Application of a dynamically-coupled modelling framework for comparative resilience assessment in participatory, socio-environmental resource management

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Jordan M. Carper

Under the Supervision of Dr. Jan Adamowski

Department of Bioresource Engineering

McGill University

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Department of Bioresource Engineering
Macdonald Campus of McGill University
2111 Lakeshore Road, H9X 3V9
Ste-Anne-de-Bellevue, Quebec, CA

ABSTRACT

The present study was conducted with the aim of developing and testing a new method for resilience quantification by assessing the resilience of three important socio-environmental variables (farm income, seasonal crop revenue, and water-table depth) with respect to two different watershed-level shock scenarios. The agroecological shocks (i.e. system disturbances) used in this study include variations in market inflation and canal water supply. Resilience was quantified by assessing the functionality-curve outputs produced by running shock simulations through a dynamically coupled Physical-Group-Built System Dynamics Model (P-GBSDM). Functionality outputs were initially normalized to a baseline-level of performance with respect to historical data trends. Following normalization and shock scenario application, five equations associated with the salient characteristics of a resilient shock response were applied to the output data for each study variable; these characteristics include: 1) variable recovery rate (to a pre-determined state of equilibrium), 2) variable recovery time, 3) net corrective impact, 4) final degree of return to the pre-determined equilibrium, and 5) cumulative variable perturbation (area above the response curve and below the baseline data set). Due to the fact that the variable response curve data were normalized to a baseline functional paradigm, the five resiliency characteristics mentioned above can be compared across all variable types to determine relative resilience for each shock-type, shock severity, and time-step.

After the initial quantification procedure was developed and tested, three NASA Earth Exchange Global Daily Downscaled Climate Projections (NEX-DGGP) were incorporated into the assessment codes as well as three stakeholder-defined policy suggestions (canal lining, rainwater harvesting, and irrigation improvement). Upon completion of the initial round of testing, it was determined that water-table depth is the most consistently resilient variable across all shock combinations in controlled climate conditions; farm income was determined to be the least resilient variable for the preliminary runs. After incorporation of climate scenarios and stakeholder policy suggestions, it was determined that rainwater harvesting is the most effective stakeholder-defined policy measure for improving or maintaining resilience of the tested study variables in the Rechna Doab basin; this holds true for every climate and shock scenario with the exception of water-table depth in the upper and mid-watershed regions under canal supply shock conditions, for which canal lining is the most effective policy measure. Model users can apply this procedure to

objectively assess the robustness, adaptive capacities, and unique vulnerabilities of different variables in an agroecosystem with respect to varying levels of disturbance.

RÉSUMÉ

La présente étude a été menée dans le but de développer et de tester une nouvelle méthode de quantification de la résilience en évaluant la résilience de trois variables socio-environnementales importantes (revenu agricole, revenus des cultures saisonnières et profondeur de la nappe phréatique) par rapport à deux bassins versants différents. scénarios de choc de niveau. Les chocs agroécologiques (c'est-à-dire les perturbations du système) utilisés dans cette étude incluent les variations de l'inflation du marché et de l'approvisionnement en eau du canal. La résilience a été quantifiée en évaluant les résultats de la courbe de fonctionnalité produits en exécutant des simulations de chocs à travers un modèle de dynamique de système construit par groupe physique (P-GBSDM) couplé dynamiquement. Les sorties de fonctionnalité ont été initialement normalisées à un niveau de performance de base par rapport aux tendances des données historiques. Après la normalisation et l'application du scénario de choc, cinq équations associées aux caractéristiques saillantes d'une réponse de choc résiliente ont été appliquées aux données de sortie pour chaque variable d'étude; ces caractéristiques comprennent: 1) taux de récupération variable (jusqu'à un état d'équilibre prédéterminé), 2) temps de récupération variable, 3) impact correctif net, 4) degré final de retour à l'équilibre prédéterminé et 5) variable cumulative perturbation (zone au-dessus de la courbe de réponse et en dessous de l'ensemble de données de base). En raison du fait que les données de la courbe de réponse variable ont été normalisées à un paradigme fonctionnel de base, les cinq caractéristiques de résilience mentionnées ci-dessus peuvent être comparées à travers tous les types de variables pour déterminer la résilience relative pour chaque type de choc, gravité de choc et pas de temps.

Une fois la procédure de quantification initiale développée et testée, trois projections climatiques quotidiennes à échelle réduite de la NASA Earth Exchange (NEX-DGGP) ont été incorporées dans les codes d'évaluation ainsi que trois suggestions de politiques définies par les parties prenantes (revêtement de canal, collecte des eaux de pluie et amélioration de l'irrigation). . À l'issue de la première série d'essais, il a été déterminé que la profondeur de la nappe phréatique est la variable la plus résiliente dans toutes les combinaisons de chocs dans des conditions climatiques contrôlées; il a été déterminé que le revenu agricole était la variable la moins résiliente

pour les essais préliminaires. Après l'incorporation des scénarios climatiques et des suggestions de politiques des parties prenantes, il a été déterminé que la collecte des eaux de pluie est la mesure politique définie par les parties prenantes la plus efficace pour améliorer ou maintenir la résilience des variables de l'étude testées dans le bassin de Rechna Doab; cela est vrai pour tous les scénarios climatiques et de choc, à l'exception de la profondeur de la nappe phréatique dans les régions du haut et du milieu du bassin versant dans des conditions de choc d'approvisionnement du canal, pour lequel le revêtement du canal est la mesure politique la plus efficace. Les utilisateurs du modèle peuvent appliquer cette procédure pour évaluer objectivement la robustesse, les capacités adaptatives et les vulnérabilités uniques de différentes variables dans un agroécosystème par rapport à différents niveaux de perturbation.

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EXPLANATION OF THESIS FORMAT

This thesis is submitted in the format of papers suitable for journal publication. This thesis format has been approved by the Faculty of Graduate and Postdoctoral Studies at McGill University, and follows the conditions outlined in the Guidelines Concerning Thesis Preparation, which are as follows:

"As an alternative to the traditional thesis format, the dissertation can consist of a collection of papers of which the student is an author or co-author. These papers must have a cohesive, unitary character making them a report of a single program of research. The structure for the manuscript-based thesis must conform to the following:

1. Candidates have the option of including, as part of the thesis, the text of one or more papers submitted, or to be submitted, for publication, or the clearly duplicated text (not the reprints) of one or more published papers. These texts must conform to the "Guidelines for Thesis Preparation" with respect to font size, line spacing and margin sizes and must be bound together as an integral part of the thesis. (Reprints of published papers can be included in the appendices at the end of the thesis.)

2. The thesis must be more than a collection of manuscripts. All components must be integrated into a cohesive unit with a logical progression from one chapter to the next. In order to ensure that the thesis has continuity, connecting texts that provide logical bridges between the different papers are mandatory.

3. The thesis must conform to all other requirements of the "Guidelines for Thesis Preparation" in addition to the manuscripts.

The thesis must include the following:

(a) A table of contents
(b) An abstract in English and French
(c) An introduction which clearly states the rational and objectives of the research
(d) A comprehensive review of the literature (in addition to that covered in the introduction to each paper)
(e) A final conclusion and summary

1. As manuscripts for publication are frequently very concise documents, where appropriate, additional material must be provided (e.g. in appendices) in sufficient detail to allow a clear and precise judgment to be made of the importance and originality of the research reported in the thesis.

2. In general, when co-authored papers are included in a thesis the candidate must have made a substantial contribution to all papers included in the thesis. In addition, the candidate is required to make an explicit statement in the thesis as to who contributed to such work and to what extent. This statement should appear in a single section entitled "Contributions of Authors" as a preface to the thesis. The supervisor must attest to the accuracy of this

statement. Since the task of the examiners (reviewers) is made more difficult in these cases, it is in the candidate's interest to clearly specify the responsibilities of all the authors of the co-authored papers."

CONTRIBUTIONS OF AUTHORS

The chapters of this thesis have been prepared for publication in peer-reviewed journals. The author of this thesis was responsible for methodological development, conceptualization of necessary codes and equations, formal analysis of the data produced during simulations using the P-GBSDM, as well as the writing and editing of the published articles included herein. The thesis supervisor, Dr. Jan Adamowski, contributed to the review and editing of the included articles.

Mohammad Reza Alizadeh was responsible for primary data curation as well as software development and validation. Mr. Alizadeh, Azhar Inam, and Julien Malard each contributed to the technical support, research, and editing and review process of the constituent parts of the present manuscript.

List of publications related to this thesis:

Carper, J.M., Mohammad Reza Alizadeh, Jan F. Adamowski, Azhar Inam, Julien J. Malard, (2021). "Quantifying the transient shock response of dynamic agroecosystem variables for improved socio-environmental resilience." *Ecology and Society*, (under review).

Carper, J.M., Mohammad Reza Alizadeh, Jan F. Adamowski, Azhar Inam, Julien J. Malard, (2021). "Climate variability in agroecosystems: a quantitative assessment of stakeholder-defined policies for enhanced socio-environmental resilience." (unsubmitted).

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LIST OF ABBREVIATIONS

AR5	5th Assessment Report
CHANS	Coupled Human and Natural System
CLD	Causal Loop Diagram
CMIP5	Coupled Model Intercomparison Project 5
CR	Crop Revenue
CSV	Comma-separated Value
DLNM	Distributed Lag Non-linear Model
EPA	Environmental Protection Agency
FI	Farm Income
FSIN	Food Security Information Network
GDP	Gross Domestic Product
HMM	Hidden Markov Model
IPCC	Intergovernmental Panel on Climate Change
ODI	Overseas Development Institute
OLS	Ordinary Least Squares
PBM	Process Based Model
P-GBSDM	Physical-Group-Built System Dynamics Model

Rci	Corrective Impact Metric
Rd	Degree of Return Metric
Rp	Perturbation Metric
Rr	Return Rate Metric
Rt	Return Time Metric
RCP	Representative Concentration Pathway
S1	Shock Scenario 1 (Market Inflation)
S2	Shock Scenario 2 (Canal Supply)
SAHYSMOD	Spatial-Agro-Hydro Salinity Model
SCARP	Salinity Control and Reclamation Project
SD	System Dynamics
SDM	Species Distribution Model
SDS	Stakeholder-defined Scenario
SES	Socio-ecological System
USAID	United States Agency for International Development
WTD	Water-table Depth

CHAPTER 1: **Introduction**

The contemporary definition of resilience can be traced to the Latin word *resalire*, which translates to "walking or leaping back" (Skeat, 1882). The concept is currently employed in many different disciplines, including psychology (Masten et al., 1990), climate studies (Bahadur et al., 2010), economics (Plummer and Armitage, 2007; Venton et al., 2012), ecology (Peterson et al., 1998; Gunderson, 2000; Standish et al., 2014; Meyer, 2016), industrial engineering (Cavallini et al., 2014), and sociology (Brown, 2014). Carpenter and Brock (2008) describe resilience as a broad, multifaceted, and loosely organized cluster of concepts, each one related to some aspect of the interplay between transformation and persistence. Although a great deal of literature is dedicated to the concept of resilience assessment in multiple spheres of research (Carpenter et al., 2001; Bennett et al., 2005; Gunderson and Folk, 2005; Folke, 2006; Walker et al., 2006; Folke et al., 2010; Bahadur et al., 2010; Cumming, 2011; Cabell and Oelofse, 2012; Anderies et al., 2013; Nemec et al., 2013; Eisenburg et al., 2014; Choularton et al., 2015; D'Lima and Medda, 2015; Lisa et al., 2015; Vollenwider, 2015; Angeler and Allen, 2016; Folke, 2016; Bizikova et al., 2017; Cantarello et al., 2017; Panerati et al., 2018), the present analysis of socio-environmental system resilience using five analytical metrics is unique in that it employs a coupled Physical-Group-Built System Dynamics Model (P-GBSDM) for scenario simulation and data development (Inam et al., 2017, 2017a). The use of this dynamically coupled modelling framework for a comprehensive and replicable resilience assessment strategy is both reliable and intentionally stakeholder-friendly. This resilience analysis framework incorporates up-to-date NASA Earth Exchange Global Daily Downscaled Climate Projections (NEX-DGGP) as well as stakeholder-defined policy suggestions into a systematic, variable-level, shock-assessment paradigm. The subsequent parsing of stakeholder-defined policy suggestions into various categories of effectiveness and the use of the present methodological framework for verifying policy aptitude for resilience improvement (i.e. policy impact monitoring) and the supporting suggestons for improved policy development are also novel additions to the increasingly relevant resilience literature. These specific methods have been designed for universal applicability, i.e. the resilience assessment methodology described herein may be applied not only at the present study site, Rechna Doab, Pakistan, but also to numerous agricultural watersheds across the globe. The Rechna Doab was selected as the study site for this research because the dynamically coupled model used to test the methodology herein was designed around this watershed. The present study is a supplemental continuation of the work conducted by Inam et al. (2015, 2017, 2017a) in the Rechna Doab basin of north-eastern Pakistan.

1.1. Exploring Resilience

Measuring resilience is extremely important in a socio-environmental context. As human and natural systems become increasingly integrated, it is imperative to think about the potential impacts of both predicted and unexpected disturbances from socioeconomic *and* environmental sources (Liu et al., 2007; Mayer et al., 2008; Alberti et al., 2011; Mayer et al., 2014). Developing resistant, robust, and recoverable socio-environmental systems will also benefit communities and ecosystems as the repercussions of global climate change become more imminent and potentially more disastrous. An effective resilience assessment can help elucidate the unique vulnerabilities of a study system while also identifying functional regime shifts and/or transformation thresholds (Carpenter, 2003; Biggs et al., 2009; Carpenter et al., 2011; Biggs et al., 2012). Vulnerabilities, shifts, and transformations are all recognizable based on the historic and average behavior of a system under normal socioenvironmental conditions; as such, it is critical for a researcher, analyst, or model-user to understand the system in its ‘natural’ state before assessing the system under simulated conditions. Once the general behavior patterns of a system or variable have been observed, it is possible to begin the process of identifying system vulnerabilities and strengths, as well as exogenous and endogenous pressure dynamics. A successful resilience analysis provides essential information to local stakeholders, decision-makers, and legislators about the specific vulnerabilities and adaptive capacities of a system under stress; this can lead to the improvement of important policy measures designed to mitigate disaster risk.

1.2. Research Theme: Coupled Modelling for Resilience Quantification

Quantitative resilience assessments often involve the use of statistical or computational modelling techniques (Cimellaro et al., 2010; Cumming, 2011; Tyler and Moench, 2012; Hodgson et al., 2015; Nimmo et al., 2015; Polhill, 2015; Bitterman and Bennett, 2016; Todman et al., 2016; Ingrisch and Bahn, 2018; Meyer et al., 2018; Schibalski et al., 2018), however coupled models that incorporate biophysical, socioecological, *and* economic variables have the greatest potential for accurately elucidating the transient dynamics involved in complex systems experiencing stress from any source (i.e. physical, environmental, social, economic, etc.). Several authors have already begun exploring the development of quantitative resilience assessment methodologies using coupled modelling frameworks. For example, in order to assess the resilience of coastal plant communities, Schibalski et al. (2018) investigated the effects of short-term groundwater levels and salinity changes on coastal vegetation in the German Baltic Sea using a hybrid model comprised of process-based (PBM) and statistical species distribution models (SDM). Like the research outlined in the present manuscript, Schibalski et al. (2018) used the quantifiable metric of return time (Rt) (to a pre-determined state) to determine the resilience of the subject plant communities undergoing stress. Unlike the present research, however, Schibalski et al. (2018) did not incorporate other metrics of a resilient response such as rate of return, degree of return, perturbation, or corrective impact measurements. Within the field of agroecology and economics, Bitterman and Bennett (2016) employed a coupled modelling framework to assess the resilience of several agricultural variables by analyzing the modelling outputs based on a pre-determined stability landscape for each variable in question. The present study uses a similar approach for quantifying resilience based on a pre-determined (baseline) state.

Quantifying resilience in an attempt to streamline and standardize resilience assessments is not a new concept, however the advent of increasingly dynamic computational technologies has progressed the concept quite considerably in recent years. Coupled models in particular allow for the incorporation of dynamic variables and feedback loops between system components, which help to better describe the patterns of complex systems over time. The integration of physical and socioeconomic models is particularly useful and unique in that it allows model users to better understand the connections between seemingly unlinked variables. With a more accurate picture of the integrated dynamics characterizing complex systems, researchers, stakeholders, and model users can conduct quantitative resilience assessments with a higher degree of confidence than ever. The present manuscript outlines a unique resilience quantification methodology and the associated results achieved through the use of a dynamically-coupled modelling framework.

This research is innovative in four aspects:

1. The use of a new, dynamically coupled Physical-Group-Built System Dynamics Model (P-GBSDM) for resilience assessment through variable-level shock scenario simulation.

2. The use of five unique metrics for resilience quantification based on simulated scenario outputs of the dynamically coupled model.
3. Use of the above P-GBSDM and quantification methodology to assess stakeholder-defined policies for their potential to confer resilience to shocked systems, while taking into account the effects of various long-term climate trends.
4. Unlike previous work on modelling and quantifying resilience, the present research focuses on variable-level comparability (as opposed to a system-level assessment), which allows the methodological user to best understand the effects of disturbance scenarios on specific system components, thereby elucidating the specific aspects of a system that are most vulnerable to particular shock conditions, and which should be the primary focus of sustainable reform efforts.

1.3. Research Questions and Objectives

The main purpose of this research is to establish a reliable, stakeholder-friendly procedure for comparative resilience analysis between dynamic variables in complex socio-environmental systems. The developed methodology will allow model users to complete comprehensive resilience analyses using highly replicable, quantifiable metrics. This newly-developed procedure for the quantification of salient metrics describing a resilient system or variable is adaptable to multiple system types, locations, and time series. For the initial stages of methodological development, the flow of research went as follows:

- Primary researcher (thesis author) conducted comprehensive literature review related to coupled human and natural systems, dynamic model coupling, current and historical resilience assessment paradigms, resilient socio-environmental systems, and modelling resilience in complex systems.
- Primary researcher gained familiarization with the dynamically-coupled Physical-Group-Built System Dynamics Model (P-GBSDM) developed by collaborators Azhar Inam, Jan Adamowski, and Julien Malard (Inam et al., 2015, 2017, 2017a) (as well as the associated model coupling package, Tinamit (Malard et al., 2017)) for simulation of complex system dynamics in the Rechna Doab basin of northeastern Pakistan.

- Using Vensim modelling software (Ventana Systems, 2018), computational switches were incorporated into the established model to allow for fluctuations in variable inputs. These manual fluctuations were subsequently termed "shocks," and were written into the Tinamit coupling package so as to maintain a streamlined method for altering shock applications to the system.
- After manual testing of the shock switches and final selection of the study variables, a code for normalization of the shocked variables to the baseline data sets and a code for extraction of five pre-determined metrics of a variable's resilient response to shock scenarios were written. Resilience metric data was subsequently extracted for each study variable and shock type using various shock intensity and duration combinations.

The second stage of this research involved the incorporation of real-world NASA Earth Exchange Global Daily Downscaled Climate Projections (NEX-DGGP) into the P-GBSDM simulation procedure and the subsequent testing of stakeholder-defined policy suggestions for improved resilience in the study variables and the system at large. Policy and climate scenarios were applied to the system and the selected study variables were analyzed under various shock conditions to determine the individual and compound effects of climate change and public policy on variable resilience.

The overall objective of this research is to assess the resilience of human-environmental system components to socioeconomic and environmental disturbances using a coupled biophysical-system-dynamics model. The specific objectives of the research are as follows:

1. Develop a stakeholder-friendly methodology for analyzing socio-environmental system resilience to variable disturbances using a coupled physical-system-dynamics modelling framework in the Rechna Doab watershed, Pakistan (applicable worldwide)

2. Use the above methodology to assess stakeholder-defined policies for their capacity toenhance socio-environmental resilience under realistic climate change conditions.

1.4. Thesis Outline

This thesis has been written as a series of manuscripts, each of which contributes to the above stated objectives.

Existing literature on the analysis and management of socio-environmental systems, traditional methods of resilience assessment, methods for modeling resilience in complex systems, as well as the dynamics associated with climate change and policy development with respect to resilience improvement and maintenance is reviewed in Chapter 2.

The literature review is followed by two connected manuscripts; the first manuscript (Chapter 3) outlines the development of the resilience quantification methodology used to assess variable resilience using a replicable, stakeholder-friendly procedure.

The second manuscript (Chapter 4) discusses the testing and subsequent analysis (using the resilience quantification methodology outlined in Chapter 3) of select variables under shock conditions with consideration for NASA-generated climate eventualities and with the application of stakeholder-defined policy suggestions. This section highlights the significance of this work with respect to real-world applicability and use for resilience monitoring and improvement in various socio-environmental systems.

Chapter 5 discusses the conclusions derived from the most important results of this research, and Chapter 6 lists the major contributions to this field of study and recommendations for future research.

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CHAPTER 2: **Literature Review**

When analyzing resilience in a participatory context, it is important to keep in mind that social-ecological systems are complex adaptive systems. These dynamic systems possess critical thresholds, multiple drivers of change, and iterative feedbacks between social and ecological components (Levin et al., 2013). Participants undertaking a socio-environmental resiliency analysis need to be aware of the interrelated nature of human and ecological systems and of the specific shocks and drivers present in the system of interest. Climate change, in particular, has an immense capacity to bring about both unexpected shocks as well as long-term disturbance trends to agricultural communities; as such, resilience analyses are becoming increasingly important as methods of measuring and developing adaptation strategies (Malard et al., 2018). In order to more accurately and reliably establish a replicable resilience assessment methodology, it is important to first acknowledge, and become familiar with, the complex feedback loops and inter-variable dynamics associated with the system of interest.

2.1. Socio-environmental Systems

Gallopin et al. (2001) have argued that the natural analytical unit for sustainable development research is the socio-ecological system (SES), which is defined as a dynamic system that includes societal (human) and ecological (biophysical) subsystems in mutual interaction (Gallopin, 1991). Similarly, coupled human and natural systems (CHANS) are defined as integrated systems where humans and nature interact, i.e. human-environment systems. Several specific features characterize CHANS research; for example, Liu et al. (2007) describe four overlapping characteristics in a review of six CHANS research projects: (1) attention to feedbacks between systems, (2) interdisciplinary research teams, (3) use of methodological tools from diverse disciplines, and (4) longitudinal data collection. Much attention has been paid to studying systemic changes in ecology as well as in economics, however the attempts to do so for coupled socio-environmental systems are rarer (Polhill et al., 2015). Exogenous disturbances (i.e. shocks and stresses from a source outside the system of interest) may prompt systemic change, but often changes emerge endogenously either through the behavior of the system itself, or through accumulated responses of the system to relatively small exogenous stressors (Walker and Meyers, 2004; Biggs et al., 2009; Carpenter et al., 2011). In fact, while many climate adaptation proponents focus on extreme events, a series of small events or a shift in patterns to a nonequilibrium dynamic can be more damaging (Scoones, 2004). Slow changes in endogenous processes, which provide resilience, such as stabilizing feedbacks, can make a system vulnerable to random shocks or rare disturbance events, which can trigger a sudden dramatic change and loss of structural or functional integrity (Folke et al., 2010). Systemic change may also be understood as the propagation and amplification of a shock throughout the system, in this context, changes themselves may be described as disturbances; these disturbances could subsequently lead to a long-term change in the way the system is structured. In addition to nonlinear dynamics, the sheer number of interacting elements that compose real-world systems contributes to their overall complexity (Anderies et al., 2013).

2.1.1. Participatory Resource Management in Socio-environmental Systems

Classic ideas of environmental management are often centralized and exclusionary; passive or active managerial measures are often implemented by bureaucratic hierarchies that exclude public input and participation. However, there is a growing body of literature supporting a participatory approach which is decentralized, community oriented, and holistic in its view of the environment. Participatory environmental management is aimed at making environmental decision-making socially inclusive and sustainable (Kapoor, 2001). Stakeholder engagement and participation in socio-environmental decision-making is increasingly recognized as a critical aspect of sustainable agricultural and water resources management (Saadat et al., 2011; Adamowski et al., 2012; Halbe et al., 2014; Medema et al., 2014; Inam et al., 2015). There are many potential benefits to involving the public in decision-making processes, including the improvement of policy solutions that are put forward, however this inclusion may come at the expense of requiring more time and effort put towards facilitating and supporting stakeholders throughout the process (Butler and Adamowski, 2015).

Due to their intimate relationship with the environment and its resources, indigenous peoples are among the first to face the direct consequences of climate-related disturbances. Climate change exacerbates the difficulties already faced by vulnerable indigenous communities, including political and economic marginalization, loss of land and resources, human rights violations, discrimination, and unemployment. Therefore, enhancing and supporting the adaptive capacity of indigenous peoples will only be successful if this is integrated with other strategies such as disaster preparation, land-use planning, environmental conservation and national plans for sustainable development. However, adaptation to new conditions may often require additional financial resources and the transfer of technological know-how that most indigenous communities do not currently possess. Identification of key system elements and perceptions of how historical events have shaped these elements should reflect the values and interpretations of what local people feel is important; in other words, the ways researchers think about socio-environmental thresholds is quite different from the ways that resource users and stakeholders view thresholds. (Andrachuk and Armitage, 2015). Many ecologists and resource practitioners view humans and their actions as external to the systems in question, they fail to take into account the interdependencies and feedbacks between ecosystem development and social dynamics (Gunderson and Folke, 2005). Local stakeholders and native populations can easily address this misjudgment by contributing what they know about the local socio-environmental system and its cross-scale dynamics to the resource management process.

2.1.2. Climate Change in Socio-environmental Systems

All socio-environmental systems deal with exogenous and endogenous perturbations and disturbances; climate change, in particular, has the formidable potential to inflict both unexpected shocks as well as longer-term stresses to smallholder farmers; as such, exploring the idea of resilience to systemic threats is gaining acceptance as a promising approach for measuring and establishing adaptation strategies (Malard et al., 2018). Altered availability of water resources is often the first noticeable impact of climate change in the "causal chain" of reactionary processes after a stressor has been established. Precipitation changes have a direct effect on the water balance, affecting runoff generation, river flow and surface water storage (Krol and Bronstert, 2007). Although a change in the dimension of water accessibility is frequently the *first* marked effect of a climate disturbance, it will likely not be the only appreciable systemic response to perturbation. System-level disturbances of ecological or anthropogenic sources may be interrelated and/or occur simultaneously, and one type of functional disruption may contribute to another; for example, high food prices or changes in water availability can lead to social unrest and political instability (Lagi et al., 2011). Furthermore, disturbances in one geographic region or higher-level system may affect adjacent areas or associated systems. For example, if agricultural employment opportunities become limited in one area, this same area may suffer reduced agricultural production as a result of a social or environmental disturbance; shocks and stressors seldom occur as isolated events (Maxwell et al., 2015). Conceptually, the initial effect of climate change that reduces crop yields, assuming current farming practices remain stable, is a leftward shift of the supply curve, which subsequently reduces production and raises prices. Consumers respond to this increase in price by reducing consumption of more expensive crops and deviating from their normal purchasing patterns. Producers respond by altering farm management practices and increasing overall crop acreage. Due to negative crop and financial productivity as a result of climate change, prices increase and bring about more demanding and accelerated management practices, area expansion, international trade, and reduced product consumption (Nelson et al., 2013).

According to the Arab Water Council (2009), there is an expected precipitation decrease of 20% or more in arid regions over the next century. Even if attempts to reduce greenhouse gas emissions are successful, it is no longer possible to avoid some degree of global warming and climate change. Adaptation strategies for anticipating and dealing with these impending climatic impacts include crop-type divergence to varieties with greater heat and drought tolerance, modernization of irrigation infrastructure and establishment of water-saving technologies, integrated watershed management, reforestation of certain catchment areas, and construction of additional water storage infrastructure. The overall water demands of a region, community, or agricultural system equate to the sum of direct use and leaching demand; leaching demand is the amount of water, in addition to crop water requirements, needed to leach excessive salts from the crop root zone. Water supply comes from different sources (e.g. canal supplies, rainfall, groundwater, surface storage, snowmelt, glacial runoff, etc.) and is further constrained by the total volume of stored surface water and groundwater extraction capacity (Inam et al., 2017). Recently, technological innovations – including deep tube wells and high-powered pumps – significantly altered water management behaviors in arid regions, including Pakistan. Deep tube wells have allowed continual, unsustainable drawdown of aquifers as well as access to previously unused groundwater sources, wherever available. Pumps have allowed faster abstraction from canals and rivers than previously possible, disrupting historical patterns of water consumption and disrupting the sustainable water management landscape in terms of resource allocation and organizational arrangements. Concurrently, populations have continued to grow, increasing the demand for water. As a consequence, the probability that poor water resource management and allocation alternations will significantly limit the socioeconomic development of many arid and semi-arid regions is quite high; these trends in cascading socio-environmental vulnerability and fragility are only exacerbated by the pressures of global climate change (Arab Water Council, 2009). Climate change has the formidable potential to affect socio-environmental systems at all livelihood and management levels, it is therefore crucial that all dynamic communities, especially those in the highly-vulnerable arid and semi-arid regions, examine the current state of their socio-environmental systems with respect to unique adaptive capacities and potential for developmental transformation.

