Both energy and power capacity savings from demand-side management (DSM) techniques (Sri Lanka Sustainable Energy Authority, 2017) are considered for this alternative. Projected power capacity and energy demands are reduced by the projected savings from DSM. Power capacity is planned with conventional thermal power plant options and both large hydropower and VRE power plant options. Additional contingency reserves to meet the variability of VRE resources (Hummon, Denholm, Jorgenson, Palchak, & Kirby, 2013; Ueckerdt, Hirth, Luderer, & Edenhofer, 2013) are considered.
4. Maximum indigenous resource case (IR):	Priority is given for indigenous resources such as local natural gas (NG) (currently, under investigation) and maximum use of renewable power sources. Conventional thermal power plant options are used to balance power demand and availability.
5. Low emission case (LE):	Power capacity is planned with maximum use of renewable sources and gas-fired thermal power plants. Oil is considered as a candidate for near future power supply; coal is not considered. Power capacity contribution from VRE is considered with additional contingency reserves.
6. *Energy security case (ES)*:	Power capacity is planned with a combination of fossil fuel-fired thermal power mix (coal, oil, and natural gas) and renewable power sources. Power capacity contribution from VRE is considered with additional contingency reserves

6.5 Development of Possible Pathways

Various energy pathways – the scheduling across 20 years of the addition of power plants of different types – can be envisioned. Some of these will be more or less favorable with respect to the objectives implied by the alternatives in Table 6.1. An optimal pathway for each alternative can be determined by minimizing costs within constraints.

6.5.1 Candidate Power Plants to Develop Energy Pathways

Table 6.2. Candidate power plants for future power generation capacity addition (Ceylon Electricity Board, 2015; Institute of Policy Studies, Associates, Resource Management Associates, & Tiruchelvam Associates, 2011; Japan International Corporation Agency, 2015; JPower, 2014; Oriental Consultants, Tokyo Electric Power Services, & Consulting Engineers and Architects, 2014).

Candidate power technology	Unit Capacity
1. Diesel fired gas turbine power plants	35 MW, 70 MW, 105 MW
2. Diesel fired combined cycle power plants	150 MW, 300 MW
3. Coal fired sub critical thermal power plants	225 MW, 290 MW
4. Coal fired super critical thermal power plant	500 MW
5. Natural gas fired combined cycle power plant	270 MW
6. Biomass fired thermal power plant	5 MW
7. Nuclear power plant	500 MW
8. Interconnection to power grid of India (stage I)	550 MW
9. Pumped storage hydropower plants	200 MW
10. Large and small hydropower plants (site specific)	35 MW, 120 MW, 31 MW
11. Wind power plants (site specific)	50 MW, 25 MW
12. Solar photovoltaic power plants (site specific)	10 MW, 15 MW

Pathways are developed for forecasted electricity demand (Table D. 1 (a) in Appendix D) using candidate power plants considered by Ceylon Electricity Board (2015) (Table 6.3). The projected average electrical energy and power capacity growth rates for the 20-year planning horizon are 5.2% and 4.6%, respectively (Ceylon Electricity Board, 2015). Power generation options are screened against the load duration curve (Shape of the electricity demand (a) Daily demand profile evolution through past 25 years (b) Load duration curve of present and forecasted for year 2034

to identify suitable candidate power plant options (International Atomic Energy Agency, 1984; Mohan Munasinghe & Peter Meier, 2005). In addition, power system operation security constraints such as contingency reserve requirements, isolated grid operation of important areas under emergency, and diversity of resources to face the uncertainty of availability (renewable, fossil fuel) are considered. Due to the long lead-time to introduce new technology (e.g., NG, nuclear), short-term candidate options (e.g., oil fired power plants) are considered to address immediate demands, including for the *Low emissions* case.

6.5.2 Pathway Optimization

The Wien Automatic System Planning version IV (WASP-IV) optimization package developed by the International Atomic Energy Agency (International Atomic Energy Agency, 2001) is used to identify the new power plant additions to the system under each pathway. Inputs for the WASP-IV model include existing and candidate power plant characteristics (Table D. 2, Table D. 5), fuel cost, hydrology (Table D.4), discount rate (10%), economic loss of electrical energy not served (ENS: Economic loss to society not supplying energy due to outage of power plants or shortage power plant capacity) to the country, plant depreciation rate, maintenance schedules, reliability standards, and environmental emissions. Environmental emissions of power plants are given by levels of CO_2, SO_x, NO_x and particulate matters (PM) (Table D. 3, Table D. 6) (Ceylon Electricity Board, 2015).

The objective function (B_i) to be optimized is a combination of cost elements: capital investment cost ($I_{i,t}$), salvage value of investment cost ($S_{i,t}$), fuel cost ($F_{i,t}$), fuel inventory cost ($L_{i,t}$), nonfuel operation and maintenance cost ($M_{i,t}$) and cost of energy not served ($O_{i,t}$), (6.51).

$$B_i = \sum_{t=1}^{T}[I_{i,t} - S_{i,t} + F_{i,t} + L_{i,t} + M_{i,t} + O_{i,t}] \tag{6.51}$$

To avoid end effect distortions (bias against capital intensive plants near the end of the time horizon) an extended simulation period of 30 years is selected with results reported for the 20-year planning period. The discounted cost of the plan for the 30-year study period is minimized under given constraints and a probabilistic hydrology forecast. Constraints for the optimization are reliability standards, system level emissions, and installation schedule limitations for candidate power plants. The WASP-IV model reports the power plant schedule to be added to the system, cost (capital investment, salvage of investment cost, fuel cost, maintenance cost and ENS cost), fuel quantities, and emissions to the environment (CO_2, SO_x, NO_x, PM) (International Atomic Energy Agency, 2001).

The resulting optimal schedule for addition of power plants for each alternative is the best implementation of a pathway in terms of the criterion and constraints above. In what follows, we refer to these optimal pathways simply as "pathways" as there should not be any ambiguity going forward. Six alternative pathways are generated by six optimization exercises carried out using WASP-IV separately.

6.5.3 Identify the Criteria and Attributes and Measure the Performance of Attributes

We identify five criteria to evaluate the different pathways, (1) economic aspects, (2) technical flexibility of the power system, (3) uncertainties, (4) environmental stewardship, and (5) social aspects. We use 15 attributes to measure these criteria.

(1) Economic performances of alternatives are measured with two attributes, the present value of the revenue requirement to recover the 20-year cost (PVRR) and the revenue requirement per unit of electricity (1 MWh) for the first 10 years of the planning period (Unit Cost). The discounted total cost of the 20-year plan to 2015 is calculated using a 10% discount rate. The revenue requirement is calculated using estimated annual sales and cost, (Tennessee Valley Authority, 2015).

$$Unit\ Cost = \frac{1}{10}\sum_{i=2015}^{2024}\left[\frac{Annual\ total\ system\ cost}{Annual\ sales}\right]_i \tag{6.52}$$

In addition to the PVRR, the investment requirement for alternatives is examined. For the first years 2015-2024 investment (Cost1) and second years 2025-2034 investment (Cost2) are used.

(2) Technical flexibility for operating the power system is improved with high peaking power capacities and high dispatchable power capacities. Therefore, peaking power share (capacity of peaking power plants /capacity of total power plants) (P-share) and dispatchable power share (capacity of dispatchable power plants/capacity of total power plants) (D-share) are used as the attributes for measuring the technical flexibility of the system (Tennessee Valley Authority,

2015). For the calculation, large hydropower plants and diesel fired gas turbine power plants are considered as the peaking power plants. In addition, variable renewable capacity is not considered as dispatchable power sources.

(3) Uncertainty is measured by four attributes, (1) risk exposure of the cost of the plan, (2) risk-benefit ratio, (3) diversity of fuel mix for power generation, and (4) dependency on energy sources from foreign countries. The economic cost of alternative plans is uncertain due to variables related to climate, fossil fuel prices (BP Global, 2017; Mundi Index, 2017), demands, and financial parameters. For this study, variation of hydropower generation according to the climate variation (Figure D.4) (Ceylon Electricity Board, 2015) and fossil fuel (NG, oil, coal) price variation (International Energy Agency, 2016) are used to calculate the uncertainty of the planning cost. Fossil fuel price volatility of individual fuel types is assumed independent from other fuel types. The 95th percentile ($PVRR\ P(95)$) cost is reported as the measurement of risk exposure of the plan.

The risk-benefit ratio of the plan (RBR) is computed as the risk of exposure of the cost exceeding its expected value divided by the benefit of having the plan cost less than the expected value (Tennessee Valley Authority, 2015).

$$RBR = \frac{PVRR\ P(95) - Expected\ value}{Expected\ value - PVRR\ P(5)} \tag{6.53}$$

The diversity of the fuel mix is calculated using the Shannon Wiener index (H) (Jansen, Arkel, & Boots, 2004) and the dependency on foreign countries energy sources is measured by the NEID index (Kruyt, van Vuuren, de Vries, & Groenenberg, 2009).

$$H = -\sum_{i=1}^{n} p_i \ln p_i \tag{6.54}$$

$$NEID = \frac{\sum_{i=1}^{n} m_i p_i \ln p_i}{\sum_{i=1}^{n} p_i \ln p_i} \tag{6.55}$$

In (6.54) and (6.55), p_i is the share of fuel *i* in the fuel mix, and m_i is the share of net imports of fuel carrier *i*.

(4) The power plants' impact to the environment is assessed by gases and solid waste emitted, water use, and damage to flora and fauna. The land-use requirement for power plants has both social and environmental impacts. For this study, we select the sum of annual average emission of CO_2, SO_x, NO_x, PM (Table D. 3, Table D. 6) and the land requirement for the 20-year

planning period (Table D. 7) as attributes to measure the environmental stewardship of each alternative (Chatzimouratidis & Pilavachi, 2008; Simons & T. Peterson, 2001; Singh & Fehrs, 2001).

(5) Power generation has both positive and negative impacts on society, and stakeholders have diverse views regarding such implications. To account for positive impacts to society which are not measured from other attributes, we select *new job opportunities* from power plant construction and operation and evaluate using values from literature on similar studies carried out for other countries (Table D. 7) (Chatzimouratidis & Pilavachi, 2008; Simons & T. Peterson, 2001; Singh & Fehrs, 2001; U.S. Department of Energy, 2017). Further, *social acceptance* is selected to account for general public opinion on the positive and negative impacts of the power generation technologies. Assessment of *social acceptance* is based on a short survey conducted among 23 energy sector stakeholders including the power utility, social and environmental agencies, financing institutes, regulators, and professional bodies of Sri Lanka. These professionals are actively involved in the system level power generation planning as well as implementation of projects representing multiple sectors. They ranked the different power technologies according to their understanding of public opinion from the experience of previous power generation and other infrastructure project developments. According to the rankings, we calculate weights, which indicate social acceptance per MW capacity of each power technology (Table D. 7). The value of social acceptance for each alternative plan is the sum of technology capacities (MW) weighted by the social acceptance of the technologies (per MW).

6.5.4 Evaluation of Pathways

Within the MCDA framework the evaluation of multiple criteria is accomplished by assigning different weights to each attribute to reflect the priorities of each stakeholder (Malkawi et al., 2017; Ribeiro et al., 2013; Shackley & McLachlan, 2006; Talinli, Topuz, & Uygar Akbay, 2010). In this work, we consider three hypothetical stakeholders, a regulator, a power utility operator, and an environmental protection agency representative to represent agents that would have important input into the decision-making process. The weights chosen for the criteria are deliberately selected to emphasize particular values assumed for each stakeholder. The weights for attributes are distributed equally within each criterion for all cases. Below we present the weight distribution for each simulated stakeholder.

Regulator: Equal importance for all the criteria is considered. Economic, technical flexibility, environmental stewardship, uncertainty, and social criteria are each assigned an overall weight of 0.2, which is then distributed equally among the attributes associated with each criterion.

Utility Operator: Power generation is considered as a business and economic, reliability and uncertainty criteria are considered as more important than others. Economic, technical flexibility, environmental stewardship, uncertainty, and social criteria are each assigned overall weights of 0.3, 0.25, 0.1, 0.25, and 0.1, respectively.

Environmental Agency: Environmental and social impacts are taken to be priortized by the stakeholder for this case. Economic, technical flexibility, environmental stewardship, uncertainty, and social criteria are assigned overall weights of 0.1, 0.1, 0.4, 0.1, and 0.25, respectively.

The outranking method ELECTRE III is used to explore how stakeholder preferences can be expressed in energy planning. The advantages of this method include the ability to deal with quantitative and qualitative scales (Pohekar & Ramachandran, 2004) and non-compensatory effects (avoiding the choice of alternatives with a very low value for the criterion that is compensated by higher values for the rest of the criteria).

6.5.5 ELECTRE III

The elimination and choice translating reality (ELECTRE) method was developed in the late 1960s by Bernard Roy and his team (Benayoun et al., 1966; Roy, 1991). The family of ELECTRE methods (ELECTRE I, II, III, IV, TRI) is widely used in Energy planning (B. Hobbs & Meier, 2000; J. J. Wang, Jing, Zhang, & Zhao, 2009). The method involves comparing two pathways at a time across all the attributes. Brief technical details are presented here; detailed descriptions can be found in the references provided.

Ranking of pathways is done through modelling of preference by outranking relations and ordering them. The outranking technique of the method handles four type of preferences through three thresholds. The strength of one pathway over another is represented by a concordance index ($C(i,i')$). Concordance index values are calculated using outranking relationship (Eq.(6.(5.48))) and weights associated with attributes (w_j) (Eq. (6.56) and (6.57)). The difference ($diff$) between pair of attribute values for the pathways, $(g_j(i) - g_j(i'))$, is compared with a preference threshold (p_j) and an indifference threshold (q_j) to assess the outranking relationship; indifference (i as good as i'), weak preference and incomparability (Roy, 1991).

$$C(i,i') = \frac{1}{W}\sum_{j=1}^{n} \mathrm{w}_j \mathrm{c}_j(i,i') \tag{6.56}$$

$$W = \sum_{i=1}^{n} w_j \tag{6.57}$$

$$c_j(i,i') = \begin{cases} 1 & if\ diff \geq\ q_j\left(g_j(i)\right) \\ 0 & if\ \ diff\ \ \leq p_j\left(g_j(i)\right) \\ \dfrac{p_j\left(g_j(i)\right) + diff}{p_j\left(g_j(i)\right) - q_j\left(g_j(i)\right)} & otherwise \end{cases} \tag{6.58}$$

The discordance index $(d_j(i,i'))$ measures the degree of opposition of pathway i over pathway i' using outranking relationship (6.59) and weights of each attributes similar to (6.56) and (6.57). The discordance is measured with respect to the veto threshold (v_i), which is associated with the most important criterion or with all the criteria. The relative values of the three thresholds have the relationship $v > p > q$ (Rogers & Bruen, 1998). For this study, we choose 2 as the ratio between the thresholds, the values 2% for q, 5% for p, and 10% for v.

$$d_j(i,i') = \begin{cases} 1 & if\ diff \geq\ -v_j\left(g_j(i)\right) \\ 0 & if\ \ diff\ \ \geq p_j\left(g_j(i)\right) \\ \dfrac{-p_j\left(g_j(i)\right) + diff}{v_j\left(g_j(i)\right) - p_j\left(g_j(i)\right)} & otherwise \end{cases} \tag{6.59}$$

The credibility index $(\sigma(i,i'))$ is calculated combining the both concordance index and discordance index. If the concordance index is higher than or equal to the discordance index over all the attributes, the credibility index is equal to the concordance index. Otherwise the credibility index is calculated by (6.60).

$$\sigma(i,i') = c(i,i')\prod T(i,i') \tag{6.60}$$

$$T(i,i') = \frac{1-d_j(i,i')}{1-c(i,i')} \text{ , if } d(i,j) > c(i,j), \text{ otherwise } T(i,i') = 1$$

The ranking of pathways is based on two pre-orders ascending distillation and descending distillation according to the credibility indices(Marzouk, 2011; Rogers & Bruen, 2000; B. X. Wang & Triantaphyllou, 2006).

6.5.6 Value Path and Weight Tradeoff

A value path is a graphical representation of the pathways' performance over the attributes (B. Hobbs & Meier, 2000). Transforming the attribute performance to commensurate units through standardization is the first step of representing the value path. We use interval standardization, using (6.61) and (6.62) (Clemen, Robert T., Reilly, 2001). (6.61) is used for the criteria to be maximized and (6.62) is used for the criteria to be minimized. Linearity across the attributes' performance interval is assumed.

$$e(j,i) = \frac{g(j,i) - min\ g(j)}{max\ g(j) - min\ g(j)} \tag{6.61}$$

$$e(j,i) = \frac{\max g(j) - g(j,i)}{\max\ g(j) - \min\ g(j)} \tag{6.62}$$

Next, a dominance analysis of pathways can be performed using two concepts, significant dominance and strict dominance. If all the attributes of a pathway are better than or equal to another pathway, it is identified as strictly dominant. If only several attributes are better, the pathway is identified as significantly dominant (B. Hobbs & Meier, 2000).

Further, decision makers' preferences can be interpreted in monetary terms to illustrate the tradeoffs implied by the weights they assign to the attributes (B. Hobbs & Meier, 2000). That is, the equivalent monetary value for one unit of an attribute, $w'(j, PVRR)$, is calculated by dividing its normalized weight by the normalized weight for the present value of the revenue requirement (6.13).

$$w'(j,PVRR) = \left(\frac{w\ (g(j))}{max\ g(j) - \min g(j)}\right) / \left(\frac{w\ (PVRR(j))}{max\ PVRR(j) - \min PVRR(j)}\right) \tag{6.13}$$

6.5.7 Sensitivity Analysis

Uncertainties are associated with assumptions of alternative plans development, attributes assessment and decision makers' weights on the attributes. We perform a sensitivity analysis of decision makers' weights and attributes using Monte Carlo simulation. We use a uniform distribution of decision makers' weights around ±20% and a uniform distribution of attribute performance around ±5% to study the sensitivity of the ranking of pathways to the uncertainty in the attributes.

6.6 Results

The WASP-IV model results indicate that the addition of power generation capacity from different sources varies under different pathways according to constraints for the technologies and the environment (Figure 6.2). Investment for power capacity expansion varies according to the unit capacity of power plants and contingency reserves requirement for the power system. The power source mix and power capacity additions at the end of the 20-year planning period represent the specific policy goal of each alternative. For example, the pathway for the *Low Emission* alternative consists of 28% large hydropower, 3% diesel fired gas turbines, 9% coal fired steam generators, 36% natural gas fired combined cycle plants and 24% mix of solar, wind and run-of river small hydro power plants, which is the mix that minimizes emissions within constraints (Figure 6.3).