2.1.3. Adaptive Capacity and Transformation in Socio-environmental Systems

High adaptive capacity imparts resilience to an individual, community, or social-ecological system, improving the likelihood of maintaining a desired level of functioning, or imparting the ability to transition to a new favorable state when the current state is untenable or undesirable (Folke, 2006). According to Berkes and Folke (1998), successful adaptive approaches for ecosystem management under uncertainty must: (1) build knowledge and understanding of resource and ecosystem dynamics, (2) develop practices that interpret and respond to ecological feedbacks, and (3) support flexible institutions/organizations and adaptive management processes. Adaptability has been defined as the capacity of actors in a system to influence resilience; by contrast, transformability has been defined as the capacity to create a fundamentally new system when ecological, economic, or social structures make the existing system untenable (Walker et al., 2004).Transformations have alternatively been defined as purposeful, anticipatory responses to environmental change (e.g. Nelson et al., 2007; Kates et al., 2012), processes of transitioning toward sustainability (e.g. Frantzeskaki et al. 2012), concepts to aid in confronting power imbalances and sources of vulnerability (e.g. O'Brien, 2012), or as socio-environmental characteristics associated with the loss of resilience (e.g. Walker et al., 2004; Folke et al., 2010). Systemic transformation is conceptually linked with the process of regime shifts, and in a substantial portion of the socio-environmental and resilience literature, the two terms are used synonymously.

Regime shifts are large, abrupt, persistent changes in the structure and functioning of ecosystems (Biggs et al., 2012). A regime shift is a deviation of the system from one basin of attraction to another when a critical threshold or tipping point is exceeded. In ecology, regime shifts (or transformations) have been modelled as bifurcations in dynamic systems, comprehensively assessed with regard to changes in the dominance of positive (reinforcing) and negative (dampening) feedback loops (Polhill et al., 2015). An important and notable characteristic of regime shifts is that once they have occurred, they can be difficult or impossible to reverse due to the fact that degraded system states are often highly resilient. A popular and highly-examined example of a regime shift in an ecosystem is the shift of a shallow lake from a clear water state dominated by macrophytes, to a turbid state dominated by planktonic algae (Carpenter, 2003; Scheffer, 2009). This shift is caused, in part, by the flow of untreated sewage water into the lake, as well as the inflow of nutrients - notably phosphorus – from neighboring agricultural expanses. The creation of new stability landscapes and new basins of attraction during a transformation or regime shift may take decades (Folke et al., 2010); however, the final stage of transformation, the movement from one basin of attraction to another, can happen quite quickly (months to years) and may even come unexpectedly (Anderies et al., 2013).The characteristics of socio-environmental transformability have much in common with those of general resilience, including high levels of all forms of capital, diversity in landscapes, institutions, participants and their networks, learning platforms, collective action, and support from higher levels of government (Folke et al., 2010). When a socio-environmental system exhibits high adaptive capacity or is able to smoothly transition from one functional basin of attraction to another, the system in question is classified as being highly resilient.

2.2. Resilience In-depth

Resilience thinking may attribute much of its current popularity to its widespread conceptual and practical applicability; resilience has different meanings and implications depending on the reference frame or field in which it is used. Increasingly, publications are produced with the primary goal of comprehensively reviewing the different definitions and connotations of resilience (e.g. Walker et al., 2004; Folke, 2006; Bahadur et al., 2010; Martin-Breen and Anderies, 2011). Many publications focus on the semantics and lexical intricacies of the term as opposed to concrete applications or practical uses; this has resulted in a breadth of resilience literature consisting of contrasting ideas and a general lack of objective understanding; however, across disciplines, resilience consistently denotes the capacity to rebound or recover after a shock or disturbance (Gunderson, 2010). In recent years, the concept of resilience has gained not only scientific recognition, but also colloquial acceptance. Figure 2.1 shows the increase in monthly internet search trends for the term “resilience” since January 2004. Numbers represent search interest relative to the highest point on the chart for the given time. A value of 100 is the peak popularity for the term. A value of 50 means that the term is half as popular. A score of 0 means there was not enough data for this term.

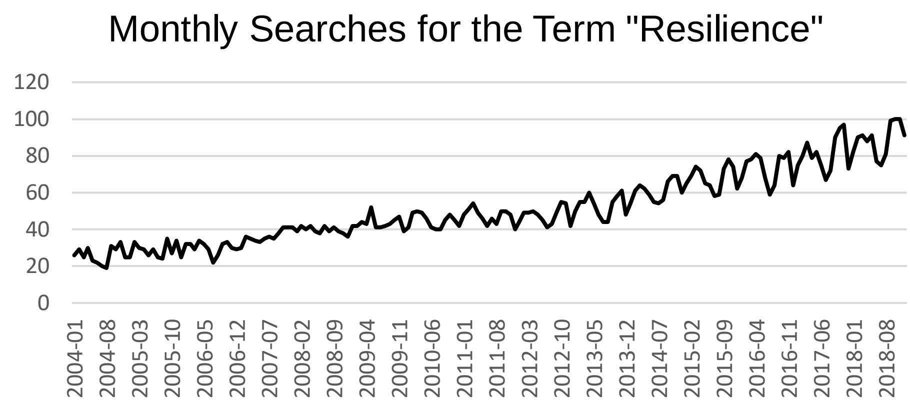

Fig. 2.1. Google search trends for the term "resilience" (2004-2018).

Walker et al. (2004, 2006) describe resilience as the ability of a system or entity to sustain a shock and continue to function and, more generally, cope with change. Among the assorted scientific spheres, resilience has emerged as a cognitive framework for understanding how dynamic systems self-regulate and evolve over time. Carpenter et al. (2001) suggested the need to address the query: "resilience of what to what" in relation to regime shifts, including specific measures of early warning signals or functional diversity (Elmqvist et al. 2003, Scheffer et al. 2009). When variables, drivers, and behavioral dynamics are properly understood for a system of interest, the "of what to what", described by Carpenter et al. (2001), is referred to as *specified* resilience. Specified resilience is often defined in contrast to the conceptually related term *general* resilience. General resilience refers to wide-swath, system-level characteristics, such as the capacity to construct and enhance adaptive learning skills (Walker et al., 2009; Folke et al., 2010). The working explanation of specified resilience frequently implies a more discrete definition of system boundaries. There have been several detailed studies of specified resilience in socio-environmental contexts with regard to the size of basins of attraction for both the baseline and ideal states of a system; these 'basin of attraction' metrics measure the shock magnitude a system can tolerate before its behavior fundamentally shifts (Carpenter et al., 1999; Anderies et al., 2002, 2006; Anderies, 2005; Peterson et al., 2009). Key strategists may utilize resilience concepts to reliably navigate a decision-making paradigm for short term choices; resilience thinking may also be used to provide clarification of how a system could change or transform over longer periods (Anderies et al., 2013). Generally speaking, definitions of resilience (i.e. specified versus general resilience) are scale dependent; consequently, temporal scales are system-dependent and may be short, intermediate, or long-term. To reiterate, resilience is a function of the size of basins of attraction, thresholds, regime shifts, and – in a natural sciences context – the extent to which environmental systems regulate these domains by affecting the topology of basins of attraction, avoiding thresholds, or actively crossing them as appropriate (Anderies et al., 2013). Table 2.1 contains a selection of different definitions of resilience from various scientific domains and sub-disciplines.

Table 2.1: Resilience definitions across disciplines (*Francis and Bekera, 2014; Quinlan et al., 2015*)

System	Relevant Resilience Sub-types	Resilient Properties	Resilience Metrics
Infrastructure	Engineering Resilience	Ability to anticipate, absorb, adapt, or rapidly recover from shock event	Time to recover, rate of recovery return to equilibrium
Safety Management	Engineering Resilience, Psychological Resilience, Social Resilience, Ecological Resilience	Ability to anticipate and avoid threats, ability to preserve functional identity & goals	Anticipation, vulnerability, robustness adaptive capacity
Organizational	Ecological Resilience, Social Resilience, Community Resilience	Ability to recognize unanticipated disturbances, evaluate existing model of preparedness, and improve adaptive capacity	Robustness, stability, response efficiency
Economic	Ecological Resilience, Social Resilience, Economic Resilience	Resourcefulness, ability to withstand different shocks Without losing the ability to efficiently use/disperse resources	Economic response capacity
Social	Developmental Resilience, Community Resilience Psychological Resilience, Social Resilience	Ability to cope with stress and degrade gracefully	Coping, adaptation, processing efficiency
Personal	Developmental Resilience, Psychological Resilience Social Resilience	Ability to tolerate stress, adaptive capacity, learning new coping skills	Vulnerability, robustness
Ecological	Ecological Resilience, Engineering Resilience Community Resilience	Reorganize while undergoing change, retain similar structure, functioning, and feedbacks	Buffer capacity, persistence, robustness
Socio-environmental	Ecological Resilience, Engineering Resilience Economic Resilience, Social Resilience	Ability to retain structure and functioning, resist change, retain relationships between system variables (i.e. people and resources)	Adaptive capacity, learning, innovation

System uncertainty is partially determined and greatly influenced by the combination of specified and general resilience; as such, resilience theorists do not attempt to circumscribe all of the uncertainty in a particular system of interest, instead, system boundary definition is treated as a function of the distinction between general and specified resilience, and between resilience and robustness more generally. Several terms appear in the resiliency literature acting both as distinct concepts and elemental descriptors of resilient systems and processes. For example, Anderies et al. (2013) define the terms "sustainability," "resilience," and "robustness" separately, and take great care in distinguishing, and subsequently relating, the concepts in a greater environmental context. They argue that each of the three ideas has distinct strengths for addressing specific problems at discrete scales and socio-ecological tiers, but not one of the terms covers the entire breadth of relevant scales, levels, and problems. Robustness focuses on the fundamental rules governing feedback systems, and the fragility tradeoffs associated with a range of policy measures or governance structures. The concept of robustness explicitly links system dynamics to performance measures, whereas sustainability is a blanket-concept necessarily consisting of attributes from both resilience and robustness conceptual frameworks. In a resilience context, the nature of persistence and transformation in complex systems may be linked using a robustness framework. We can use the concept of robustness to assess performance measures and to operationalize a sustainable decision-making paradigm. Shocks are distinct examples of variation in system inputs, therefore, reduced sensitivity of outputs to shock regimes may be interpreted as increased system robustness; if outputs are associated with the continued functional performance of a system (or the efficient recovery of that system), then robustness and resilience are related. Anderies et al. (2013) recommend aligning notions of sustainability (resilience + robustness) with key concepts from system dynamics to elucidate the effects individual actions have at the system level. The present study focuses on system-component resilience as an imperative and fundamental element in the grander scheme of socio-environmental sustainability.

Instead of characterizing resilience as ‘specific’ or ‘general,’ or defining it as a component of general systemic sustainability, many researchers have opted to explore two additional, complementary perspectives on resilience. The first idea focuses on the transient impact of disturbance and the subsequent recovery of an ecosystem; this has been termed *engineering* resilience. The second view, *ecological* resilience, considers resilience as the capacity of an (eco)system to withstand a transition to an alternative state in the face of disturbance (Ingrisch and Bahn, 2018). In the realm of engineering resilience, researchers focus on sustaining system-level functional efficiency, constancy of the system, and the maintenance of a single, predictable steady state. Engineering resilience – often employed in industrial or urban resiliency domains – is about resisting disturbance and alteration to conserve predictable functionality in the current state-space (Folke, 2006; Folke et al., 2010). Figure 2.2 (2a and 2b) represents the paradigmatic difference between engineering and ecological resilience illustrated by a ball-and-cup heuristic (Scheffer et al., 1993; Walker et al., 2004). Engineering resilience is concerned with whether the system can remain at the *bottom* of the stability basin; while the notion of ecological resilience is concerned with whether the system can remain within the current basin, or whether the system will experience a sustainable regime shift (Holling, 1996). In an effort to comprehensively determine the comparative resilience exhibited by adjacent system-components under varied shock conditions, the present study defines a new procedure for quantifying characteristic elements from both engineering and ecological resiliency frameworks.

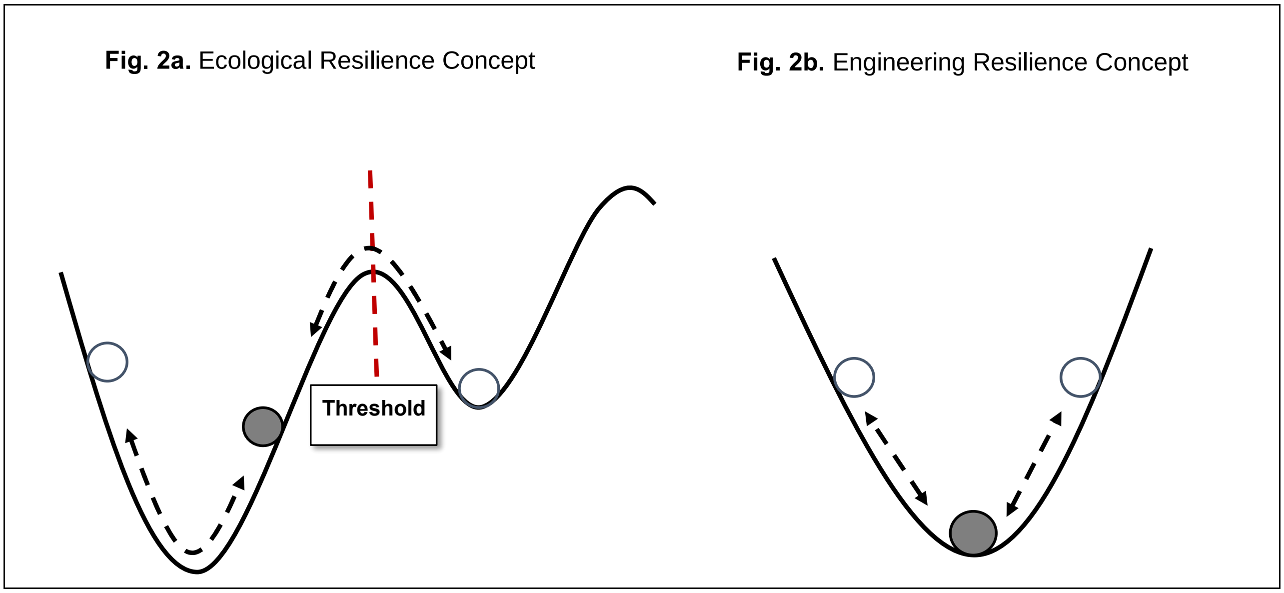

Fig. 2.2: 2a, 2b. Ecological vs. Engineering Resilience (*modified from Walker et al., 2004*)

The concepts of ecological and engineering resilience are not mutually exclusive; urban and industrial spaces still exist under an ecosystem paradigm and may exhibit 'behaviors' consistent with ecologically resilient systems. Vale and Campanella (2005) define urban resilience as the capacity of a city to rebound from destruction; this is comparable to Holling's (1996) definition of engineering resilience. The EPA's definition of urban climate resilience is "a city's ability to reduce exposure and sensitivity to, and recover and learn from, gradual climatic changes or extreme climate events" (EPA, 2017). With the imminent threats of climatic catastrophes and increased global urbanization, many researchers have begun studying critical infrastructure resilience using system dynamics in a climate change context (Cavallini et al., 2014).

Resilience narratives have been accused of reframing issues in ways that reposition the responsibility for socio-ecological security onto the populations affected by shocks and disasters. Resilience has also been interpreted by some as a potential form of 'governmentality' through which neoliberal ideas and discourses are perpetuated and adopted in certain municipal systems.

Internationally, the compilation of frameworks and agreements developed for the post-2015 era, including goals on climate change, disasters, and humanitarian and development assistance, have all contained significant reference to, and framing around, resilience. Indeed, resilience is a compelling conceptual metric for measuring the efficacy of development assistance and humanitarian aid. Resilience thinking highlights the positive capacity of a dynamic system to mitigate and adapt to disturbances; as such, the establishment of a reliable method for resilience monitoring and measurement could prevent individuals, households, and communities from suffering long-term adverse consequences of shocks, disturbances, or compound stresses.

2.2.1. Measuring Resilience

Many authors have acknowledged the inherent challenges in measuring resilience and suggest several divergent methods for doing so (Carpenter et al., 2001; Bennett et al., 2005; Cumming et al., 2005; Fletcher et al., 2006; Darnhofer et al., 2010). Some researchers advocate the development of context-dependent *surrogates* of resilience for each system to be measured in place of resilience itself (e.g. Bennett et al., 2005); others take a more quantified approach by applying mathematical models (e.g. Fletcher et al., 2006), using a stochastic systems-level approach for modeling and analysis (D'Lima and Medda, 2015; Klammler et al., 2018), using entropy to define and measure resilience (Tamvakis and Xenidis, 2013), quantifying resilience using a spatially explicit model of forest dynamics (Cantarello et al., 2017), quantifying seismic resilience of infrastructure (Cimellaro et al., 2006), or studying resilience through the application of Hidden Markov Models (HMM) (Panerati et al., 2018).

Generally speaking, the first step of a systematic resilience assessment should involve local context and site documentation. Researchers should document essential demographics, capacities, livelihood networks, and coping mechanisms already present in the system of interest; relevant shocks and stressors should also be identified at this stage. Step two focuses on data collection strategy; researchers must note what, when, and how to measure shocks, as well as the ideal frequency of data recording. The third step is comprised of the actual data analysis; this is done in order to gain holistic, descriptive comprehension of the current and future states of the study system. Thorough qualitative data assessments prior to shock implementation and/or analysis allows researchers to make important inferences about the adaptive capacity of local stakeholders, communities, and ecosystems.

An effective, long-term resilience study should inherently incorporate both *pulse* and *press* types of system disruption, i.e. short disturbances *and* long-term perturbations of varying magnitudes (Walker et al., 2006; Shade et al., 2012; Cantarello et al., 2017). However, regardless of the type, intensity, or duration of a system-level shock or disturbance, a reliable method for obtaining data relevant to the functional responses of a system experiencing stress is critical to the resilience assessment process. When attempting to identify and gauge the level of resilience exhibited by a particular system, there are several methods for obtaining concrete, analyzable data; these methods are typically separated into qualitative and quantitative analytical processes.

2.2.1.1. Qualitative Assessment Methods

There are currently many useful frameworks for measuring resilient development in social, environmental, economic, and governmental systems (Resilience Alliance, 2010; Lisa, 2015). However, it is admittedly challenging to bring together all elements of a system (e.g. economy, society, environment), in such a way as to successfully identify what makes a complex system resilient. Researchers and stakeholders must explore which elements of the system in question need to be strengthened and which elements might undermine resilience; in order to do this, many resilience specialists recommend using indicators. Indicators aid in identifying specific vulnerabilities and gaps in resilience with respect to concrete objectives; this encourages targeted policies to be defined and, with concurrent evaluations of the effectiveness of adaptation actions or programs, allows complex systems to achieve greater resilience (Bizikova et al., 2017). Socioeconomic systems are dynamic and interactive, as such, many socio-environmental resilience indicators are similar to those that assess socioeconomic vulnerability and adaptive capacity. Indicators are important tools that can be useful when trying to gain greater understanding of a system and its elements and feedbacks; however, while the indicator approach is valuable for monitoring trends and exploring conceptual frameworks, indices are characterized by several limiting factors, including considerable subjectivity in the selection of variables, relative weights of the variables and metrics in question, the availability of data at various scales, and by the difficulty of testing or validating the different metrics (Luers et al., 2003).

A participatory resilience assessment is one good example of a qualitative framework for vulnerability and adaptive capacity analysis. As the name suggests, a participatory resilience assessment involves the active participation of relevant stakeholders in some or all of the steps required for building a holistic understanding of the socio-environmental dynamics of a stressed system. The resilience assessment framework presented by the Resilience Alliance (2010) is a participatory procedure, which starts by using strategic questions and activities to construct a conceptual model that represents the socio-ecological system of interest, along with its associated resources, stakeholders, institutions, and issues. This assessment guides the user through the identification of potential thresholds between alternative system states and helps illuminate the factors contributing to or eroding system resilience. A simple assessment like this can provide insight into developing strategies for preparing or adapting to both known and unexpected disturbances (Resilience Alliance, 2010). Qualitative rapid assessment approaches have also been developed that focus on surveys and stakeholder knowledge of the systems in which they reside (Nemec et al., 2013). Although this approach is not strictly data-intensive, it provides metrics which can be used to assess uncertainty, relative resilience among similar systems, and the capacity to assess trade-offs among social, economic and ecological facets of complex systems. A qualitative strategy, much like the frameworks devised by the Resilience Alliance (2010) and Nemec et al. (2013), was used during the participatory model-building process that took place prior to implementation of the current study's quantitative assessment regime. However, these qualitative methods can often seem arbitrary and, while this might be beneficial during the initial stages of system exploration, qualitative indicators may eventually become too vague or subjective for the execution of an effective, replicable resilience analysis.

2.2.1.2. Quantitative Measurement Methods

While the qualitative information gained through in-depth discussions and workshops involving local community members and key stakeholders is highly valuable during the initial assessments of an unfamiliar system, the process of resiliency analysis cannot be made truly replicable and concrete until certain parameters and measurement heuristics are *quantified*. Quantitative methods for measuring resilience have been explored for climate change adaptation (Tyler and Moench, 2012) and military applications for improving risk analysis (Eisenberg et al.

2014). Advances in the development of resilience parameters have also come from the field of economics, with the application of inclusive wealth measurements as an economic dimension of sustainability (Pearson et al. 2013).

Since the early explorations of Holling (1973), researchers have developed the concept of resilience so as to also explicitly focus on *intentional* socio-environmental systemic changes; these are transformations or regime shifts that may be necessary to maintain the general (or positive) functioning of a system when state-space conditions are altered (Folke et al., 2010). Spatial approaches for resilience quantification utilizing the geometric relationships among spatial attributes of systems have also been recently developed (Cumming, 2011). Substantial methodological improvements have been made in recent years in ecology, with many approaches, including network analyses, discontinuity analyses, time-series and spatial analyses, allowing for the quantification of attributes of resilience. However, much of the social resilience research remains qualitative, and the implementation of quantitative approaches is partly limited due to the skepticism of scholars about the capacity to make complex system dynamics sufficiently accessible (Angeler and Allen, 2016). Although there are many more functional methods for analyzing the resilience of a system qualitatively, the literature on quantitative resiliency analysis is beginning to appear more diverse and substantial; the improved quantitative literature will surely result in more comprehensive resiliency analyses, particularly when paired with effective qualitative methods. For example, in a quantitative analysis of soil resilience, Todman et al. (2016) assume that the variable under investigation is an observed function of the system, but the variable could also represent a *state* of the system, as it does in the present study; i.e. due to the integrative and dynamic nature of the coupled P-GBSDM used in this study, the functional responses of component-level variables in the system are indicative and representative of overall system vulnerability and stability.

The collection of long-term reliable data sets is one frequently-cited hinderance to the resilience quantification (and assessment, more generally) process. However, this lack of data can be addressed by combining related data sources to form a more complete picture of system processes. Since panel datasets are costly to collect and, where they are available, are collected at low frequency, USAID has used climate and weather indices to measure vulnerability and resilience via two different estimation techniques, namely, standard ordinary least squares (OLS) regressions to estimate the climate-consumption relationships, and a distributed lag non-linear model (DLNM) to account for consumption dynamics (Vollenweider, 2015).

Several authors have explored the concept of quantifying resilience based on the functional response of systems or variables to relevant shock scenarios (e.g. Cimellaro, 2010; Todman et al., 2016; Ingrisch and Bahn, 2018). This method for resilience quantification is centered on the identification of several metrics of a resilient response to disturbance, which are quantified based on the study system's variable-level reaction to being pushed out of a normal functional state. Figure 2.3 illustrates the initial shock and rebound of a system undergoing a disturbance; the functionality of the system – and by proxy the system's resilience – is described by a very basic differential equation where 'Q' is defined as overall system performance.

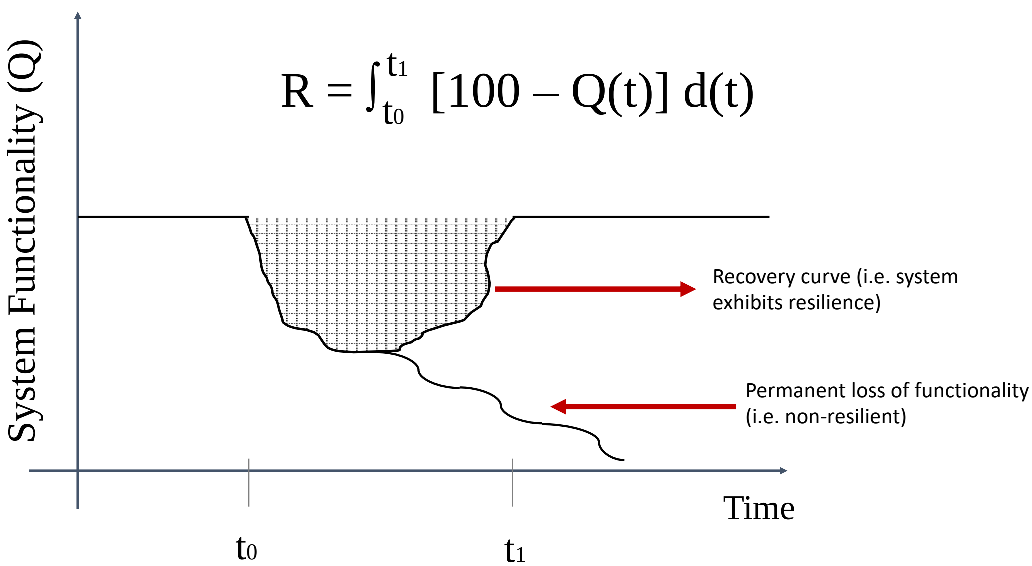

Fig. 2.3. System performance before, during, and after disturbance (adapted from *Yodo and Wang, 2016*)

However, it should be noted that the application of qualitative methods for the development of the system dynamics (SD) portion of the dynamically coupled model used in this study was paramount to the successful completion of this research.

2.2.1.3. Shock Scenario Simulation

Shocks can be strictly anthropogenic (e.g. market or industrial disturbances) or naturally occurring (e.g. droughts, floods, or disease epidemics). Each type of shock will affect individuals, networks, and higher-level system processes in distinct ways. For example, economic shocks can affect labor demand, asset holdings, food consumption patterns, market functions, or commodity prices, which in turn affect individual or household well-being (Choularton et al., 2015). The effects of natural system disturbances include: crop yield fluctuations, infrastructure and market problems, as well as personal property and asset destruction. Personal health and socio-agricultural shocks can affect the productivity, income-generating capacity, and food consumption patterns of individuals and communities (Choularton et al., 2015). Figure 2.4 includes notable examples of common shocks and stressors from the resiliency literature.

Environmental Shocks	Anthropogenic Shocks	Biological Shocks	Industrial Shocks
- Tornadoes - Flooding - Climate Variability - Hurricanes/Cyclones - Earthquakes - Landslides - Tsunamis - Volcanoes - Heat Waves - Drought - Severe Thunderstorms - Wildfires	- Fire/Arson - Crime - Violence/Conflict - Terrorism - Market Failures - Poverty - Population Pressures - Migration - Landscape Degradation - Discrimination - Coups - Poor sanitation	- Vector-borne diseases (e.g. flu, malaria, dengue fever) - Hepatitis - Cholera - HIV/AIDS - Ebola - SARS - Polio	- Toxic spills - Power grid failure - Nuclear disaster - Dam/Levy failure - Factory fires - Explosions - Pollution - Infrastructure Degradation

Fig. 2.4. Common shocks and stressors (*adapted from Sagara, 2018*)

2.2.2. Modelling Resilience

The aspect of this thesis research that makes the findings herein particularly innovative and unique, is the application of a dynamically coupled, group-built system dynamics and physical model (P-GBSDM) for a comprehensive and comparative socio-environmental resilience assessment. A resilience assessment of this nature has, until the publication of the present research, never been conducted using this unique type of modelling framework. The P-GBSDM employed in this study was originally constructed through the use of participatory modelling methods with local stakeholders in the Rechna Doab Basin of northeastern Pakistan. The group-built, socioeconomic and environmental SD model was subsequently coupled with a biophysical soil salinity model (SAHYSMOD) using a dynamic model-wrapping technique and innovative programming package, Tinamit, which allows the coupled model to exchange data between its constituent parts at run-time (Malard et al., 2017).

There are several different modelling approaches (explained in greater detail below) that have the potential to provide useful information in a socio-environmental resilience assessment. In participatory modelling, stakeholders are encouraged to identify and define key system variables and relationships in order to build a more cohesive and realistic representation of system dynamics (Halbe and Adamowski, 2011; Butler and Adamowski, 2015; Inam et al., 2015, 2017). Participatory modelling often results in the development of indicators or qualitative indices of risk and adaptive capacity (Schipper and Langston, 2015). Participatory modeling approaches are particularly appropriate for complex problems, especially ones where conflict is anticipated. Potential benefits of the participatory modelling process can include team learning, improved information sharing between stakeholders, enhanced future vision, stakeholder consensus development, and/or the generation of commitment to change and adaptation (Langsdale et al., 2009).

Several authors have suggested modeling resilience using differential equations (Boker et al., 2010; Todman et al., 2016); these authors often use the analogy of a damped spring or oscillator system to represent a resilient ecological response, which is reliable considering the functionality of a system (e.g. structural, organizational, etc.) can often be described by nonlinear differential equations similar to the ones that apply to the fundamental laws of mechanical systems (Cimellaro et al., 2010). Each method relies on the basic assumption that systems experience a measurable amount of change when confronted with varying degrees of stress. In equation-based models, for example, systemic change implies that, not only will change occur in variable values, but the spectrum of functional relationships within the model will transform as well; this transformation could result in new variables and/or processes being introduced and old ones being deleted (Polhill et al., 2015). Modelling resilience has become increasingly common in both natural and human-based system studies; however different models and modelling frameworks provide different types of information with respect to identifiable metrics of a resilient response to stress.