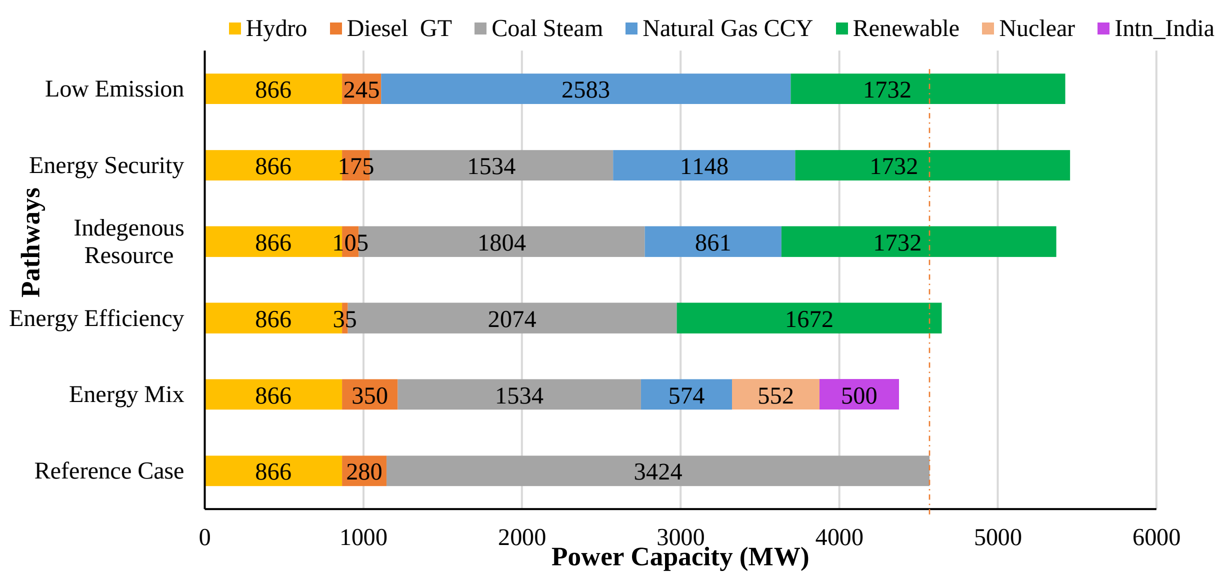

Figure 6.2 New power capacity addition of different power plants using different primary energy sources

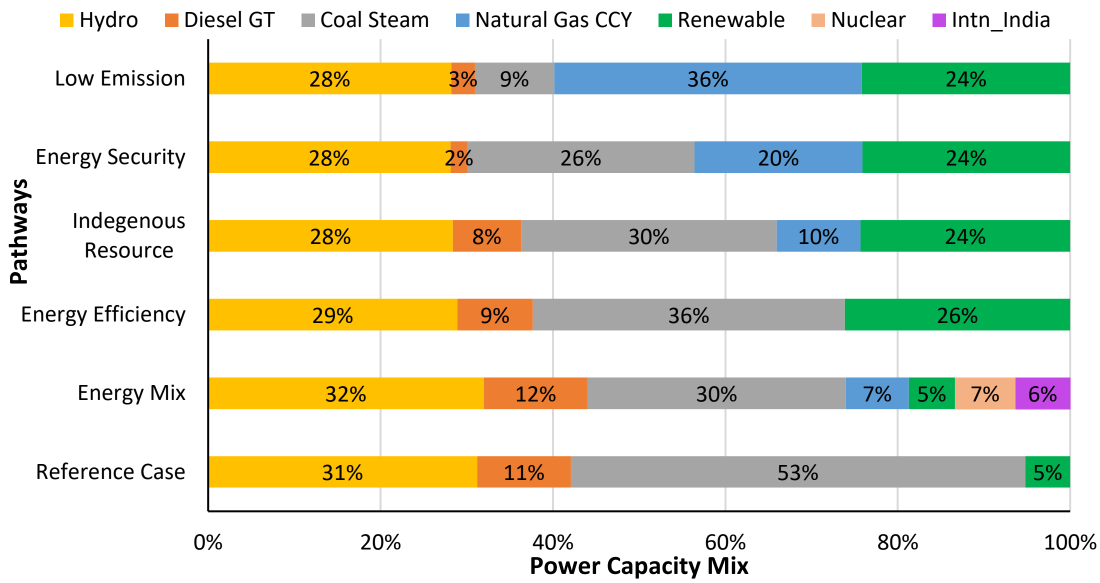

Figure 6.3 Power capacity mix in 2034 including existing power plants and new power plants

Table 6.3. Performance of power generation pathways over the criteria and their attributes (values are rounded to report three significant figures).

Criteria		Reference Case	Energy Mix	Energy Efficiency	Max. Ind. Resource	Low Emission	Energy Security
Economic[a]	PVRR ($M)	12800	13400	10900	12300	14000	12700
	Unit Price ($/MWh)	57.7	56.8	55.8	64.8	68.2	62.8
Technical Flexibility[b]	P- share (%)	26	27	21	22	22	22
	D- share (%)	86	86	67	65	68	68
Environment Stewardship[c]	SO_x (kT)	741	777	637	400	379	398
	NO_x (kT)	456	417	323	312	181	293
	PM (kT)	34.9	34	28.8	30.4	14.2	29.7
	CO_2 (MT)	301	260	209	223	165	216
	Land requirement (km^2)	659	658	1873	2284	2284	2284
Uncertainty[d]	PVRR P(95) (M$)	15000	15800	13600	13900	15300	14300
	RBR	0.70	0.61	1.03	0.63	0.35	0.47
	SWI - H	1.10	1.69	1.13	1.49	1.39	1.44
	NEID	52.8	69.2	51.8	37.7	49.5	51.5
Social[e]	New jobs	22800	21800	37700	47500	47700	47800
	Social acceptance	540	700	680	760	870	790

[a]Figure D. 2, [b]Figure D. 3, [c]Figure D. 4, [d]Figure D. 5, [e]Figure D. 6

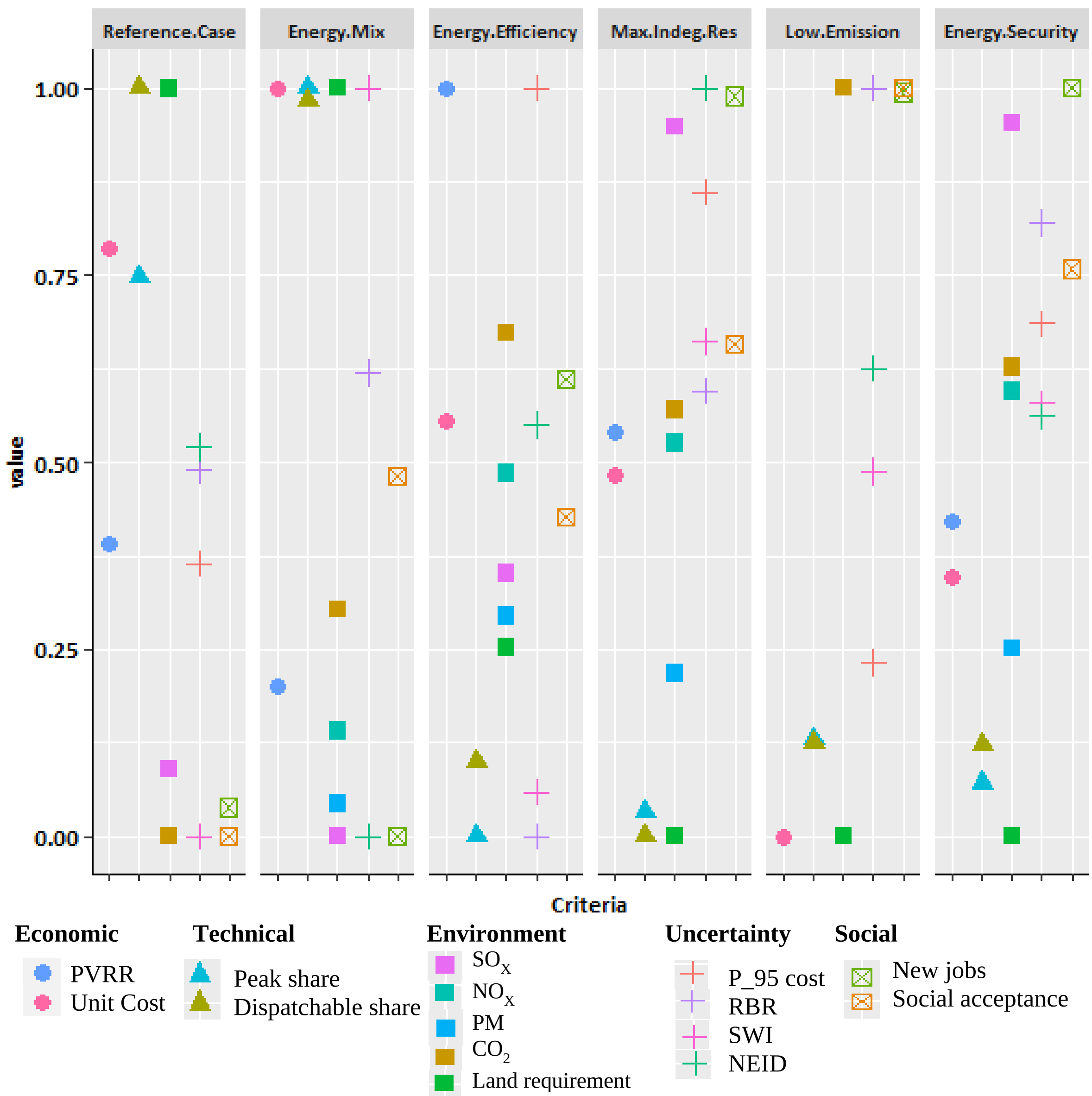

Figure 6.4 Value path of power generation pathways.

The pathways have diverse performances over the various attributes (Table 6.3, Figure D. 2, Figure D. 3, Figure D. 4, Figure D. 5, Figure D. 6). Some of the pathways are dominant in several attributes, while others are dominant in very few (Table D. 8). The value paths of 15 attributes illustrate that no pathway strictly dominates the others (Figure D. 4). For example, *Energy mix* has the best peak power share among the alternatives, but the worst new jobs (Table 6.3). On the other hand, *Low emission* is the lowest in the emissions (SO_x, NO_x, PM, CO_2) but worst in the cost.

Equivalent monetary values assigned to the *Environmental Stewardship* attributes vary among decision makers (Table 6.4). For example, 1kT of SO_X is valued at about 3 M$ by the regulator and about 12 M$ by the environmental agency stakeholder.

Table 6.4. Equivalent monetary values for decision makers' weights assigned to attributes of Environmental Stewardship criteria ($M)

Criteria		Regulator	Utility operator	Environmental agency
Environmental Stewardship	SO_x (kT)	3.0	1.0	12.1
	NO_x (kT)	4.4	1.5	17.6
	PM (kT)	58.3	19.4	233.2
	CO_2 (kT)	0.009	0.003	0.036

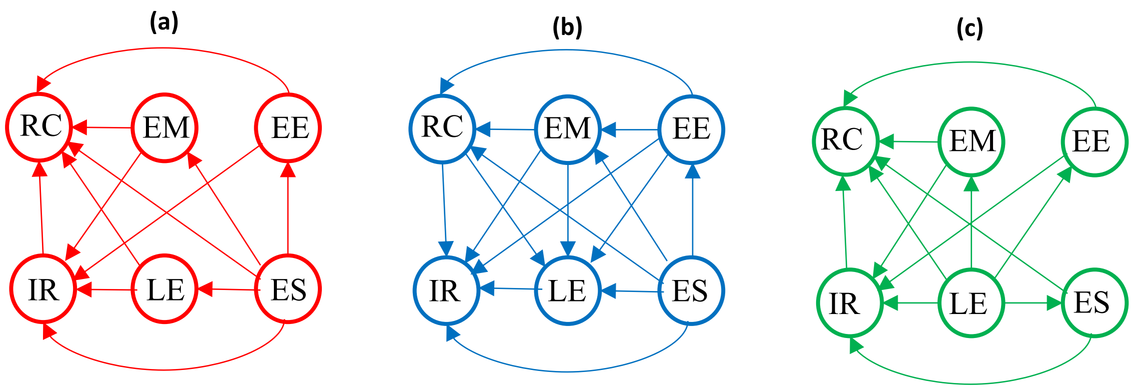

Figure 6.5 Decision graphs for hypothetical decision makers (a) Regulator (b) Utility operator (c) Environmental agency representative. Direction of an arrow indicates that one pathway outranks the other

Weights assigned to attributes for the three stakeholder groups resulted in variation in the preferred energy pathway. *Energy security* outranks all other pathways according to the weights of Regulator and Utility Operator. *Low emission* outranks other pathways according to the Environmental Agency Representative weights (Figure 6.5). The Utility Operator weights rank pathways clearly as *Energy security*, *Energy efficiency*, *Energy mix*, *Reference case*, *Low emission* and *Maximum Indigenous resources* respectively. However, according to the other two decision makers, the second place in the ranking is not unique, since several pathways have the same ranking.

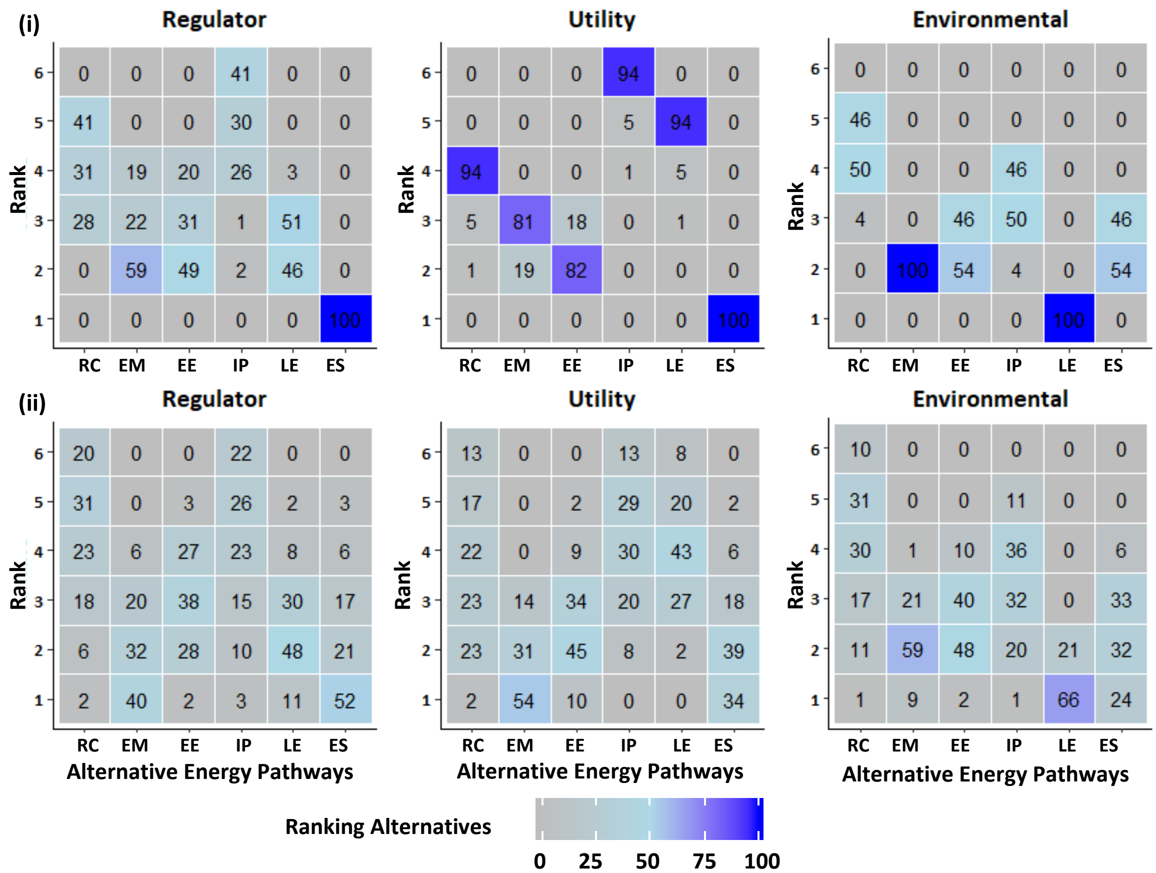

Figure 6.6 Sensitivity of pathway ranking. Percentage of the ranks obtained by each pathway for (i) decision makers weight uncertainty and (ii) decision makers' weight and performance uncertainty.

The ranking of the preferred choice for each decision maker is robust under uncertainty in the decision weights (Figure 6.6 (i)). However, the ranking for the second through sixth pathway is fairly stable only for the Utility Operator, whereas for others there is more variability under uncertainty of weight (Figure 6.6(i)). Incorporation of performance uncertainty results in higher variability in the rankings (Figure 6.6(ii)).

6.7 Discussion

For our study, none of the six energy pathways was dominant (Figure 6.4) across all criteria. Therefore, tradeoffs have to be assessed by the different stakeholders. In the *Low emission* pathway, the large NG thermal power share increases the cost and the VRE decreases the technical flexibility. However, these attributes make this pathway superior in the environmental and social criteria and the Environmental agency's weights elevated the preference for this pathway. On the other hand, the *Energy mix* pathway, based on conventional power technologies, performs well in cost and technical criteria and relatively poorly in environmental and social criteria due to high coal power share and lack of VRE development. The utility stakeholder's high weights on cost and technical criteria indicate acceptance of the tradeoff between (1) cost and technical flexibility and (2) environmental and social criteria implicit in the *Energy mix* pathway.

The analysis from ELECTRE III also indicates that the *Regulator* and *Utility* stakeholders have a preference for the *Energy security* pathway, while the *Environmental* stakeholder favors the *Low emission* pathway (Figure 6.5). As such, there is not a "clear winner." Nevertheless, there is consistency in the rankings that suggests that the *Energy security* and *Energy mix* pathways have high potential for reaching an agreement among parties (Figure 6.6). These two pathways can be used as a foundation to develop a power generation pathway that satisfies multiple criteria and reflects decision makers' preferences.

The expression of the weights of the environmental attributes in terms of dollars provides a chance to compare with other valuations. In our analysis for Sri Lanka 1 kT of CO_2 is valued as 9-36 \$/ton (Table 6.4) and can be compared with world carbon market taxes that range from 1 to 139 \$/ton. Although these values are high for a developing country (World Bank, 2018), they are not unreasonable. The equivalent weight values in our analysis range from 3,000 to 12,000 \$/ton for SO_x, from 1,500 to 17,000 \$/ton for NO_x, and from 19,000 to 231,000 \$/ton for $PM_{2.5}$ (Table 6.4). These can be compared with estimated costs of health impacts in the U.S. of 28,000, 5,000, and 52,000 \$/ton respectively (Jaramillo & Muller, 2016). Although the cost of the health impacts of emission are highly dependent on the local conditions, our assumed Environmental agency's weights tradeoff between economic and environmental criteria imply very higher monetary values for the SO_X, NO_X, PM emissions compared to the values estimated for the U.S. If the MCDA were implemented in an iterative way by providing feedback to stakeholders, the participants might be led to alter the weights assigned to environmental attributes to make them conform more closely with estimated values for health impacts. Hence, the method provides a platform for decision makers to do the trade-off analysis among the criteria with ranking of the energy pathways, while incorporating their preferences into the energy choices.

There are some limitations of the MCDA model in capturing the range of multiple criteria and the information available for evaluating alternatives. Some of the uncertainties in the pathway development such as the implementation of DSM measures, the use of local NG, the use of biomass as an energy resource, the political uncertainty of connecting to the grid of a neighboring country, and the probable public opposition for a nuclear power plant construction are not captured in the MCDA decision analysis. For example, implementation of DSM measures is carried out by individuals so is not easily subject to central control for the power utility and the power utility is not able to judge the likelihood of the success of DSM to the same extent as for other options (Greacen et al., 2013; Tennessee Valley Authority, 2015; Wilson & Biewald, 2013). Other limitations include the lack of specification for the availability of land to satisfy production of biofuels and challenges in the fuel supply chain (Ariyadasa, 2015; UNDP, 2017).

Analysis of social aspects in power generation choices is complex given that power generation has direct and indirect implications and positive and negative impacts on society. For example, society benefits from new employment opportunities created during the plant's construction and operation as well as from new foreign investment opportunities that can arise due to low electricity prices. Household livelihood is enriched by enabling the use of electricity-driven technologies. On the other hand, society can be negatively impacted by air and water pollution, noise, aesthetic disturbance, and displacement through land requirements. The various aspects and impacts were taken into account in this study by including available measures for attributes across the different environmental, technical, and social criteria.

Considering the captured and uncaptured uncertainties, the *Energy security* alternative may be a practical approach for Sri Lanka if our assumed stakeholders and their preference weights are found to be reasonable. This option shows average performance across all the criteria including economic, technical, environmental and social aspects (Figure 6.4). In the past, Sri Lanka examined the tradeoff between economic and environmental objectives in power planning (Economic Consulting Associates et al., 2010; Meier & Munasinghe, 1994). Most studies concluded with recommendations for state-of-the art coal power technologies and DSM options, since NG and VRE were not economically favorable in the past. However, presently, NG and VRE technologies are more competitive economically than they were in the past and low carbon technologies are welcomed by society. Our multiple objective analysis provides an approach for identifying a mix of renewable and fossil fuel alternatives for future power generation that incorporates attributes that go beyond economic and environmental considerations and illuminate possible pathways that are broadly acceptable to a spectrum of stakeholders.

In practice, the method described here is likely to be most useful to help make sensible decisions through an iterative process with the presence of multiple stakeholders. The MCDA approach can be used repetitively to assess, refine, and reassess options to collaboratively identify priorities and develop pathways accordingly. An actual decision would be selected with wide energy sector stakeholder consultation with the MCDA model providing a platform for the collaborative process.

Since conditions that dictate preferences for power generation options change over time, it is essential to use an iterative and adaptive planning approach that considers future variations of planning strategies, multiple attributes and stakeholder preferences. Such an approach is clearly needed given that our analyses show that ranking of alternatives is highly sensitive to attribute performance and decision makers' preferences (Figure 6.6). Measures of the performance associated with various attributes will be altered as technology advances, as better information and data become available, and as social, environmental, and economic conditions of a country evolve. New power generation strategies may become feasible. Similarly, decision-makers' preferences regarding the attributes will change through time. The methods illustrated in this paper can be adapted to take future variations into account through an iterative process.

Provision of adequate electricity is vital for a modern society. Selection of an appropriate plan for future power generation aims at achieving multiple objectives, which in part are not directly related to the generation or use of power. Therefore, the selection of pathways for power generation to meet future demands has to account for multiple criteria. The alternative pathway selection through optimization and MCDA is a good fit for power generation planning, allowing decision makers to navigate the advantages and disadvantages of different pathways and understand the impact of stakeholder preference weights on the value placed on different criteria. The approach can inform decisions for energy development as shown in the example for Sri Lanka. The results indicate that the methods would be useful for decision analysis in other similar energy planning studies.

CHAPTER 7

Synthesis

Planning and managing of water and energy infrastructure for increasing demand is challenging. Developed and developing countries face serious difficulties in meeting the infrastructure needs for mitigating poverty and hunger and increasing access to clean water, energy, and economic growth. Like other countries, Sri Lanka, a densely populated small island, faces problems related to infrastructure with some aspects unique to them. The obstacles facing the country in meeting the infrastructure needs include securing the necessary technical and financial resources as well as determining how to take into account the differences of opinion about the best options held by different stakeholders. In addition, demographic, economic and environmental changes increase the complexity of planning and management of water-energy infrastructure of the country.

This dissertation research used systematic approaches for infrastructure planning considering multiple interdependent objectives, variability of resources in a changing environment, and diverse stakeholder views about infrastructure planning. Evaluation of issues was done using a number of mathematical modelling methods. Understanding the influence of climate variability is required for informing water-energy infrastructure decisions. Specifically, understanding climate teleconnections such as ENSO and IOD with river basin precipitation can assist in making choices for adaptation to drought conditions by water users in the agricultural and energy sectors. Understanding how trade-offs among agricultural yield, electricity generation and environmental impacts are affected by both climate variables and operational rules for infrastructure can inform policy decisions. We integrated a reservoir cascade simulation model with reliability, resilience and vulnerability concepts to understand the variability of water stresses to the agricultural and energy sectors. Further, using an optimization algorithm in conjunction with the cascade model, a trade-off frontier was developed to illustrate how current operating rules can be adjusted to provide improved performance of the system. In our research, we examined the trade-offs implicit in the allocation of water resources for various purposes by considering the agricultural yield and electricity generation, the yield and land use, and the differences among reliability, resilience, and vulnerability indices associated with reservoir cascade operation decisions.

This research also addressed infrastructure expansion planning, which involves estimating the future resource availability and the demands placed on them and then optimizing use to meet multiple objectives of diverse stakeholders. Integrating physical infrastructure models with decision models allows the examination of the trade-offs among the competing goals considering the uncertainty of resources, economics, technologies and decision makers' priorities associated with them. Interdependent competing objectives of water-energy infrastructure expansion can be measured with economic, technical, social and environmental metrics. This research combined mulcriteria decision models with physical simulation models that represent interdependencies among the sectors through multiple constraints and optimization tools to provide information that can assist decision makers in selecting water and energy infrastructure systems that achieve technically reliable, economically efficient, environmentally sustainable and socially acceptable outcomes.

This dissertation included research that integrates a variety of information and perspectives. Nevertheless, there is a need to go beyond even these approaches. The complexity of socio-technical systems indicates that novel modeling methods will have to be developed. Multidisciplinary study approaches that integrate economic and social behavior models to engineering and decision models are badly needed to address infrastructure needs for a future with large uncertainties (Sharmina et al., 2019). Integrated planning for water and energy resources jointly will require the involvement of stakeholders who will be affected by the energy-water projects (Rodriguez et al., 2013) and models will have to be developed to incorporate the co-evolution of individual and social behavior with infrastructure. In Sri Lanka in particular, moving beyond the government owned and operated current strategy to transparent, efficient strategies will require further research investments to enhance economic, social, and environmental modelling capabilities.

The research skills of bringing together diverse modeling capabilities to study how the coupled technical, economic, environmental and social aspects of planning to meet the water and energy infrastructure needs of a small developing country are also applicable for addressing the complex issues in infrastructure systems of larger countries. One example is consideration of water related impacts on energy infrastructure that affect the reliability of the power grid. Water stresses for hydropower generation and thermal power generation, which must be managed in consideration of the needs of other water users and the natural environment, place serious constraints on large power systems such as in the United States. The complexity of the issue is multiplied because of climate variability and change (e.g. systematic variations in ENSO and stochastic changes in extreme weather events) and because of social behavior and economic factors (Voisin et al., 2016). The infrastructure issues that arise are addressed through integrated water resource management models, socioeconomic water and energy demand models, and power grid cost and technical operation models (Miara et al., 2017). Hence, decision support tools based on integrated diverse modelling capabilities are essential to inform the strategies for addressing the increasing demands of water and energy infrastructure for using variable resources for every nation. The research reported in this dissertation provides a base for such future work.

APPENDIX A

Additional Results for Identifying ENSO Influences on Rainfall with Classification Methods

A.1 Normality Testing

The Shapiro-Wilk's method is used to identify the normality of rainfall anomaly distribution. The Manampitiya NEM normality test results are given below as an example.

Data 1: original data

W = 0.96675, p-value = 0.08185

Data 2: data transformed by square root

W = 0.98772, p-value = 0.7772

Data 3: data transformed by log

W = 0.91577, p-value = 0.0003325

Further, from data plots (Figure A. 1) and the S-W statistic, we conclude that the square root transformed data is closer to being normally distributed than the other forms.

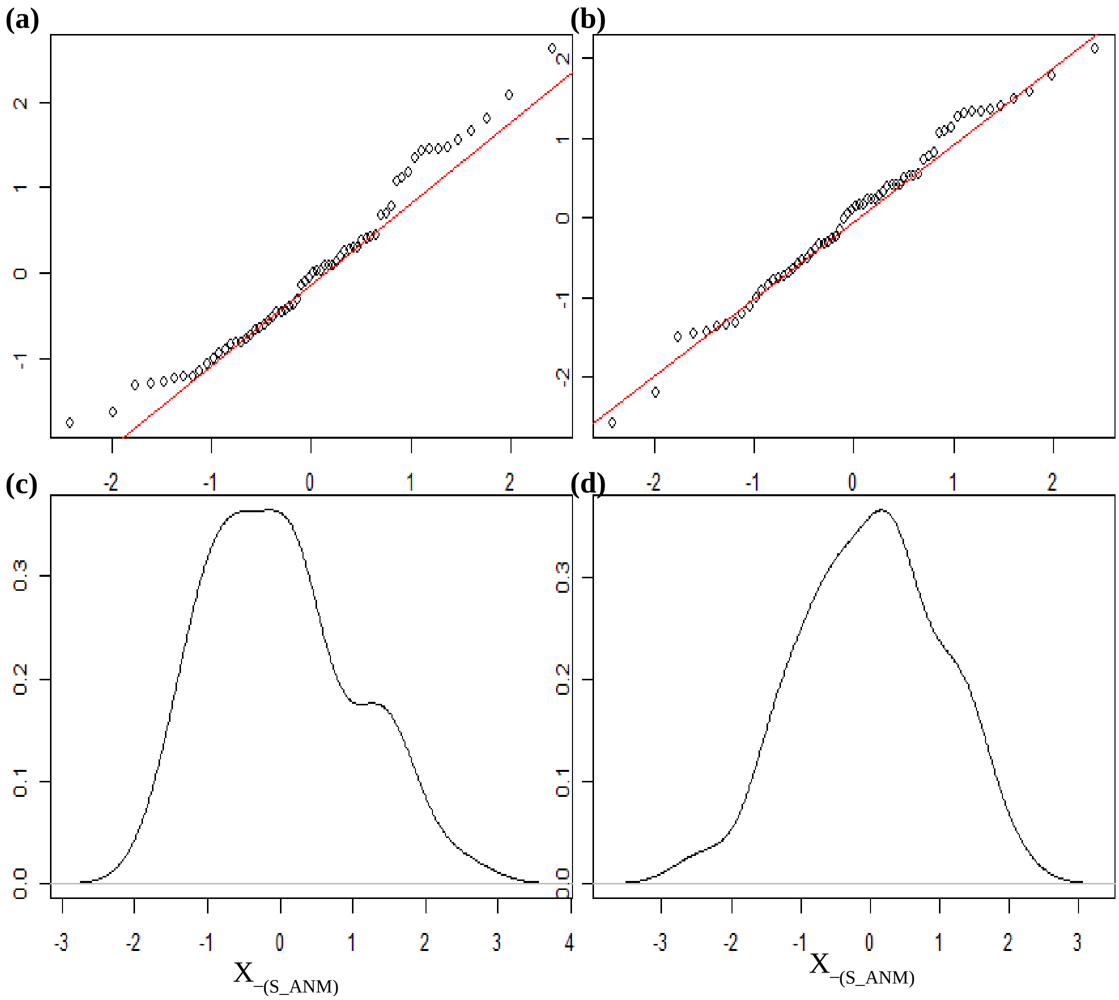

Figure A. 1 Manampitiya NEM standardized data (a) original form qqplot (b) square root form qqplot (c) original form density plot (d) square root form density plot

A.2 Classification of Data

Using 0.5 as a threshold for a normal distribution defines portions of the data that are fairly evenly distributed into three categories – about 31 %, 38 %, and 31 % for a normal distribution (Figure A. 2). We deemed this a reasonable choice for our analysis.

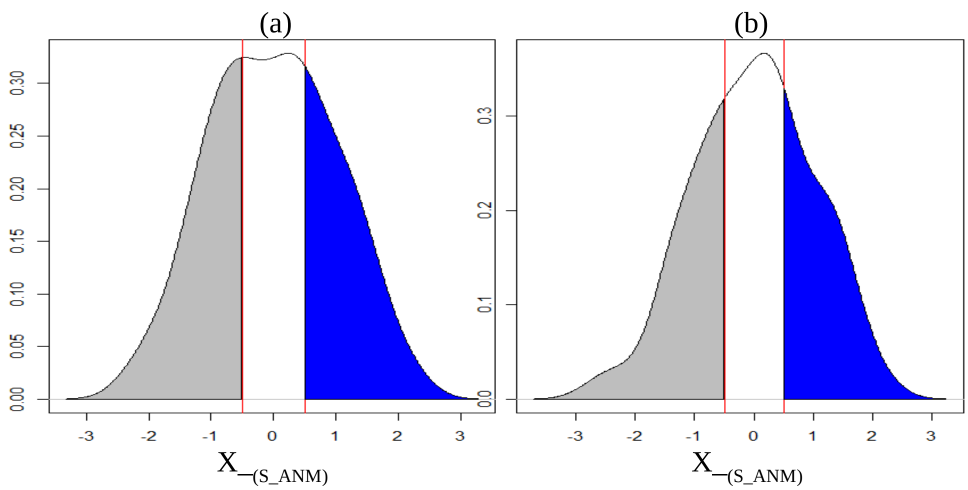

Figure A. 2 (a) Norton Bridge SWM rainfall anomaly distribution (b) Manampitiya NEM rainfall anomaly distribution

A.3 Correlation Analysis with Multiple Climate Indices

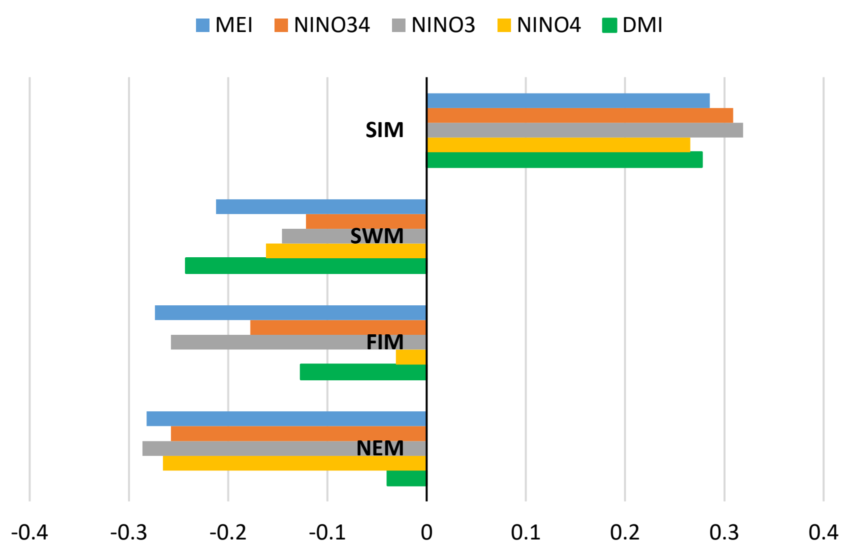

Figure A. 3 Correlation between Norwood rainfall anomalies with multiple climate indices

We examined the correlation between rainfall anomalies and multiple climate indices to choose the two climate indices MEI and DMI (Figure A. 3, Table A. 1). The ENSO phenomenon is represented by MEI, NINO34, NINO3, NINO4 indices. Correlation analysis indicates that MEI, which is estimated using several climate factors such as sea-level pressure, zonal and meridional components of the surface wind, sea surface temperature, surface air temperature, and total cloudiness fraction of the sky (National Oceanic and Atmospheric Administration, 2017), demonstrates higher correlation with rainfall anomalies in sub-basins for all rainfall seasons compared to the NINO34, NINO3 and NINO4. The Indian Ocean dipole phenomenon is represented by the DMI index, which represents the gradient of the sea surface temperature. Based on the correlation analysis and the content of the indices, we selected MEI as the indicator for ENSO and DMI as the indicator for IOD.

Table A. 1 Correlation analysis of rainfall anomalies and climate indices

Rainfall			**Morape**					**Peradeniya**		
Month	MEI	NINO34	NINO3	NINO4	*DMI*	MEI	NINO34	NINO3	NINO4	*DMI*
NEM	-0.35	-0.35	-0.34	-0.38	*-0.09*	-0.38	-0.40	-0.39	-0.42	*-0.11*
FIM	-0.28	-0.19	-0.28	-0.07	*-0.11*	-0.27	-0.18	-0.30	-0.06	*-0.06*
SWM	-0.35	-0.24	-0.23	-0.26	*-0.29*	-0.35	-0.26	-0.25	-0.27	*-0.31*
SIM	0.21	0.23	0.27	0.19	*0.12*	0.17	0.19	0.21	0.15	*0.09*
Rainfall			**Laxapana**					**Norwood**		
Month	MEI	NINO34	NINO3	NINO4	*DMI*	MEI	NINO34	NINO3	NINO4	*DMI*
NEM	-0.27	-0.26	-0.28	-0.27	*-0.01*	-0.28	-0.26	-0.29	-0.27	*-0.04*
FIM	-0.28	-0.16	-0.27	-0.03	*-0.07*	-0.27	-0.18	-0.26	-0.03	*-0.13*
SWM	-0.3	-0.23	-0.21	-0.25	*-0.31*	-0.21	-0.12	-0.15	-0.16	*-0.24*
SIM	0.1	0.10	0.14	0.06	*0.08*	0.29	0.31	0.32	0.27	*0.28*
Rainfall			**Randenigala**					**Bowatenna**		
Month	MEI	NINO34	NINO3	NINO4	*DMI*	MEI	NINO34	NINO3	NINO4	*DMI*
NEM	-0.30	-0.31	-0.29	-0.34	*-0.11*	-0.35	-0.36	-0.35	-0.38	*-0.2*
FIM	-0.29	-0.23	-0.33	-0.10	*-0.04*	-0.23	-0.17	-0.25	-0.09	*-0.02*
SWM	-0.17	-0.12	-0.09	-0.18	*-0.24*	-0.18	-0.09	-0.05	-0.11	*-0.12*
SIM	0.37	0.38	0.41	0.36	*0.35*	0.35	0.41	0.40	0.40	*0.36*
Rainfall			**Norton Bridge**					**Manampitiya**		
Month	MEI	NINO34	NINO3	NINO4	*DMI*	MEI	NINO34	NINO3	NINO4	*DMI*
NEM	-0.32	-0.30	-0.33	-0.33	*-0.01*	-0.26	-0.28	-0.26	-0.28	*-0.16*
FIM	-0.18	-0.12	-0.21	-0.01	*-0.08*	-0.2	-0.17	-0.31	-0.06	*-0.14*
SWM	-0.31	-0.22	-0.21	-0.22	*-0.37*	-0.07	0.08	0.08	-0.01	*-0.03*
SIM	0.02	-0.02	0.03	-0.04	*-0.15*	0.45	0.46	0.44	0.46	*0.51*

A.4 Correlation Analysis with MEI and DMI Climate Indices

Correlation coefficients between rainfall anomalies and MEI and DMI are negative for the NEM, FIM and SWM seasons and positive for the SIM season. Rainfall anomalies correlations to the

DMI are not stronger as the correlations to the MEI. However, there are strong correlations for the anomalies of major monsoons to the sub basins and DMI values. For example, wet sub basins (Morape, Peradeniya, Laxapana, Norwood, Norton Bridge) have high correlation coefficient between SWM rainfall anomalies and DMI, while dry zone (Manampitiya) and intermediate zone (Randenigala, Bowatenna) sub basins have high correlation coefficient between NEM and SIM rainfall anomalies.

Table A. 2 Correlation between rainfall anomalies and MEI, DMI indices. High correlation coefficients are highlighted.