2.2.2.1. Resilience Analysis: System-dynamics Modelling

System-dynamics (SD) (Forrester, 1961) is one of the most encouraging and useful approaches for modelling socioeconomic processes. Due to its intuitiveness and capacity to integrate various inputs from a range of different viewpoints, disciplines and processes, SD modelling allows for holistic environmental impact assessments (Malard et al., 2017). SD organizational structures are of particular interest in participatory model building as they permit participants to construct models of the environmental systems they work with using a highly visual procedure (Stave, 2003; Simonovic, 2009). *Participatory* system dynamics modelling is a method by which stakeholders develop conceptual models of environmental and socioeconomic systems based on inherent feedbacks present within the system of interest; these feedback loops are then quantified to test scenarios (Renger et al., 2008). According to Beall and Ford (2010), when faced with complex, multi-stakeholder environmental issues, system dynamics modelling efforts have the greatest potential for success when used in a participatory fashion by scientists and managers working together with decision-makers or local citizens who also have a stake in land management decisions. The elucidation of key elements within the organizational structure of systems models also allows for the improved identification of slowly-changing variables, stabilizing and destabilizing forces, and important thresholds that aid in determining overall system resilience (Bennett et al., 2015).

Several authors have explored the concept of quantifiable resilience characteristics in the context of SD modelling. For example, Simonovic and Peck (2013) were the first to establish a framework for quantifying resilience as an evolving, transient, dynamic value through the use of a SD simulation approach. Simonovic and Peck (2013) developed their resilience analysis methodology by considering the economic, social, organizational, health, and physical impacts of climate change on the frequency and severity of coastal urban flooding. Gotangco et al. (2016) used a generic SD modelling template to analyze the impacts of flooding on community and government assets in Pasig City, Metro Manila. The SD simulations employed in the Gotangco et al. (2016) study were used to quantify the loss of system performance as well as the recovery of the system in adverse conditions. Likewise, Candy et al. (2015) used SD scenario modelling to analyze the long-term resilience of the Australian food system to different climatic pressures.

2.2.2.2. Resilience Analysis: Physical Modelling

Qualifying different aspects of resilience using a SD approach is useful and relatively accurate, but *quantifying* resilience using SD methods is a complex and relatively new endeavor in the world of modelling. However, researchers have been modelling physical systems and their respective responses to endogenous and exogenous disturbances for many years. For example, in the area of infrastructure systems, Cox et al. (2011) developed a set of operational metrics (vulnerability, flexibility, and resource availability) for estimating the resilience of a transportation system facing sudden shocks. Miller-Hooks et al. (2012) measured the resilience of freight transportation networks as the fraction of the post-shock product-demand that can be confidently delivered. Todman et al. (2016) and Ingrisch and Bahn (2018) used physical modelling approaches to better understand the shock-response dynamics of soils under different levels of chemical and physical stress. In the hydrological field, Fowler et al. (2003) modeled changes in weather type frequency, mean rainfall, and potential evapotranspiration in order to reliably assess the impacts of climate change on water resource reliability, resilience, and vulnerability in Yorkshire, UK. Data produced by physical models are often highly replicable and reliable, however physical models often lack the dynamic feedback mechanisms and loops which can be incorporated in SD frameworks. It is for this reason that a comprehensive assessment of any complex system is likely to be more realistic if model users employ a coupled modelling framework, consisting of both physical and SD model variables and connections.

2.2.2.3. Resilience Analysis: Coupled Modelling

Coupled models are integrated computational structures which are able to represent the variables from each constituent model type and are also capable of facilitating the flow of feedback information between variables of each individual model. Coupled modelling for the purposes of conducting quantifiable resilience assessments is not a new concept, however the practical *application* of coupled models for producing reliable measurements of systems resilience is still quite rare. Schibalski et al. (2018) have suggested a framework for coupling a process-based model (PBM) and a statistical species distribution model (SDM); their integrated model is able to transfer the outputs of a resilience analysis by the PBM to SDM predictions. The resulting hybrid model combines the advantages of both approaches: the convenient applicability of SDMs and the relevant process detail of PBMs. Using the coupled model, Schibalski et al. (2018) investigated the effects of abrupt, short-term groundwater level and salinity changes on coastal vegetation at the German Baltic Sea.

The spatially explicit model used by Bitterman and Bennett (2016) couples land use, biophysical models, and economic drivers with an agent-based model in an attempt to better understand the effects of disturbances and policy alterations on system behavior. The spatially explicit model used by Bitterman and Bennett (2016) couples land use, biophysical models, and economic drivers with an agent-based model in an attempt to better understand the effects of disturbances and policy alterations on system behavior. In order to assess system-state resilience, Bitterman and Bennett (2016) analyzed the capacity of local farmers to remain “in business” by the end of various disturbance scenario simulations. Farmers were labeled *resilient* if farm profits returned to a stable equilibrium equivalent to that of the pre-disturbance state. A coupled modelling approach (described in detail in subsequent sections) similar to that employed by Bitterman and Bennett (2016), was used in both studies constituting the present research to quantify five metrics of a resilient response to disturbance in the Rechna Doab basin of northeastern Pakistan.

2.2.3. Resilience and Public Policy

Policy-making for the improved resilience of infrastructure, individuals, economics, and environmental systems is quite an old process. The goal of resilience policy-making is almost always to improve disaster mitigation measures and enhance system robustness to shocks or disturbances; but how does a researcher, stakeholder, or interested third-party go about classifying policies based on their influence of a system with respect to resilience? It is clearly important to consider which features of the response are being sought or understood by the resilience analysis in any given context, in order that participants can compare and contrast the truly salient features of the data sets. It is crucial that the key questions surrounding the resilience of each system are carefully framed; in other words, researchers must know what a non-resilient response will look like for the variables measured in relation to the desired outcome for the system in question (Todman et al., 2016). Once the characteristics or metrics of resilience for a system have been identified, it is theoretically quite easy to integrate those measurements into sustainable and impactful policy measures; however, in practice this process is not always seamless. If legislators, decision-makers, or key stakeholders do not a have a reason to trust the information constituting the foundation of any new policy changes, these changes are not likely to be enacted or abided by; as such, policy decisions must be grounded in stakeholder-supported informational pathways. Participatory modelling and enhanced stakeholder engagement throughout the resilience assessment process can greatly alleviate this propensity for mistrust.

Inam et al. (2015, 2017, 2017a) were able to identify and test five stakeholder-defined policy suggestions (SDS): 1. Canal lining, 2. Equal water distribution, 3. Reallocation of irrigation water, 4. Water banking, and 5. Salinity Control and Reclamation Project (SCARP) (three of which were tested in the second study of the present research) through a participatory modelling process in the Rechna Doab basin. One key objective for the research conducted by Inam et al. (2015, 2017, 2017a) was understanding possible means for improving agricultural sustainability, particularly through water resources management. According to Inam et al. (2017a), the general effects for each policy suggestion on soil salinity were as follows: The canal lining scenario (SDS1) produced a considerable reduction in root zone salt concentrations both spatially and temporally. The canal water reallocation scenarios (SDS2 and SDS3) produced a gradual reduction in soil salinity on the watershed scale. The water banking scenario (SDS4) produced an insignificant effect when compared with the baseline scenario. The SCARP scenario (SDS5) produced a considerable spatiotemporal increase in soil salinity over the entire watershed, which is a high undesirable response, but was entirely expected. The solutions with respect to water availability elicited the following results: SDS1 showed a temporal increase in water availability over the entire watershed. Compared to the base case scenario no increase in water availability was observed in SDS2 and a 0.35% increase was observed in SDS3. Scenario 4 showed similar trends when compared to the base case scenario. Scenario SDS5 produced a considerable increase in water availability over the entire watershed; however, the increase was mainly due to groundwater extraction from high-capacity tube wells. The SCARP project showed positive impacts in terms of water availability and farm income via increased water supplies but had adverse results with regard to soil salinity and is therefore not a sustainable policy. The farm income results for scenario 1 were promising; this option produced a 39% increase in farm income when compared to the base case scenario. This considerable increase in farm income can be attributed to an increase in canal water supplies due to reduced seepage losses. Scenario 2 produced a 6% increase in incomes and in SDS3 an 11% increase was observed when compared to the base case scenario. Scenario 4 trends did not deviate substantially when compared to the base case scenario, this indicates that water banking might not be a feasible option, likely due to the scarcity of water attributable to the arid climate.

The present study employs three of the stakeholder-suggested policy measures outlined above (i.e. 1. Canal lining, 2. Irrigation improvement (via equal water distribution and reallocation), and 3. Water banking (via rainwater harvesting). Based in part on the detailed information gathered from Inam et al. (2017a), the resilience quantification methodology described herein was used to determine the capacity of each policy scenario to confer or hinder resilience in the Rechna Doab watershed.

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CONNECTING TEXT TO CHAPTER 3

This chapter outlines the background, development, and testing of the primary resilience quantification methodology explored in this thesis. Methodological development was informed by an extensive literature review related to the background of resilience assessments in dynamic systems, current methods of resilience measurement, resilience in modelling, and existing methods for quantifying resilience using a coupled modelling approach. This methodology makes use of 30 years of socioeconomic, environmental, and biophysical data (1989-2019) in the Rechna Doab basin to produce functionality curves from which five resilience metrics can be assessed based on the average behavior of each study variable over the 30-year testing window. Each study variable tested in this chapter was subjected to multiple different shock scenarios of varying type, intensity, and duration in order to determine the degree of resilience exhibited by each individual variable compared to the other variables in this study under identical shock conditions. The methodology described in Chapter 3 was designed to be streamlined, replicable, and stakeholder-friendly, thereby promoting its use as a legitimate and effective tool for resilience analysis in complex systems where modelling experts are not always present.

This chapter was submitted for peer-review in the journal Ecology and Society (Carper *et al.*, under review). The format has been modified to be consistent with the remainder of this thesis. All literature cited in this chapter is listed at the end of the chapter.

CHAPTER 3: **Quantifying the transient shock-response of dynamic agroecosystem variables for improved socio-environmental resilience**

Jordan M. Carper, Mohammad Reza Alizadeh, Jan F. Adamowski, Azhar Inam, Julien J. Malard

Abstract

In classic resilience thinking, there is an implicit focus on controlling functional variation to maintain system stability. Modern approaches to resilience thinking deal with complex, adaptive system-dynamics and true uncertainty; these contemporary frameworks involve the process of learning to live with change and make use of the consequences of transformation and development. In a socio-environmental context, the identification of metrics by which resilience can be effectively and reliably measured is fundamental to the understanding of the unique vulnerabilities that characterize coupled human and natural systems. The present study involves the development of an innovative procedure for the stakeholder-friendly quantification of socio-environmental resilience metrics. These metrics were calculated and analyzed through the application of discrete disturbance simulations, which were produced using a dynamically coupled, biophysical-socioeconomic modelling framework. Following the development of a unique shock-response assessment regime, five metrics: 1. time to baseline-level recovery, 2. rate of return to baseline, 3. degree of return to baseline, 4. overall post-disturbance perturbation, and 5. corrective impact of disturbance, describing distinct aspects of systemic resilience were quantified for three agroecosystem variables (farm income, water table depth, and crop revenue) over a period of 30 years (1989-2019) in the Rechna Doab basin of northeastern Pakistan. Using this procedure, it was determined that farm income is the least resilient variable of the three tested in this study. Farm income was easily diverted from the 'normal' functional paradigm for the Rechna Doab socio-environmental system, regardless of shock type, intensity, or duration combination. Crop revenue was the least stable variable (i.e. outputs fluctuated significantly between very high and very low values) and water-table depth was consistently the most robust and resistant to change, even under physical shock conditions. The procedure developed in this study should improve the ease with which stakeholders are able to conduct quantitative resilience analyses, and thereby bolster the adaptive capacities of socio-environmental systems with respect to both predictable and unanticipated shocks or disturbances.

Keywords: coupled modelling, metrics, quantification, resilience assessment, socio-environmental systems, *Tinamït*

3.1. Introduction

3.1.1. Defining Resilience

The term *resilience* has been used in a narrow sense to refer to the rate at which a perturbed system is restored to equilibrium; in a slightly broader context, it has been interpreted as the post-disturbance rebound time or the degree of functional recovery to a baseline of performance. Recently, resilience has emerged as a cognitive framework for understanding how dynamic systems self-regulate and evolve over time. Since the first published definition of ecological resilience by Holling (1973), researchers in the social and natural sciences have gained a vastly improved understanding of 'resiliency thinking,' which has informed the enhancement of disaster mitigation strategies, resilient infrastructure, personal and communal coping mechanisms, and adaptive capacities. In the present study, resilience is defined as the combined ability of a system-component variable to resist, and efficiently recover from, an array of socio-environmental shocks (i.e. disturbances in variable behavior that force the system to operate outside of its normal functional paradigm).

3.1.2. Measuring Resilience

Many research teams, special interest groups, official government entities, and think tanks have adopted similar yet slightly divergent heuristics for understanding resilience in socio-ecological systems (Gunderson, 2003; Walker et al., 2006; Gunderson, 2010; Angeler and Allen, 2016; Asadzadeh et al., 2017; Allen et al., 2018; Salomon et al., 2019; Cains and Henschel, 2020). Several of these heuristics are used by different groups to frame their specialized definition(s) of systemic resilience; for example, Folke et al. (2010) outline resilience as social-ecological persistence, adaptability, and transformability, while Gallopin (2006) defines the *linkages* between vulnerability, resilience, and adaptive capacity. Although many of these definitions have over-lapping elements, there still seems to be a lack of consensus regarding which aspects or behaviors of a system best exemplify resilient patterns. Several researchers have begun measuring resilience with specific respect to dynamic agroecosystems. Agroecosystem resilience has been assessed by applying ecological-resilience-based (e.g. Peterson et al., 2018) or behavior-based (e.g. Cabell and

Oelofse, 2012) indicator frameworks or, as is the case of the present study, by using the stability, resistance (robustness), and recovery of system processes as a basic framework for resilience monitoring (e.g. Hodgson et al., 2015; Oliver et al., 2015; Ingrisch and Bahn, 2018; Lamothe et al., 2019; Bardgett and Caruso, 2020).

3.1.3. Quantitative Measurement Methods

In this study, an approach was developed for quantifying the resilience of three socio-environmental variables in the Rechna Doab watershed. The approach developed herein was informed by the work of previous research teams (e.g. Hodgson et al., 2015; Nimmo et al., 2015; Ingrisch and Bahn, 2018) who developed independent but related methods for successfully quantifying the effects of anthropogenic pressures on ecological systems. Hodgson et al. (2015) and Nimmo et al. (2015) suggest mapping behavioral-response metrics onto a bivariate state space with joint consideration for the *resistance* and *recovery* characteristics of a system. Ingrisch and Bahn (2018) propose a similar method for disturbance response measurement by using the normalized impact of disturbance and the normalized recovery rate to define the bivariate space. Not unlike the preceding studies, the present study outlines the use of quantifiable metrics for developing a comprehensive understanding of the resilience of a given system or variable. The five metrics identified in the present paper as salient characteristics of a resilient functional response to disturbance (i.e. degree of return, rate of return, perturbation, time to return, and corrective impact) are based on the metrics used by Cimellaro et al. (2010), Todman et al. (2016), and Ingrisch and Bahn (2018) for analyzing the resilience of systems (using a physical model of soils, and computational and statistical models of industries, and ecosystems, respectively) and system-components to different exogenous and endogenous shocks. These characteristics could be applied to any time-series dataset that measures a change in variable functionality after a disturbance; in fact, when it comes to identifying robust, replicable methods for quantifying resilient behavior, one of the most reliable methods involves the monitored application of shock scenario simulations (e.g. Hodgson et al., 2015; Nimmo et al., 2015; Bitterman and Bennett, 2016; Todman et al. 2016; Meyer et al., 2018; Schibalski et al., 2018).

3.1.3.1. Shock Scenario Application

Shocks are disturbance events, which have the capacity to reduce the baseline (i.e. normal functional state) of any or all components within a dynamic system. The process of measuring and analyzing resilience using a shock-response regime is not conceptually complex, but it requires a systematic approach and sufficient knowledge of the variables involved. When a system or entity is ‘shocked,’ its response can be quantified based on the behavior of its constituent outputs over a known time-series. In other words, when the average behavior of system-components is known, a pronounced deviation in that behavior (as a result of shock application) belies inherent system vulnerabilities (Carpenter et al., 2009; Angeler et al., 2010; Anderies et al., 2013; Choularton et al., 2015; Todman et al., 2016; Ingrisch and Bahn, 2018). According to Sagara (2018), there are two primary benefits of incorporating shock-based measurements into the monitoring and evaluation process of a comprehensive resilience assessment. First, shock scenario analysis improves the conceptual understanding of complex relationships between disturbances, critical capacities, and socio-environmental well-being. Second, shocks and stressors pose significant operational threats to development gains; as such, acknowledging and understanding the capacity for efficient hazard-responses is a vital step in the assessment of overall resilience for any complex system (Sagara, 2018).

3.1.4. Modelling Resilience

Quantitative resilience assessment methods often involve the use of statistical or computational modelling techniques (Cimellaro et al., 2010; Cumming, 2011; Tyler and Moench, 2012; Hodgeson et al., 2015; Nimmo et al., 2015; Polhill, 2015; Bitterman and Bennett, 2016; Todman et al., 2016; Ingrisch and Bahn, 2018; Meyer et al., 2018; Schibalski et al., 2018). These methods allow for a more explicit description of system processes, enabling the user to obtain concrete, replicable data related to the specific vulnerabilities and adaptive capacities of individual variables within a system. Several authors have explored the concept of quantifiable resilience characteristics through the application of System Dynamics (SD) (e.g. Simonovic and Peck, 2013; Candy et al., 2015; Gotangco et al., 2016; Herrerra, 2017; Herrera and Kopainsky, 2020) and physically based models (e.g. Fowler et al., 2003; Cox et al., 2011; Miller and Hooks, 2012). However, it can be argued that the dynamic nature of complex socio-environmental systems is most reliably represented using a coupled physical-SD modelling approach, as coupled models are able to incorporate the concrete nature of physical data modelling with the connectivity and feedback flow of SD models.

Coupled modelling (i.e. the use of an integrated system of two or more models in which the communication and interchange of information between constituent models is facilitated computationally) with respect to resiliency analysis is still in its developmental infancy; however, there are several authors who have led the way in terms of coupled model applications for hazard vulnerability assessments (e.g. Schibalski et al., 2018). Through the use of a coupled modeling approach within the resilience and stability landscape domains, Bitterman and Bennett (2016) were able to sufficiently measure select aspects of agroecosystem resilience using a pre- and post-disturbance comparative functionality procedure. The present study employs a similar, baseline-reference methodology for analyzing resilience, with several important distinctions: First, the present methodology was developed in a participatory context, i.e. the resiliency assessment procedure has been devised with the ultimate goal of encouraging uninhibited, non-expert, stakeholder use; therefore, the methods described herein are intentionally user-friendly. Second, the methods employed by Bitterman and Bennett (2016) focus directly on system-level resilience with respect to stability landscapes, whereas the present study attempts to concretely quantify system-component *variable* resilience with discrete values relating to the variables' transient shock response, as opposed to average basins of behavior. Third, the integrated model employed in the present study was developed by coupling a stakeholder-built, system dynamics model with a biophysical model using the dynamic coupling software *Tinamït*, which allows the models to exchange information at runtime (Malard et al., 2017). This innovative form of model coupling allows for the improved exploration of complex relationships among various system elements, as well as the resulting behavioral dynamics of the system, while retaining stakeholder values and inputs (Inam et al., 2017). Fourth, Bitterman and Bennett (2016) performed repeated scenario simulations based on a set of contemporary farm data, whereas the present methodology involves the extraction of thirty years of historical dynamics and trends to better elucidate how system variables have interacted over time and how they are likely to respond to disturbances in the future. Finally, while Bitterman and Bennett (2016) were primarily interested in understanding how cross-scale processes within and between social and ecological domains contribute to *overall* system resilience, the present study seeks to analyze the resilience of specific system variables in a *comparative* context, i.e. the extent to which certain variables exhibit resilience compared to other variables under identical shock conditions. The coupled model employed in this study has been used to show that certain variables are more critical to overall system stability than others (e.g. canal water supply, government subsidies), and that shocks applied to these keystone variables have stronger effects on the system as a whole than those applied to variables with fewer adjacent connections or dynamic feedbacks. This approach is beneficial in that it allows the model user to pinpoint specific, variable-level failures in a system during a shock or disturbance event, thereby facilitating the development and application of more tailored damage-mitigation and adaptive capacity measures.

The primary objective of this paper involves the application of a dynamically-coupled modelling framework for the development of a stakeholder-friendly, replicable methodology for the quantification of resilience metrics in a dynamic agroecosystem experiencing a range of socioenvironmental shocks; this includes the use of these metrics for 1. Comparative variable resilience analyses and 2. The identification of potential regime shifts, transformations, and previously unidentified system vulnerabilities. The application of a dynamically coupled P-GBSDM for the purpose of quantifying socioenvironmental resilience is particularly unique, as is the choice to analyze specific variables within a complex system instead of solely assessing the system itself (e.g. Bitterman and Bennett, 2016; Todman et al., 2016; Ingrisch and Bahn, 2018). The coupled model used in this study contributes feedbacks and incorporates complex variable linkages that other models are not able to reliably produce, while the incorporation of the five metrics allows for the notable malleability and adaptability of the resilience assessment procedure for other socioenvironmental systems and/or variables.

3.2. Methodology

3.2.1. Study Site

Rechna Doab is a sub-watershed located in the Indus Plain of central-northeastern Pakistan. The study area lies in a region defined by the latitudinal range 30° 32’ N to 31° 08’ N, and the longitudinal range 72° 14’ E to 71° 49’ E. The area of interest covers about 732.50 square kilometers and has been divided into 215 discrete polygons (Figure 3.2), each with its own unique topology, agricultural divisions, and soil composition. The Rechna ‘Doab’ (‘two waters’) basin lies just above the confluence of the Ravi and Chenab Rivers and sits within the Haveli Canal command area. Figure 3.1 contains a specific regional indication of the study area within a map of Pakistan. Thirty percent of potentially cultivatable land in the Rechna Doab watershed is presently unexploited due to high soil salinity levels. This is a highly agriculture-dependent culture and economy, with many inhabitants' livelihoods being directly affected by socio-environmental change as a result of climatic or socioeconomic disturbances (Inam et al., 2017a).

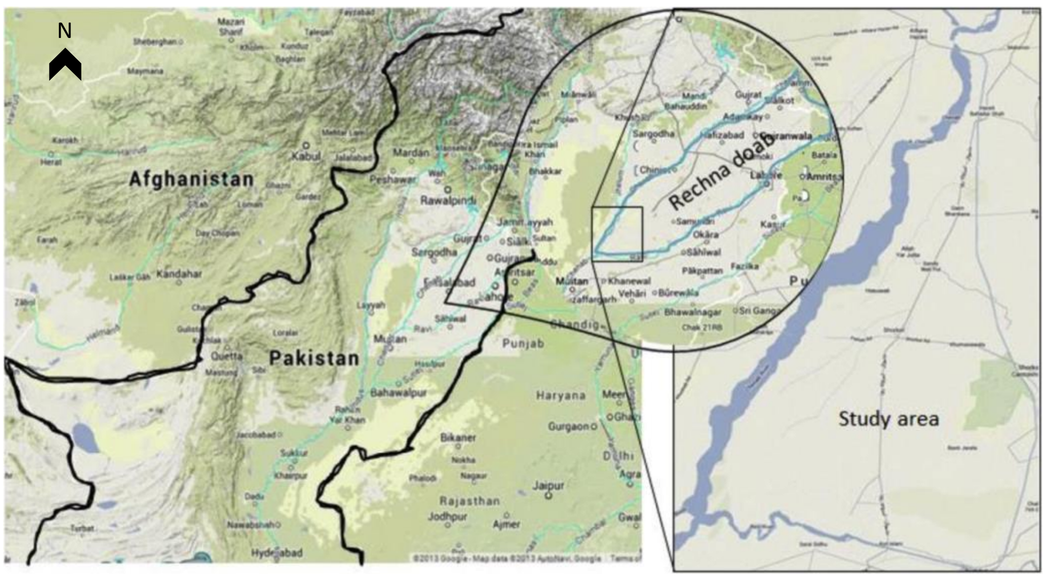

Fig. 3.1. Map of study area: Rechna Doab Watershed, Pakistan (reproduced with permission: *Inam et al., 2017a*)

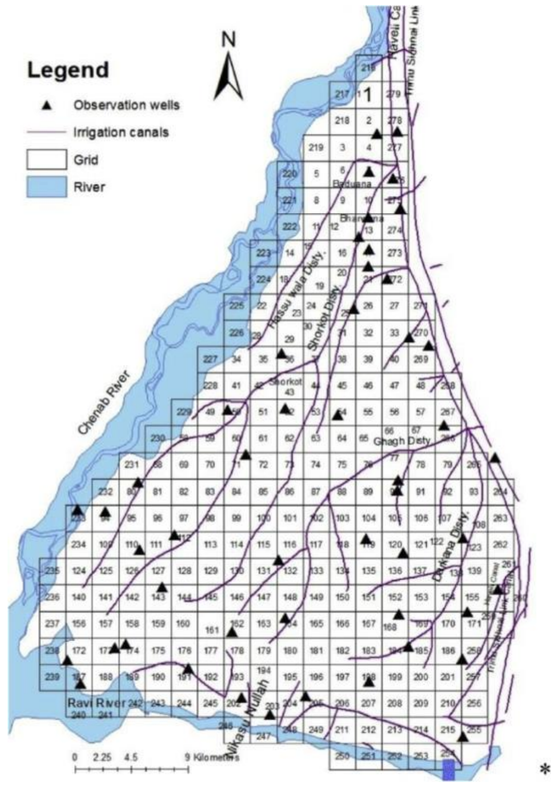

Fig. 3.2. Nodal network polygonal configuration of the Rechna Doab watershed with observation wells, canal network, and grid (reproduced with permission: Inam et al., 2017a)

3.2.2. The P-GBSD Model

The present study demonstrates the use of a coupled Physical-Group-Built System Dynamics Model (P-GBSDM) for shock scenario simulation and data extraction. This model was selected for the present study due to 1) its capacity to accurately represent complex socio-environmental systems as a result of its dynamically coupled structure and built-in feedback networks and 2) the participatory nature of model development, including variables and system level flow networks defined by local stakeholders. The P-GBSDM, built by Inam, Adamowski, and Malard of the present paper, was created by integrating the physical Spatial Agro Hydro Salinity Model (SAHYSMOD) with a participatory, group-built system dynamics model (GBSDM) consisting of social, environmental, and economic variables. The GBSDM is a participatory model and all of its assumptions (e.g. farmer perceptions, government loan pay-back ratio, sedimentation rate, farm water storage potential, surface water /groundwater use ratio, crop rotation etc.) were refined through interviews with local stakeholders. Moreover, constants/parameters were defined through discussions with scientists with the necessary and relevant expertise (e.g., irrigation engineers, land reclamation experts, research officers, modelers etc.).The overall participatory (GBSD) model and its structure, equations, development methodology, and component details are presented in Inam et al. (2017). Socioeconomic interdependencies and feedbacks were determined through the participatory model-building process (conducted by Inam, Adamowski and Malard of the present paper) with local stakeholders in the Rechna Doab basin of northeastern Pakistan (Inam et al., 2015). The participatory model-building approach used in the initial stages of P-GBSDM development involved the application of stakeholder-built causal loop diagrams (CLD). The particular CLDs used for the GBSDM initialization were constructed by local Rechna Doab stakeholders in response to neutral situational prompts posed by researchers relating to local agricultural and community livelihood dynamics. Individual stakeholders created their own diagrams and the individual thought maps were eventually integrated to form one large, cohesive, group diagram. After the group CLD construction, the final CLD was digitized using Vensim Software (Ventana Systems, 2015). The necessary variables and their links and feedbacks were integrated in Vensim as an organized, digital version of the stakeholder-designed, group-CLD. Sub-modules of the GBSDM describing agricultural, economic, water, and farm management factors were linked together with these feedbacks and finally integrated with the physically based SAHYSMOD. The model was coupled, in part, through the application of Tinamit (developed by Malard, Inam, and Adamowski of the present paper), a novel tool used to couple SD and physically-based models, which allows the integrated models to exchange data at runtime (Malard et al., 2017). Tinamit, which itself consists of three Python classes that code for model wrappers: one for physically-based models, one for system dynamics models, and one for coupled models, greatly facilitates the process of coupling SD and physically-based models. Figure 3.3 illustrates the basic concept behind the model coupling process using Tinamit as a wrapper program. This special form of model coupling allows for the exploration of the complex relationships among various system elements, as well as the resulting behavioral dynamics of the system, while retaining stakeholder values and inputs. Following the development of the integrated model, a validation approach was used to substantiate and test the structure and behavior of the coupled model. The model's performance has been investigated for optimum calibration and validation using a behavior pattern-based sensitivity analysis (Peng et al., 2020). Model robustness under different operating conditions was also assessed (Inam et al., 2017). Detailed information related to data input requirements for each model as well as data sourcing techniques and processes is outlined in Inam et al. (2015, 2017, 2017a), while the resilience code is available upon request of the primary author. Model documentation can be found at: https://tinamit.readthedocs.io/es/latest/.