Rainfall	**Morape**		**Peradeniya**		**Randenigala**		**Bowatenna**	
Month	MEI	DMI	MEI	DMI	MEI	DMI	MEI	DMI
NEM	**-0.35**	-0.09	**-0.38**	-0.11	**-0.30**	-0.11	**-0.35**	**-0.20**
FIM	**-0.28**	-0.11	**-0.27**	-0.06	**-0.29**	-0.04	**-0.23**	-0.02
SWM	**-0.35**	**-0.29**	**-0.35**	**-0.31**	-0.17	**-0.24**	-0.18	-0.12
SIM	**0.21**	0.12	0.17	0.09	**0.37**	**0.35**	**0.35**	**0.36**
Rainfall	**Laxapana**		**Norwood**		**Norton Bridge**		**Manampitiya**	
Month	MEI	DMI	MEI	DMI	MEI	DMI	MEI	DMI
NEM	**-0.27**	-0.01	**-0.28**	-0.04	**-0.32**	-0.01	**-0.26**	**-0.16**
FIM	**-0.28**	-0.07	**-0.27**	-0.13	**-0.18**	-0.08	**-0.20**	-0.14
SWM	**-0.30**	**-0.31**	**-0.21**	**-0.24**	**-0.31**	**-0.37**	-0.07	-0.03
SIM	0.10	0.08	**0.29**	**0.28**	0.02	-0.15	**0.45**	**0.51**

Classification methods classification tree models, random forest and quadratic discriminant analysis identify the relationship between standardized rainfall anomaly classes (dry, average, wet) and MEI and DMI values (Figure A. 4, Figure A. 5, Figure A. 6, Figure A. 7). Positive values of MEI and DMI values resulted dry or average rainfall class for the NEM, FIM and SWM seasons. However, for SIM rainfall has wet or average class for the positive values of MEI and DMI. Accuracy of model result are high for the dominant monsoon rainfall seasons of each sub basin (Table A. 3, Table A. 4, Table A. 5). Ensemble model approach with random forest has given comparatively lower out-of-bag error rate for the dominant monsoons' rainfall anomaly classification (Table A. 5). For example, wet zone sub basins such as Norton Bridge, Norwood, Laxapana, Peradeniya and Morape random forest error rate is lower for the SWM and SIM seasons.

Same as, dry and intermediate sub basins Manampitiya, Randenigala and Bowatenna NEM and SIM rainfall classes accuracy rate is high than other rainfall seasons. Also all three models have higher accuracy rate in identifying dry events and error rate of identifying wet and dry class also less 15 % (Table A. 3, Table A. 4, Table A. 5). Further analysis of two rainfall classes dry and not dry rainfall classes are identified relevant to the MEI and DMI values with classification tree and random forest methods (Figure A. 8, Figure A. 9). Classification tree models for two classes have higher accuracy rate as 65 % - 84 % for eight sub basins (Table A. 6). Random forest out-of-bag error for two classes models are vary between 20 % - 39 % and shows higher skill in identifying rainfall classes for major monsoons of the sub basins (Table A. 7). MEI shows higher variable importance of identifying the rainfall classes compare to the DMI values. Specially, for NEM and SIM which are important to the dry zone sub basins importance of MEI is high in the classification. However, some of the wet zone sub basins shows equal importance of DMI variable in identifying two rainfall classes in FIM and SWM (Figure A. 10).

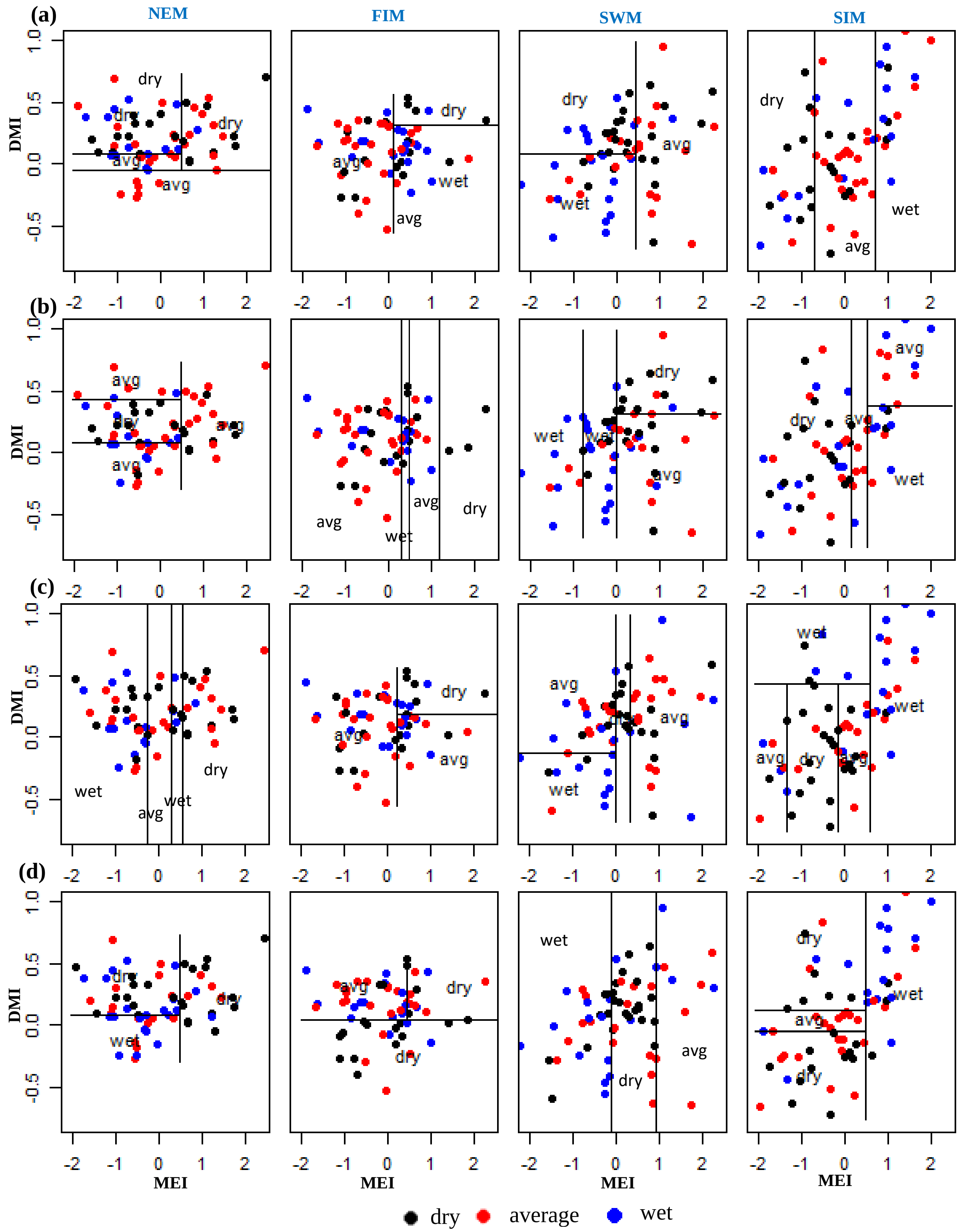

Figure A. 4 Identifying relationships between three rainfall classes (dry, average, wet) and MEI and DMI values using classification tree models. (a)Morape (b)Peradeniya (c)Randenigala (d)Bowatenna

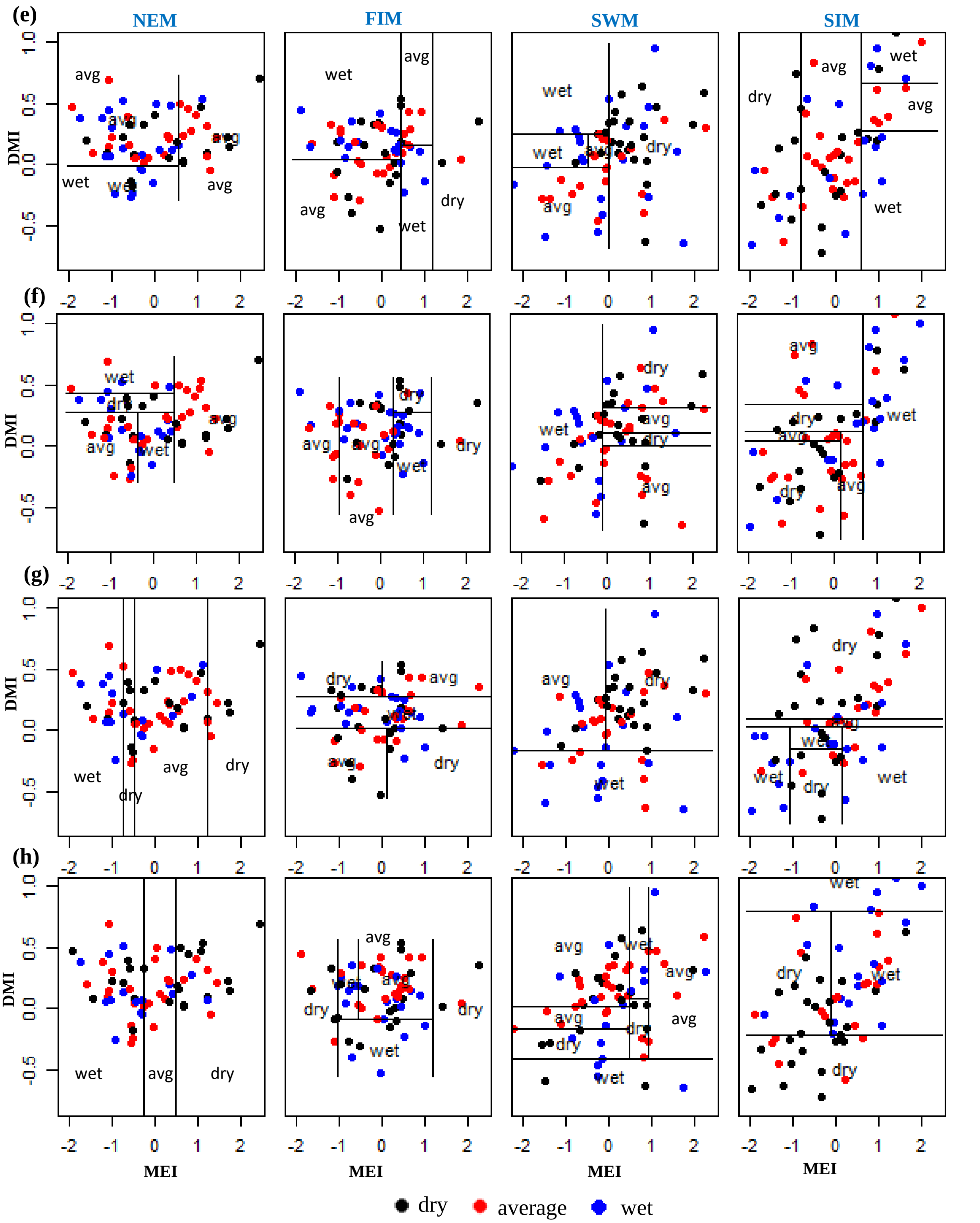

Figure A. 5 Identifying relationships between three rainfall classes (dry, average, wet) and MEI and DMI values using classification tree models. €Laxapana (f)Norwood (g)Norton Bridge (h)Manampitiya

Table A. 3 Classification tree model results. Highlighted cells indicate where there may be information content with respect to forecasting either dry or wet anomaly classes

Season	**Morape**			**Peradeniya**		
	Dry	Normal	Wet	Dry	Normal	Wet
NEM	21/21	13/29	0/14	10/20	24/31	0/13
FIM	5/19	19/25	12/20	5/20	28/28	6/16
SWM	12/24	13/21	12/19	9/23	11/19	18/22
SIM	8/19	18/28	9/17	12/25	16/19	5/20
Season	**Randenigala**			**Bowatenna**		
	Dry	Normal	Wet	Dry	Normal	Wet
NEM	11/24	11/25	12/15	24/24	12/19	0/21
FIM	8/20	24/25	3/19	17/21	17/25	0/18
SWM	8/21	23/24	8/19	18/25	6/21	12/18
SIM	14/24	11/21	15/19	17/21	9/26	13/17
Season	**Laxapana**			**Norwood**		
	Dry	Normal	Wet	Dry	Normal	Wet
NEM	0/19	24/24	6/21	4/19	22/28	10/17
FIM	2/20	14/26	18/18	7/19	19/21	12/24
SWM	19/23	14/20	8/21	10/20	14/27	11/17
SIM	8/21	22/26	9/17	16/20	15/25	11/19
Season	**Norton Bridge**			**Manampitiya**		
	Dry	Normal	Wet	Dry	Normal	Wet
NEM	11/20	18/29	8/15	12/23	9/25	11/16
FIM	13/21	6/23	15/20	9/21	19/24	8/19
SWM	19/22	8/22	9/20	6/21	25/27	7/16
SIM	19/22	5/22	14/20	20/25	0/20	17/19

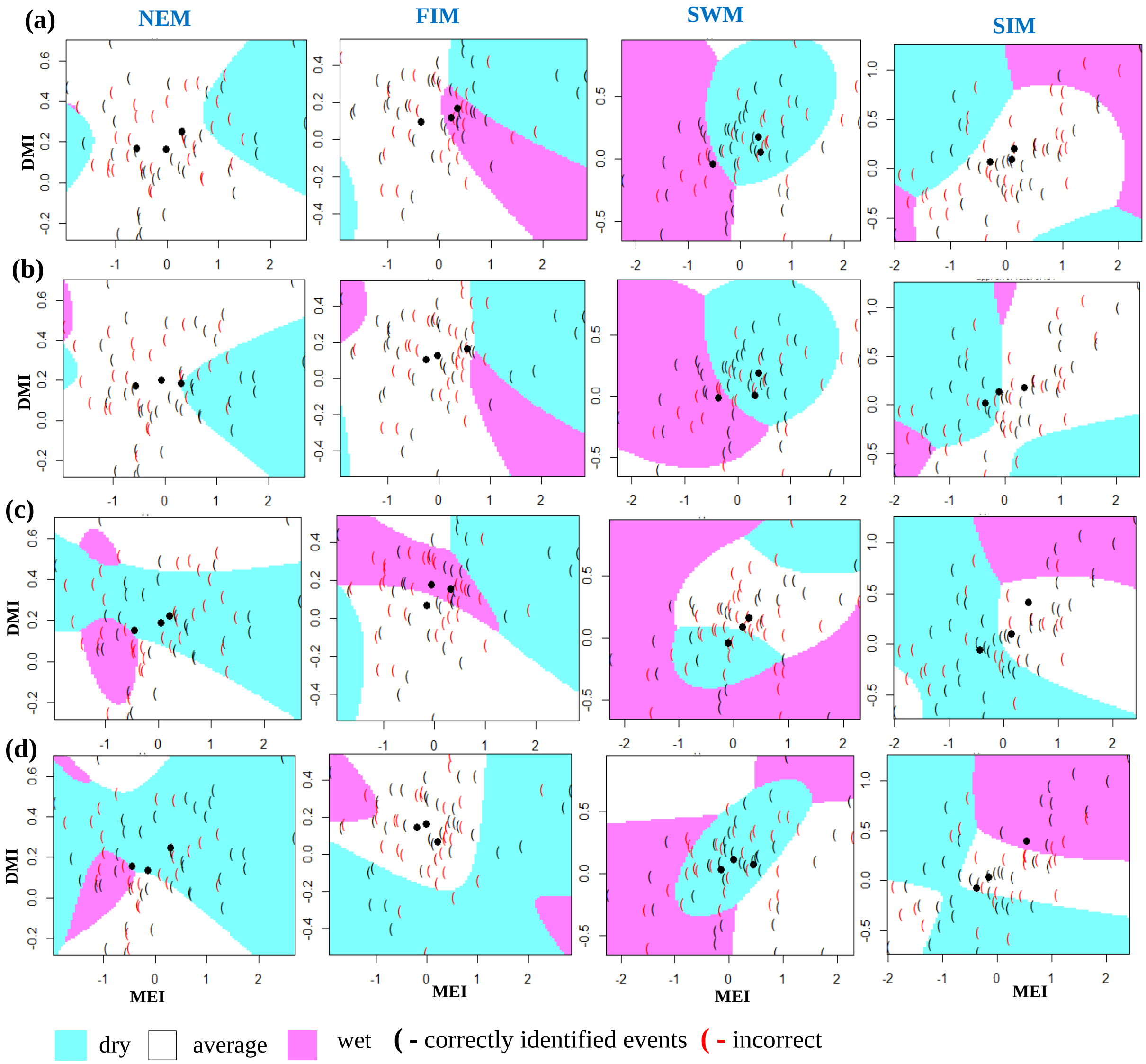

Figure A. 6 Identifying relationships between three rainfall classes (dry, average, wet) and MEI and DMI values using QDA models.(a) Morape (b) Peradeniya (c) Randenigala (d) Bowatenna

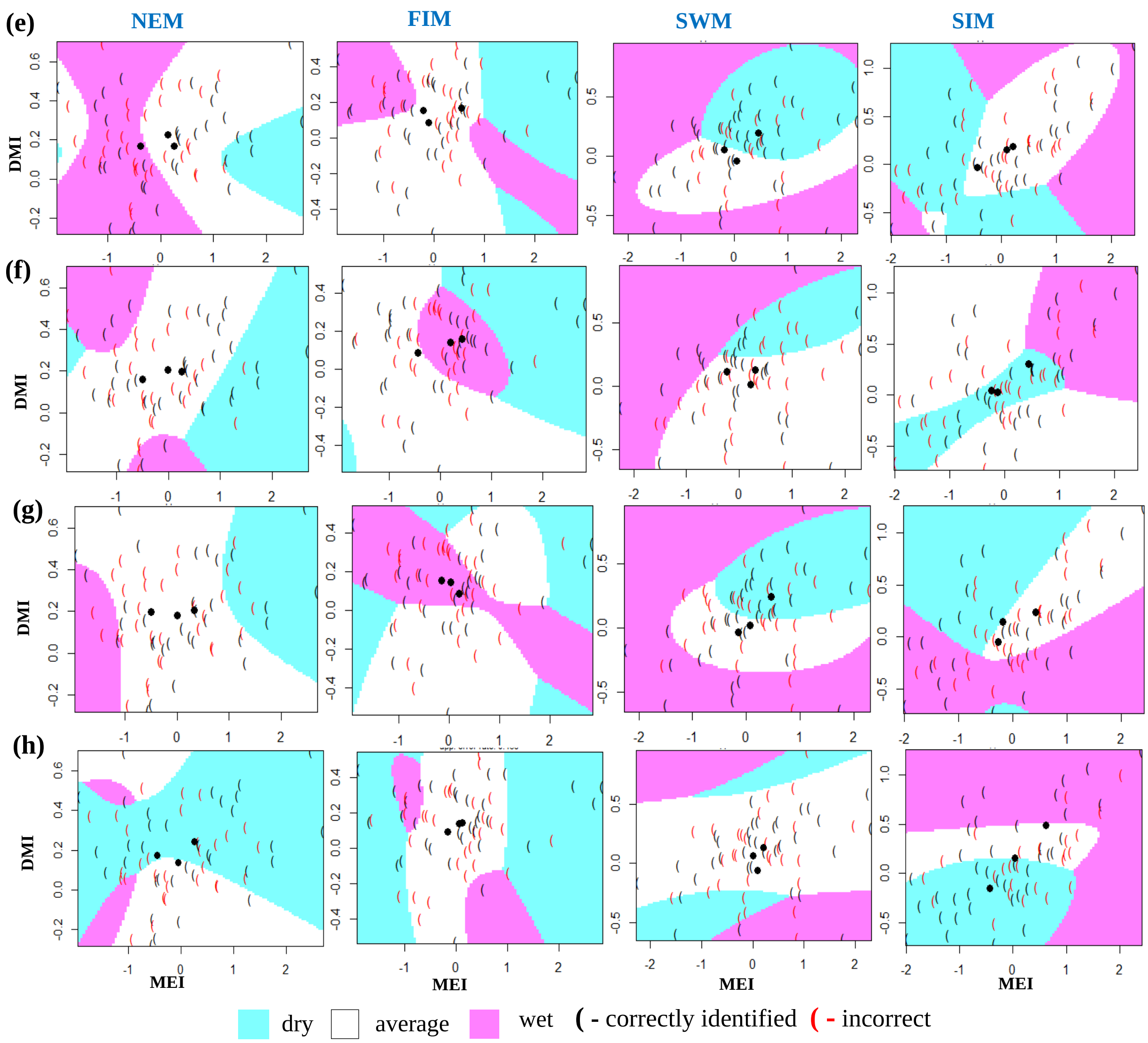

Figure A. 7 Identifying relationships between three rainfall classes (dry, average, wet) and MEI and DMI values using classification tree models. (e) Laxapana (f) Norwood (g) Norton Bridge (h) Manampitiya

Table A. 4 Classification QDA model results. Highlighted cells indicate where there may be information content with respect to forecasting either dry or wet anomaly classes

Season	**Morape**			**Peradeniya**		
	Dry	Normal	Wet	Dry	Normal	Wet
NEM	6/21	28/29	0/14	10/20	28/31	0/13
FIM	7/19	22/25	9/20	5/20	28/28	2/16
SWM	19/24	6/21	13/19	20/23	6/19	13/22
SIM	5/19	26/28	2/17	13/25	16/19	4/20
Season	**Randenigala**			**Bowatenna**		
	Dry	Normal	Wet	Dry	Normal	Wet
NEM	17/24	8/25	4/15	24/24	9/19	3/21
FIM	8/20	13/25	12/19	9/21	23/25	1/18
SWM	4/21	13/24	8/19	19/25	7/21	8/18
SIM	19/24	16/21	6/19	13/21	15/26	10/17
Season	**Laxapana**			**Norwood**		
	Dry	Normal	Wet	Dry	Normal	Wet
NEM	4/19	15/24	14/21	8/19	23/28	6/17
FIM	4/20	22/26	8/18	6/19	16/21	13/24
SWM	20/23	13/20	10/21	6/20	19/27	8/17
SIM	9/21	22/26	3/17	11/20	13/25	8/19
Season	**Norton Bridge**			**Manampitiya**		
	Dry	Normal	Wet	Dry	Normal	Wet
NEM	5/20	25/29	2/15	22/23	11/25	1/16
FIM	3/20	14/23	14/20	9/21	20/24	5/19
SWM	16/22	9/22	9/20	2/21	26/27	6/16
SIM	7/22	15/22	11/20	17/25	13/20	7/19

Table A. 5 Random forest model results. Highlighted cells indicate where there may be information content with respect to forecasting either dry or wet anomaly classes

Season	**Morape**			**Peradeniya**		
	Dry	Normal	Wet	Dry	Normal	Wet
NEM	12/21	12/29	5/14	9/20	17/31	5/13
FIM	8/19	14/25	10/20	7/20	17/28	6/16
SWM	11/24	6/21	11/19	11/23	1/19	13/22
SIM	8/19	16/28	2/17	5/25	9/19	6/20
Season	**Randenigala**			**Bowatenna**		
	Dry	Normal	Wet	Dry	Normal	Wet
NEM	10/24	8/25	4/15	16/24	6/19	11/21
FIM	9/20	8/25	8/19	16/21	14/25	4/18
SWM	9/21	14/24	6/19	14/25	7/21	5/18
SIM	15/24	6/21	7/19	3/21	14/26	11/17
Season	**Laxapana**			**Norwood**		
	Dry	Normal	Wet	Dry	Normal	Wet
NEM	3/19	11/24	9/21	9/19	16/28	8/17
FIM	1/20	18/26	1/18	8/19	10/21	12/24
SWM	19/23	9/20	4/21	6/20	15/27	4/17
SIM	10/21	12/26	3/17	8/20	14/25	8/19
Season	**Norton Bridge**			**Manampitiya**		
	Dry	Normal	Wet	Dry	Normal	Wet
NEM	11/20	12/29	6/15	14/23	10/25	5/16
FIM	7/21	8/23	8/20	10/21	11/24	6/19
SWM	9/22	6/22	8/20	6/21	17/27	5/16
SIM	13/22	9/22	9/20	15/25	8/20	7/19

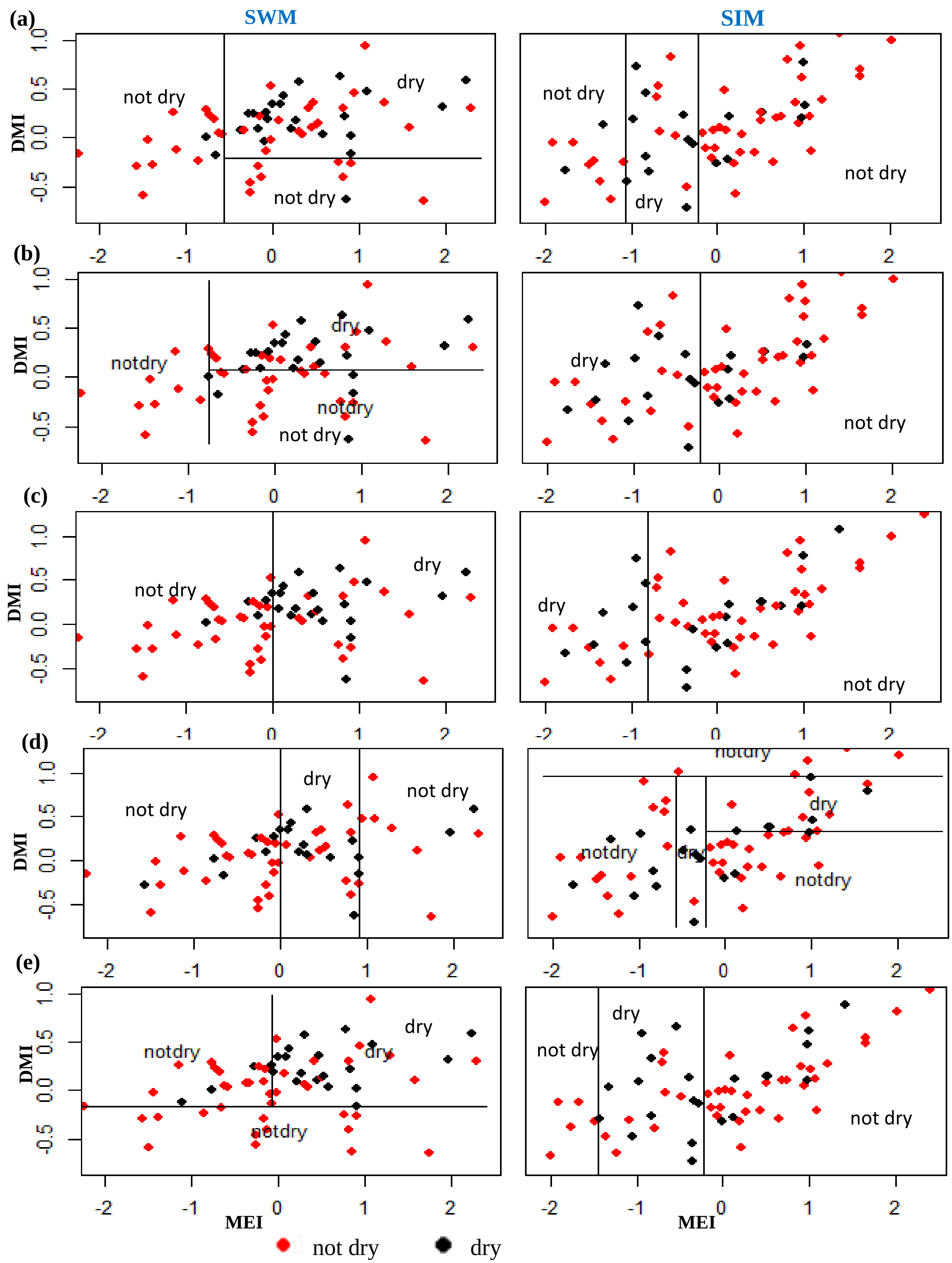

Figure A. 8 Identifying relationships between two rainfall classes (dry, not dry) and MEI and DMI values using classification tree models for wet zone sub basins for SWM and SIM seasons. (a) Morape (b) Peradeniya (c) Laxapana (d) Norwood (e) Norton Bridge

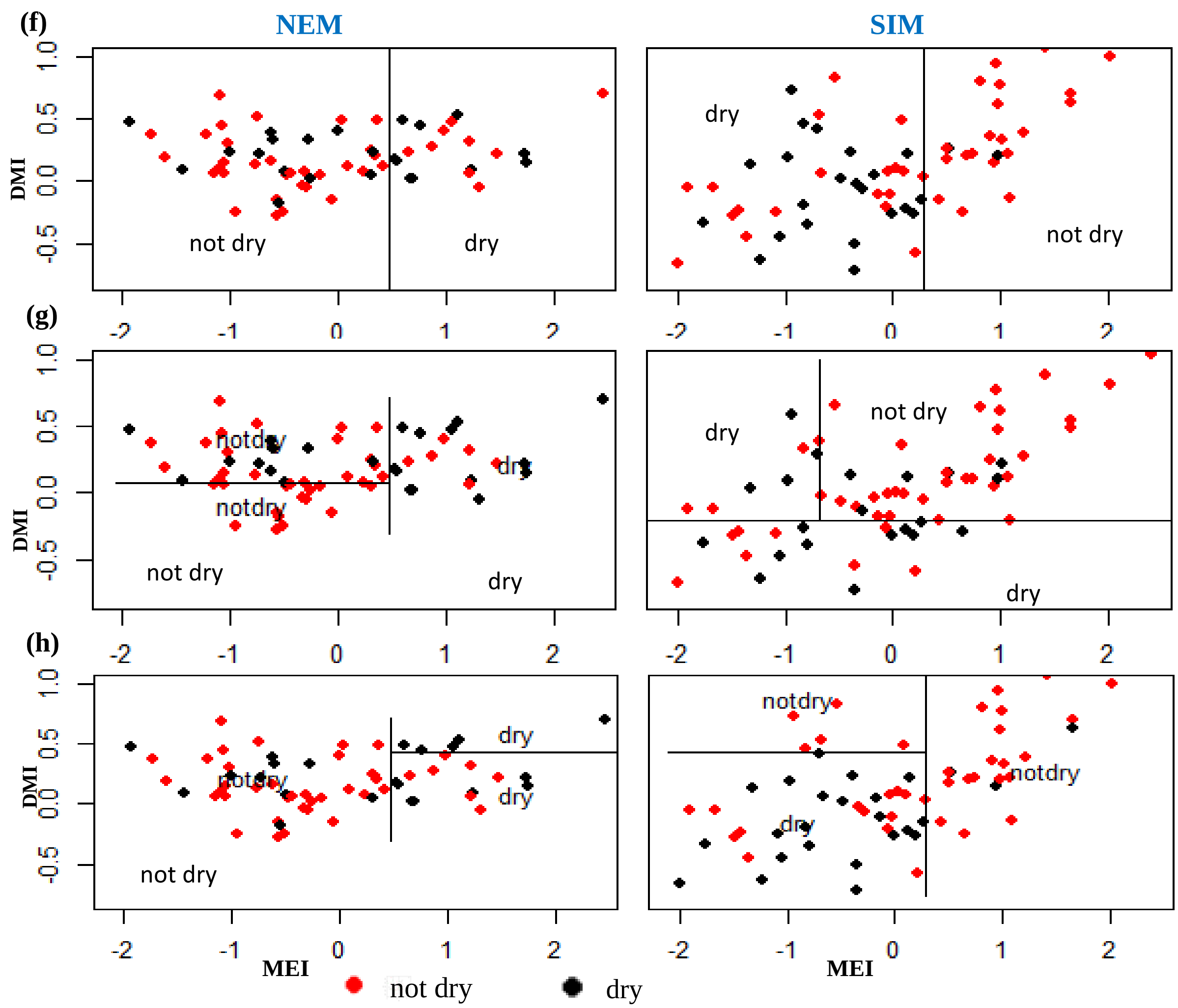

Figure A. 9 Identifying relationships between two rainfall classes (dry, not dry) and MEI and DMI values using classification tree models for dry and intermediate zone sub basins for NEM and SIM seasons. (f) Randenigala (g) Bowatenna (h) Manampitiya

Table A. 6 Classification tree model results for major rainfall season to the sub basins.

Season	**Morape**		**Peradeniya**		**Laxapana**		**Norwood**		**Norton Bridge**	
	Dry	Not dry	Dry	Not dry	Dry	Not dry	Dry	Not dry	Dry	Not dry
SWM	21/24	22/40	18/23	26/41	19/23	27/41	12/20	34/44	19/22	29/42
SIM	10/19	39/45	12/19	30/45	8/21	36/43	11/20	38/44	13/22	36/42

Season	**Randenigala**		**Bowatenna**		**Manampitiya**	
	Dry	Not dry	Dry	Not dry	Dry	Not dry
NEM	11/24	31/40	14/24	34/40	13/23	34/41
SIM	23/24	22/40	15/21	32/43	22/25	26/39

Table A. 7 Random forest model results.

Season	Morape			Peradeniya		
	Dry	Not dry	OOB Error	Dry	Not dry	OOB Error
NEM	10/21	33/43	33%	8/20	34/44	34%
FIM	5/19	36/45	36%	6/20	37/44	33%
SWM	11/24	29/40	38%	11/23	28/41	39%
SIM	5/19	39/45	33%	5/19	37/45	34%
Season	**Randenigala**			**Bowatenna**		
	Dry	Not dry	OOB Error	Dry	Not dry	OOB Error
NEM	8/24	31/40	39%	15/24	33/40	25%
FIM	6/20	39/44	30%	13/21	38/43	20%
SWM	7/21	38/43	30%	11/25	29/39	38%
SIM	13/24	31/40	31%	6/21	35/43	36%
Season	**Laxapana**			**Norwood**		
	Dry	Not dry	OOB Error	Dry	Not dry	OOB Error
NEM	8/20	37/45	30%	10/19	39/45	23%
FIM	7/20	37/44	31%	8/19	39/45	26%
SWM	12/23	27/41	39%	7/20	37/44	31%
SIM	9/21	34/43	33%	7/20	37/44	31%
Season	**Norton Bridge**			**Manampitiya**		
	Dry	Not dry	OOB Error	Dry	Not dry	OOB Error
NEM	9/20	36/44	30%	13/23	33/41	28%
FIM	5/21	35/43	38%	8/21	35/43	33%
SWM	9/22	32/42	36%	5/16	34/43	39%
SIM	10/22	36/42	28%	16/25	34/39	22%

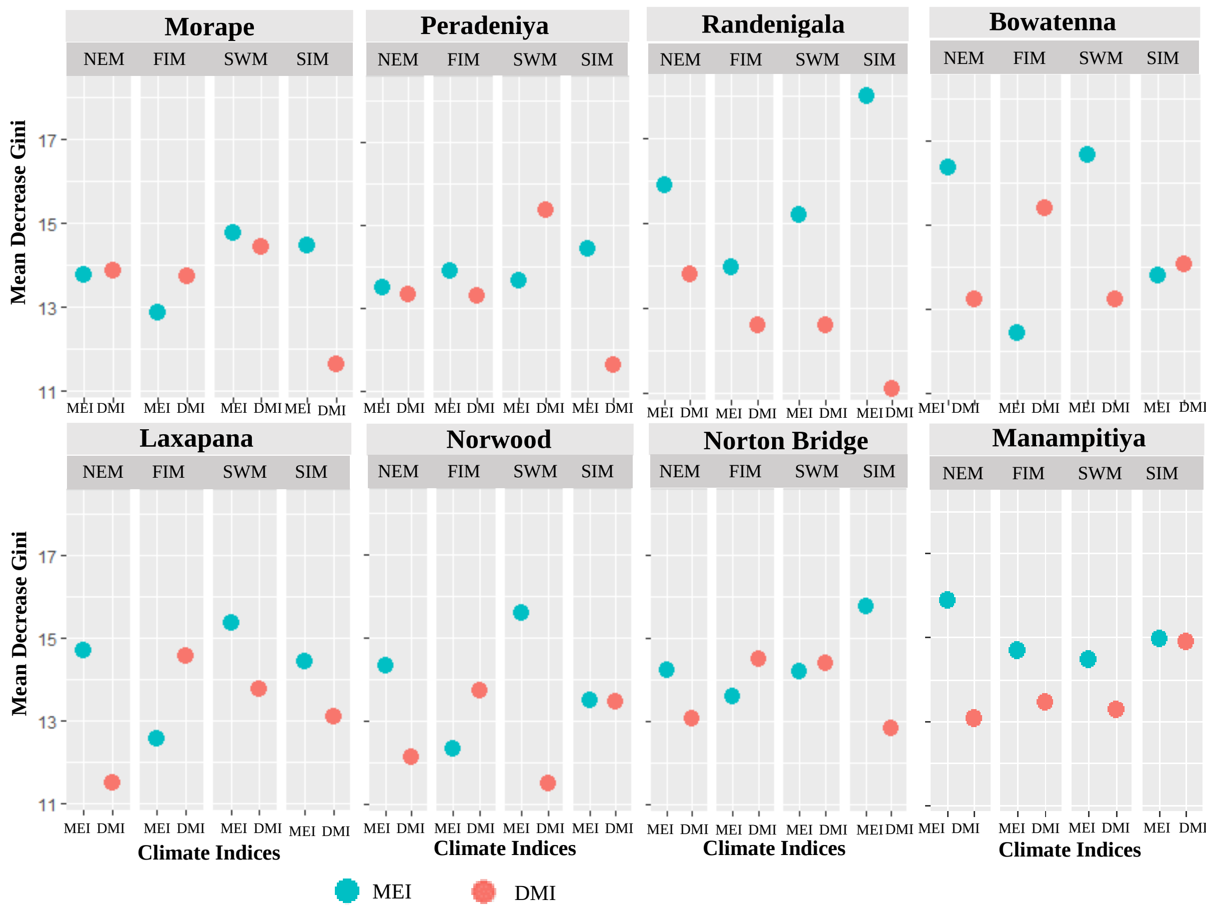

Figure A. 10 Random forest importance of variable to identify the dry and not dry classes of rainfall anomalies

APPENDIX B

Additional Results Relevant to the Deriving Reservoir Cascade Operation Rules

B.1 Synthetic Inflows

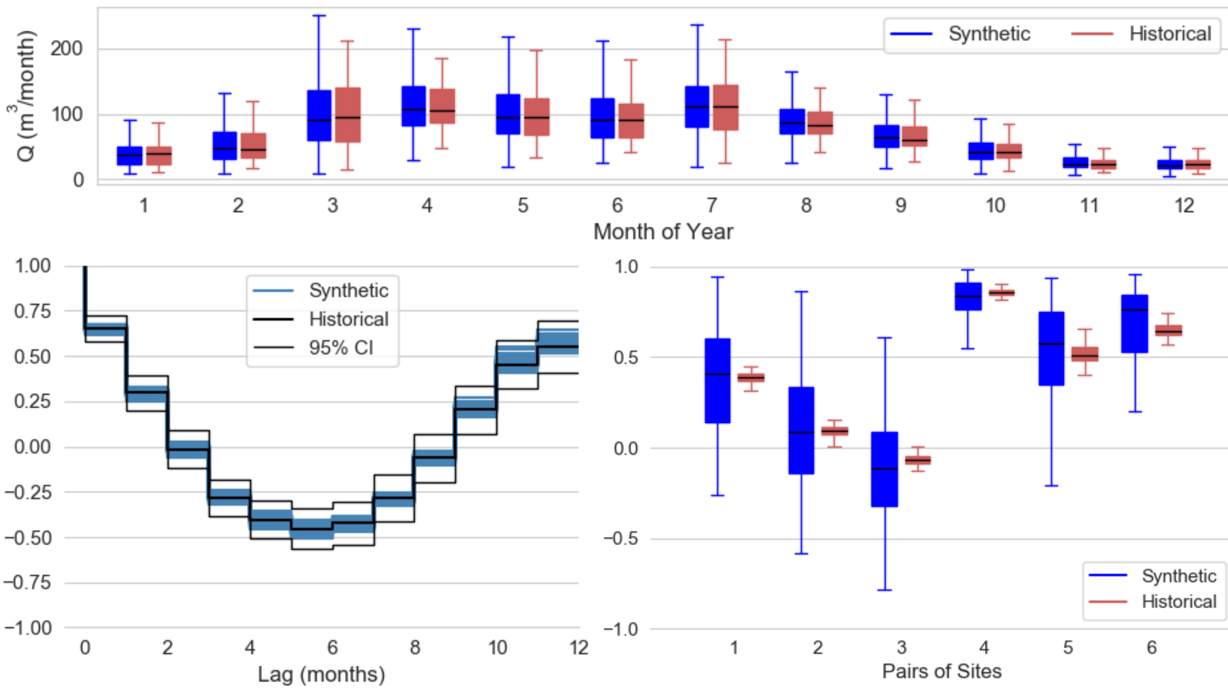

Figure B. 1 Validation of Synthetic inflow data (a) Kotmale inflow statistical prope rites (b) autocorrelation of Kotmale inflow (c) pairwise space correlation of Kotmale, Victoria, Randenigala and Rantambe inflow data

Visual and statistical comparison of historical and synthetically generated data confirm that synthetic data follow the distribution, statistical properties (mean, variance), autocorrelation and spatial correlation of the historical data (Figure B. 1).