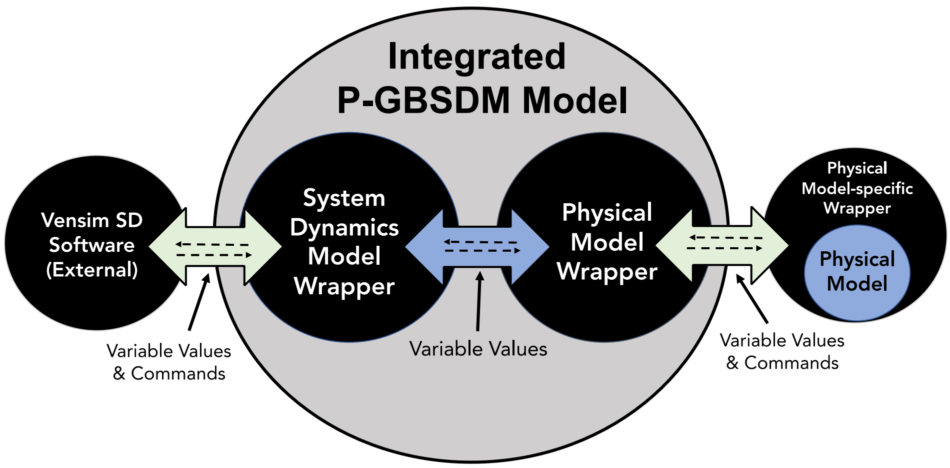

Fig. 3.3. Diagram of P-GBSDM coupling using Tinamit as a wrapper (*adapted from Malard et al., 2017*)

The model was tested and validated many times using different techniques. In the first technique, model components (i.e. SDM and Physical model (SAHYSMOD)) were tested individually. Conventional model testing techniques based on statistical methods (e.g. RMSE, NSE, R2, ME, etc.) (Moriasi et al., 2012) are difficult to apply for an SDM component of a coupled model, Barlas (1989) comprehensively describes the reasons for that, hence, a model testing framework based on procedures (reality check, unit consistency, extreme value test, behavior test etc. (see section 6.0 of Inam et al., 2017)) described in the system dynamics model literature (Barlas, 1989; Sterman, 2000; Qudrat- Ullah and Seong, 2010) were used to validate the SDM. For testing the physical side of the coupled model, conventional model calibration and validation techniques based on statistical indicators (e.g. RMSE, NSE, R2, ME, etc.) (Moriasi et al., 2012) were used (see Inam et al., 2017). Later, a behavior-based sensitivity analysis of the coupled model was carried out to determine the influence of input parameters on the general behavior trends (rather than numerical point values) of the coupled model outputs (see Peng, et al. (2020) for details).

The fully integrated model consists of several stocks (i.e. system reservoirs or known quantities), including irrigation efficiency, lined canal length, constructed capacity, silted capacity, water requirements, farmer income, and tube well numbers. The model also uses flows (usage/exchange rates, such as seepage, runoff, income, expenditure, decay, construction, and water consumption) and table functions (lining, water harvesting and irrigation efficiency policies, inflation factors, perception states, and canal water distribution) that comprehensively define the system. The coupled model is deterministic and uses a simulated time-step of six months (one season) (Inam et al., 2017a); for this study, a time series of 30 years (i.e. 60 seasons) was established for the periods between 1989 and 2019. The GBSDM transfers values of seepage, irrigation use, groundwater extraction, and water application efficiency *to* SAHYSMOD and takes values of cropped area, water table depth, groundwater quality, drainage volume, and root zone salinity *from* SAHYSMOD. The stock and flow structure of the model allows the user to test different socio-environmental scenarios with special regard for aquifer sustainability, controlled tube well growth, and the design of cropping patterns for maximum yield. Simulations using the coupled P-GBSDM allow the user to identify and test economically feasible, stakeholder-developed and accepted strategies, as well as potential solutions and policy changes.

3.2.3. Study Variables

Three influential agroecosystem variables were chosen as the targets for the shock scenario-based resilience assessment in this study. Farm Income (FI) was the first variable that was analyzed. Farm income is directly related to crop yield, which is strongly affected by soil salinity and water stress. Net income per study system polygon (215) was calculated in terms of seasonal gross margin and estimated by the difference in farm expenditures and revenue. Farm Income is a stock variable in the farm economics submodule of the GBSDM and is involved in numerous complex linkages and feedbacks between other variables throughout the coupled model. The second variable of interest in this study was Crop Revenue (CR) and was measured as the cropped income produced by each set of two crops per seasonal growing period (four different crop types in total for one year). Total crop revenue is a function of cropped area, seasonal yield, and market rates; this variable allowed the research team to distinguish between fluctuations in agricultural resilience due to increased expenditures or decreased profits. The final variable of interest examined in this study was Water-table Depth (WTD). Water-table depth is a key indicator of seasonal weather patterns, climatic trends, and anthropogenic influences on the landscape. Low water-table depth can lead to decreased soil health, crop revenue and farm income losses, and may contribute to increased social tensions between local farmers based on unequal distribution of finite water resources. Conversely, very high water-table depth may lead to flooding and soil saturation and may contribute to excess mineral and contaminant leaching to and from the soil.

There are several reasons for the selection of these three specific study variables: first, an effort was made to represent both the socio-environmental capabilities of the coupled model (e.g. farm income, crop revenue) as well as the biophysical contributions (e.g. water-table depth). Second, the capacity of the coupled model to incorporate the dynamic feedbacks between the socioeconomic and environmental variables is what makes this resilience modelling strategy particularly unique; the use of complexly interrelated variables further elucidates the connections of all adjacent variables in the watershed system. Finally, the implications of a resilient response from one or all of the study variables are interesting, unique, and informative; for example, if farm income were to exhibit high resilience under a shock scenario that devastates the normal 'functionality' of water table depth, we would gain new insights and understanding of the dynamic relationship between agricultural productivity, vulnerability, and water access.

3.2.4. Shock Scenarios

Shocks were applied to the P-GBSDM in order to assess the response of the three study variables to varied levels of disturbance. In an effort to simulate response trajectories under the most realistic circumstances, shock scenarios were selected from both a socioeconomic and environmental domain. The following two shock types were used: 1) Increased market inflation, and 2) Decreased canal water supply. These shocks were selected based on their connectivity to most adjacent variables within the system, making their impact on the study variables particularly influential. The selected shock scenarios also represent both the socioeconomic and biophysical capabilities of the coupled model, thereby producing the most reliable and realistic results for each run; i.e. these shocks are two of the most prevalent disturbance scenarios in semi-arid agricultural basins like the Rechna Doab watershed. Each shock was applied to the model individually (i.e. compound shocks were not employed in this study) with varying magnitudes of intensity and duration. The discrete application of the shock scenarios allows for a better understanding of the precise influence a specific disturbance event may have on the resilience of an individual variable, thereby allowing for a more accurate assessment of each variables' unique vulnerabilities and enhancing the opportunity for more effective, targeted legislative or organizational counter-measures. The inflation shock was applied as an increase in Pakistan's documented annual inflation (values of x2, x5, x10, and x15 with respect to market data collected for the year 2003) (Pakistan Bureau of Statistics, 2020). 2003 was selected as the reference year due to the comparatively high amount of consistent, reliable socioeconomic data collected by the Government of Pakistan for that year; as such, 2003 was used as the market inflation reference year for the original incorporation of this variable into the P-GBSD model. Intensity values for the inflation shock were initially determined by examining historical inflation trends in Pakistan. According to the World Bank, Pakistan's highest inflation rate on record occurred in 1974, with a rate of 26.7%; this is a nearly ten-fold difference from the rate of 2.9% documented in 2003; as such, the inflation shock factors were selected based on the extreme historical values experienced in Pakistan (IMF, 2019). Outputs from the coupled model support the general socioeconomic data trends in the region which indicate that market inflation is greatly influenced not only by societal or political fluctuations, but to an even greater extent by the state of agroecological variables such as crop yield, soil salinity, and water-table depth, among others. In other words, with the exception of a catastrophic event akin to the declaration of civil war, a bad crop year tends to elicit more cascading socioeconomic repercussions than a change in agricultural policy or social practice. The canal supply shock was applied as a decrease in canal water supply of 10%, 25%, 50%, and 90%; these values were selected based on historical precipitation and water use patterns in the Rechna Doab and were subsequently tested using a manual shock testing methodology in the participatory-built model drafted in Vensim. The manual shock testing in Vensim resulted in canal supply outputs supporting the claims that increasingly frequent and severe drought in the region coupled with high soil salinity and sub-par water management infrastructure can lead to increased instances of reduced canal water supply in the Rechna Doab watershed (Inam et al., 2015; World Bank, 2020). Each shock intensity was 'held' in the model for periods of one, five, ten, or twenty years; in other words, each shock type was run for 16 different intensity and duration scenario combinations (32 unique shock combinations for each study variable) (Figure 3.4). The responses of the three study variables to each of the unique shock combinations was analyzed for a period of 30 years between 1989 and 2019. Each shock was initially applied ('turned on') in the final season of the year 1989 and removed in either 1991, 1995, 2000, or 2019, depending on the duration stipulation for that run.

Response data was obtained for the three study variables after each unique shock scenario simulation. In order to ensure a cross-variable, comparative resiliency analysis, each set of response data was normalized to the base-case state of the study variable for that run. In other words, the ‘shocked’ response data was divided by the normal functionality data for each variable under each disturbance scenario. Each result was normalized to the base-case state of the variable for each individual polygon at each unique time-step, resulting in 215 unique base-case sets of 60 points (i.e. seasons) for each study variable. The normalization process resulted in response data that showed the degree of fluctuation or change experienced by each variable compared to the business as usual state. This normalized data was suitable for resilience metric calculation without fear of the variation in system units altering the comparability of the final resiliency outputs. Figure 8 shows an example of the shock intensity/duration combinations applied to each of the study variables. The outputs change dynamically over time, i.e. the values fluctuate over the course of the 30-year evaluation window, but the model is not stochastic and subsequent runs of the same data sets return identical output patterns. The inherent replicability of the output values in this methodology precluded the need for an uncertainty analysis.

	Shock 1 (Inflation)				Shock 2 (Canal Supply)			
INTENSITY	X2	X5	X10	X15	10%	25%	50%	90%
DURATION								
1 yr	S1,X2,01	S1,X5,01	S1, X10, 01	S1, X15, 01	S2, 10, 01	S2, 25, 01	S2, 50, 01	S2, 90, 01
5 yr	S1,X2,05	S1,X5,05	S1, X10, 05	S1, X15, 05	S2, 10, 05	S2, 25, 05	S2, 50, 05	S2, 90, 05
10 yr	S1,X2,10	S1,X5,10	S1, X10, 10	S1, X15, 10	S2, 10, 10	S2, 25, 10	S2, 50, 10	S2, 90, 10
20 yr	S1,X2,20	S1,X5,20	S1, X10, 20	S1, X15, 20	S2, 10, 20	S2, 25, 20	S2, 50, 20	S2, 90, 20

Fig. 3.4. Shock type (S1: Inflation, S2: Canal Supply), intensity (x2, x5, x10, x15 (factor with reference to base-case inflation) and 10, 25, 50, 90 (% reduction in canal water supply), and duration (01, 05, 10, 20 (in years)) combinations for each of the three interest variables

3.2.5. Resilience Metrics

In order to determine the degree of resilience exhibited by each variable in each unique shock scenario, five metrics, each describing a unique feature of a resilient response to disturbance, were applied to the normalized data for each intensity/duration combination. The five metrics chosen for this study were based on metrics used by several authors (e.g. Cimellaro et al., 2010; Todman et al., 2016; Ingrisch and Bahn, 2018) for the quantification of resilience based on a functional response curve.

When analyzing a functional response curve, i.e. the function that computationally represents the outputs of a system under different shock scenarios, there are several metrics by which one may assess the response of a particular variable in a resiliency context. In this study, the following five metrics and their associated equations were applied to the normalized data sets obtained after the shock simulation procedure: 1) Time to baseline-level recovery, 2) Rate of return to baseline, 3) Degree of return to baseline, 4) Overall post-disturbance perturbation, and 5) Corrective impact of disturbance. These five metrics were chosen due to their combined potential for accurately describing the resilience of the study variables based on a transient shock response. Considered individually, these metrics only give a partial explanation of the overall resilience of a shocked entity; however, when examined coincidently, these five metrics describe three important aspects of a completely resilient shock-response. First, these metrics demonstrate the capacity of a variable to withstand and resist stress, second, they indicate the efficiency with which a variable can recover from disturbance, and third, they account for the very real possibility that a variable will not return to a pre-disturbance functional equilibrium, allowing for the recognition of potential regime shifts and transformations in the variables of interest. Figure 3.5 shows a theoretical shock-response curve and the data boundaries determining each of the five resiliency metrics, where Rt represents the time of functional return to the baseline state, Rr represents the rate of post-disturbance functional return to baseline, Rd represents the degree of final functional return to the baseline state, Rp represents the perturbation experienced by the system between initial disturbance time and the first return to baseline, and Rci represents the corrective impact of the disturbance on system functionality, accounting for an overshooting of the response after the first return to baseline.

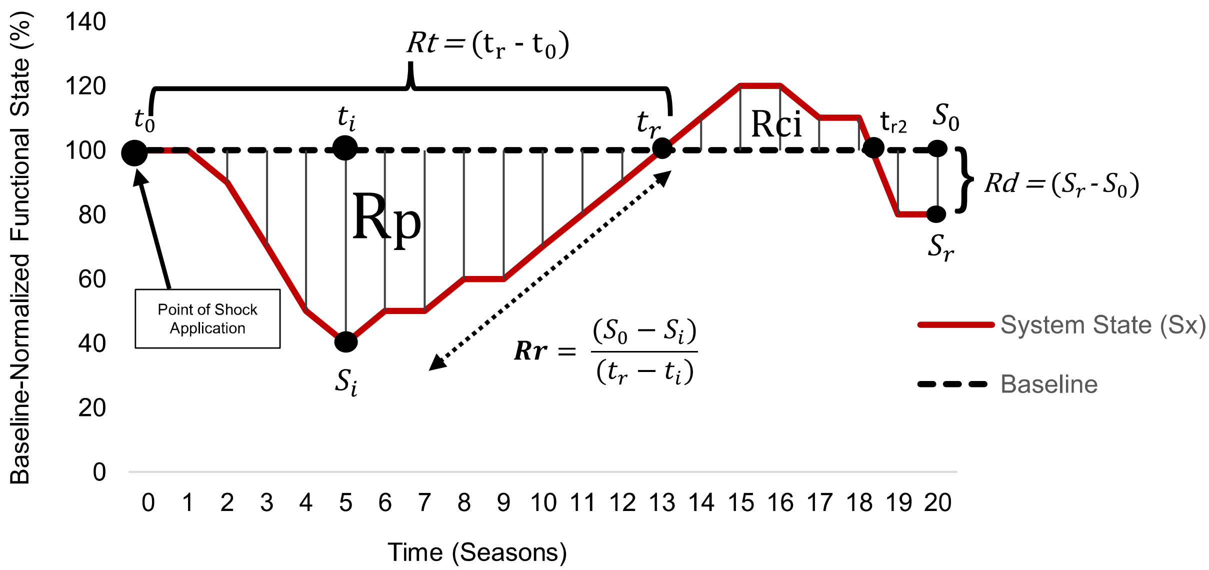

Fig. 3.5. Functional response curve with visualization of R-metrics

The first important metric examined in this study was the return time (Rt), or time to baseline recovery. Simply put, the time to baseline recovery is the amount of time it takes a system or variable of interest to return to a pre-disturbance state of functionality after a shock event. The *return time* is similar to Holling's (1996) original definition of engineering resilience; this metric quantifies the length of the transient response period of the observed function. If a variable exhibits a relatively high level of resilience in response to the disturbance scenario, then we would expect to see a relatively low time of return to the baseline functionality level.

The second metric used for this resiliency analysis was the rate of return (Rr). A resilient system or variable will return to a stable level of functioning more quickly than one that is not resilient, i.e. at a faster pace or steeper gradient. *Rate of return* is a combined measure of the return time and the magnitude of the impact of the function during the transient response (Cimellaro et al., 2010; Hodgson et al., 2015; Todman et al., 2016; Ingrisch and Bahn, 2018).

The third metric applied for assessing post-disturbance resilience was the functional degree of return (Rd). Variables that exhibited a resilient response (with respect to the baseline functional state) were represented by a curve (i.e. data set) that returned to a stable level of functionality closer to that of the reference level. To be more explicit, the *degree of return* is a measure of the extent to which the observed function comes back to a prescribed reference level; this reference level could be the level of a baseline function before the disturbance (as was determined in this study), or the level of a completely controlled, hypothetical system. The degree of return was measured as the difference between the base-case (i.e. un-shocked, pre-disturbance state) functionality value and the final output value after 30 years of simulations (Todman et al., 2016).

The fourth resiliency metric used in this study was a measurement of the post-disturbance perturbation experienced by the study variables (Rp). The perturbation was measured using the area above the output response curve but below the base-case data line; using this metric, a more resilient system produces a smaller area between the functional response curve and the baseline boundary (Cimellaro et al., 2010; Todman et al., 2016). If the shocked variable never returned to the baseline state of functioning, then the vertical boundary for the perturbation metric was drawn at the point the variable settled into a new equilibrium. For the purposes of this study, a new equilibrium was defined as the occurrence (post-maximum perturbation) of identical variable outputs (to the nearest hundredth degree) for at least two consecutive years (i.e. four seasons). If a new equilibrium was never reached, the boundary was drawn at the end of the viewing window, i.e. after 30 years of simulations. The methodology presented herein was developed with the presupposition that the transient changes in function as a result of variable disturbance were undesirable; as such, the most resilient response, as described by the perturbation metric, was that which produced a function *unperturbed* by disturbance, i.e. perturbation = 0. With respect to the perturbation metric, if there was any loss of variable functionality, the area above the functional response output curve was negative; this indicated a cumulative loss in function when the system was shocked.

The final metric employed in this assessment was the corrective impact metric (Rci). This metric accounts for the potential overshooting of a variable upon return to baseline after disturbance; it was calculated as any area above the functional response baseline curve in the event of a post-disturbance increase in functional behavior (Bahn and Ingrisch, 2018; Yeung and Richardson, 2018). A high corrective impact metric may, upon initial inspection, appear to be a constructive response to a shock event; however, this response could also bely a systemic inefficiency if it means that a limited resource is being used more quickly. It is important to keep these complex feedback dynamics in mind when analyzing socio-environmental data for resilient characteristics.

Table 3.1 includes brief descriptions and equations for each of the metrics, where t_0 is the initial time measurement at the beginning of the simulation period (i.e. $t_0 = 0$), t_r is the time measurement for the point at which the functionality curve returns to baseline post-disturbance, S_i is the functional state of the system at maximum shock impact, S_r is the functional state of the system after 30 years of simulations, i.e. the functional value at time t = 60 seasons, and may be equivalent to S_0 if the final state of the system is equal to that of the base-case (i.e. S_0 and $S_r = 1$). t_i is the time (x-value) at maximum impact, S_0 is the functional state of the system before the first moment of disturbance (i.e. $S_0 = 1$), and t_{r2} is the time of second baseline return in the case of overshooting.

Resilience Metrics	Definitions	Equation
1) Return Time (R_t)	Time required to return to baseline or equilibrium level of functioning; measured from time of initial disturbance.	$R_t = (t_r - t_0)$
2) Rate of Return (R_r)	Gradient of functionality curve; measured from maximum impact to baseline return.	$R_r = \frac{(S_r - S_i)}{(t_r - t_i)}$
3) Perturbation (R_p)	Area between the functional response curve and the baseline; measured from initial time of disturbance to first baseline return.	$R_p = \int_{t_0}^{t_r} f(t)\,dt$
4) Degree of Return (R_d)	Discrepancy between initial baseline functional state and final equilibrium.	$R_d = (S_r - S_0)$
5) Corrective Impact (R_{ci})	Overall 'positive' corrective behavior experienced by the system post-disturbance in the case of 'over-shooting' (i.e. outputs are greater than that of the baseline value).	$R_{ci} = \int_{t_r}^{t_{r2}} f(t)\,dt$

Table 3.1. Five dimensions of resilience (*Adapted from those metrics suggested by Cimellaro et al. (2010), Todman et al. (2016), and Ingrisch and Bahn (2018)*)

The degree of shock-resistance exhibited by a variable influences the rate of return *and* perturbation metrics of a response data set, thus these two metrics (Rr and Rp) sufficiently embody the key consequences and outcomes of disturbance resistance. The return time metric (Rt) most consistently coincides with system or variable resilience when all five metrics are taken into account separately; however, the rate of return (Rr), perturbation (Rp), and corrective impact metrics (Rci) provide a more reliable measure of overall variable resilience (as opposed to calculating return time alone) as they make use of all of the available data, rather than a single point; they also negate the need to identify an additional fragility metric for measuring system vulnerability (Todman et al., 2016). The degree of return metric (Rd) rounds out the set of five metrics by accounting for the very real possibility of a shocked variable not returning to a state of pre-disturbance functionality.

3.2.6. Simulation and Analysis Procedure

Links between the shock nodes in the coupled P-GBSD model and each of the three study variables were initially tested manually using Vensim software to ensure feedbacks and connecting loops between adjacent variables were sound and reasonable. Using this manual testing method, we first noticed the trend indicating that severe reduction in precipitation coupled with soil salinity and no policy changes resulted in canal supply reduction. The variables present in the Vensim diagram were initially programmed with their own equations and values based on the stakeholder-built CLDs, as well as up-to-date socioeconomic data from the government of Pakistan. To improve the ease with which data could be transferred between the Vensim model and the Tinamit programming interface, shock *switches* were incorporated into Vensim allowing for the manual adjustment of shock durations and intensities. The intensity switches were created by establishing new dimensionless constants, which were subsequently written into the equations for the system components they were modifying. The duration switches were created as new constants in the Vensim model with seasonal time units. The initial equations assigned to each shock factor were altered to include if-then-else statements, accounting for the changes experienced by the variables when intensity and duration values were modified. For example, the initial equation for the incorporation of real-world data (compiled in a separate Excel file) into the canal supply factor was written as follows: *GET XLS DATA (‘?test’, ‘Canals supply, ‘b’, ‘c4’)*. After the incorporation of the intensity and duration switches into this shock, the canal water supply equation read as follows: *IF THEN ELSE (Time<=Duration canal supply, Canal Supply at head[canal] * Intensity Canal Supply, Canal Supply at head[canal])*. The original, unaltered equations for the shock variables were written back into the modified equations to account for the base-case state of the variable; these loops also accounted for the times when the shock needed to be strategically ‘shut off,’ i.e. intensity = 1. Shock and variable connections were tested manually in Vensim for a second time to ensure the accuracy of the modified equations and to test the links and feedbacks. Once the shock switches were confidently assessed in Vensim, the new duration and intensity metrics were coded into the Tinamit programming interface using a simple Python script. Figure 3.6 shows the structure of the Vensim model before and after incorporation of one of the shock scenario switch nodes, Canal Supply.

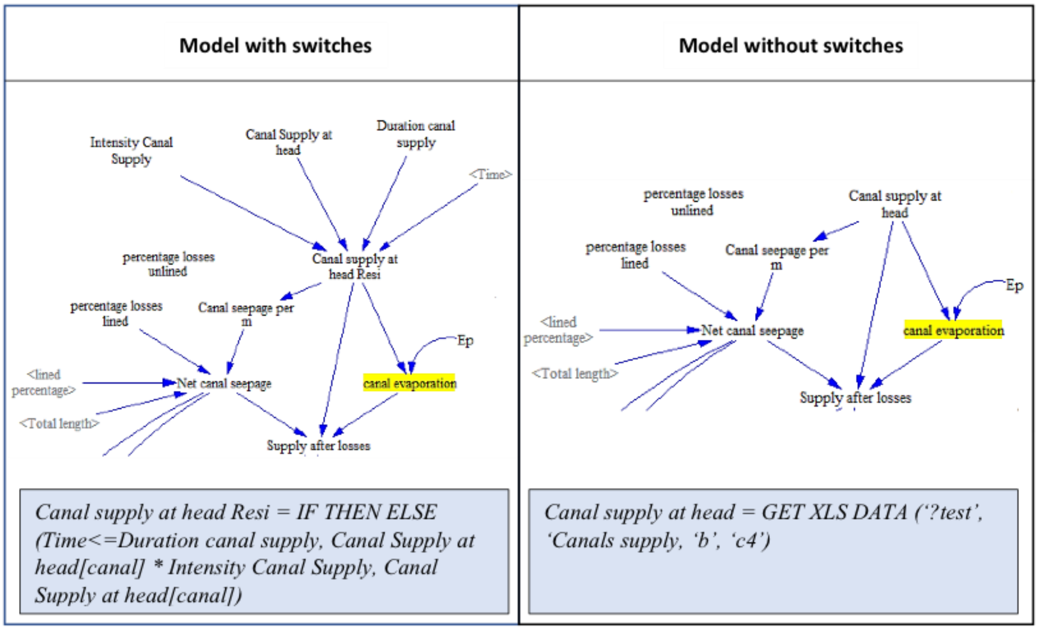

Fig. 3.6. Vensim model with (left) and without (right) the constituent switches for the Canal Supply shock

In order to make the simulation and data procuring process more streamlined, four Python codes were written to interface with the Tinamit package for automatic data modification. The first code involved the intensity and duration shock switches initially established in Vensim. When run using the P-GBSDM, this script creates unique CSV files that contain the shocked data outputs for each simulation of the switch scenarios. The second code was written for the normalization of the shocked data to the base-case state of the interest variables, which allows the CSV files created using the first code to be read, organized, and subsequently converted to base-case normalized data frames. All data points were included for the full 30-year time range across all 215 polygons. Time, as a unique metric standardized across all variable and shock types, was not normalized to a base-case scenario but was instead recorded as a raw data figure in each run.

Once the data was normalized to the base-case scenario for each variable, a third code was written for the procurement of the five resilience metric outputs for each variable and shock scenario combination (32 total files). This code assigned the five metric equations to each polygonal data series in the variable set for each shock combination; in other words, each of the 32 baseline-normalized shock files (containing data for all three study variables in each of the 215 polygons over 30 years) was modified by the five resiliency metric equations, and each of the three variable data sets in each file received five new output values pertaining to the resilience metrics for that polygon. The outputs were then assessed for their comparative levels of resilience based on ideal values. The ideal metric values for a perfectly resilient system are as follows: Return time = 0, rate of return = + , degree of return = 0, perturbation = 0, corrective impact = 0 or + (for a perfectly shock-resistant system this metric would be zero, but in the case that a variable is not perfectly robust (i.e. the variable is not resistant to shock damage, which is likely to be the case), then a high corrective impact metric is ideal). These values are consistent with the definition for this study that a perfectly resilient result will exhibit similar behavior patterns to those of a system that has not been shocked, i.e. a pre-disturbance state. However, exceptionally large values for degree of return or corrective impact are likely indicators that a regime shift has taken place; a regime shift may have positive or negative consequences based on the specific shock conditions and variables involved. In contrast, a notably large value for the return time metric coupled with a large value for the degree of return may indicate that the system has fallen out of functionality altogether and may be irreparably damaged. Once the final simulation had been run, 32 files containing the five resilience metric values for each variable-type and shock combination were available for further analysis.

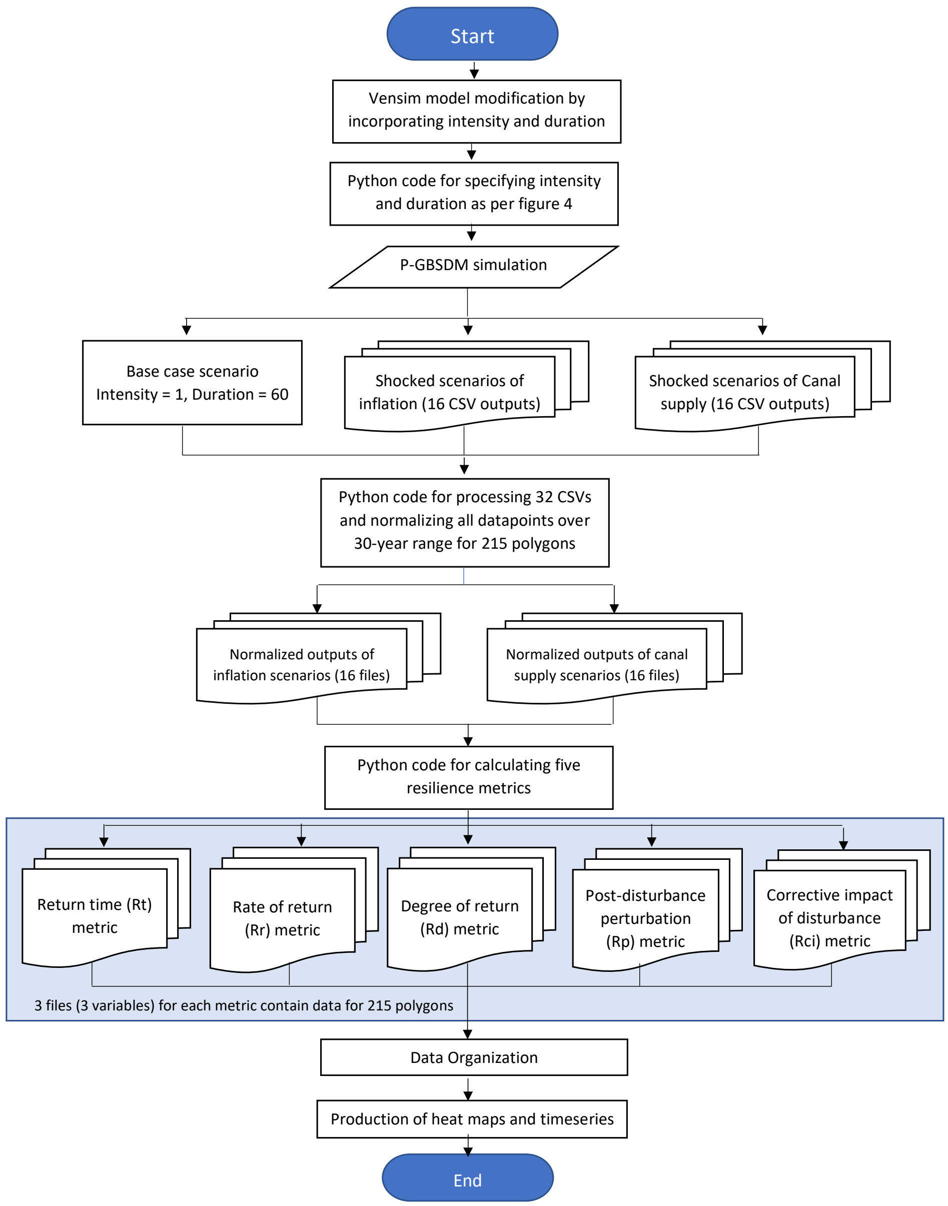

Fig. 3.7. Simulation and analysis procedure

3.3. Results

As predicted, the three variables assessed in this study each exhibited unique reactions to shocks of varying duration and intensity. The normalized timeseries responses of each variable (i.e. the curves used to quantify the resilience metrics) to two different shock types (1. Market inflation X10 for 10 years, and 2. Canal supply reduction of 50% for 5 years) are provided below for the lower (fig. 3.8, 3.9), middle (fig. 3.10, 3.11), and upper (fig. 3.12, 3.13) watershed regions.

These shock scenarios were chosen due to their realistic probability of real-world occurrence, and also because their outputs are representative of the variable behaviors overall for the respective shock types.

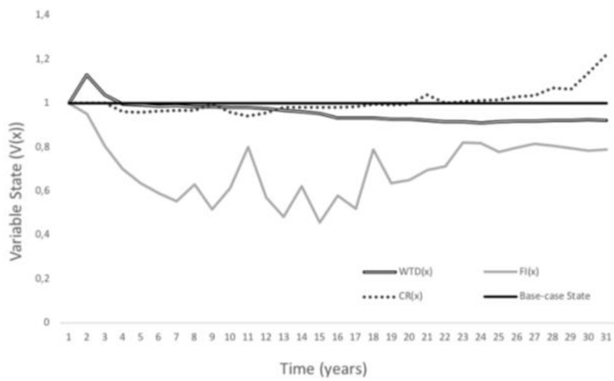

Fig. 3.8. Market inflation shock, lower watershed

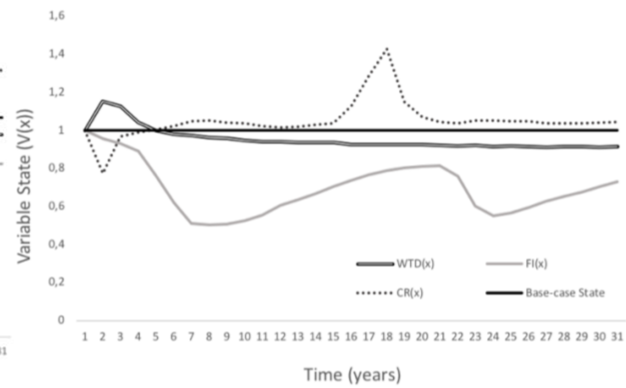

Fig. 3.9. Canal supply shock, lower watershed

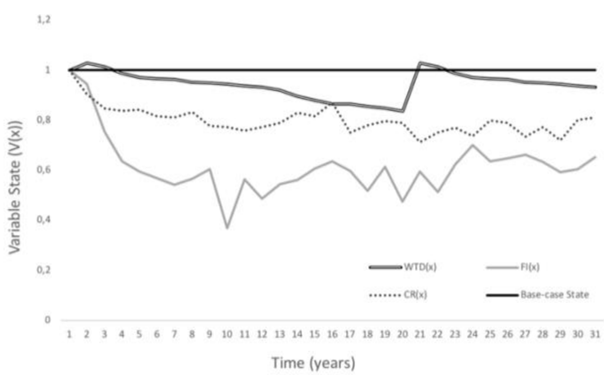

Fig. 3.10. Market inflation shock, middle watershed

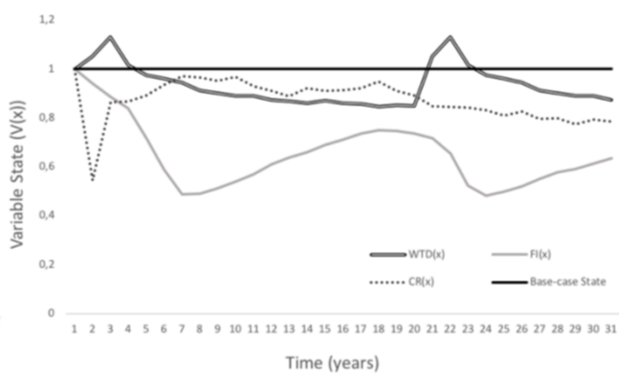

Fig. 3.11. Canal supply shock, middle watershed

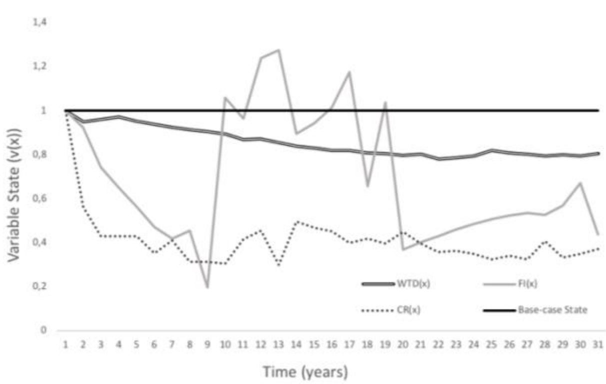

Fig. 3.12. Market inflation shock, upper watershed

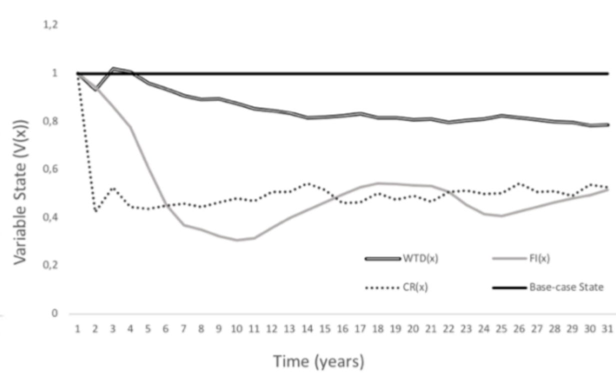

Fig. 3.13. Canal supply shock, upper watershed

Farm income exhibited high perturbation values and long return times, even under the least severe inflation scenario (x2 for 1 year). Water-table depth and crop revenue began exhibiting vulnerabilities under an inflation factor of x5 for 5 years; under these shock conditions, all three variables exhibited very high Rp values, mostly from upper-watershed polygons, indicating they were all pushed very far out of their normal functional patterns before returning to baseline. At this point there were also very high instances of 61 Rt (indicating the variable did not return to the base-case functional state after 60 seasons) and 0 Rci for water-table depth, indicating that water-table depth performed very poorly overall for this trial. With an inflation factor of x10, the pattern emerged of crop revenue exhibiting high Rps and extremely high Rcis with a very large degree of return; this indicates high fragility and instability in this variable for this shock type. Water-table depth began to perform the best of the three variables under this shock scenario, while the two socioeconomic variables became increasingly vulnerable to the inflation shock type at higher intensities. With an inflation intensity of x10 for 20 years, the farm income variable lost the capacity to return to baseline after shock application, i.e. farm income was never able to recover from inflation of this intensity (X10) held for this duration (20 years). With respect to the ideal resilience values, farm income performed the worst under inflation shock conditions. Crop revenue was the most inconsistent variable and water-table depth was the most stable, although also nominally faltered as duration increased. All five metric values of water-table depth increased as the duration of the shock increased, including the Rci value, which indicates that the shock induces erratic variable behavior and shock duration has a greater effect on water-table depth than intensity. Rci decreased notably for crop revenue as the shock duration increased.

Under canal supply shock conditions, high Rp and Rci values frequently occurred at the head of the watershed, indicating that these polygons are both highly adept at recovering from a shock but also highly unstable throughout all canal supply shock runs. All "lowest" metric values actually decreased from run S2, 10, 01 to run S2, 10, 10 (i.e. as shock duration increased from 1 to 10 years for a reduction of 10% in canal water supply), and most of the metrics on the high end increased from run S2, 10, 01 to S2,10,10, but not all; this indicates higher rates of fluctuation or instability in functionality for variables as the shock duration increases. The canal supply shock induced large values of Rt and Rp for farm income compared to the other two variables; this indicates that farm income experienced the most difficulty recovering to a pre-disturbance state after the shock event. Rci values for crop revenue were also very high compared to the other two variables, and crop revenue showed comparatively high values for rate of return and degree of return across all intensities and durations of this shock type. These high values indicate that crop revenue is generally resilient under these shock conditions, but some polygons are unpredictably unstable and may have experienced functional regime shifts. All low values for all three variables in Rci were 0 for this shock, which was not the case for the inflation shock at any intensity; this indicates that the variables were better able to maintain a level of homeostasis under these shock conditions than they were for the inflation shock. All metric values for water-table depth increased from run S2,50,01 to S2,50,20 (i.e. 50% reduction in canal water supply sustained from 1 to 20 years); this was not the case for crop revenue and farm income, which both saw a decrease in Rci from run S2,50,01 to S2,50,20 while farm income saw negative changes in all metrics from run S2,50,01 to S2,50,20 (i.e. increased Rp, Rt, and Rd, and decreased Rci and Rr). Rci decreased for all variables and Rp increased for all variables from run S2,90,01 to S2,90,20 (i.e. 90% reduction in canal water supply sustained for 1 to 20 years). Meaning, an increase in intensity seems to decrease the capacity of the variables to commit sufficient corrective behaviors. Crop revenue and farm income saw negative changes for every single metric between runs S2,90,01 and S2,90,20 (i.e. increased Rt, Rp, Rd, and decreased Rr and Rci.) Water-table depth remained remarkably consistent throughout all canal supply runs, indicating that this variable is highly resilient, especially when considering that this is a physical shock (canal water supply reduction).

Watershed-level heat maps (fig. 3.14 – 3.17) and a regional resilience metric table (table 3.2) are provided below. These plots were produced with a market inflation intensity of x10 for a duration of 10 years (figs. 3.14, 3.16), and a canal supply reduction of 50% for 5 years (figs. 3.15, 3.17.). Figures 3.14 and 3.15 are presented in a relative scale to show the precise measurements taken in each polygon, while figures 3.16 and 3.17 are presented in a standardized scale (i.e. each metric column is presented in the same scale across each of the three variables) for watershed-level comparative purposes.

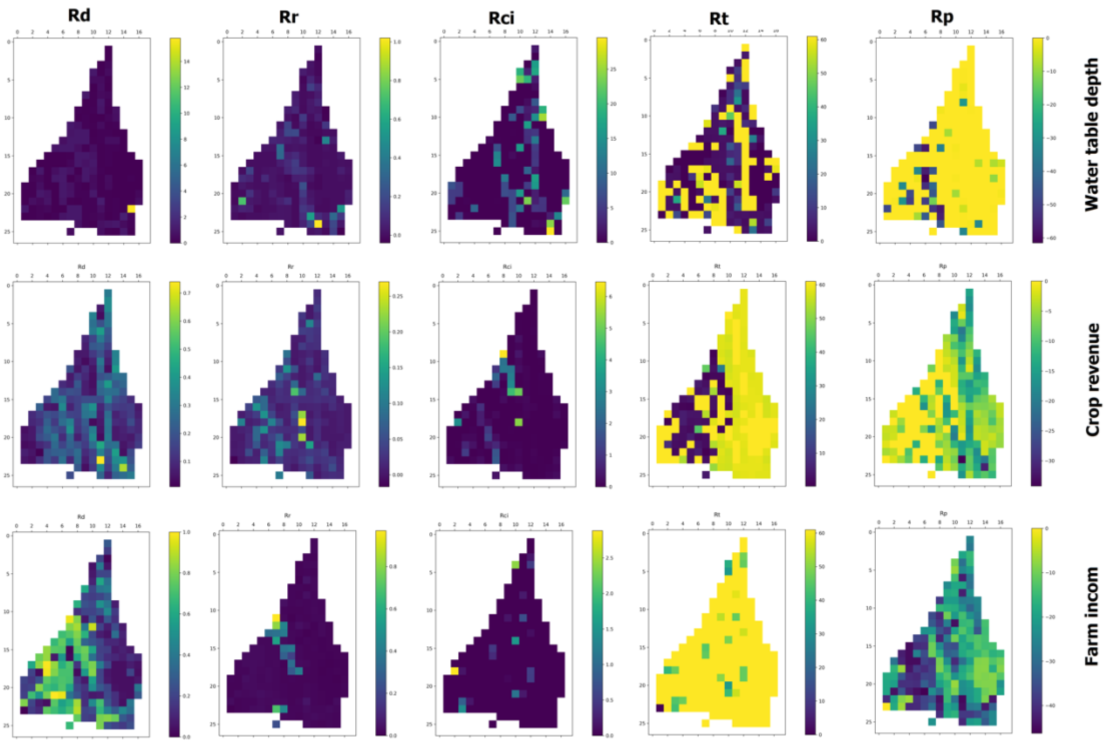

Fig. 3.14. Resilience metric heat maps across the watershed for market inflation shock of X10 sustained for 10 years, in relative scale

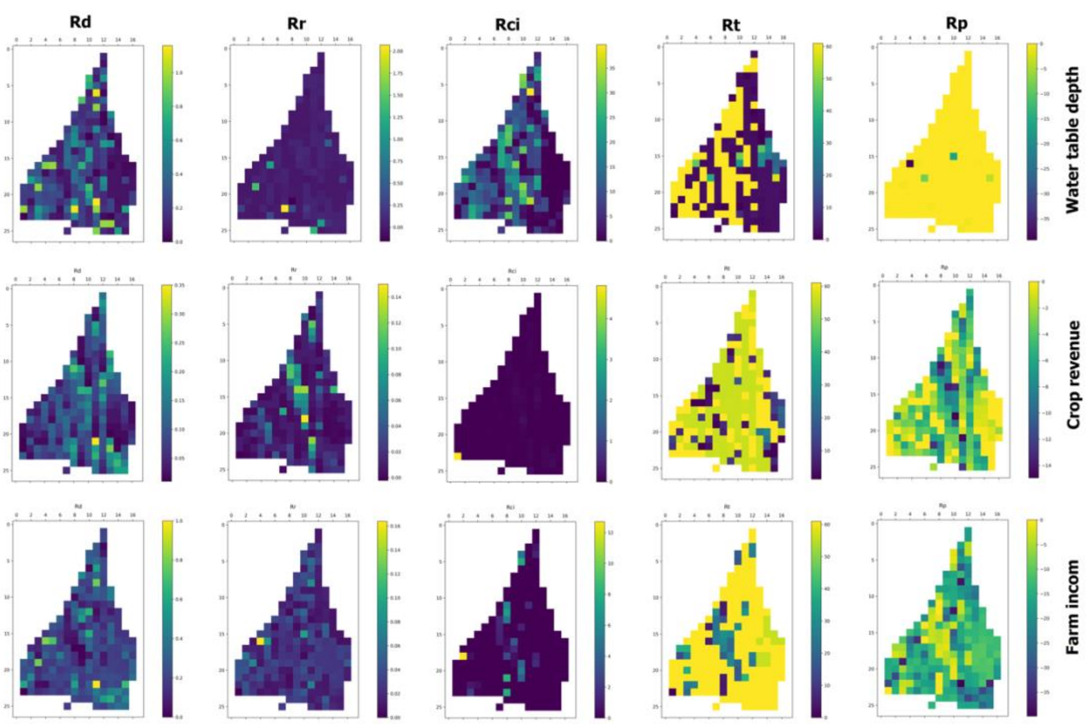

Fig. 3.15. Resilience metric heat maps across the watershed for canal supply shock of -50% sustained for 5 years, in relative scale

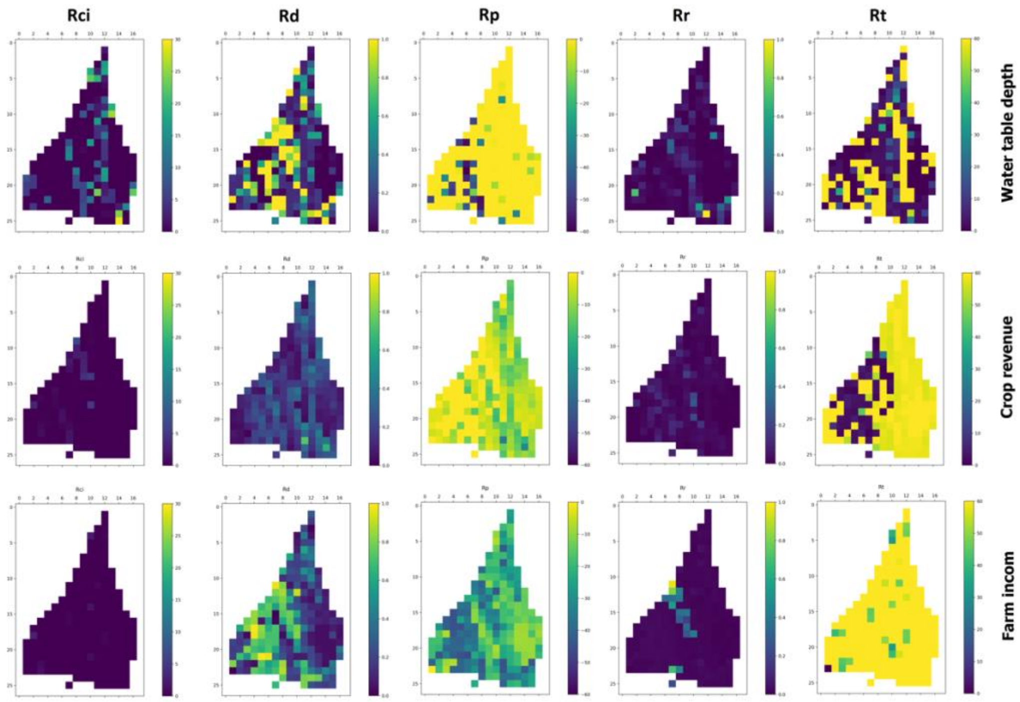

Fig. 3.16. Resilience metric heat maps across the watershed for market inflation shock of X10 sustained for 10 years, in standardized scale

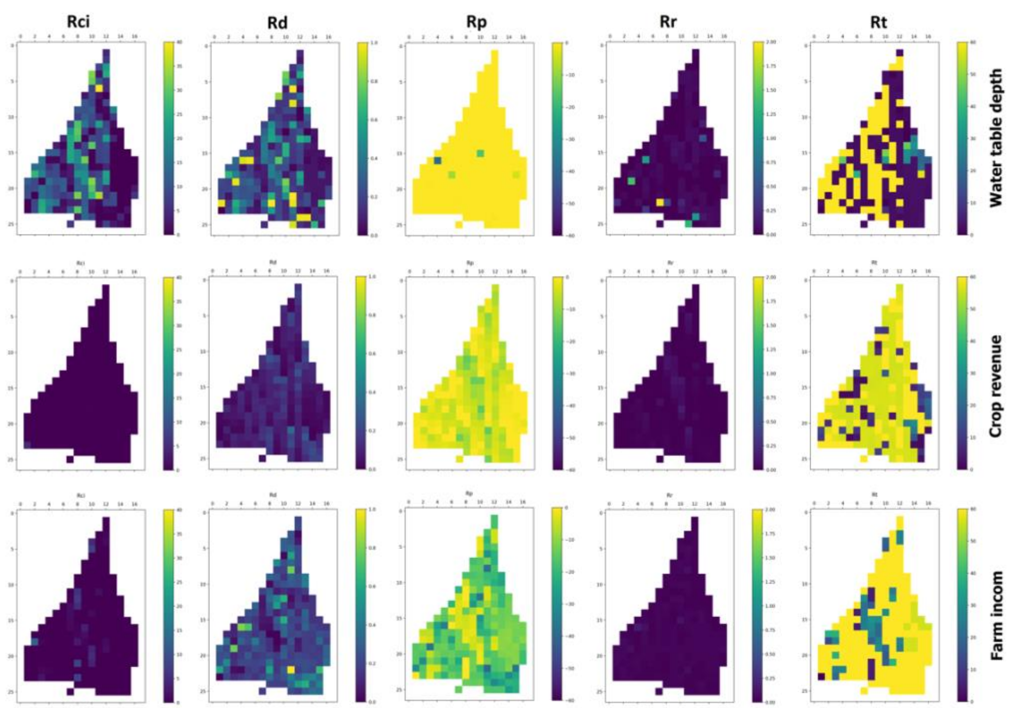

Fig. 3.17. Resilience metric heat maps across the watershed for canal supply shock of -50% sustained for 5 years, in standardized scale

		Upper Watershed			Middle Watershed			Lower Watershed		
Shock	Metrics	WTD	FI	CR	WTD	FI	CR	WTD	FI	CR
S1	Rr	0.280	0.970	1.020	0.120	0.053	0.544	0.027	0.007	0.002
	Rt	0.001	32.750	12.123	32.230	61.000	48.223	58.234	61.000	61.000
	Rd	0.010	0.013	0.010	0.231	0.532	12.232	0.744	1.000	15.79
	Rp	0.001	35.706	37.321	14.210	38.012	38.760	34.221	37.770	36.452
	Rci	0	2.342	29.560	3.232	5.210	31.231	6.460	12.812	40.511
S2	Rr	0.470	1.16	1.160	0.450	0.651	0.555	0.051	0.007	0.004
	Rt	0.530	16.571	10.221	7.230	53.221	32.112	20.323	61.000	61.000
	Rd	0.001	0.011	0.121	0.024	0.430	1.143	0.731	0.94	2.431
	Rp	17.320	40.121	45.231	16.324	42.223	33.288	33.954	45.770	32.231
	Rci	0.020	3.23	31.210	1.780	3.211	24.211	6.832	12.830	38.512

Table 3.2. Regional resilience metric outputs; S1**:** market inflation shock of X10 sustained for 10 years, S2: canal supply shock of -50% sustained for 5 years

As evidenced by the heat maps and metric table, a regional pattern emerged based on the comparative metrics of the three study variables under identical shock conditions. In the upper-watershed, water-table depth displayed the most resilient behavior under both socio-economic and physical shock conditions. Farm income was unable to fully return to baseline in either shock scenario, while both farm income and crop revenue displayed massive perturbation values for the market inflation shock type. Farm income fared the worst under canal supply shock conditions and crop revenue displayed signs of overcompensation under the canal supply shock, indicating a potential functional regime shift; both socioeconomic variables showed a comparable level of resilience (or lack thereof) under the market inflation shock. Water-table depth was extremely stable throughout both shock trials in the upper watershed. These trends held true for the mid-watershed polygons as well, with farm income performing poorly under market inflation shock conditions and crop revenue exhibiting strong over-corrective patterns under canal supply shock conditions. It is not until the lower-watershed region is examined that a change in water-table depth patterns can be identified. In the lower watershed (i.e. polygons farthest from the head or source of the watershed) water-table depth begins exhibiting higher values for perturbation, degree of return, and return time, all indicating a general loss in resilience for the water-table depth variable for both shock-types. In the lower watershed, farm income continues to perform poorly under both shock conditions while crop revenue actually exhibits the greatest robustness (resistance to shock influence) for the shocks in this region. Interestingly, the data (table 2.3) indicate regional differences between each of the regions from North to South, while the heat maps indicate additional differences between East and West (particularly the southwestern corner of the watershed, wherein crop revenue exhibits particularly high resilience). These results indicate the importance of analyzing regional trends from multiple perspectives. The clear difference in resilience of the study variables based on watershed regions and individual polygons is a textbook example of spatial resilience, whereby trends and outcomes at different scales both impact, and are impacted by, local system resilience (Cumming, 2011).

3.4. Discussion

Through each shock trial and for each of the watershed regions, water-table depth was the variable that most consistently aligned with the ideal resilience metric values. This was to be expected under socioeconomic shock conditions (i.e. market inflation) but it was notable that water-table depth continued to exhibit the greatest resilience and robustness even during canal supply shock scenarios. One reason for this seemingly inherent robustness is that water-table depth is a "slow" variable, meaning this variable reacts less dramatically (at least initially) in response to socio-ecological drivers, and also has the capacity to influence "fast" variables (e.g. farm income, crop revenue) which are adjacent in the system and experience the same system-level stresses (Walker et al., 2012). The present study addresses issues related to internal drivers that are incorporated on a variable-level scale but which, owing to the dynamic nature of the coupled model, act as system-level drivers affecting most variables in the system; this is evidenced by the time-series plots showing the marked responses of each variable type to each different shock type. However, water-table depth did show the greatest signs of resilience loss in the lower watershed regions; this makes intuitive sense, as the lower regions are farthest from the source stream and least likely to receive water in amounts copious enough to reserve for times of scarcity. The extreme robustness (i.e. shock resistance) exhibited by water-table depth in the upper and middle regions of the watershed can be explained by the capacity of these regions to exercise water reservation practices based on their more advantageous location in the basin (compared to the lower watershed farms) closer to the head of the watershed. These results indicate areas for improvement in watershed-level supply allocation, irrigation infrastructure, and water banking policy; the identification of these specific sectors requiring improvements are supported by the findings of Inam et al. (2015, 2017a) in the Rechna Doab Basin.

Interestingly, farm income showed the lowest capacity for resilience and/or shock resistance of any of the three study variables, regardless of shock-type, duration, or intensity. This indicates that farm income is itself a very fragile variable, influenced by watershed-level disturbance events of both socioeconomic and biophysical origins. Likewise, crop revenue, the other socioeconomic variable in this study, exhibited extreme fluctuation in perturbation values, while also maintaining consistently large corrective impact values. This erratic behavior indicates that crop revenue is the variable most likely to experience regime shifts in times of stress. Transition to a different baseline level of functionality can be an indicator of extreme functionality loss and also tremendous adaptive capacity; whether it is the former or the latter depends on the response of this transition by closely adjacent variables in the system. For a socioeconomic variable, however, it is likely the former. That is to say, if there were a notable increase in crop revenue as the result of high inflation or a drop in water supply, this revenue increase would be quite unsustainable over a long time period. The spatial resilience exhibited by the study variables (as evidenced in fig. 3.8 – 3.17 and table 3.2) has roots in several socioeconomic and ecological processes, most notably, the unequal distribution of water resources from upper to lower watershed polygons. Not only do upper watershed farmers have more reliable access to fresh water than their downstream counterparts, but government subsidies have incited farmers of all regions to increase cropping intensities, leading to unsustainable drawdown of groundwater resources, especially in the mid-watershed (Inam et al., 2015). This depletion of groundwater resources exacerbates the fragility of variables in the mid- and lower watershed regions by reducing the adaptive capacities of these regions in times of systemic stress; this inability to effectively adapt to changing conditions is reflected in the spatial data collected in this study.

The P-GBSD model was built with multiple feedback loops and complex socioenvironmental relationships linking the variables in the system, and it is therefore unsurprising that the variables which reacted strongly to one shock type also experienced changes when exposed to another, even starkly different type. This innovative resilience assessment scheme will allow stakeholders and model-users to better understand the unique vulnerabilities and adaptive capacities of certain variables in dynamic agroecosystems. The stakeholder knowledge used to develop the GBSD half of the dynamically coupled model was absolutely critical to the understanding of the study system and its constituent variables and feedbacks. The methodology developed in the present study was designed to test the capacity of the dynamically coupled model to produce realistic scenarios that can be used in real-world resilience assessments. Application of the methodology by stakeholders is a continuation of the present research and will be explored in detail in future publications but is beyond the scope of the present study.

The methods and results described herein are directly applicable and relevant to classic resilience theory, whereby resilience is understood as the capacity of a system to absorb or withstand perturbations, disturbances, and various stressors such that the system remains within the same regime (or stability landscape), essentially maintaining its structure and functions (Holling, 1973; Gunderson and Holling, 2002; Walker et al., 2004). The use of a stakeholder-informed, dynamically coupled model for variable-level resilience quantification provides a valuable contribution to the resilience literature in that it combines the concepts of ecological and engineering resilience (Holling, 1996; Walker et al., 2004) and comprehensive socio-ecological indicator frameworks (e.g. Resilience Alliance, 2010; Lisa, 2015; Schipper and Langston, 2015; Bizikova et al., 2017), with the added benefits of participatory modelling (Stave, 2003; Renger et al., 2008 Simonovic, 2009; Beall and Ford, 2010; Halbe and Adamowski, 2011; Butler and Adamowski, 2015; Inam et al., 2015, 2017) and replicable, quantifiable metric analysis.