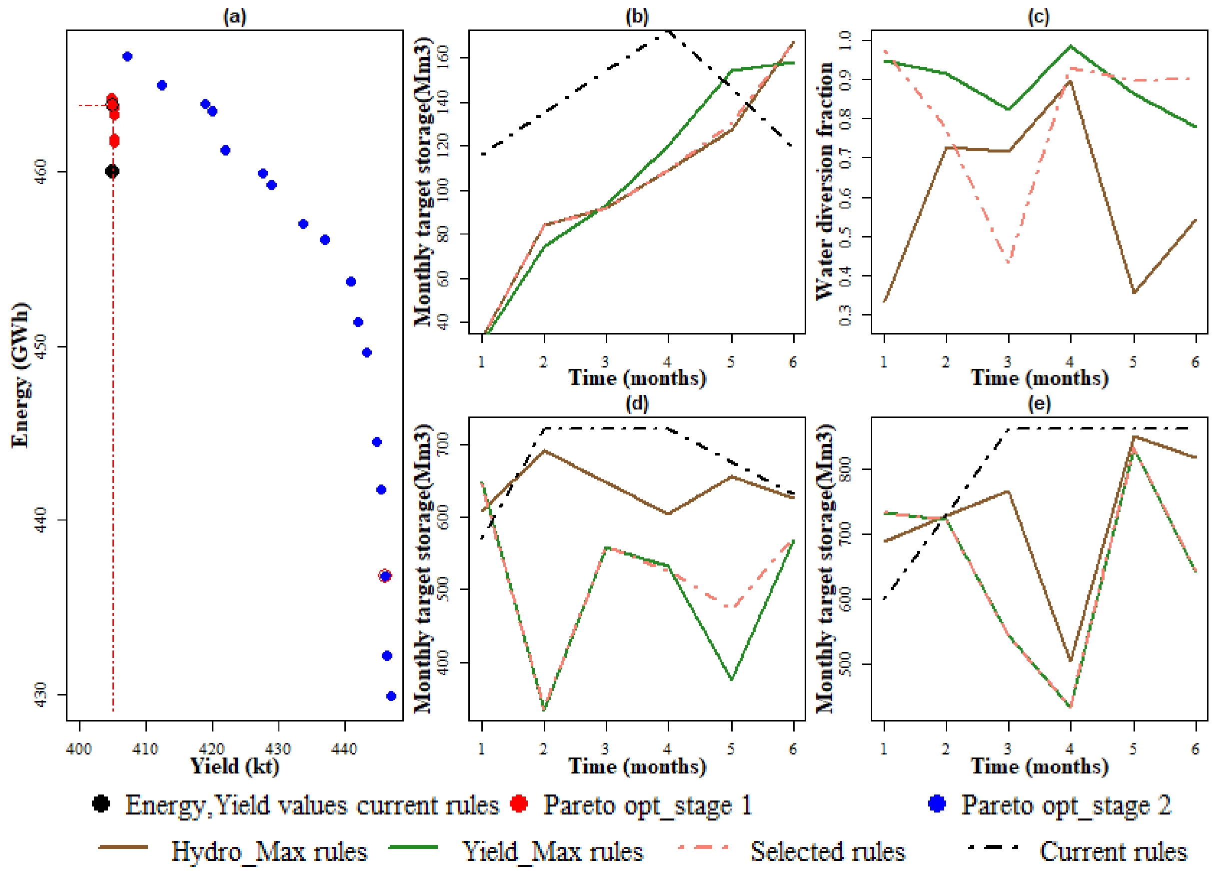

Figure B. 2 Trade-off curves and operation rules for minimum 10th percentile optimization of Maha (a) Pareto front for stage 1 & 2, and objective values for current rules, and operation rules corresponding to maximum hydropower, maximum yield and current operation rules and an example intermediate point on the Pareto front (the red-circled blue dot in (a)) of (b) Kotmale target storage for each month (c) Polgolla water diversion fraction of total inflow to the north for each month (d) Victoria target storage for each month (e) Randenigala target storage for each month

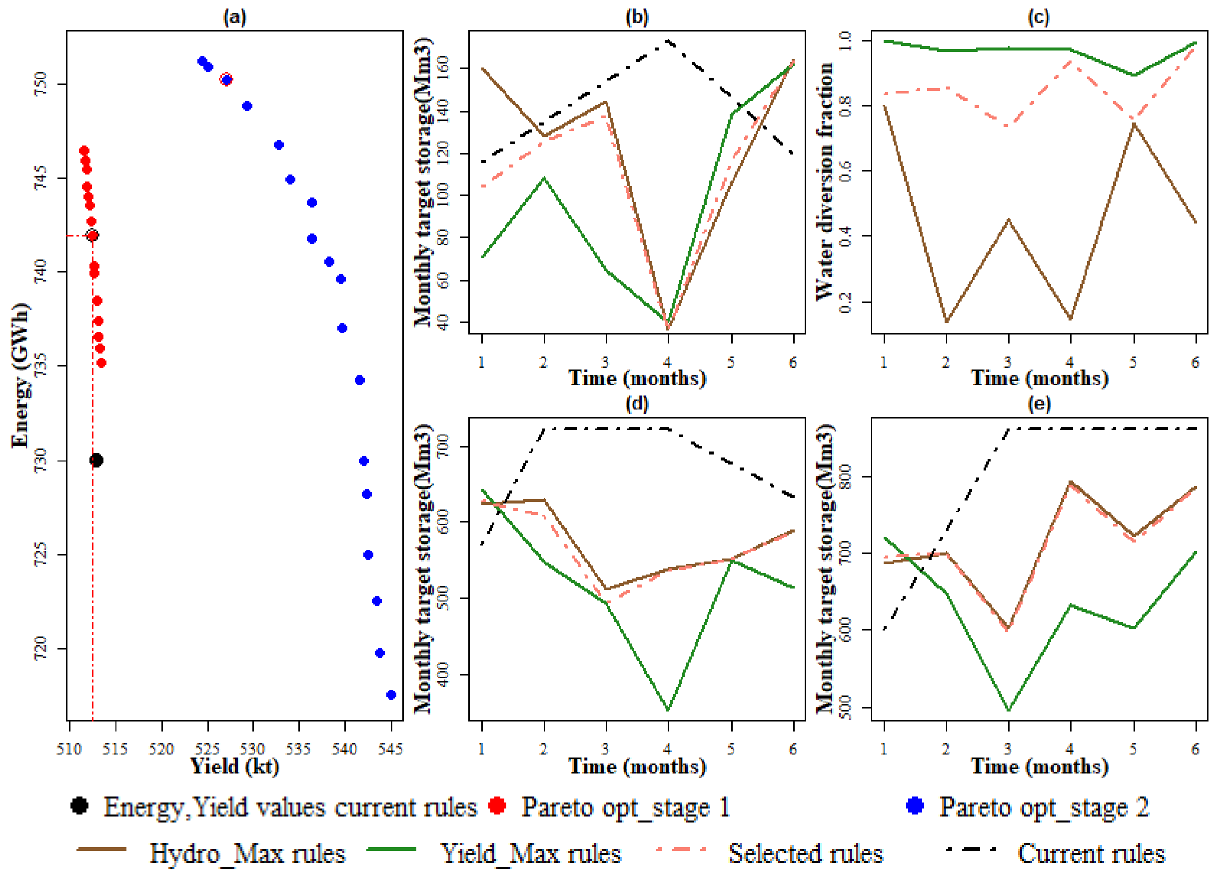

Figure B. 3 Trade-off curves and operation rules for average objective optimization of Maha (a) Pareto front for stage 1 & 2, and objective values for current rules, and operation rules corresponding to maximum hydropower, maximum yield and current operation rules, and an example intermediate point on the Pareto front (the red-circled blue dot in (a)) of (b) Kotmale target storage for each month (c) Polgolla water diversion fraction of total inflow to the north for each month (d) Victoria target storage for each month (e) Randenigala target storage for each month

APPENDIX C

Additional Information and Results for Decision Analysis of Mahaweli Project Expansion

C.1 Mahaweli Multipurpose Project

Mahaweli is the largest multipurpose project of Sri Lanka use for potable water, irrigation and hydropower generation (Figure C. 1). The project associated with six river basin spread through variable rainfall zones (Figure C. 2). Sri Lanka gets rainfall from two monsoons (south-west and north-east) and two inter-monsoons (First and second). Different parts of the Mahaweli project benefit from these rainfall seasons. Upper catchment of the Mahaweli river basin, high elevation land mass have large amount of rain from south-west monsoon and second inter-monsoon. Hydropower plants; Upper Kotmale, Kotmale, Randenigala, Rantambe, Ukuwela and Bowatenna are associated with the major reservoirs that use to store monsoon water. Mahaweli water transfer to other five river basin for irrigation systems.

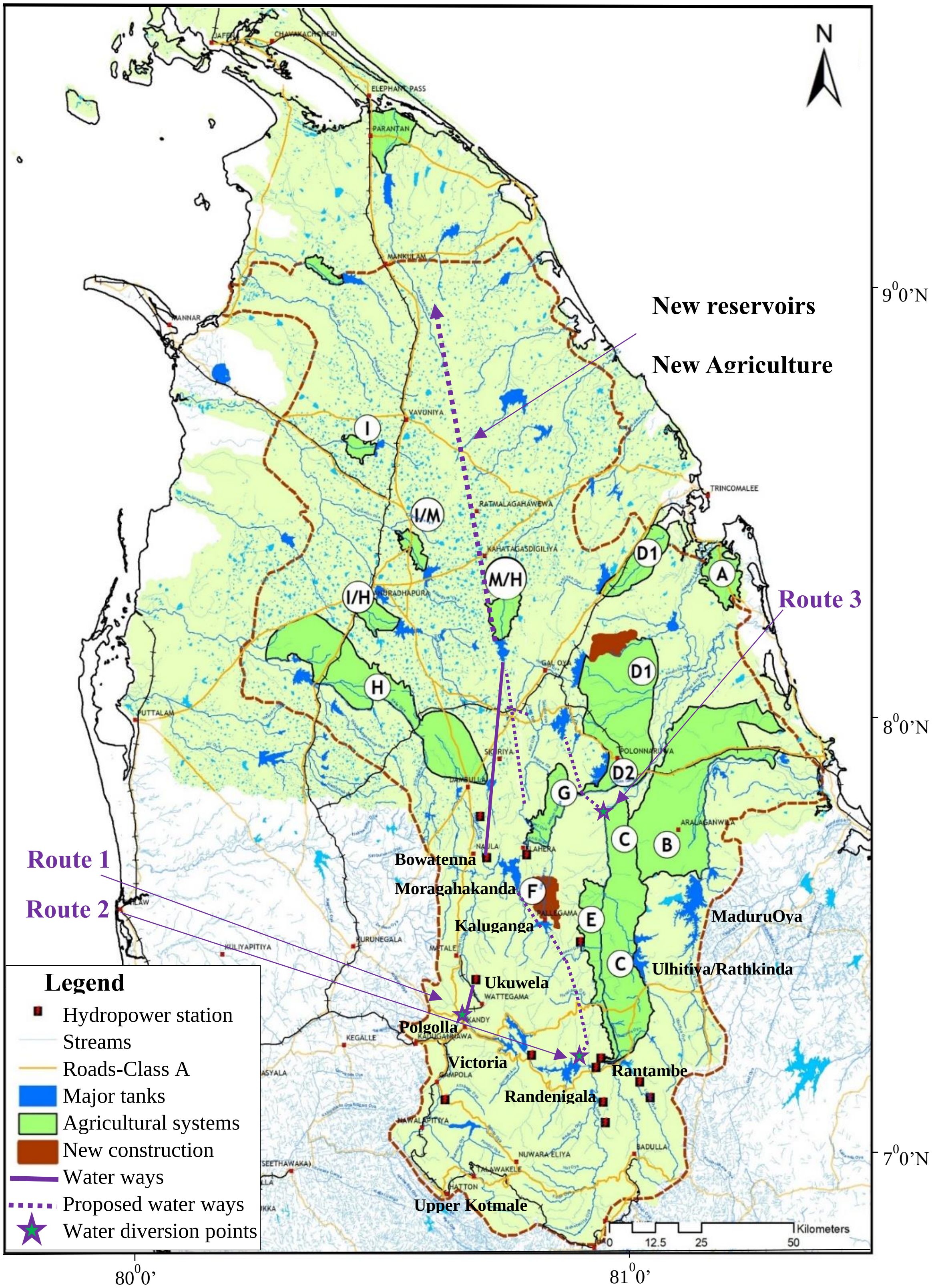

Figure C. 1 Mahaweli multipurpose project map reservoirs, stream network and irrigated agricultural systems spread through 25500km^2

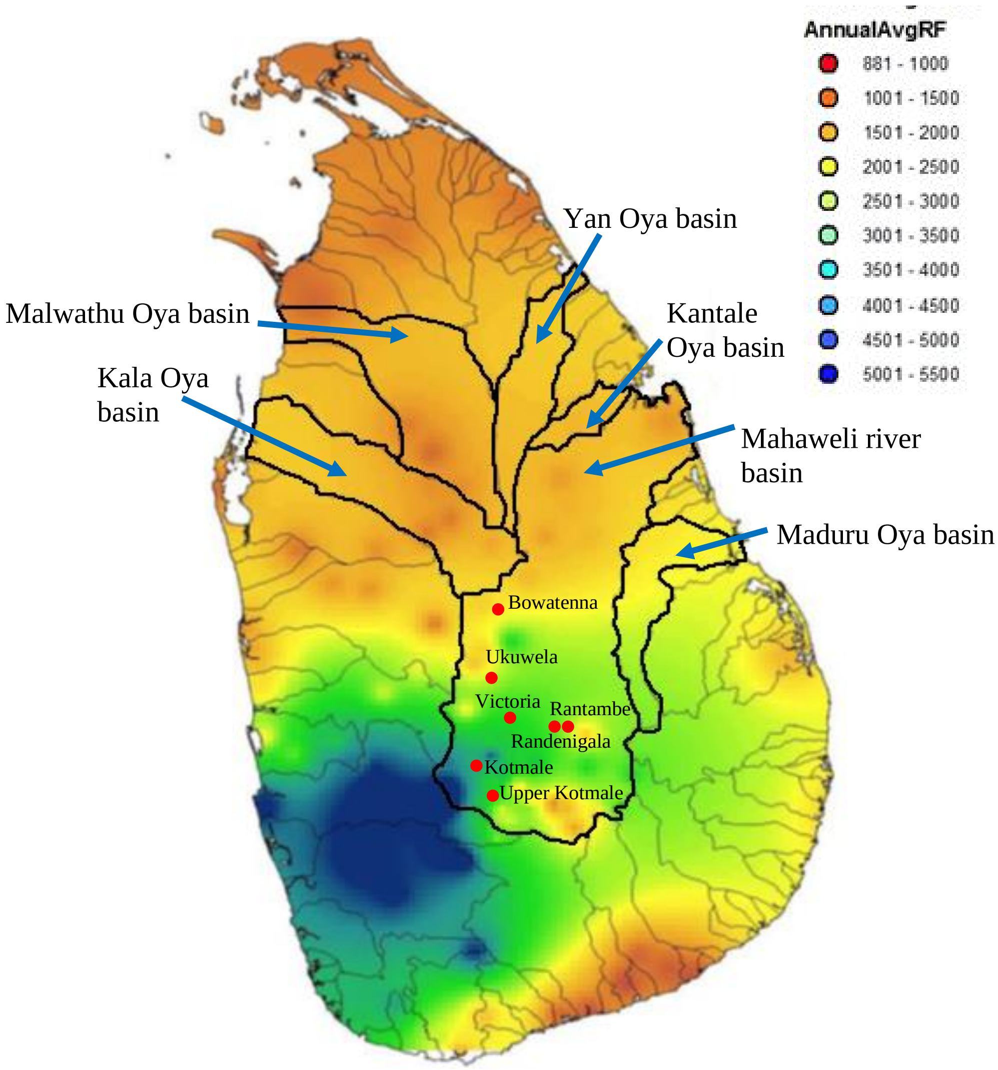

Figure C. 2 Rainfall pattern of six river basins of Mahaweli multipurpose project

C.3 Calculation of Performance of Criteria

Performance of 4 decision criteria; economic development, economic viability of the project, social development and environment stewardship are measured with 10 attributes. Calculation of the values for these attributes, use published results from the Ministry of Irrigation and Water Resources Management (2013), Ministry of Mahaweli Development and Environment (2016), and other published data sources.

C.4 Agriculture Benefits

Benefits are due to the improvement of cropping intensity of existing agricultural lands and new developed lands with high water availability. The cropping patterns are a mix of paddy and other field crops (OFC) such as black gram, chili and sugar cane. The highest increment of irrigated lands, an area of 83,380 ha, will be achieved with Plan 3 and the lowest increment, 68,900 ha, will be achieved with Plan 1. The price of OFCs varies according to the type of product; detailed calculation has been carried out under the Ministry of Irrigation and Water Resources Management (2013) and the average values estimated from that report was used for this study. The cost of new agricultural land development is in the range of 11750USD/ha – 13400USD/ha.

Table C. 1 Agriculture benefits from the project (Ministry of Irrigation and Water Resources Management 2013)

Description	Unit	Plan 1	Plan 2	Plan 3	Plan 4
Average Yield					
Paddy - Maha Season	tonnes/ha	5.4	5.4	5.4	5.4
Paddy - Yala Season	tonnes/ha	5.3	5.3	5.3	5.3
OFC - Maha Season	tonnes/ha	21.9 (av.)	18.8 (av.)	18.7 (av.)	21.9 (av.)
OFC - Yala Season	tonnes/ha	24.4 (av.)	21.1 (av.)	21.0 (av.)	24.4 (av.)
Irrigated Agriculture (total)					
Area – Maha Season					
Paddy	000 ha.	13	13	13	13
OFC	000 ha.	6.3	14.2	14.3	6.3
Total – Maha Season	000 ha.	21.4	27.2	27.3	21.4
Area – Yala Season					
Paddy	000 ha.	43.6	43.6	43.6	43.6
OFC	000 ha.	6.1	12.4	12.5	6.1
Total – Yala Season	000 ha.	49.7	56	56.1	49.7
Total Production (total)					
Paddy	tonnes 000 p.a.	303.5	303.5	303.5	303.5
OFC	tonnes 000 p.a.	286.8	529.7	530.5	286.8
Total	tonnes 000 p.a.	590.3	833.2	834	590.3
Agriculture Annual Benefits					
Paddy (48.84 $/tonnes)	$M	14.82	14.82	14.82	14.82
OFC (61.63$/tonnes)	$M	17.67	32.64	32.98	17.67
Total	$M	32.50	47.47	47.80	32.50

C.5 Hydropower Benefits

Hydropower has several roles in the power system according to the capacity of generators and reservoir capacity associated with the plant. Large capacity machines (major) with large capacity reservoirs serve roles as peaking, spinning reserve, and frequency control of the power system while power plants with small reservoirs (Run-of-River) cater to energy needs of the power system. The alternative to a major hydropower plant is a conventional plant with combustion turbines. Energy prices for combustion plants are higher than the energy price of small hydro power plants.

Table C. 2 Energy from hydropower (Ministry of Irrigation and Water Resources Management 2013)

Description	Present	Plan 1	Plan 2	Plan 3	Plan 4
Existing Peak HPP					
Upper Kotmale (GWh)	409	409	409	409	409
Kotmale (GWh)	432	468	468	433	432
Ukuwela (GWh)	190	324	324	187	190
Victoria (GWh)	567	306	306	519.6	567
Randenigala (GWh)	333	265	265	276.7	333
Rantembe (GWh)	187	129	129	153.9	187
Bowatenna (GWh)	38	24	88	39.8	38
Total exst. peak energy (GWh)	2156	1924.7	1989	2019	2156
New Peak HPP					
Heenganga (GWh)		19.5	19.5	6.1	19.5
Hasalaka (GWh)		64	64	46.7	64
Lower Umaoya (GWh)		27.7	27.7	28.4	27.7
Moragahakanda (GWh)		47.3	104.9	91.2	47.3
Total new peak energy (GWh)		158.5	216.1	172.4	158.5
Peak Energy Loss (GWh)		72.8	-49.1	-35.4	-158.5

A large portion of the hydropower from existing major power plants will be reduced by implementation of Plan 1, Plan 2 or Plan 3. The basic objective of Plan 4 is to not disturb the existing hydropower facilities and send a sufficient amount of water to irrigation. New development of small hydropower plants is considered for peaking power since they are associated with reservoirs more than $7Mm^3$. The cost of peaking energy is considered to be0.2$/kWh and the cost of the base energy as 0.1$/kWh. The construction cost of a new hydropower plant is assumed as 1.42 $M/MW.

Table C. 3 Hydro power benefit calculation (Ministry of Irrigation and Water Resources Management 2013)

Description	Plan 1	Plan 2	Plan 3	Plan 4
Exst. PP peak energy (GWh)	1515.7	1580	1610	1747
Peak energy loss exst.PP (GWh)	231.3	167	137	0
New PP peak energy (GWh)	158.5	216.1	172.4	158.5
Pumping energy(GWh)		24	40	120
Energy gain (GWh)	66.8	260.4	230.7	273.8
Net peak enery loss(GWh)	72.8	-49.1	-35.4	-158.5
Peak (0.2$/kwh)	-14.56	9.82	7.08	31.7
offPeak (0.1$/kwh)	13.96	21.13	19.53	11.53
Net Hydropower benefit ($)	-0.6	30.95	26.61	43.23

C.6 Potable Water Supply Benefits

The main infrastructure for water management is part of the indirect cost associated with domestic and industrial water supply. Ministry of Irrigation and Water Resources Management (2014) shows it equal to 30% of the total cost of water supply. The cost per connection of domestic water supply ranges between 978$ and 2560$ and the cost of industrial water supply is between 5235$ and 11,788$. The benefit from the domestic water is the willingness to pay, 0.62$/m^3 which is double the commercial price of a water unit. The industrial water benefit is considered as the replacement with a desalination plant with a water unit cost of 1.6$/m^3.

Table C. 4 Potable water benefit calculation (Ministry of Irrigation and Water Resources Management 2013)

Alternatives	Plan 1	Plan 2	Plan 3	Plan 4
Population served (1000 nos.)	2099	2099	2099	2099
Domestic Connections (1000 nos.)	420	420	420	420
Commercial & Industrial connections (1000 nos.)	8	8	8	8
Water supply Domestic (Mm^3/year)	114.9	114.9	114.9	114.9
Water supply Industrial (Mm^3/year)	12.8	12.8	12.8	12.8
Total water supply (Mm^3/year)	127.7	127.7	127.7	127.7
Additional cost of potable water infrastructure ($M)	581.4	581.4	581.4	581.4
Total annual benefits from potable water supply ($M)	71.3	71.3	71.3	71.3
Annual benefits from potable water ($M)	7.13	7.13	7.13	7.13

According to Ministry of Irrigation and Water Resources Management (2013), the water supply infrastructure cost is approximately 30%-45% of the total project cost and benefits are at least 50% of the total benefits. Construction of end user potable water supply infrastructure will not be implemented with the main project. The basic objective of the study is to inform investment for common infrastructure by selecting the best path to divert water to the northern part of the country. Therefore, the addition of the cost of potable water infrastructure is not considered.

C.7 Project Cost Calculation

Table C. 5 Project cost calculation (Ministry of Irrigation and Water Resources Management 2013)

Description	Estimated Costs in $ Millions (2012 prices)			
	Plan 1	Plan 2	Plan 3	Plan 4
Upper Elahera canal cost (42 m^3/s)	0	175	175	175
Hasalaka reservoir and power house	71	71	71	71
Heen Ganga reservoir and power house	111	111	111	111
Investment on water duty improvements	24	24	24	24
Construction of NCP canal from Huruluwewa to Chemmadukulam ; 0 - 32 km	63	102	102	102
Distribution system to feed small tanks	9	14	14	14
Kalu Ganga – Moragahakanda transfer canal capacity - 35 m^3/s			43	0
Second Bowatenne tunnel & expansion of KHFC canal to 42 m3/s	66			0
Domestic and industrial water supply (115 Mm^3)	581	581	581	581
NWPC construction (96km+.94km tunnel)	20	20	20	20
Raising of Minipe anicut by 4 m	5	5	5	5
Raising Kotmale dam & spill	108	108		
Transfer canal from Randenigala to Kalu Ganga reservoir.			204	0
Development of 8,500 ha in NCP		100	100	100
Facilities for pumping from Kalinganuwara		133	166	333
Lower Uma Oya reservoir, transfer canal to Randenigala and power house	159	159	159	159
Development of 10,000 ha in System B	134	134	134	134
Project Cost (with domestic+industrial water)	1,357	1,736	1,915	1,651
Project Cost (without domestic+industrial water)	**775**	**1,155**	**1,333**	**1,070**

Ministry of Irrigation and Water Resources Management (2013) and (2014) prepared the cost data from the past projects of Sri Lanka and neighboring countries. Ministry of Irrigation and Water Resources Management (2014) considered only Plan-3 and the cost data were not sufficient for this study. Therefore, Ministry of Irrigation and Water Resources Management (2013) cost data were used for the study with costs given in terms of 2012 prices.

C.8 Economic Internal Rate of Return of the Project (EIRR)

The calculation of EIRR a 4-year single investment is considered with a 30-year return period. Annual operation and maintenance cost (0.5% of capital cost) are included with annual benefits from agriculture, hydropower and potable water.

The EIRR is calculated without additional end use infrastructure for potable water and considering 10% of potable water (P.W.) benefits to the project from the main infrastructure. Both EIRR values with and without 100% potable water construction are given in the Table C. 6 and without EIRR value for the MCDA.

Table C. 6 EIRR calculation

Alternatives	Capital	O&M	Total Benefits	EIRR
Plan 1 (with P.W.)	1357	6.68	128.38	7.35
Plan 1 (without P.W.)	775	3.88	48.19	3.61
Plan 2 (with P.W.)	1736	8.68	165.97	7.44
Plan 2 (without P.W.)	1155	5.77	85.78	5.12
Plan 3 (with P.W.)	1915	9.57	161.93	6.27
Plan 3 (without P.W.)	1333	6.67	81.74	3.5
Plan 4 (with P.W.)	1651	9.91	178.55	8.59
Plan 4 (without P.W.)	1070	6.42	98.36	6.96

C.9 New Employment

Table C. 7 New employment (Ministry of Irrigation and Water Resources Management 2013)

Alternatives	Plan 1	Plan 2	Plan 3	Plan 4
Construction period (1000 person-days)	24,563	27,719	30,892	24,563
Irrigated agriculture (1000 person-days/annum)	6,453	7,127	7,163	6,453
Domestic water supply (1000 person-days/annum)	806	806	806	806
Industry water supply (1000 person-days/annum)	319	319	319	319
Total (without water supply)	31,016	34,846	38,055	31,016

New employment will be created during the construction period and after project completion. The increased employment during construction is measured in 1000 person-days and 1000 person-days per annum after the construction during operation period.

C.10 Resettlement

Ministry of Irrigation and Water Resources Management (2013) reported the number of families required to resettle for Plans 1-3. The number of resettlements under Plan 4 was estimated from the same study considering new infrastructure construction areas. The number of persons to be resettled for the 4 plans are 3475, 7880, 8114 and 4910 consequently. The number of families to be resettled are 695, 1576, 1623 and 982 consequently for the 4 plans.

C.11 Water Sharing

The main objective of the project is enhancing water management of the Mahaweli basin with new infrastructure addition. The present water management capability is about 2400 Mm^3. With the new infrastructure this will increase to 4100Mm^3. After 30 years of civil war, water sharing with northern areas is highly important. Plan 1 water diversion route is Bowatenna to Huruluwewa via the 2nd Huruluwewa feeder canal (HFC). For Plans 2-4 the water diversion route is Moragahakanda to Huruluwewa via Upper Elahera canal (UEC). The amount of water received by Huruluwewa is used for the MCDA.

Table C. 8 Water diversion to post conflict areas (Ministry of Irrigation and Water Resources Management 2013)

Location water diverting	Location water diversion to	Quantity in Mm^3			
		Plan 1	Plan 2	Plan 3	Plan 4
Polgolla	Bowatenne	1400	1250	887	887
Randenigala	Heen Ganga	0	0	430	0
Heen Ganga	Kalu Ganga	0	0	530	100
Kalu Ganga	Moragahakanda	102	102	632	202
Angamedilla	Minneriya	0	150	250	600
Bowatenne	2nd HFC / Huruluwewa	830	0	0	0
Moragahakanda	UEC / Huruluwewa	0	1030	1050	900
Huruluwewa	NCP canal	548	738	758	600

C.12 Violation of Natural River Flow

Environmental and social assessments are considered as an integral part of the river basin planning process. This project alters the natural flow regime as well as inter basin water transfers which affect aquatic biodiversity. Modifications of the water flow leads to changes in diversity of aquatic communities, loss of biodiversity of native species and introduction of exotic species which can be harmful. There are social activities associated with the downstream river such as drinking water, irrigation, among others. Therefore, sufficient water flow downstream from the water diversion point is extremely important. The number of river flow violations with the four plans was calculated from hydrology data and basic surveys.

C.13 Disturbance to Wild Life

Some of the new infrastructure such as water diversion routes and new reservoirs are inside the wild life reservations. Impact to the wild life is measured as an index (1-10) based on the land use pattern and literature survey. Assessment of disturbance to wildlife was based on the findings of Ministry of Mahaweli Development and Environment (2016) as shown in Table S9.

Table C. 9 Calculation of index for disturbance to wildlife (Ministry of Mahaweli Development and Environment 2016)

Alternatives	**Plan 1**	**Plan 2**	**Plan 3**	**Plan 4**
Presence of the protected habitats	4	5	8	5
Habitat fragmentation	2	4	6	4
Presence of species richness	4	5	6	5
Presence of critical species (including endemic)	2	3	3	3
Presence of protected areas	1	3	7	3
Impact on wildlife migratory routes	1	2	3	2
Total Qualitative values (MWSIP,2016)	14	22	33	22
Total Land (ha)	450	710	600	295
Land above reservoir (ha)	0	220	500	220
Score for Disturbance to Wildlife				
Land without reservoirs (divide 50)	9	9.8	2	1.5
Land above reservoir (divide 10)		22	50	22
Total Qualitative values (MWSIP,2016)	14	22	33	19
Total score	23	53.8	85	42.5
Score (1-10)	**3**	**6**	**10**	**5**

C.14 MAVT Method Calculation

MAVT method calculated six decision makers' degree of approval $(s(i,k)$ and multi-attribute value function of each alternative,$(u(i))$ is the degree of approval of plan i by all decision makers (Table C. 9). Ranking of plans according to six decision makers' degree of approval (columns:2-

7) as well as overall ranking order (columns: Total score, Rank) are important to understand insight of the decision analysis.

Table C. 10 Plan support matrix and multi-attribute value vector

Alternative	DM1 Agriculture	DM2 Power	DM3 Environment	DM4 Social	DM5 Hydrology	DM6 Other	Total Score		Rank
							original	norm	
Plan 1	0.35	0.40	0.46	0.41	0.35	0.40	2.36	0.38	4
Plan 2	0.66	0.64	0.63	0.62	0.67	0.63	3.86	0.68	1
Plan 3	0.51	0.41	0.40	0.46	0.51	0.45	2.73	0.48	3
Plan 4	0.56	0.64	0.62	0.57	0.60	0.59	3.57	0.62	2

C.15 ELECTRE III Calculation of Decision Indices

To compare the performance of each criterion in the four alternatives, we use the average weight to calculate the concordance index and discordance index.

Table C. 11 Concordance indices

Concordance				
	Plan 1	Plan 2	Plan 3	Plan 4
Plan 1		0.37	0.53	0.52
Plan 2	0.63		0.91	0.71
Plan 3	0.63	0.40		0.39
Plan 4	0.56	0.57	0.71	

Table C. 12 Discordance indices

Discordance				
	Plan 1	Plan 2	Plan 3	Plan 4
Plan 1		0.63	0.47	0.48
Plan 2	0.37		0.06	0.29
Plan 3	0.37	0.53		0.60
Plan 4	0.44	0.43	0.29	

Table C. 13 Credibility indices

Credibility Index				
	Plan 1	Plan 2	Plan 3	Plan 4
Plan 1		0.04	0.53	0.52
Plan 2	0.63		0.91	0.71
Plan 3	0.63	0.40		0.06
Plan 4	0.56	0.57	0.71	

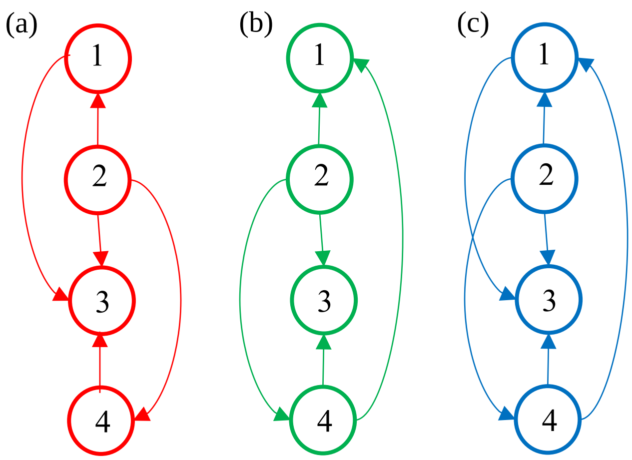

Figure C. 3 Decision graph of outranking of alternative plan using ELECTRE method according to average weight of decision makers (a) ascending distillation (b) descending distillation (c) final ranking

A credibility indices are equal to the concordance indices for most of the cases while few occasions are lowered due to some attributes are highly discordant than the overall credibility index (Table C. 10, Table C. 11). For example, Plan 2 dominates Plan 3 by 0.91 (Table C. 10) and without any highly discordant attribute than credibility index. However, Plan 1 over Plan 2 and Plan 3 over Plan 4 dominance are lowered to 0.04 and 0.06 due to the higher discordant attributes (Table C. 11).

APPENDIX D

Additional Information and Results for Selection of Future Power Generation Pathways

D.1 Demand Forecast

Table D. 1 Demand forecasts prepared considering base assumptions of social and economic factors and considering savings from implementation of demand side management measures [63]

Year	Base demand forecast		Demand forecast with DSM	
	Energy (GWh)	Capacity (MW)	Energy (GWh)	Capacity (MW)
2015	12901	2401	12580	2342
2016	13451	2483	12893	2380
2017	14368	2631	13561	2483
2018	15348	2788	14208	2581
2019	16394	2954	14812	2669
2020	17512	3131	15396	2752
2021	18376	3259	15687	2782
2022	19283	3394	16075	2829
2023	20238	3534	16499	2881
2024	21243	3681	16988	2944
2025	22303	3836	17672	3039
2026	23421	4014	18328	3141
2027	24601	4203	19104	3263
2028	25829	4398	19950	3397
2029	27100	4599	20866	3541
2030	28410	4805	21847	3695
2031	29756	5018	22886	3859
2032	31135	5235	23983	4032
2033	32565	5459	25156	4217
2034	34055	5692	26413	4415

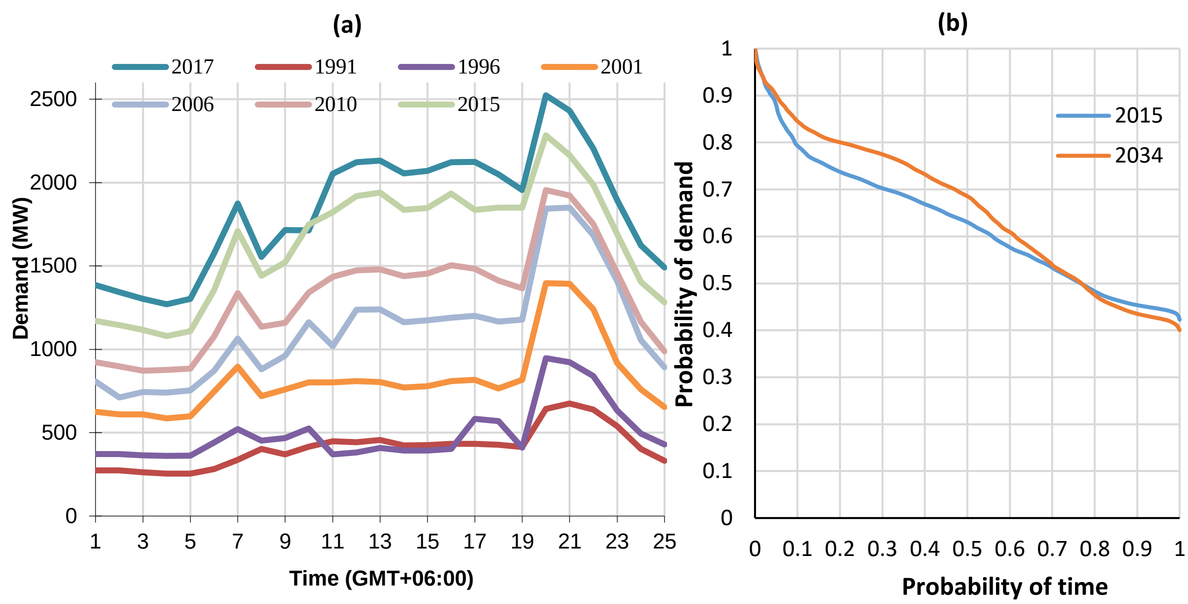

Figure D. 1 Shape of the electricity demand (a) Daily demand profile evolution through past 25 years (b) Load duration curve of present and forecasted for year 2034

D.2 Existing Power System Thermal Power Plants and Hydropower

All the cost data are in Year 2015 dollar terms.