3.5. Conclusion

Using the integrated P-GBSD model, discrete variable-level shock scenarios were simulated in order to determine the dynamic response patterns of farm income, water table depth, and total crop revenue in each unique regional polygon of the Rechna Doab basin. Following shock-scenario simulations, the output data from each variable was analyzed using five metrics describing a resilient response to disturbance. The five resiliency metric outputs were subsequently analyzed for each of the three interest variables under identical shock conditions. Each polygon in the watershed was assessed separately, each receiving a comprehensive analysis of the comparative resilience of the study variables according to the five calculated resiliency metrics. A comprehensive assessment relating to regional and watershed-level resilience was conducted based on the outcomes of the metric analysis for each variable, under each shock condition, in each unique polygon. This study has shown that the present methodology allows the user to examine the intricate differences and discrepancies between variable reactions to stress for both socioeconomic and environmental/physical variables and shock scenarios. Due to the realistic outputs provided by the dynamically coupled model, this approach for variable-level resilience quantification has some beneficial real-world applications in the spheres of disaster-mitigation policy, vulnerability and adaptive capacity assessments, and long-term risk analyses.

The practical limitations of the present methods could present some challenges for the widespread application of this approach to other systems; these limitations include potential deficiencies in the data required for an accurate model of a chosen study system, as well as any difficulties related to the inclusion of stakeholder-defined variables and processes in a coupled model which relies heavily on accurate feedbacks. With these limitations in mind, there are several elements of the present study that could provide the basis for further scientific investigation; for example, the present study explored shock scenarios from a discrete perspective; i.e. simultaneous disturbances were not taken into account, it is recommended that future research, applying a similar methodology, should be conducted using compound disturbance scenarios, in different regions, climates, and with additional focus variables.

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CONNECTING TEXT TO CHAPTER 4

The resilience quantification methodology described in Chapter 3 was further tested and procedurally expanded by incorporating realistic climate projections and stakeholder-defined policy scenarios into the shock testing regime, this complementary work is outlined in Chapter 4. Two NASA Earth Exchange Global Daily Downscaled Climate Projections (NEX-DGGP) (i.e. representative concentration pathways (RCP) of greenhouse gas concentrations, which were used for climate modeling and research for the IPCC fifth Assessment Report (AR5) in 2014) were incorporated into the P-GBSDM (in addition to the RCP trajectory of zero used for the methodological development described in Chapter 3) and simulated individually for each shock and policy scenario combination in order to determine: 1. The effects of increasingly severe climate-related stresses on the study variables in their shocked and unshocked states, and 2. Any changes in the resilience of the study variables as a combined result of increasingly severe climate trends and any of the three stakeholder-defined policy suggestions.

This chapter is currently undergoing supplementary editing before being submitted for journal review. All literature cited in this chapter is listed at the end of the chapter.

CHAPTER 4: **Climate variability in agroecosystems: a quantitative assessment of stakeholder-defined policies for enhanced socio-environmental resilience**

Jordan M. Carper, Mohammad Reza Alizadeh, Jan F. Adamowski, Azhar Inam, Julien J. Malard

Abstract

Resilient systems are those capable of resisting, withstanding, or efficiently recovering from a variety of abrupt shocks and/or chronic stressors. The development of methods for improving the resilience of socio-environmental systems has become increasingly essential as the severity and variability of global climate patterns continue to compound and intensify. The present study was conducted with the aim of quantifying the degree of resilience conferred to two important socio-environmental variables, farm income and water table depth, through the application of stakeholder defined policy measures in the Rechna Doab basin of northeastern Pakistan. This was accomplished using three NASA Earth Exchange Global Daily Downscaled Climate Projections (NEX-DGGP), two relevant socioenvironmental shock scenarios (market inflation and canal water supply variability), and three stakeholder-defined policy measures. Resilience was assessed using the following system functionality metrics: 1) The degree of return for each variable after a perturbation i.e. the extent to which the observed variable returns to baseline functioning, 2) The return time of the variable to baseline functioning, 3) The rate of variable return to baseline, 4) Overall perturbation of the system post-disturbance, and 5) The corrective impact of the shock on system functionality. Cross-variable differences in the resilience metrics were subsequently compared based on the behavioral change(s) of the study variables in response to the application of the three selected policy scenarios. The results presented here indicate that rainwater harvesting is the most effective stakeholder-defined policy measure for improving or maintaining resilience of the tested study variables in the Rechna Doab basin; this holds true for every climate and shock scenario with the exception of water-table depth in the upper and mid-watershed regions under canal supply shock conditions, for which canal lining is the most effective policy measure. Results were obtained through the use of a dynamically coupled, physical-socio-environmental modelling framework for scenario testing and output development. This unique approach for modelling quantifiable resilience metrics can improve decision-making processes with respect to socio-environmental legislation and climate change mitigation strategies.

Keywords: Resilience, climate change, socio-environmental policy, stakeholders, agroecosystems, coupled modelling

4.1. Introduction

Resilience is broadly understood as the ability of a system or entity to resist, withstand, or rebound from a shock, disturbance, or stressor. Resilience thinking originally emerged from the observational discovery that living systems have multiple basins of attraction (Holling, 1973); the concept has since developed into an approach for understanding complex adaptive systems while serving as a platform for interdisciplinary and transdisciplinary socio-environmental systems research (e.g. Levin et al., 2013). In coupled human and natural systems (CHANS), the concept of resilience is often associated with an effort to attain sustainable development goals (Mayer et al., 2014). Under the ever-increasing threat of climate related disaster, resilient CHANS stand a much better chance of achieving and maintaining sustainable functional states than do those systems operating within less resilient paradigms. Dynamic and complex adaptive systems, e.g. socioenvironmental networks, benefit both directly and indirectly from empirical resilience analyses. The qualitative information gained through a detailed resilience analysis allows community members and non-expert stakeholders to make local economic, lifestyle, and organizational changes that often result in improved socio-environmental sustainability, community cohesion, and adaptive capacities. The quantitative knowledge acquired during a resilience analysis allows government officials and key decision-makers to better understand the dynamics of socio-environmental vulnerability and thus, greatly informs the improvement of legislative measures.

4.1.1. Resilience and Climate Change

The Intergovernmental Panel on Climate Change's (IPCC) Fifth Assessment Report (AR5) for the Asia region recognized that vulnerability to climate change-related hazards in agriculture-based economies, such as Pakistan, is a direct result of distinct geography, demographic trends, socioeconomic factors, and a general lack of adaptive capacity. The climate change projections of the AR5 reveal that warming in South Asia is above the global mean, resulting in substantial changes in glacial melting rates and precipitation patterns; these climatic changes particularly affect the timing and intensity of monsoon rainfall. Consequently, these physical patterns significantly affect the productivity and efficiency of water-dependent sectors, e.g. agriculture and energy. According to the official records produced by the government of Pakistan, agriculture contributes 21% to the country's gross domestic product (GDP), employs 45% of the total workforce, and contributes about 60% to Pakistan's economic exports (Government of Pakistan, Ministry of Planning, Development, and Reforms, 2015). The agriculture of Pakistan is significantly climate-dependent, and each region has its own crops and products according to the local climate. The most important crops are grown in the winter season, however, if there is any shift in general climate patterns, the nation struggles for the entire year and there is a substantial loss to the economy (Shah, 2008). Pakistan's particular vulnerability to the effects of global climate change makes it an ideal setting for the development of an effective procedure for resiliency assessment and socio-environmental policy analysis. Socio-environmental systems, and agricultural communities in particular, which exhibit high resilience with respect to socioeconomic and/or ecological disturbances tend to be those with efficient early warning systems and effective prevention and risk-management tools (Perrings, 2004; Olsson et al., 2006; Gunderson, 2010; Comes et al., 2014). The establishment of a streamlined, stakeholder-friendly resilience assessment procedure can greatly reduce the vulnerability of socioenvironmental and agroecosystems to climate-related shocks and stressors.

4.1.2. Resilience in Modelling

As environmental, ecological, and physical resilience studies have demonstrated, variations in systems-level behavior occur according to rules that govern the physical environment; these physical responses and 'rules' can generally be understood through a series of known equations (Bitterman and Bennett, 2016; Carpenter and Brock, 2006). However, the inclusion of social drivers and their respective impacts is still a relatively rare practice in the sphere of environmental modelling. Using traditional estimation techniques, resilience measurement approaches generally require microeconomic panel data, preferably of high frequency, to directly analyze consumption dynamics. Another common challenge is that measurement can bias action towards elements that can be more easily measured and more easily quantified. A review of recent international resilience-building efforts by Weichselgartner and Kelman (2015) found that international recommendations for resilience-building are often based on unchallenged assumptions about the social world. Scientists are often heavily reliant on strictly quantitative data; as such, they fail to recognize the importance of qualitative information and the role of factors that cannot be obtained or analyzed through quantitative data such as power, governance, and social capital. This scientific predilection for concrete, quantitative data is important and useful, but can also result in 'conceptual blind spots' surrounding the concepts of human agency. A constructive approach for addressing this lack of contextual insight is to involve local resource users in monitoring; this enhances the incentive to learn about local ecosystem dynamics and increases the probability of successfully managing complex systems (Olsson et al., 2004). In fact, stakeholder participation in the development of computer models (i.e. participatory modelling) for socio-environmental decision-making is a rapidly developing area of research.

Participatory modeling has evolved from a number of different fields, the term 'participatory modeling' came from the field of integrated assessment (Rotmans and van Asselt, 2002; van de Kerkhof, 2004), while 'group model building' developed in the system dynamics community (Richardson and Andersen, 1995; Vennix, 1996; Stave, 2002). Participatory modeling methods encourage stakeholder appreciation for a model's limitations, this also helps to ensure that the model is customized to their needs. Active participation in model construction or the early stages of parameter development improves trust in the resulting model and can increase the likelihood that stakeholders will actually use the model results (Cockerill et al., 2004; van den Belt, 2004; Vennix, 1996). The results of participatory modeling are likely to justify most disadvantages brought about by the inclusive modeling approach, however a common challenge associated with participatory modeling is the increased requirements of financial resources, time, and logistical planning needed to engage the participants in the process (Langsdale et al., 2009). These limitations have been addressed in previous studies involving a step-wise process for the initialization of stakeholder participation in agricultural watershed management through qualitative causal loop diagram construction under the constraints of limited time, expertise, and financial resources (Inam et al., 2015). The present paper presents a quantitative methodology that was developed from the foundation of these qualitatively constructed system-dynamics relationships in the agricultural watershed of Rechna Doab, Pakistan. The qualitative foundation for initial model organization and construction (carried out by Inam, Malard, and Adamowski of the present paper) has allowed for the development of a quantitative assessment procedure with a high degree of confidence in the fundamental feedback loops of the modelled study system. The present study makes use of the resilience quantification methodology developed by Carper et al. (under review, *Ecology and Society*), using the physical group-built system dynamics modelling framework (P-GBSDM) developed by Inam, Adamowski, and Malard of the present paper, to effectively measure the characteristics of a resilient response to socioenvironmental disturbances in semi-arid agricultural watersheds, while also assessing the efficacy of certain policy measures to improve the resilience of agroecosystem variables in these scenarios.

4.1.3. Resilience and Public Policy

Enabling local people to be participants in long-term ecosystem management rather than managed as subjects requires governments to transfer power to local authorities and other local decision-makers (Ribot, 2002). Participatory and group-based model-building are tested strategies for improving policy development, effectiveness, and sustainability. Enhanced policy formulation begins with increasing stakeholder understanding of the mechanisms that both improve and degrade the capacity for adaptive and sustainable development. Lockwood et al. (2015) have suggested that the most important factors influencing the perceived adaptive capacity of landholders are related to their management style(s), particularly their change orientation. In other words, if stakeholders are willing to be flexible in their approach to maintaining their agricultural livelihoods, their capacity to withstand and evolve through the continued threat of socio-environmental stressors will be greatly improved. A number of studies have identified indicators of adaptive capacity, often parsing and classifying indicators from the vulnerability and resilience literatures. Indicators have been compiled into indices (Schröter et al. 2005, Cabell and Oelofse 2012, Schneiderbauer et al. 2013) or sorted into dimensions (Yohe and Tol 2002, Gupta et al. 2010), which are typically measured using secondary data sources.

Inam et al. (2017a) tested stakeholder-recommended, socio-environmental policy scenarios (identified during the stakeholder interview phase of the Group-Built System Dynamics (GBSD) modelling process (Inam et al., 2015)) for their capacity to maintain or improve agroecosystem sustainability. Scenarios were selected with the overall intent of improving surface water access in downstream areas in order to better understand the effects of surface water availability on soil salinity and farm income. The present study uses these stakeholder-defined policy solutions (identified, collected, and modelled by Inam et al. (2015)) as test scenarios for the capacity of given policy measures to hinder or confer resilience to agroecosystem variables under socioenvironmental and climatic stress. In the study conducted by Inam et al. (2017a), canal lining was found to be the most suitable, long-term policy that exhibited consistently positive effects (with respect to soil salinity and farm income sustainability) on watershed dynamics. Canal lining requires an initial investment from the government, but Inam et al. (2017a) showed that the study system experienced soil salinity reduction, water availability improvements, increased farm income, and a reduction in aquifer drawdown as a result of the canal lining policy. These policy results were used as a baseline reference for the validation of the present resiliency analysis methodology. In other words, a resilient policy in the context of the present study is a policy measure that reduces the negative impact(s) of socioenvironmental shocks on the study variables; in this respect, it was hypothesized that the canal lining policy would confer the greatest amount of resilience to the study variables under socioenvironmental shock conditions, as this policy has been seen to improve variable functionality under 'normal' (i.e. non-shock) conditions.

Analyzing socioenvironmental systems from a resiliency perspective implies that the composition of the system's asset base is critically important, in other words, it is crucial to be aware of all the resources at the disposal of a dynamic system. A resilient policy or strategy will be one that is effective long-term and could be applied at different spatial scales with relative ease. The most resilient policies (i.e. resilience-conferring policies) reflect the capacity of a disturbed system to adapt to changing conditions within a relatively predictable basin of attraction (Anderies et al., 2013; Polhill et al., 2015); they may also improve the capacity of a system or variable to successfully maintain function during and after a transformation or regime shift (Biggs et al., 2012).

Socioenvironmental policies that confer resilience in the initial stages of implementation may have unforeseen feedbacks or consequences, for example, a policy that initially improves resilience through greater resource allocation may be detrimental in the long term as valuable resources get used at an unsustainable rate. Policies may also experience some degree of efficacy lag, i.e. a policy may be ostensibly inert at the outset but could deliver highly resilient and sustainable returns after several years of implementation; for this reason, it is crucial to develop research criteria around the appropriate variables and for a sufficient timeframe (Levin et al., 2013;

Inam et al., 2017a). Finally, it is important to note that the resilience of a particular system or variable is not always equivalent to the resilience of system governance; that is to say, a government may adapt its policies or practices to improve socioenvironmental resilience based on current information, but the system or variables which are the target(s) of newly implemented policies may react in unforeseen ways. It is important to keep the concepts of spatial variation, temporal variation, and exogenous influences in mind when conducting a thorough resilience assessment and when drafting policies based on such analyses (Carpenter et al., 2001; Walker et al., 2004; Perrings, 2006; Walker et al., 2006; Cumming, 2011; Anderies et al., 2013).

4.2. Methodology

The present study outlines a stakeholder-friendly resilience assessment procedure, based on the work conducted by Carper et al. (under review, *Ecology and Society*), which allows model users to analyze the state of socio-environmental shock and climate scenario resilience for salient agroecosystem variables in a semi-arid agricultural watershed, while also assessing the effectiveness of stakeholder-proposed policy scenarios for shock mitigation. This procedure can be a valuable tool for key decision-makers and stakeholders in climate-vulnerable areas such as Pakistan.

The present methodology involves the use of three different sets of simulation data for the development of a stakeholder-friendly resilience and policy assessment regime based on the functional response outputs of two salient agroecosystem variables (farm income and water table depth). First, two categorically discrete shock types were programed into the dynamically coupled P-GBSD model: 1) Market inflation and 2) Canal water supply variability. These shocks were selected based on their connectivity to most adjacent variables within the system, which is the direct result of the stakeholder-defined feedback loops identified during the initial model development stage in the Rechna Doab Basin (Inam et al., 2015). The selected shock scenarios also represent both the socioeconomic and biophysical capabilities of the coupled model. The shocks were applied discretely to a 30-year historical data set (divided into biannual seasons for 60 total measurement points per variable, per run) for each of the study variables between the years 1989 and 2019; the two shock types were applied with different degrees of intensity and duration over this time period. Simultaneously, one of three NASA Earth Exchange Global Daily Downscaled Climate Projections (NEX-DGGP) was applied in an attempt to better understand the variation in resilience exhibited by the study variables as a direct result of climate pressures. Finally, one of three stakeholder-defined policies was applied to the system for each shock and climate scenario combination in order to determine which policies confer the greatest resilience to the system in any given disturbance paradigm.

4.2.1. The P-GBSD Model

The model used for shock, climate, and policy scenario simulation in this study is a dynamically coupled, physical group-built system dynamics model (P-GBSDM) originally developed by Inam et al. (2015, 2017, 2017a) in collaboration with local stakeholders in the Rechna Doab Basin of northeastern Pakistan. The P-GBSDM is a result of the dynamic coupling of a socioeconomic and environmental system dynamics model, the variables and feedbacks for which were defined by local stakeholders, with the biophysical soil salinity model SAHYSMOD. The initial modelling team used Tinamït Software to couple the physical and SD models. Tinamït is an innovative programming package, which allows the integrated models to exchange data at runtime (Malard et al., 2017). Tinamit, which itself consists of three Python classes that code for model wrappers (one for physically-based models, one for system dynamics models, and one for coupled models), greatly facilitates the process of coupling SD and physically-based models (Malard et al., 2018).

4.2.2. Study Variables

The two variables analyzed in this study were farm income and water table depth. There are several reasons for the selection of these specific study variables; first, an effort was made to represent both the system dynamics capabilities of the coupled model (e.g. farm income) as well as the biophysical contributions (e.g. water table depth). Second, the selected variables represent crucial aspects of agricultural livelihoods that are being increasingly threatened by the impacts of climate change. Finally, as discovered through several rounds of interviews, workshops, and modeling exercises conducted by Inam, Adamowski, and Malard of the present paper, these two variables are of particular interest and value to the local stakeholders of our study region (Inam et al., 2015, 2017a).

4.2.3. Climate Scenarios

The climate scenarios used in this study are NASA Earth Exchange Global Daily Downscaled Climate Projections (NEX-DGGP), which is a dataset comprised of downscaled climate scenarios for the globe that are derived from the General Circulation Model (GCM) runs conducted under the Coupled Model Intercomparison Project Phase 5 (CMIP5) (Taylor et al., 2012). There are three bands in the dataset providing precipitation as well as maximum and minimum temperatures for any selected climate scenario. These data were defined as inputs to the P-GBSDM and the model outputs followed the trajectory of the defined climate parameters for each unique run. The scenarios used here are Representative Concentration Pathways (RCP) of varying intensities, i.e. trajectories of potential climate futures based on greenhouse gas emissions. The three pathways used in this study all describe potential climate futures and are labeled based on their possible range of radiative forcing values in the year 2100 (i.e. current (0), 4.5, and 8.5). These climate scenarios were applied to the 30-year range of historical data used in this study (1989-2019) to better understand the capacity of an applied policy to mitigate the disastrous effects of long-term climate change.

4.2.4. Policy Scenarios

The following stakeholder-defined scenarios (SDSs) (previously collected and tested by Inam et al. (2015) and Inam et al. (2017a)) were selected for inclusion in the resiliency testing simulations: Scenario 1: Canal lining, Scenario 2: Equal water distribution via irrigation improvement, and Scenario 3: Water banking via rainwater harvesting. These scenario suggestions were simulated using the integrated P-GBSD model for each climate and shock combination; the three stakeholder-suggested policies were then analyzed based on their capacity to improve variable resilience in the study system. Each policy was tested with the dynamically coupled P-GBSD model to determine the policies' efficacy with respect to improving resilience of the two primary study variables. This analysis was done using five descriptive metrics of resilience: 1) The policy reduces the degree of variable return after a disturbance, 2) The policy decreases return time to baseline functioning, 3) The policy increases variable return rate, 4) The policy results in a smaller area above the variable response curve, i.e. the magnitude of functional degradation before a new state is reached will be decreased, and 5) The policy decreases *or* increases the corrective impact behavior of the variable (the more resilient response for this metric will depend on the outputs of the other variables; e.g. if time to return and perturbation are decreased while rate of return is increased, then an increase in corrective impact would be the most resilient outcome, however, if degree of return and time to return are greatly increased, a high corrective impact value could indicate a regime shift or unsustainable system transformation, in which case, a decrease in this metric would be the most resilient outcome).

4.2.5. Study Site

Pakistan extends over an area of 796,000 square kilometers with a great diversity in temperature and precipitation. The Rechna Doab Basin is a sub-watershed located in the Indus Plain of central-northeastern Pakistan, a region defined by the latitudinal range 30° 32' N to 31° 08' N, and the longitudinal range 72° 14' E to 71° 49' E. The study area covers 732.50 square kilometers and has been divided into 215 discrete polygons, each with its own unique topology, agricultural divisions, and soil composition. The Rechna 'Doab' ('two waters') basin lies just above the confluence of the Ravi and Chenab Rivers and sits within the Haveli Canal command area. The summer monsoon accounts for around 60% of the total annual precipitation in Pakistan, and with the exception of the southern slopes of the Himalaya and the sub-mountain regions in the North (where annual rainfall ranges from 760 mm to 2,000 mm), 75% of the country receives rainfall of less than 250 millimeters annually; as such, the general climate of Pakistan is considered to be arid or semiarid (Chaudhry, 2017).

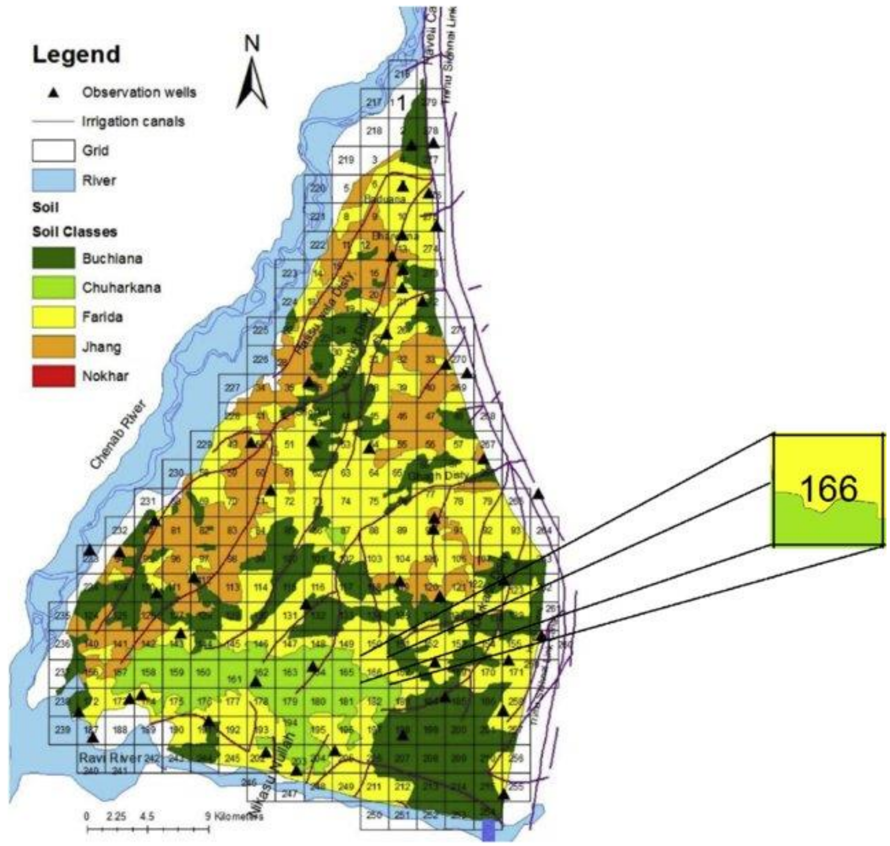


Fig. 4.1. Classification map of the Rechna Doab study area with nodal network numbers, soil classes, and polygonal grid (Inam et al., 2017a): Reproduction permission granted by Elsevier

4.2.6. Data Simulation

Using the Tinamit package (Malard et al., 2017) and coupled programming interface, a baseline set of data was produced for the two study variables through the application of the P-GBSD model. Shock, climate, and policy scenario combinations were subsequently applied to the modelled study system allowing for a comparative resilience assessment between both study variables and the selected policy measures. In order to ensure a cross-variable, comparative resiliency analysis, each set of response data was normalized to the base-case state of the study variable for that run. In other words, the shock, climate, and policy response data was divided by the normal functionality data for each variable over the 60-season simulation period. Each result was normalized to the base-case state of the variable for each individual polygon at each unique time-step. The normalization process resulted in response data that showed the degree of fluctuation or change experienced by each variable compared to the business as usual state (i.e. no shock, climate scenario 0, and no policy application). This normalized data was suitable for resilience metric calculation without fear of the variation in system units altering the comparability of the final resiliency outputs (Carper et al., under review, *Ecology and Society*). Simulations were run for a 30-year period between the years 1989 and 2019 using a 6-month seasonal timestep, i.e. one season is represented by a time period of six months in the model and 60 total data points were collected over a 30-year period for each variable (2) in each run (24). Shock, climate, and policy scenarios were applied starting in the winter season of 1989; the shocks were 'held' in the system for the period of time designated by the 'duration' factor in the model. The duration and intensity factors for the Market Inflation shock were 10 years and x15, respectively, while the factors for the Canal Supply shock were a 90% reduction in canal water supply for five years. These specific shock scenarios were selected due to their combination of severity and real-world applicability; based on data collected by Carper et al. (under review, *Ecology and Society),* these specific shock combinations are not only possible in the Rechna Doab basin, but will also have profound impacts on socio-environmental livelihoods in the region due to their high intensities. Climate and policy scenarios were concurrently incorporated into each unique shock regime, i.e. three climate patterns were administered with combinations of three policy scenarios over a 30-year time period using two different shock-types, this resulted in 54 unique sets of output combinations for this experiment (24 unique runs + 3 basecase scenario runs for each study variable).

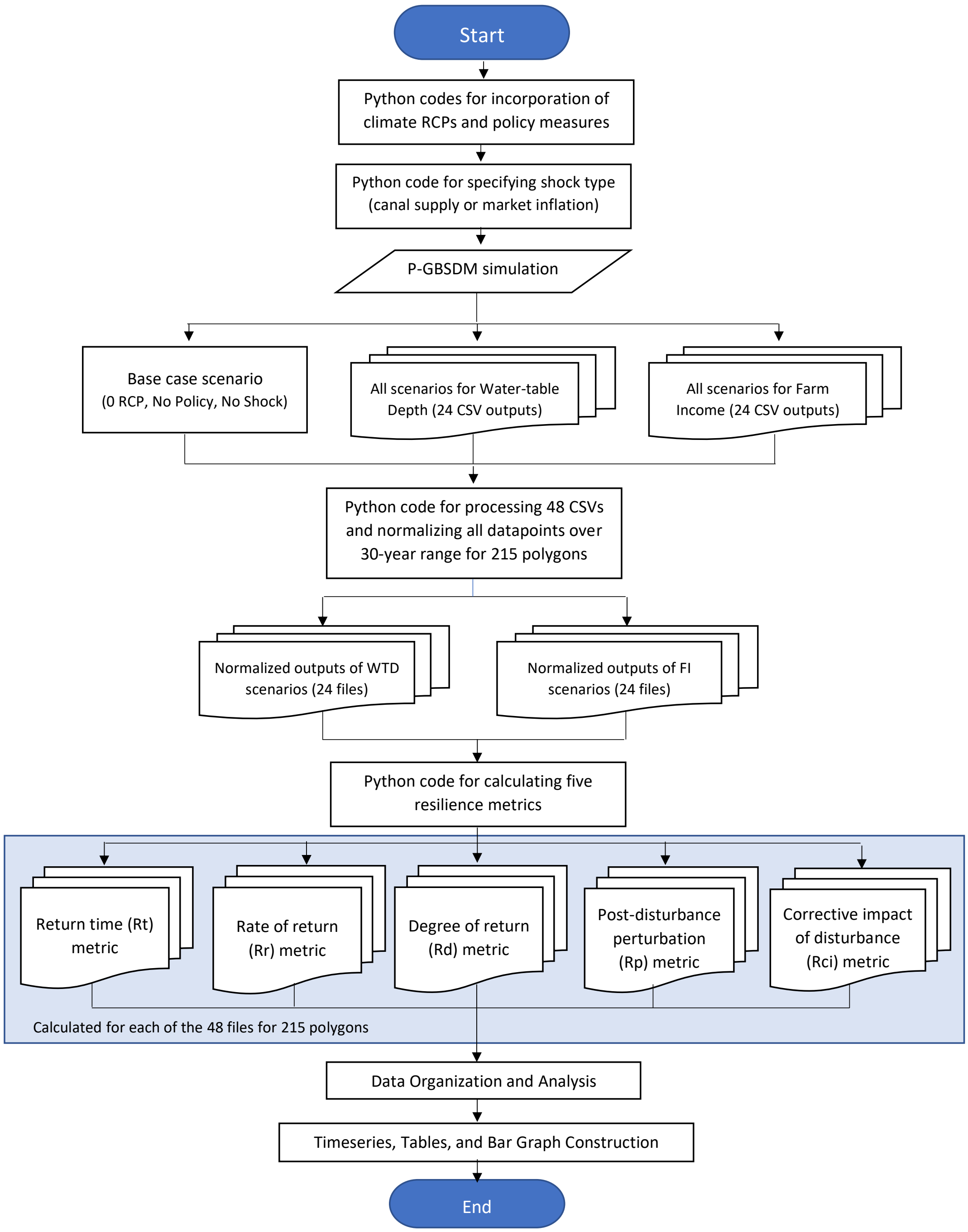


Fig. 4.2. Simulation and results development procedure

4.2.7. Analysis Process

The results of the resilience analysis on the two study variables were evaluated separately for each policy. Each policy was categorized based on the variable of interest (farm income or water-table depth) and resilience metric of interest. The five resilience metrics, originally devised and tested by Carper et al. (under review, *Ecology and Society*), were used as quantifiable benchmarks for the assessment of overall resilience for a variable in any given shock, climate, or policy scenario.

The first resilience metric used in this study, degree of return (Rd), is a measurement of the difference between the end-state of the variable response to disturbance and the reference curve or baseline state. The reference curve could be the baseline variable function under stress *before* a policy is applied or could be an idealized curve representing a highly resilient response to the stressor; in this case, the data were compared against the pre-policy state of a variable under identical shock conditions. The second metric, return time (Rt), is a time measurement of the rebound interval from disturbed state to business as usual state or functional plateau of the data post-disturbance. The third analysis metric, return rate (Rr), is a measurement of the speed at which the variable returns to a state of normal functionality after a disturbance event. The fourth metric, perturbation (Rp), is a measurement of the area above the variable response curve and below the base-case data line, this represents the magnitude and scope of damage caused by any given shock event. Finally, the fifth metric, corrective impact (Rci), is a measurement of the area above the base-case data line and below the variable response curve; this metric allows for the recognition of cases in which a variable may 'over-shoot' the baseline functional state, i.e. a case in which a variable's function is at least partially *improved* by shock application.

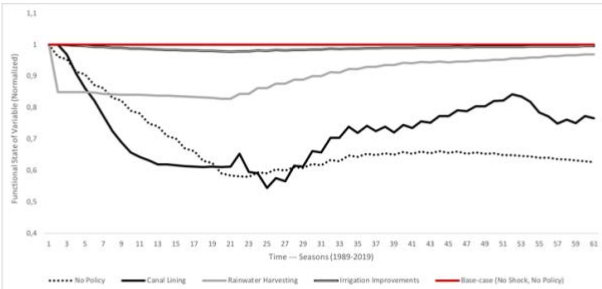
The study variables in each shock and climate condition were assessed for their comparative levels of resilience based on ideal values. "The ideal metric values for a perfectly resilient system are as follows: Return time = 0, rate of return = + , degree of return = 0, perturbation = 0, corrective impact = 0 or + (for a perfectly shock-resistant system this metric would be zero, but in the case that a variable is not perfectly robust (i.e. the variable is not resistant to shock damage, which is likely to be the case), then a high corrective impact metric is ideal)" (Carper et al., under review, *Ecology and Society*). After scenario simulations were completed, the five resilience metrics were compared between variables under identical shock and policy conditions in order to discover: 1) Which variables exhibited the greatest resilience in any given shock or climate scenario and 2) Which policy measures were able to confer (or hinder) resilience to the study variables under socioenvironmental and climatic stress. The following table depicts the full range of scenario runs (24 + 3 basecase scenarios) applied to each of the 2 study variables (farm income and water-table depth) in each of the 215 polygons in this study.

Table 4.1. Scenario simulations applied to farm income and water-table depth for each individual polygon

Run	Climate Scenario	Policy Scenario	Shock Scenario
1	0	No Policy (NP)	Inflation (10yr, x15)
2	0	No Policy (NP)	Canal Supply (5yr, -90%)
3	0	Canal Lining (CL)	Inflation (10yr, x15)
4	0	Canal Lining (CL)	Canal Supply (5yr, -90%)
5	0	Rainwater Harvesting (RH)	Inflation (10yr, x15)
6	0	Rainwater Harvesting (RH)	Canal Supply (5yr, -90%)
7	0	Irrigation Improvement (II)	Inflation (10yr, x15)
8	0	Irrigation Improvement (II)	Canal Supply (5yr, -90%)
9	4.5	No Policy (NP)	Inflation (10yr, x15)
10	4.5	No Policy (NP)	Canal Supply (5yr, -90%)
11	4.5	Canal Lining (CL)	Inflation (10yr, x15)
12	4.5	Canal Lining (CL)	Canal Supply (5yr, -90%)
13	4.5	Rainwater Harvesting (RH)	Inflation (10yr, x15)
14	4.5	Rainwater Harvesting (RH)	Canal Supply (5yr, -90%)
15	4.5	Irrigation Improvement (II)	Inflation (10yr, x15)
16	4.5	Irrigation Improvement (II)	Canal Supply (5yr, -90%)
17	8.5	No Policy (NP)	Inflation (10yr, x15)
18	8.5	No Policy (NP)	Canal Supply (5yr, -90%)
19	8.5	Canal Lining (CL)	Inflation (10yr, x15)
20	8.5	Canal Lining (CL)	Canal Supply (5yr, -90%)
21	8.5	Rainwater Harvesting (RH)	Inflation (10yr, x15)
22	8.5	Rainwater Harvesting (RH)	Canal Supply (5yr, -90%)
23	8.5	Irrigation Improvement (II)	Inflation (10yr, x15)
24	8.5	Irrigation Improvement (II)	Canal Supply (5yr, -90%)
Basecase	0, 4.5, 8.5	No Policy	No Shock

4.3. Results

The following timeseries show the comparative behavior of each study variable with respect to each of the three stakeholder-defined policy suggestions in each climate and shock scenario. These series depict the average behavior of each variable across the entire watershed for 30 years.



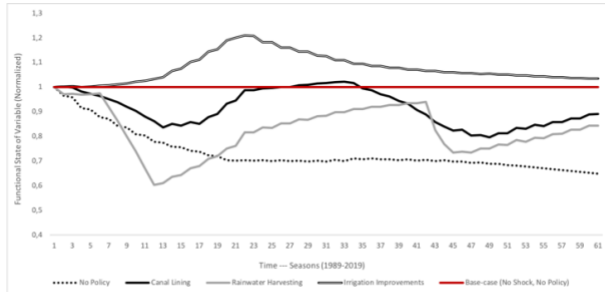
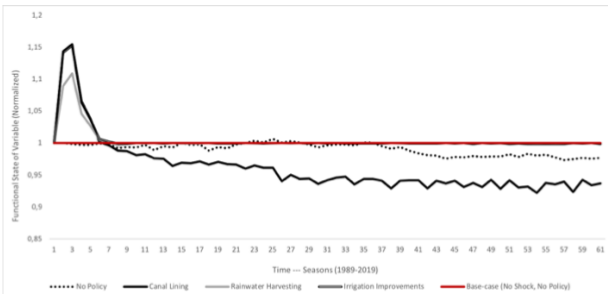


Fig. 4.3. RCP 0, Farm Income, Market Inflation Shock

Fig. 4.4. RCP 0, Farm Income, Canal Supply Shock



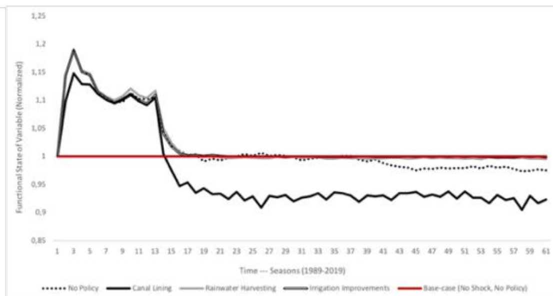
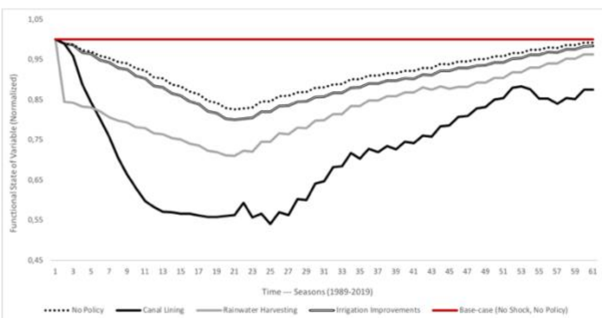


Fig. 4.5. RCP 0, Water-table Depth, Market Inflation Shock

Fig. 4.6. RCP 0, Water-table Depth, Canal Supply Shock



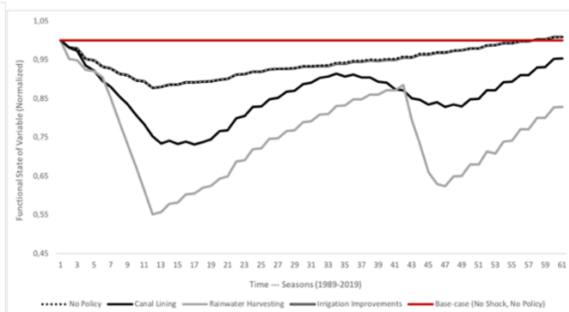
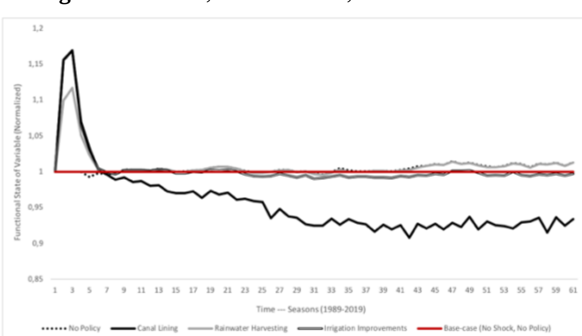


Fig. 4.7. RCP 4.5, Farm Income, Market Inflation Shock

Fig. 4.8. RCP 4.5, Farm Income, Canal Supply Shock



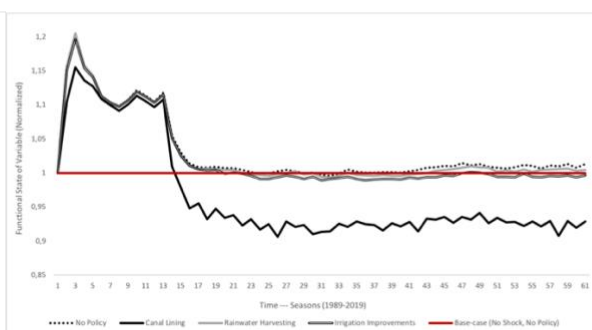


Fig. 4.9. RCP 4.5, Water-table Depth, Market Inflation Shock

Fig. 4.10. RCP 4.5, Water-table Depth, Canal Supply Shock

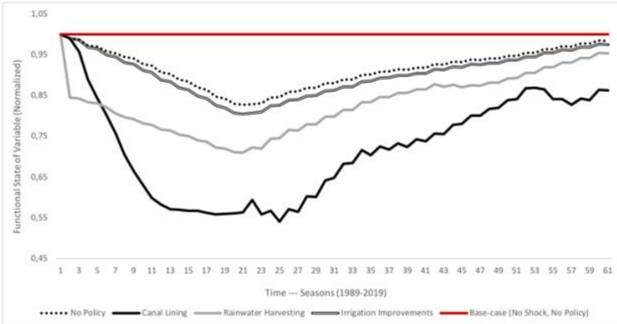


Fig. 4.11. RCP 8.5, Farm Income, Market Inflation Shock

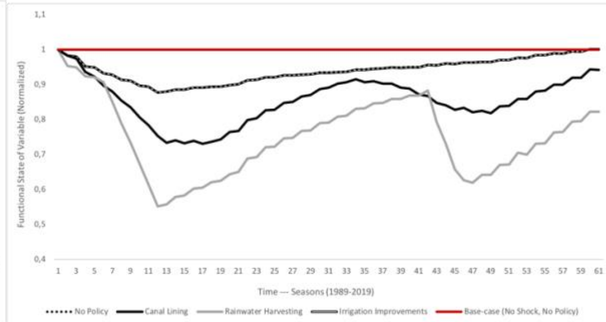


Fig. 4.12. RCP 8.5, Farm Income, Canal Supply Shock

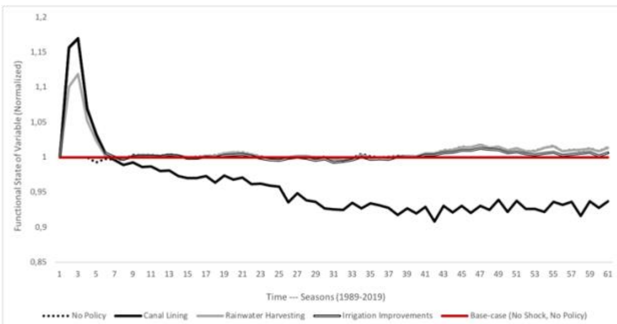


Fig. 4.13. RCP 8.5, Water-table Depth, Market Inflation Shock

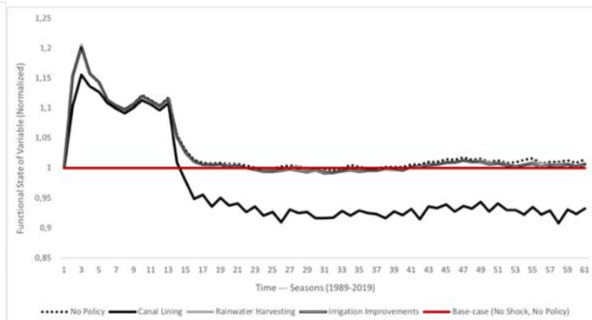


Fig. 4.14. RCP 8.5, Water-table Depth, Canal Supply Shock

The following bar graphs depict the precise resilience metric values for one polygon (#73) in the mid-watershed region of the Rechna Doab basin. This polygon was selected for graphical representation as its values most consistently align with the results from all polygons in the mid-watershed region. Each of the 215 polygons in the watershed were analyzed with the same metrics shown below, polygon #73 is just one example of the 215 sets of results collected for this watershed. S1 and S2 refer to shock #1 (15-fold market inflation for 10 years) and shock #2 (90% reduction in canal supply for 5 years), respectively.

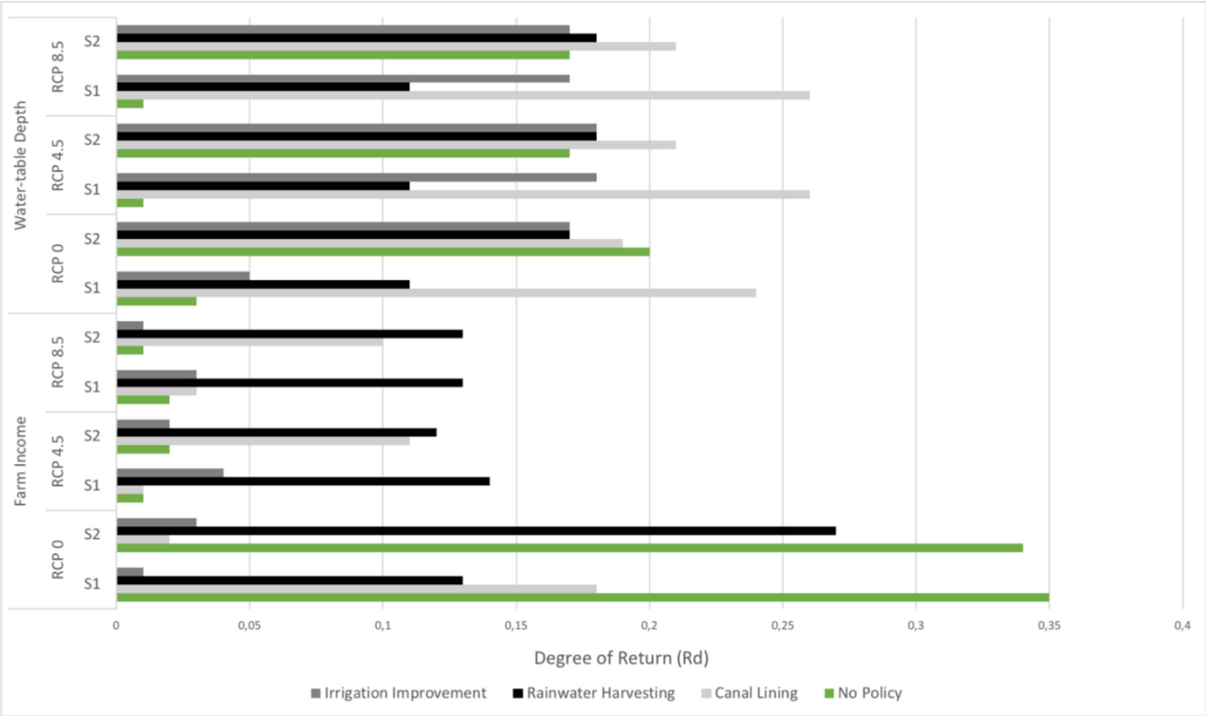


Fig. 4.15. Degree of return (Rd) metric, polygon #73

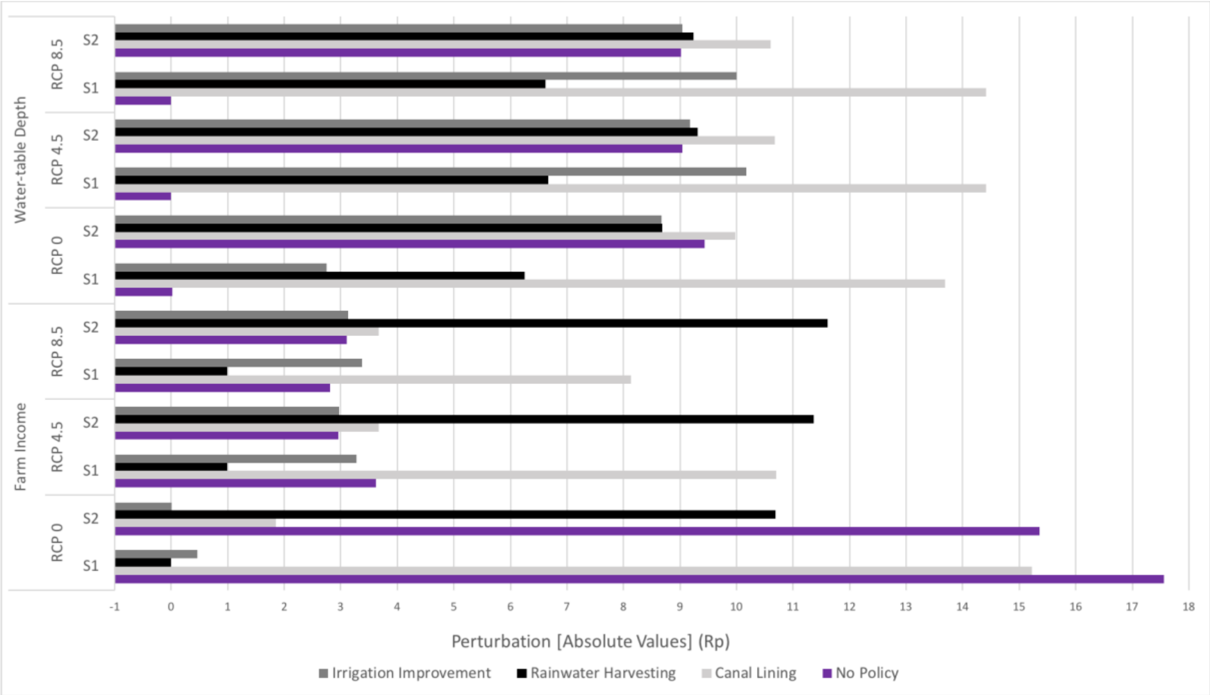


Fig. 4.16. Perturbation (Rp) metric, polygon #73 in absolute values (i.e. most values for Rp were calculated with a negative sign, as perturbation measurements occur below the base-case reference line, but are represented here in their absolute value forms)

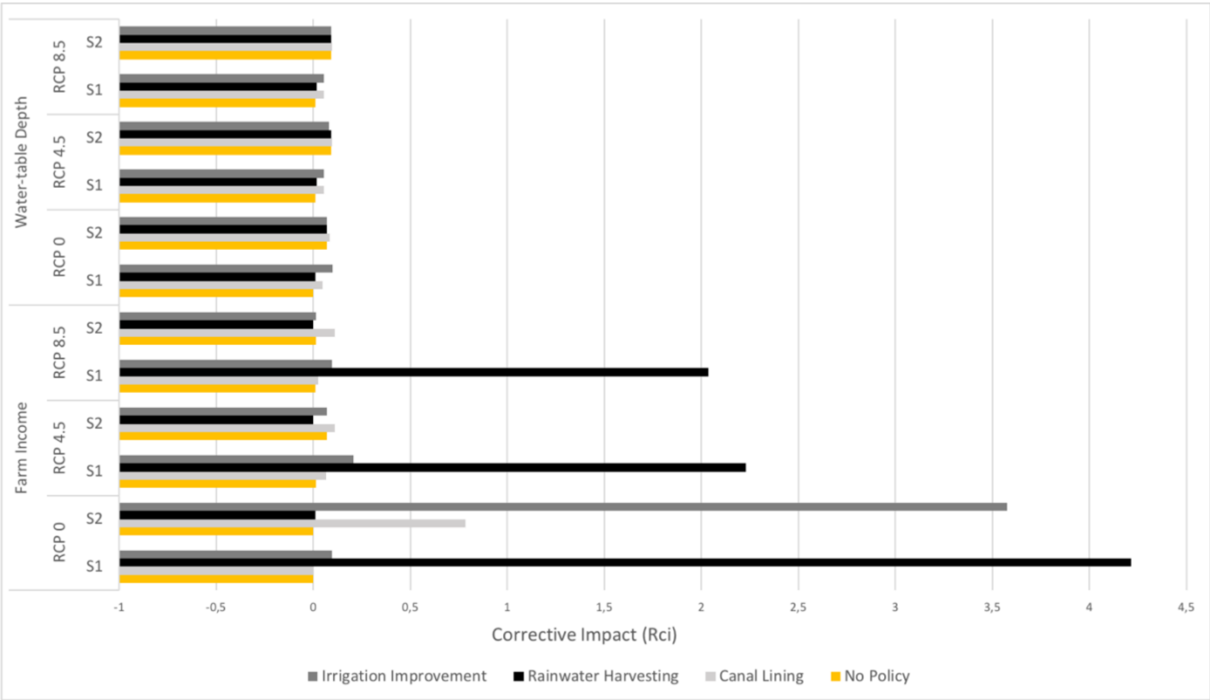


Fig. 4.17. Corrective impact (Rci) metric, polygon #73

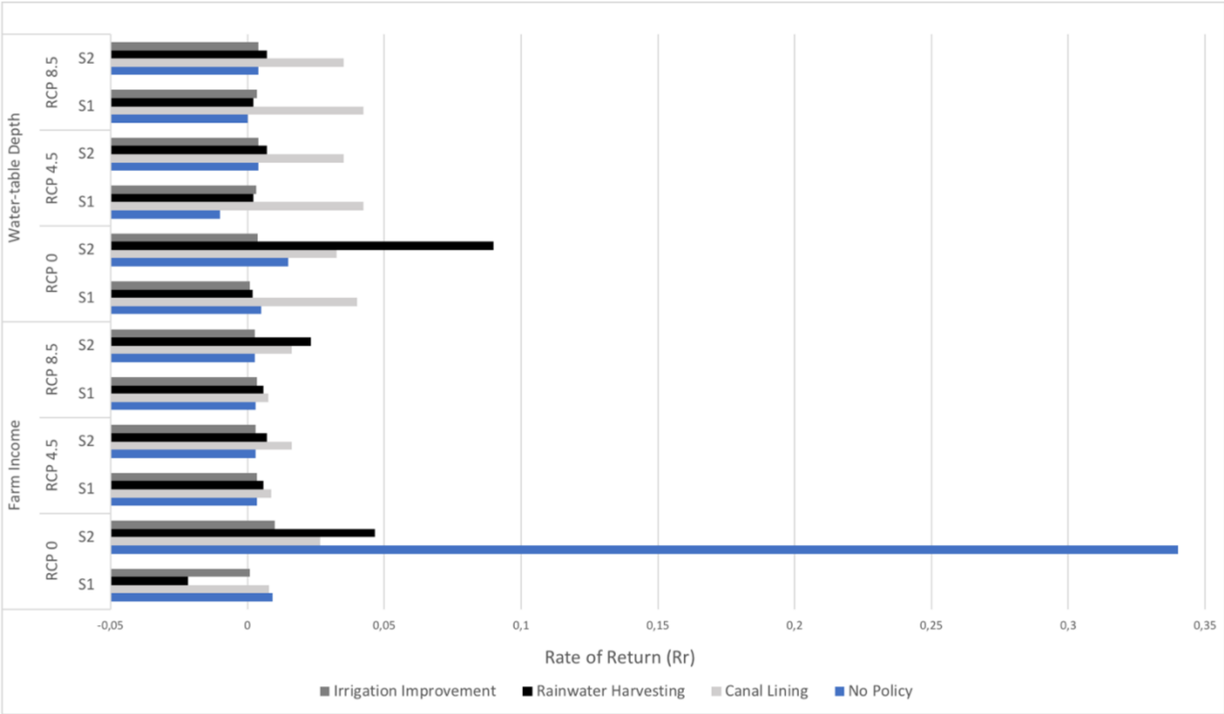


Fig. 4.18. Rate of return (Rr) metric, polygon #73

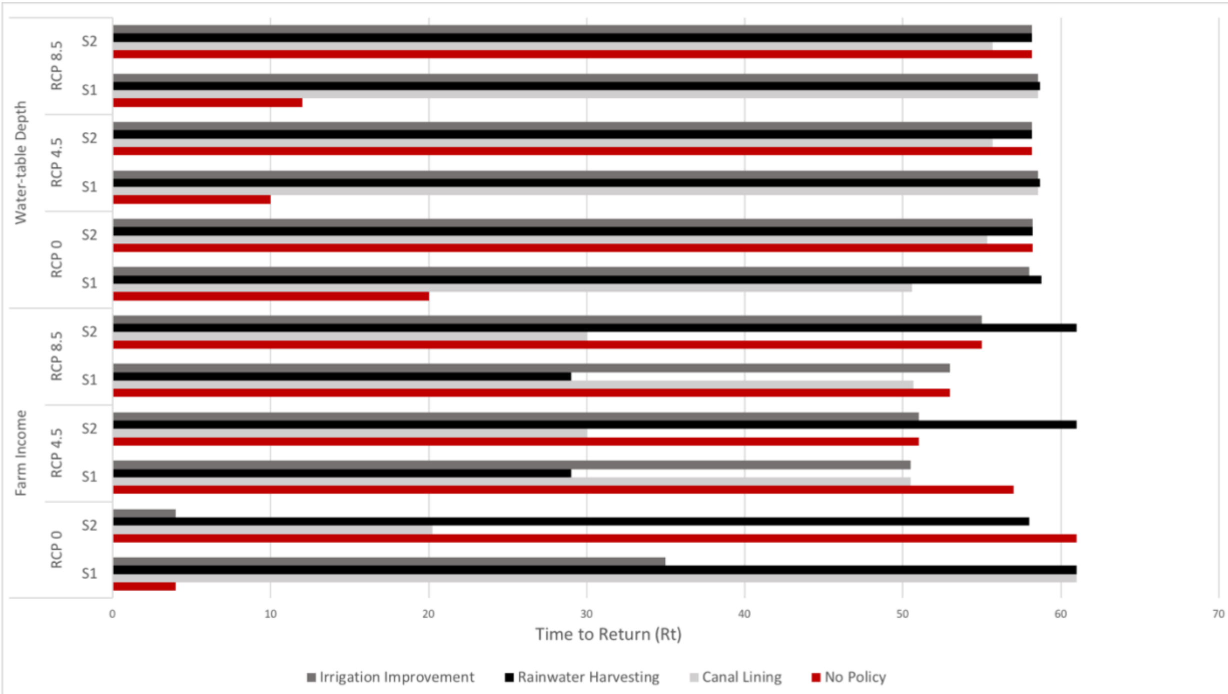


Fig. 4.19. Time to return (Rt) metric, polygon #73

Under climate scenario 0 (i.e. RCP of *current* radiative forcing values), farm income performed the best (i.e. displayed resilience metric outputs most consistent with the values of an ideally resilient variable, see figs. 4.3 – 4.6 and figs. 4.15 – 4.19 above) with the application of the rainwater harvesting policy scenario for both the canal supply and market inflation shock conditions in the upper watershed. The irrigation improvement policy scenario was most effective for farm income in both shock conditions for the mid and lower watershed regions. The farm income variable performed worst with the application of the canal lining policy scenario for both shock conditions in the upper, mid, and lower watershed regions. It should be noted here that the application of 'No Policy' was actually less detrimental to the resilience of the farm income variable in the lower watershed under market inflation shock conditions than was the irrigation improvement policy. Under the same climate conditions, water-table depth performed best with the application of the canal lining policy scenario for canal supply shock conditions in each of the three watershed regions, as well as for market inflation shock conditions in the upper and mid watershed regions; rainwater harvesting was the most effective policy suggestion for the lower-watershed region in market inflation shock conditions. Water-table depth was consistently more resilient than farm income when the market inflation shock was applied, and these results were consistent for upper, mid, and lower watershed polygons.