Table D. 2 Existing thermal power plant data and fuel data.

Power Plant	Unit Capacity MW	Fuel Calorific Value kCal/kg	Heat Rate kCal/kWh	Fuel Cost USCts/GCal	Fixed O&M Cost $/kWmonth	Variable O&M Cost $/MWh
GT-1	64	10500	4022	8858	3.56	0.77
GT-2	113	10300	3085	6187	10.05	6.82
Diesel Engine-1	68	10300	2245	6187	9.21	2.03
Diesel Engine-2	72	10500	2015	8858	0.21	5.98
Diesel Engine-3	27	10300	2178	6508	2.08	9.91
Diesel Engine-4	100	10300	2230	6508	1.33	10.63
Diesel Engine-5	60	10300	2265	6508	6.02	13.33
Diesel Engine-6	50	10300	2222	6187	4.56	16.28
Diesel Engine-7	30	10300	2217	6508	1.12	30.15
Comb.Cycle-1	161	10880	2269	8282	2.22	3.23
Comb.Cycle-2	270	10300	3109	6779	2.36	13.85
Comb.Cycle-3	163	10300	2731	8858	1.55	1.17
Coal	825	6300	2597	1553	5.02	3.49
Biomass-1	13	3224	5694	857	2.75	5.05
Biomass-2	10	3224	5694	1714	2.75	5.05

(Ceylon Electricity Board, 2015)

Table D. 3 Emissions of fossil fuel burning from existing thermal power plants.

Power Plant	CO_2 g/MJ	SO_2 g/MJ	NO_X g/MJ	PM mg/MJ
GT-1	74.1	0.453	0.28	5
GT-2	74.1	0.453	0.28	5
Diesel Engine-1	77.4	1.109	1.2	13
Diesel Engine-2	77.4	1.109	1.2	13
Diesel Engine-3	76.3	1.639	0.96	13
Diesel Engine-4	76.3	1.639	0.96	13
Diesel Engine-5	76.3	1.639	0.96	13
Diesel Engine-6	77.4	1.639	0.96	13
Diesel Engine-7	76.3	1.639	0.96	13
Comb.Cycle-1	73.3	0.03	0.28	2.5
Comb.Cycle-2	77.4	0.453	0.28	5
Comb.Cycle-3	74.1	0.03	0.28	13
Coal	94.6	0.455	0.3	40
Biomass-1[a]	0.0	0.0	0.0	255.1
Biomass-2[a]	0.0	0.0	0.0	255.1

(Ceylon Electricity Board, 2015) [a] *Assuming CO_2 absorption from the trees for biomass, CO_2 emission from biomass power plants is considered as zero.*

Table D. 4 Energy and capacity of total hydropower plants according to variability of hydrology represented as five discrete hydrology conditions calculated from the past 50 years of record.

Month	Very Wet probability 0.1		Wet probability 0.2		Medium probability 0.4		Dry probability 0.2		Very Dry probability 0.1	
	Energy (GWh)	Power (MW)	Energy (GWh)	Power (MW)	Energy (GWh)	Power (MW)	Energy (GWh)	Power (MW)	Energy (GWh)	Power (MW)
January	140.1	680.3	126.6	740.6	105.3	663.1	94.1	635.9	84.8	604.2
February	225.0	712.0	214.0	705.2	197.2	668.0	213.7	715.6	183.6	642.5
March	344.8	962.1	311.0	899.6	309.6	877.7	308.7	883.3	284.5	839.1
April	408.7	999.3	362.0	946.4	343.8	919.0	314.5	854.9	307.7	871.3
May	484.1	1138.2	466.2	1111.1	407.8	1021.0	365.7	932.6	321.3	841.4
June	484.8	1100.1	450.0	1084.2	394.8	1049.3	357.6	994.8	323.7	972.5
July	479.0	1033.9	469.5	1036.1	433.8	1007.5	386.8	971.4	335.2	919.3
August	431.4	967.6	437.5	970.0	376.0	943.2	346.1	902.6	319.5	890.4
September	494.3	1059.5	452.2	1021.2	397.5	943.8	351.5	853.0	311.5	787.8
October	617.2	1135.3	566.0	1109.3	483.2	1033.8	424.2	986.9	411.2	948.6
November	579.2	1129.9	526.0	1108.2	482.1	1044.8	348.4	930.3	320.8	871.5
December	554.4	1161.5	536.2	1151.6	443.2	1053.1	328.7	891.2	277.6	862.5

(Ceylon Electricity Board, 2015)

D.3 Candidate Thermal Power Plant Options for Next 20 years

Table D. 5 Candidate thermal power plant data and fuel data.

Power Plant	Unit Capacity MW	Fuel Calorific Value kCal/kg	Heat Rate (Min load) kCal/kWh	Fuel Cost USCts/GCal	Fixed O&M Cost $/kWmonth	Variable O&M Cost $/MWh
GT-3	35	10500	3060	8858	0.69	5.57
GT-4	105	10500	4134	8858	0.53	4.17
Comb.Cycle-4	144	10500	2614	8858	0.55	4.7
Comb.Cycle-5	288	10500	2457	8858	0.41	3.55
Coal-2	227	5500	2895	1485	2.92	5.6
Coal-3	564	6300	2248	1541	4.5	5.9
Coal-4	270	5900	2810	1515	4.47	5.9
Biomass-3	5	3224	5694	1714	2.75	5.04
Nuclear	552		2723	1160	7.62	17.6
Comb.Cycle-6	287	13000	2457	5432	0.38	4.97

(Ceylon Electricity Board, 2015)

Table D. 6 Emissions of fossil fuel burning from candidate thermal power plants.

Power Plant	CO_2 g/MJ	SO_2 g/MJ	NO_X g/MJ	PM mg/MJ
GT-3	74.1	0.453	1.2	5
GT-4	74.1	0.453	1.2	5
Comb.Cycle-4	74.1	0.453	0.2	5
Comb.Cycle-5	74.1	0.453	0.2	5
Coal-2	98.3	0.056	0.26	35
Coal-3	94.6	0.035	0.035	7
Coal-4	94.6	0.035	0.14	7
Biomass-3[a]	0.0	0.0	0.02	255.1
Nuclear	0.0	0.0	0.0	0.0
Comb.Cycle-6	56.1	0	0.02	0.0

(Ceylon Electricity Board, 2015) [a] *Assuming CO_2 absorption from the trees for biomass, CO_2 emission from biomass power plants is considered as zero.*

D.4 Assumptions for Alternative Development

Six alternative plans are developed considering several assumptions about fossil fuel and hydrology. Presently, the total fossil fuel requirement of the country is imported. A feasibility study was carried out for exploring natural gas reserves of Sri Lanka and the process is being progressed slowly (Ministry of Petroleum Resources Development, 2017). Therefore, local natural gas option is considered only for the *Maximum indigenous resource* alternative and imported liquid natural gas option is considered for other alternatives (Ceylon Electricity Board, 2015; Ministry of Petroleum Resources Development, 2017).

Electricity demand profiles for the alternative plans are based on the past daily power demand profile of Sri Lanka, which has followed a similar pattern for the last 25 years (Figure D. 1(a)). The demand profile creates bottlenecks in power generation with a high evening peak demand and an early morning off-peak demand (40% of peak value). The addition of inexpensive baseload power plants such as thermal power (coal, nuclear) and renewable power plants (without storage) is limited due to this reason. Although peak and energy demands will be growing, there is high uncertainty of growing the off-peak demand (Figure D. 1 (b)). Therefore, a 600MW (200MW x 3 nos.) pumped storage hydropower plant addition (Japan International Corporation Agency, 2015) is considered for the generation side efficiency improvement in all the alternative generation pathway developments.

Reliability and environmental standards as stipulated by regulation are incorporated for developing possible power generation pathways. Reliability standards of power planning are defined as reserve margin (difference between deliverable power generation capacity and demand of the system) and loss of load probability (LOLP: measure of the probability that a system demand will exceed capacity during a given period; often expressed as the estimated number of days over a long period). Maximum (20%) and minimum (2.5%) reserve margin (RM) and LOLP (1.5%) values are selected according to the generation planning standards of the transmission licensee of Sri Lanka (Transmission Division of Ceylon Electricity Board, 2018). The environmental standards follow the Central Environmental Authority of Sri Lanka and World bank (Ceylon Electricity Board, 2015).

D.4 Attribute Measurement

Table D. 7 New jobs, land requirement, social acceptance calculation

Technology	New jobs per 1MW	Land 10^3m^2 per MW	Social acceptance weight per MW
Coal Steam	5	2.5	0.06
Diesel GT	5	2.5	0.12
LNG CCY	4.9	2.5	0.12
Hydro	5	750	0.25
HVDC	5	0	0.12
Nuclear	5	2.5	0.01
Solar	10.7	100	0.23
Wind	11.3	35	0.2
Biomass	72.1	5000	0.15
Small hydro	5	18	0.25

D.5 Results

Performances of alternatives plans are varied across the five criteria measured through 15 attributes (Figure D. 2, Figure D. 3, Figure D. 4, Figure D. 5, Figure D. 6). Although total investment for alternative power plans are different, cost percentage for first 10 years (cost 1) and second 10 years (cost 2) are approximately same as 40% and 60% respectively (Figure D. 2).

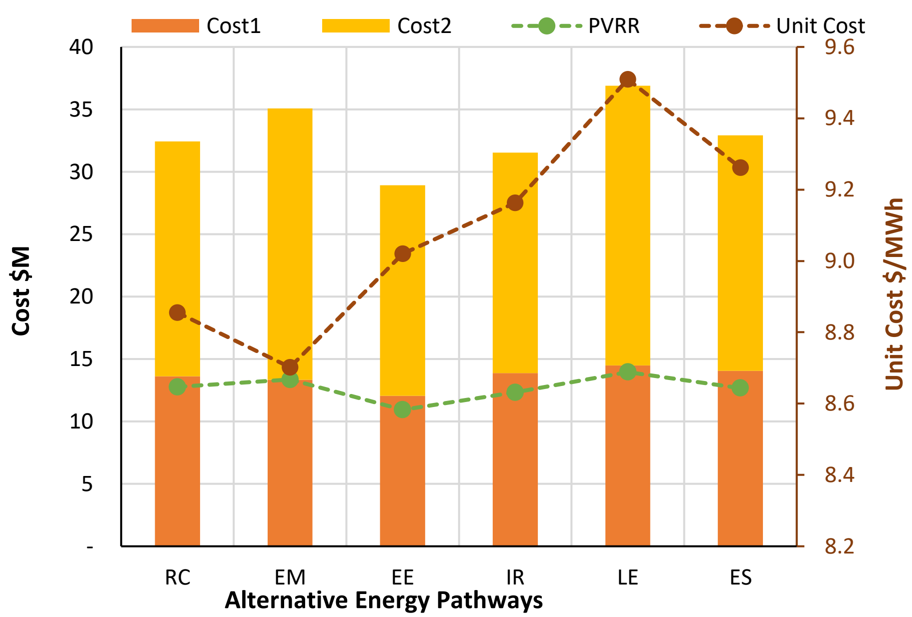

Figure D. 2 Performance of power generation pathways across economic criteria

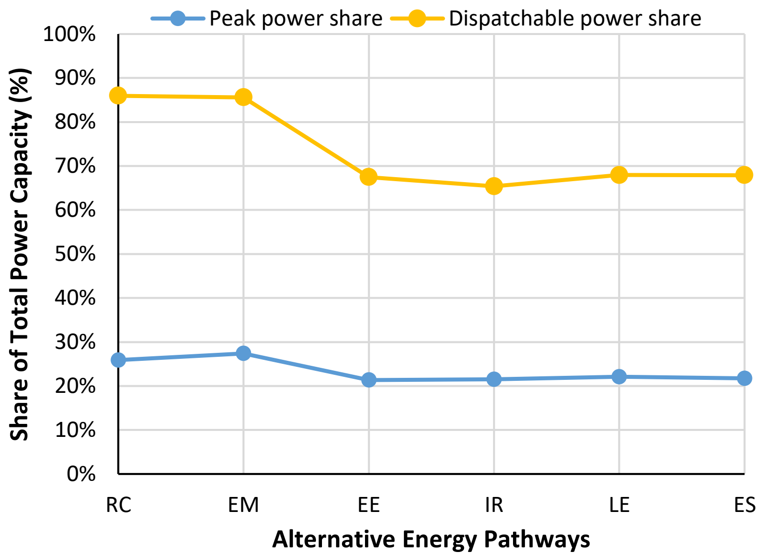

Figure D. 3 Performance of power generation pathways across technical criteria

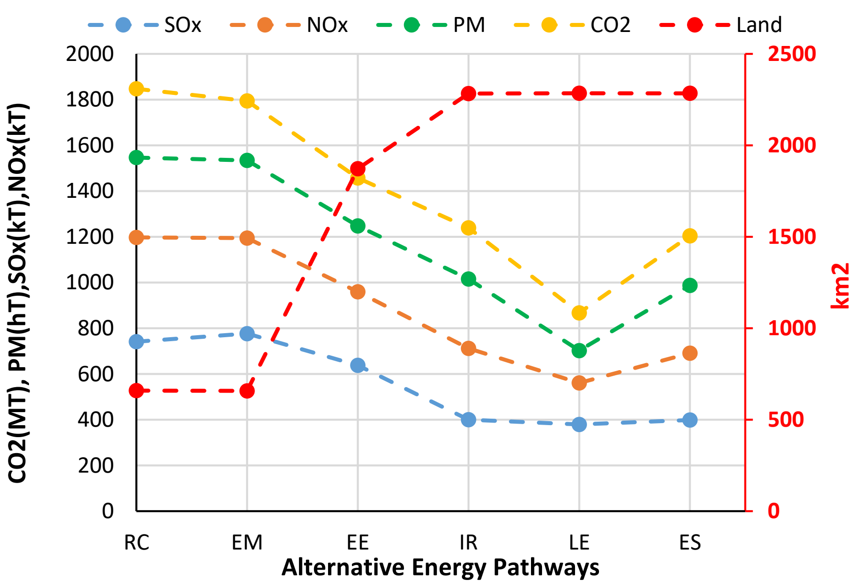

Figure D. 4 Performance of power generation pathways across environmental stewardship criteria

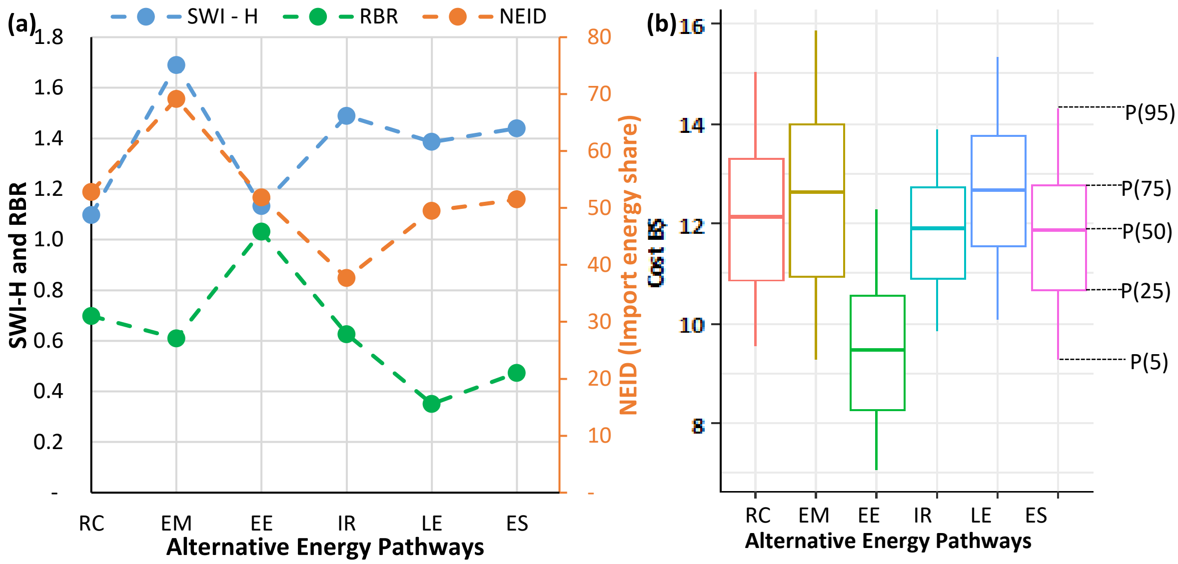

Figure D. 5 Performance of power generation pathways across uncertainty criteria. (a) Energy security (SWI-H, NEID) and risk benefit ratio (RBR) (b) Total cost distribution over the uncertainty of resources (hydrology and fossil fuel price)

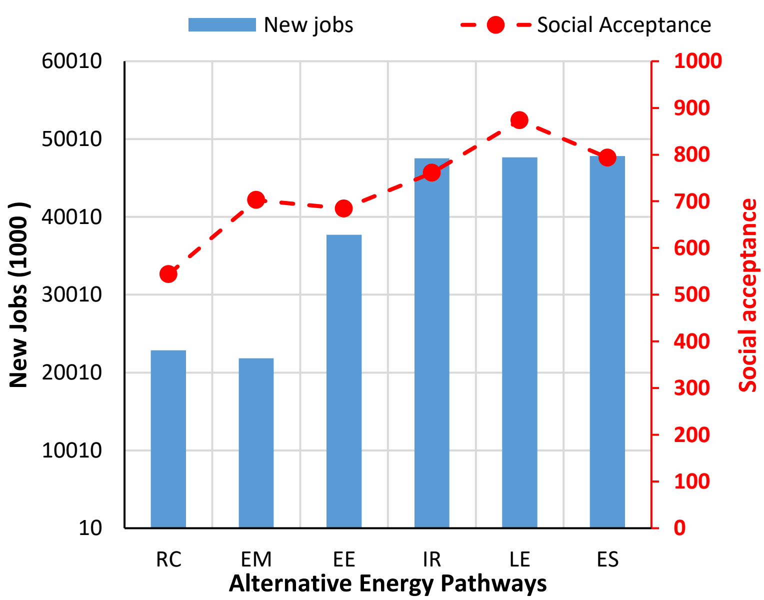

Figure D. 6 Performance of power generation pathways across social criteria

Table D. 8 Evaluation matrix, comparison with Reference case

Criteria		Energy Mix	Energy Efficiency	Max.Indeg. Resources	Low Emission	Energy Security
Economic	Present Value 20-year Plan ($M)	5%	-14%	-3%	9%	-1%
	10-year Avg. Energy Unit Price ($/MWh)	-2%	2%	3%	7%	5%
Technical Flexibility	Peak power share	6%	-17%	-17%	-14%	-16%
	Dispatchable power share	0%	-22%	-24%	-21%	-21%
Environmental Stewardship	SO_x (kT)	5%	-14%	-46%	-49%	-46%
	NO_x (kT)	-9%	-29%	-32%	-60%	-36%
	PM (kT)	-3%	-17%	-13%	-59%	-15%
	CO_2 (kT)	-14%	-30%	-26%	-45%	-28%
	Land requirement (km2)	0%	184%	247%	247%	247%
Uncertainty	95th percntile cost (M$)	6%	-10%	-7%	2%	-5%
	Risk/Benefit	-13%	48%	-10%	-50%	-32%
	SWI - H	5%	-21%	-4%	3%	-4%
	NEID	20%	-5%	-26%	-4%	-8%
Social	Job opportunities (persons/year)	-4%	65%	108%	109%	109%
	Social Acceptance	29%	26%	40%	61%	46%

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