Under climate scenario 4.5, farm income performed the best with the application of the irrigation improvement policy scenario for canal supply shock conditions in the upper watershed and the rainwater harvesting policy scenario in the mid and lower watershed regions. Farm income performed worst with the canal lining policy scenario for market inflation shock conditions in all three watershed regions. Under the same climate conditions, water-table depth performed best with the application of the canal lining policy scenario in both shock conditions initially, however water-table depth resilience greatly degrades under the canal lining policy scenario after about 16 years in the middle and lower watershed regions. The water-table depth variable performed worst with the application of the rainwater harvesting policy in the upper and mid water regions and the irrigation improvement policy scenario in the lower watershed for both shock conditions.

Under climate scenario 8.5 farm income performed the best with the application of the canal lining policy scenario for both shock conditions in the upper and mid watershed regions and the rainwater harvesting policy for the lower watershed region. The farm income variable performed worst with the application of the rainwater harvesting policy scenario for both the canal supply and market inflation shock conditions in the upper and mid watershed regions and performed worst with the application of the irrigation improvement policy in the lower watershed. Under the same climate conditions, water-table depth performed best with the application of the canal lining policy scenario for canal supply shock conditions in the upper watershed and the rainwater harvesting policy scenario in the middle and lower regions. The water-table depth variable performed worst with the application of the canal lining policy scenario for both shock conditions in the lower watershed, and with the application of rainwater harvesting for both shock conditions in the upper and mid watershed regions.

Overall, farm income displayed the most consistently resilient behavior with the application of the rainwater harvesting and the farm income variable was the most resilient of the two study variables in the mid-watershed regardless of shock, climate, or policy scenario. Water-table depth displayed the most consistently resilient behavior with the application of the canal lining policy in the upper and mid watershed regions and the rainwater harvesting policy in the lower watershed under canal supply shock conditions. On average, rainwater harvesting was the most effective policy scenario across the watershed for both variables under market inflation shock conditions.

Conversely, the least resilient responses for both variables, on average, were recorded under application of the canal lining policy scenario in all regions for market inflation shock conditions. The upper watershed polygons performed better, on average, than the mid or lower watershed polygons regardless of policy or climate scenario. The notable exception to this trend is the behavior of farm income in the mid-watershed, which exhibited the greatest degree of resilience for that variable in the majority of runs. Detailed tables supporting these findings with respect to spatial resilience are included in Appendix 1. These results are consistent with previous studies (e.g. Inam et al., 2017; Malard et al. 2017) which indicate that canal lining is a good policy scenario for long-term environmental management (in the present study this is true for the water-table depth variable), but that it requires an initial investment that temporarily decreases farm income across the watershed.

4.4. Discussion

The results from the present study indicate that the application of each of the three stakeholder-defined policy scenarios can, in fact, improve the resilience of agroecosystem variables (e.g. farm income; water-table depth) under different socio-environmental shock conditions (e.g. fluctuations in market inflation or canal water supply) at this study site. The decreased performance (in terms of resilience) of both variables under more severe climate conditions is consistent across all policy and shock scenarios and was to be expected. However, the application of each of the three policy measures did result in improved resilience metric outputs when compared with no policy application (with the exception of RCPs 4.5 and 8.5 for farm income under market inflation shock conditions); this is encouraging, as these results indicate that stakeholder-developed policy decisions can have a measurable impact on variable-level resilience under a multitude of climate patterns and socio-environmental shock regimes.

The better average performance of upper watershed polygons is likely the result of topography and the existing infrastructure dynamics of the watershed, leading to a greater percentage of seasonal water supplies being allotted to the upper watershed region. The better average performance of water-table depth across all climate, policy, and shock scenarios could be the result of the inherent differences when “fast” variables like socioeconomic factors (e.g. farm income) and “slow” variables like physical phenomena (e.g. water-table depth). For the 30-year simulation period of this study, water-table depth was the most resilient variable in nearly every scenario do to its natural robustness with respect to exogenous influences, but were we to project the data further into the future, it is possible that farm income could become the more resilient variable given the appropriate policy conditions. Overall, the results herein indicate that polygons located in the lower watershed exhibit the greatest beneficial changes when policy measures are enacted across the watershed, this is likely due to the current state of disadvantage in which the lower watershed exists with respect to water resources. The results also show that the mid-watershed regions are the most resilient areas under shock conditions but that the upper watershed fares best of the three regions in base-case conditions (i.e. no shocks).

The ostensible efficacy of the rainwater harvesting policy for farm income in all regions, but especially the lower watershed, is likely the result of poor watershed infrastructure in all regions, leading to severe water shortages in the lower watershed during more intense climate scenarios (i.e. greater instances of drought); this shortage is offset in the most financially conservative way through rainwater harvesting. The rainwater harvesting policy improved resilience of the farm income variable most concretely by being a cheap and easy solution to the water management crisis in the Rechna Doab. The irrigation improvement and canal lining policies were most effective for water-table depth as this variable is not bound so tightly by economic constraints; although there were regional differences in policy efficacy, these trends hold true, on average, for the entire watershed.

It is worth noting that the conclusions drawn herein with reference to the present results are based solely on the 30-year simulation window for the variables involved; it is entirely possible that certain policies could confer a greater degree of resilience to the study variables after 40, 50, or 100 years, especially when considering the slower 'reactions' of physical variables such as water-table depth. A longer-term analysis of these policies is advised but would involve the extrapolation of several years of socioeconomic data, which is beyond the scope of this study.

4.5. Conclusion

In the last 50 years, the annual mean temperature in Pakistan has increased by roughly 0.5°C. In the last 30 years, the number of heat wave days per year has increased nearly fivefold. Historically, annual precipitation has shown relatively high variability, but precipitation overall has increased in the last 50 years. By the end of this century, the annual mean temperature in Pakistan is expected to rise by 3 - 5°C (in a moderate global emissions scenario), while higher global emissions may yield a rise of 4 - 6°C. Sea level is expected to rise by an additional 60 centimeters before the end of the century; this will most likely affect the low-lying coastal areas south of Karachi toward Keti Bander and the Indus River delta. Demand for irrigation water will likely increase due to higher evaporation rates. Yields of wheat and basmati rice are expected to decline and may drive production into more northern territories, subject to water availability (Chaudhry, 2017). The methods presented herein, including policy scenario and climate trajectory testing are of direct relevance and significance to vulnerable communities facing imminent climate change-related hazards and stresses.

These methods should help to improve resilience modelling confidence among stakeholders by introducing a structured, accessible methodology for analyzing policy suggestions based on socio-environmental model outputs. The presented research-based methods for policy analysis with respect to resilience are user-friendly and straightforward in order to ensure the continued inclusiveness of stakeholders in the participatory socio-environmental modelling process. These methods can be utilized in single-system variable analyses as well as comparative studies across, or between, spatial and temporal boundaries (e.g. ecosystems, municipalities, or livelihood networks).

It is recommended that future studies be conducted in different study sites (potentially with different socio-environmental models) with different variables, shock-types, and policy scenarios. A follow-up study, conducted five or more years in the future, using the same data presented in this paper, would also be useful to determine whether the predictive capacity of historical data produced by the P-GBSDM is supported by empirical trends. This information would be useful in determining whether initially successful policies actually degrade variable resilience after 5, 10, 20, or even 50 years.

Appendix 1. Resilience Metric Output Tables

Table A1.1. RCP 0, resilience metrics, no policy

			Upper Watershed		Middle Watershed		Lower Watershed	
	Shock	Metrics	WTD	FI	WTD	FI	WTD	FI
No Policy, 0 RCP	S1 (Run 1)	Rr	0.012	0.019	0.009	0.055	0.007	0.027
		Rt	14.136	61	12.848	61	12.956	61
		Rd	0.025	0.323	0.030	0.345	0.030	0.334
		Rp	(-)0.020	(-)16.893	(-)0.089	(-)16.989	(-)0.032	(-)16.575
		Rci	0.0001	0	0.0014	0	0.185	0
	S2 (Run 2)	Rr	0.028	0.154	0.034	0.166	0.029	0.182
		Rt	36.232	59.896	40.051	61	48.601	59.789
		Rd	0.099	0.309	0.214	0.327	0.162	0.313
		Rp	(-)2.530	(-)14.394	(-)8.159	(-)14.784	(-)6.406	(-)12.696
		Rci	0.239	0.005	0.281	0	0.411	0.012

Table A1.2. RCP 0, resilience metrics, stakeholder-defined policies

			Upper Watershed		Middle Watershed		Lower Watershed	
	Shock	Metrics	WTD	FI	WTD	FI	WTD	FI
Canal Lining, 0 RCP	S1 (Run 3)	Rr	0.018	0.017	0.050	0.039	0.031	0.021
		Rt	50.880	60.208	55.793	56.843	57.357	61
		Rd	0.133	0.309	0.258	0.292	0.194	0.256
		Rp	(-)6.336	(-)19.852	(-)13.795	(-)17.199	(-)9.866	(-)18.654
		Rci	0.043	0.019	0.091	0.473	0.058	0
	S2 (Run 4)	Rr	0.023	0.030	0.044	0.027	0.032	0.013
		Rt	37.599	33.522	41.103	31.912	47.584	46.651
		Rd	0.128	0.192	0.193	0.200	0.189	0.150
		Rp	(-)3.521	(-)6.283	(-)7.527	(-)4.843	(-)7.033	(-)3.633
		Rci	0.399	0.175	0.654	1.576	0.359	0.175
Rainwater Harvesting, 0 RCP	S1 (Run 5)	Rr	0.002	(-)0.012	0.002	(-)0.015	0.003	(-)0.002
		Rt	52.328	44.644	57.085	47.722	59.047	38.109
		Rd	0.063	0.121	0.113	0.119	0.122	0.135
		Rp	(-)2.548	(-)0.523	(-)6.056	(-)0.607	(-)6.912	(-)0.379
		Rci	0.935	3.308	0.453	3.139	0.043	3.576
	S2 (Run 6)	Rr	0.016	0.016	0.025	0.015	0.021	0.011
		Rt	38.843	55.991	39.393	56.689	47.900	53.786
		Rd	0.077	0.151	0.189	0.151	0.147	0.101
		Rp	(-)2.469	(-)9.707	(-)7.852	(-)9.148	(-)6.157	(-)8.194
		Rci	0.286	0.017	0.310	0.012	0.433	0.043
Irrigation Improvement, 0 RCP	S1 (Run 7)	Rr	0.004	0.002	0.004	0.002	0.006	0.0003
		Rt	50.916	52.5	57.710	55.8	58.894	57.308
		Rd	0.074	0.021	0.182	0.024	0.143	0.022
		Rp	(-)3.968	(-)2.195	(-)10.379	(-)1.812	(-)8.011	(-)1.631
		Rci	0.066	0.101	0.117	0.116	0.052	0.120
	S2 (Run 8)	Rr	0.015	0.0007	0.021	0.0007	0.023	(-)0.006
		Rt	38.858	44.724	38.968	39.097	45.097	54.395
		Rd	0.075	0.039	0.184	0.033	0.145	(-)0.020
		Rp	(-)2.429	(-)0.289	(-)7.746	(-)0.373	(-)5.959	(-)0.020
		Rci	0.287	4.300	0.299	3.837	0.309	6.079

Table A1.3. RCP 4.5, resilience metrics, no policy

	Shock	Metrics	Upper Watershed WTD	Upper Watershed FI	Middle Watershed WTD	Middle Watershed FI	Lower Watershed WTD	Lower Watershed FI
No Policy, RCP 4.5	S1 (Run 1)	Rr	0.006	0.009	0.007	0.004	0.009	0.005
		Rt	19.679	56.537	12.739	54.355	10.898	57
		Rd	0.012	0.047	0.014	0.029	0.023	0.018
		Rp	(-)0.284	(-)4.739	(-)0.019	(-)3.729	(-)0.016	(-)4.807
		Rci	0.033	0.063	0.029	0.110	0.020	0.046
	S2 (Run 2)	Rr	0.016	0.004	0.028	0.004	0.019	0.012
		Rt	33.626	49.089	38.593	46.273	48.691	44.441
		Rd	0.077	0.042	0.190	0.044	0.133	0.044
		Rp	(-)2.325	(-)3.636	(-)7.776	(-)2.883	(-)6.418	(-)2.050
		Rci	0.245	0.176	0.243	0.334	0.392	0.663

Table A1.4. RCP 4.5, resilience metrics, stakeholder-defined policies

			Upper Watershed		Middle Watershed		Lower Watershed	
Canal Lining, RCP 4.5	S1 (Run 3)	Rr	0.051	0.019	0.035	0.014	0.012	0.012
		Rt	53.457	58.646	56.506	59.611	58.146	59.611
		Rd	0.147	0.204	0.277	0.225	0.206	0.152
		Rp	(-)6.669	(-)17.569	(-)15.248	(-)16.386	(-)11.064	(-)15.811
		Rci	0.043	0.196	0.087	0.739	0.059	0.079
	S2 (Run 4)	Rr	0.031	0.026	0.025	0.019	0.022	0.278
		Rt	41.947	53.812	38.764	48.293	45.526	55.457
		Rd	0.127	0.164	0.199	0.190	0.181	0.139
		Rp	(-)3.688	(-)10.242	(-)7.979	(-)8.438	(-)7.167	(-)8.744
		Rci	0.400	0.319	0.576	1.469	0.323	0.555
Rainwater Harvesting, RCP 4.5	S1 (Run 5)	Rr	0.005	0.008	0.003	0.008	0.003	0.011
		Rt	49.863	32.604	55.145	37.257	57.496	33.067
		Rd	0.057	0.120	0.116	0.107	0.109	0.139
		Rp	(-)2.379	(-)2.141	(-)6.603	(-)3.023	(-)6.959	(-)2.414
		Rci	0.833	1.754	0.324	1.551	0.046	2.113
	S2 (Run 6)	Rr	0.017	0.018	0.029	0.015	0.018	0.023
		Rt	33.877	57.409	38.585	59.584	49.086	58.407
		Rd	0.079	0.139	0.195	0.113	0.148	0.153
		Rp	(-)2.379	(-)11.996	(-)8.004	(-)11.402	(-)6.642	(-)12.388
		Rci	0.243	0.103	0.241	0.009	0.383	0.383
Irrigation Improvement, RCP 4.5	S1 (Run 7)	Rr	0.030	0.012	0.008	0.005	0.005	0.005
		Rt	51.162	58.189	57.116	54.904	58.773	56.431
		Rd	0.114	0.086	0.197	0.036	0.144	0.027
		Rp	(-)5.241	(-)8.284	(-)11.330	(-)4.688	(-)8.762	(-)5.395
		Rci	0.043	0.077	0.105	0.103	0.059	0.052
	S2 (Run 8)	Rr	0.024	0.009	0.029	0.004	0.016	0.003
		Rt	36.114	47.948	38.494	45.448	50.286	45.095
		Rd	0.099	0.071	0.195	0.045	0.139	0.038
		Rp	(-)2.561	(-)4.001	(-)7.779	(-)2.878	(-)6.629	(-)2.079
		Rci	0.346	0.336	0.242	0.379	0.397	0.429

Table A1.5. RCP 8.5, resilience metrics, no policy

			Upper Watershed		Middle Watershed		Lower Watershed	
	Shock	Metrics	WTD	FI	WTD	FI	WTD	FI
No Policy, RCP 8.5	S1 (Run 1)	Rr	0.005	0.007	0.007	0.004	0.009	0.005
		Rt	20	59.050	12.712	57.165	10.870	58.803
		Rd	0.011	0.033	0.015	0.024	0.023	0.019
		Rp	(-)0.016	(-)4.641	(-)0.019	(-)4.001	(-)0.016	(-)5.027
		Rci	0.031	0.022	0.029	0.055	0.019	0.016
	S2 (Run 2)	Rr	0.016	0.004	0.028	0.004	0.018	0.013
		Rt	33.288	52.190	38.385	48.032	48.692	46.812
		Rd	0.074	0.036	0.189	0.041	0.132	0.039
		Rp	(-)2.288	(-)3.932	(-)7.739	(-)3.076	(-)6.393	(-)2.288
		Rci	0.245	0.127	0.243	0.267	0.392	0.577

Table A1.6. RCP 8.5, resilience metrics, stakeholder-defined policies

			Upper Watershed		Middle Watershed		Lower Watershed	
Canal Lining, RCP 8.5	S1 (Run 3)	Rr	0.021	0.022	0.034	0.014	0.012	0.012
		Rt	53.477	58.872	56.506	54.211	58.147	60.097
		Rd	0.138	0.221	0.276	0.232	0.205	0.163
		Rp	(-)6.618	(-)17.780	(-)15.220	(-)16.629	(-)11.037	(-)16.176
		Rci	0.043	0.161	0.087	0.749	0.059	0.066
	S2 (Run 4)	Rr	0.019	0.035	0.026	0.019	0.022	0.036
		Rt	42.543	55.527	38.764	48.835	45.531	55.536
		Rd	0.118	0.163	0.197	0.186	0.179	0.141
		Rp	(-)3.687	(-)10.566	(-)7.923	(-)8.486	(-)7.142	(-)8.935
		Rci	0.389	0.252	0.577	1.366	0.329	0.509
Rainwater Harvesting, RCP 8.5	S1 (Run 5)	Rr	0.005	0.008	0.003	0.008	0.003	0.010
		Rt	49.727	31.920	54.693	36.775	57.308	33.385
		Rd	0.061	0.116	0.114	0.104	0.109	0.129
		Rp	(-)2.554	(-)2.036	(-)6.487	(-)2.924	(-)6.966	(-)2.458
		Rci	0.816	1.625	0.333	1.469	0.045	1.907
	S2 (Run 6)	Rr	0.017	0.017	0.029	0.016	0.019	0.023
		Rt	33.877	57.297	38.609	59.698	48.927	58.441
		Rd	0.076	0.144	0.194	0.124	0.144	0.158
		Rp	(-)2.367	(-)12.046	(-)7.984	(-)11.626	(-)6.576	(-)12.485
		Rci	0.243	0.110	0.242	0.007	0.383	0.164
Irrigation Improvement, RCP 8.5	S1 (Run 7)	Rr	0.007	0.009	0.007	0.004	0.005	0.005
		Rt	51.301	59.702	56.855	57.259	57.679	58.384
		Rd	0.079	0.045	0.193	0.031	0.146	0.028
		Rp	(-)4.295	(-)6.255	(-)11.249	(-)4.775	(-)8.589	(-)5.735
		Rci	0.043	0.016	0.110	0.057	0.059	0.024
	S2 (Run 8)	Rr	0.015	0.007	0.028	0.004	0.016	0.012
		Rt	36.072	52.055	38.263	46.786	50.127	47.865
		Rd	0.076	0.035	0.190	0.042	0.143	0.037
		Rp	(-)2.682	(-)4.105	(-)7.710	(-)3.045	(-)6.591	(-)2.302
		Rci	0.273	0.130	0.245	0.311	0.395	0.542

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CHAPTER 5: **Summary and Conclusions**

As a direct result of the formidable stresses and hazards associated with global climate change, the incorporation of resilient and sustainable practices into the personal and professional lives of vulnerable populations has become increasingly essential; this includes recognizing the potential impacts of predicted and unexpected disturbances from socioeconomic *and* ecological sources. Various specialized definitions of *resilience* exist, however there remains a lack of scientific and practical consensus with respect to reliable and replicable methods for resilience assessment and measurement. Identifying and developing a streamlined, stakeholder-friendly resilience assessment procedure can greatly improve the robustness and adaptive capacities of the dynamic communities and complex systems to which it is applied.

The primary focus of this study was to develop a methodological framework for streamlined, stakeholder-friendly, socio-environmental resilience quantification, using a dynamically-coupled model. The P-GBSDM employed in this study was developed, in part, through participatory modelling techniques including multiple rounds of stakeholder engagement via CLD conceptualization and construction. The model was dynamically-coupled to include both stakeholder-suggested, socio-environmental variables, and biophysical variables contributed by SAHYSMOD. The procedure for quantification of salient aspects of resilience was developed to include five distinct metrics characterizing an entity's response to disturbance. These five metrics, when analyzed concurrently, allow for a comprehensive understand of the unique vulnerabilities and adaptive capacities associated with individual variables in the study system. After initial shock scenario and variable testing were completed, the quantification methodology was further tested by including stakeholder-defined policy scenarios and NASA-generated climate eventualities in order to determine 1. The capacity of the resilience quantification methodology to be used in public policy analyses, and 2. The effects of climate-related stresses on the resilience of well-understood variables.

The study was divided into two primary parts (each resulting in a journal manuscript). A summary and conclusion for each part are presented below.

5.1. Methodological Development of Stakeholder-friendly Resilience Quantification Procedure

Using the integrated P-GBSD model, discrete variable-level shock scenarios were simulated in order to determine the dynamic response patterns of farm income, water table depth, and total crop revenue in each unique regional polygon of the Rechna Doab basin. Following shock-scenario simulations, the output data from each variable was analyzed using five metrics describing a resilient response to disturbance. The five resiliency metric outputs were subsequently analyzed for each of the three interest variables under identical shock conditions. Each polygon in the watershed was assessed separately, each receiving a comprehensive analysis of the comparative resilience of the study variables according to the five calculated resiliency metrics. A comprehensive assessment relating to regional and watershed-level resilience was conducted based on the outcomes of the metric analysis for each variable, under each shock condition, in each unique polygon. This study has shown that the present methodology allows the user to examine the intricate differences and discrepancies between variable reactions to stress for both socioeconomic and environmental/physical variables and shock scenarios.

The methodology described herein was developed to be intentionally streamlined and user-friendly. The participatory nature of the initial development of the P-GBSDM encourages improved model confidence from both an expert and local stakeholder perspective. The quantification of individual metrics of resilience establishes a concrete, consistent procedure for resilience assessment that can be replicated in multiple environments, with multiple study variables, and under various climatic or sociopolitical conditions.

5.2. Advanced Scenario Testing: Stakeholder-defined Policies and Climate Change Trajectories

In the last 50 years, the annual mean temperature in Pakistan has increased by roughly 0.5°C. In the last 30 years, the number of heat wave days per year has increased nearly fivefold. Historically, annual precipitation has shown relatively high variability, but precipitation overall has increased in the last 50 years. By the end of this century, the annual mean temperature in Pakistan is expected to rise by 3 - 5°C (in a moderate global emissions scenario), while higher global emissions may yield a rise of 4 - 6°C. Sea level is expected to rise by an additional 60 centimeters before the end of the century; this will most likely affect the low-lying coastal areas south of Karachi toward Keti Bander and the Indus River delta. Demand for irrigation water will likely increase due to higher evaporation rates. Yields of wheat and basmati rice are expected to decline and may drive production into more northern territories, subject to water availability. Adaptation strategies for anticipating and dealing with these impending climatic impacts include crop-type divergence to varieties with greater heat and drought tolerance, modernization of irrigation infrastructure and establishment of water-saving technologies, integrated watershed management, reforestation of certain catchment areas, and construction of additional water storage infrastructure. The methods presented herein, including policy scenario and climate trajectory testing are of direct relevance and significance to vulnerable communities facing imminent climate change-related hazards and stresses. These scenarios were tested using the resilience quantification methodology described above.

These methods should help to improve model confidence among stakeholders by introducing a structured, accessible methodology for analyzing policy suggestions based on model outputs. The presented research-based methods for policy analysis with respect to resilience are user-friendly and straightforward in order to ensure the continued inclusiveness of stakeholders in the participatory socio-environmental modelling process. These methods are applicable to individual variable analyses, system-level assessments, as well as comparative studies across, or between, spatial and temporal boundaries.

CHAPTER 6: Contributions to Knowledge and Recommendations for Future Research

6.1. Contributions to Knowledge

A streamlined, stakeholder-friendly resilience quantification methodology, which was completed through the application of a dynamically coupled Physical-Group-Built System Dynamics (P-GBSD) modelling framework, was developed in an effort to improve and standardize the procedure for measuring resilience in complex socio-environmental systems. After several rounds of testing, it has been determined that the procedure described herein is replicable and reliable. The main contributions of this thesis are outlined below.

6.1.1. Methodological

1. A new procedure has been developed for the quantification of resilience for individual variables in complex systems. This was achieved through the application of a unique, integrated modelling framework which allows for the simulation of complex variable linkages in dynamic systems. The developed methodology can help experts, decision makers, and stakeholders better determine the vulnerabilities and adaptive capacities of individual variables within complex socio-environmental systems.
2. The unique methodology for resilience quantification using a coupled modelling framework described herein is adaptable to different environments, climates, variables, and system-types across the globe. This methodology can be applied by experts and local stakeholders alike and provides concrete metrics by which to assess the individual characteristics of dynamic variables with respect to a resilient (or non-resilient) response to disturbance.

6.1.2. Practical

1. The resilience assessment procedure was tested using multiple shock scenario types, intensities, and durations, and the study variables were subjected to three realistic NASA Earth Exchange Global Daily Downscaled Climate Projections (NEX-DGGP) in order to determine the comparative resilience of the study variables in the Rechna Doab basin of northeastern Pakistan. This particular procedure was also tested using stakeholder-defined policy suggestions from local citizens of the study area; the analysis with respect to a policy's capacity to confer improved resilience to a study variable has shown that the resilience quantification methodology described herein can be used in a very practical sense to determine the overall efficacy of proposed legislative measures with regard to socio-environmental resilience improvement.
2. The specific procedure outlined in this study is tailored to the Rechna Doab basin, however the methodology of resilience quantification via metric analysis was designed to be applicable to any agricultural watershed across the globe. This method of resilience assessment can be incorporated into statistical, physical, or system dynamics models of any site. The practical implication for farmers in Pakistan are the same for any farmer worldwide in that the quantifiable metrics produced using this procedure provide concrete, replicable data with respect to the vulnerabilities and strengths of individual variables in an agroecosystem.
3. A step-by-step procedure, designed to aid stakeholders in the implementation of the procedure described herein, is included in Appendix I.

6.2. Recommendations for Future Research

1. The methodology outlined above is theoretically applicable to any number of socio-environmental systems across the globe, as such, this procedure for streamlined resilience quantification should be tested in multiple different environments with new variables, new shock types, and with different policy scenario suggestions in order to reinforce its adaptability and usefulness in different situations.
2. The methodology developed in this thesis was grounded in the supposition that the most desirable state for a variable was that which was determined by its average behavior over

a period of 30 years in unshocked conditions; however, it would be useful to identify desirable alternative states for the study variables in order to better understand the capacity for improvement of system components over time. The determination of these alternative states could be achieved through further in-depth stakeholder interviews concerning ideal functional states of the system in question and/or the application of fuzzy cognitive mapping practices for multiple perceived ideal future states. This information could be highly useful in scenarios where functional transformation as a result of shock scenario application is actually a desired outcome. In the present manuscript, the only scenarios tested were those by which shocks led to a *degradation* in functional state of the variables in question, the identification of desirable alternative states could aid in the understanding of situations in which regime shifts as a result of shock application had constructive effects and could be, in future practice, intentional.

3. The five metrics describing a resilient response outlined above are useful and comprehensive, however the current procedure classifies each metric with equal weight and importance. In real-world scenarios, the importance of each metric will likely vary based on the system under investigation; as such, it is recommended that a weighting system be explored for application to each unique study system. This weighting procedure could be easily designed by conducting further detailed stakeholder interviews in order to determine the preferred response of individual variables with respect to the resilience characteristics. Applying different weights to the resilience metrics would further incorporate stakeholder preferences, local knowledge, and expert recommendations into a comprehensive resilience analysis of any complex system.

APPENDIX I: Implementation Procedure **

Step 1 Select policy (to turn policy on insert '1,' to turn policy off insert '0')

(e.g.) 'base_vals': {'Policy Canal lining': 0, 'Policy RH': 0, 'Policy Irrigation improvement': 0}
In this example, all policies are "turned off."

Step 2 Select shock type (e.g., inflation or canal supply)

Step 3 Select duration and intensity of shock

(e.g.) 'R1': { 'Policy Canal lining': 0, 'Policy RH': 0, 'Policy Irrigation improvement': 0, 'Intensity inflation': 5, 'Duration Inflation': 20}
In this example we have selected "inflation" as the shock type with a duration of '20' (indicating 20 seasons or 10 years) and an intensity of 5 (i.e. 5 times the standardized inflation for the given year).

Step 4 Select latitude and longitude for site

(e.g.) weather = Clima(lat=32.178207, long=73.217391, elev=217, fuentes=weather_Observ)

Step 5 Normalize data to basecase scenario (code does this automatically)

Step 6 Calculate 5 resilience metrics (code does this automatically)

Step 7 Analyze the newly generated .csv files for trends, outliers, and useful patterns (the .csv files contain all 5 resilience metrics for each of the 215 polygons in the entire watershed for the unique scenario that is run (Steps 1-4 above)).

Optional: Before Step 1, specify a unique basecase scenario (i.e., a scenario other than 0 shock, 0 policy, 0 climate) to account for shifts in baseline state of the system or for hypothetical comparative purposes.

** Full code available from author upon request