

Measuring the contribution of ecological composition and functional services of ecosystems to the dynamics of Kwazulu-Natal coast fisheries

R.M. Hassan, Centre for Environmental Economics and Policy in Africa, University of Pretoria, South Africa, Rashid.hassan@up.ac.za, +27 12 420 3317

J.G. Crafford, Prime Africa, South Africa, j.crafford@primeafrica.net, +27 12 348 0317

Corresponding author:

J.G. Crafford, Prime Africa, South Africa, j.crafford@primeafrica.net, +27 12 348 0317

1 Abstract

This study extended a bio-economic fishery model to establish an explicit link between coastal and estuarine ecosystems ecological composition (biodiversity) and functional (nutrient supply) attributes and the dynamics and productivity of KZN coastal fisheries. Results confirmed the importance and strong contribution of the tested ecological attributes. In-sample simulation indicates that current fishing efforts and harvest rates are sustainable, but are sensitive to changes in nutrient influx and rainfall. This confirms the need to modify conventional fisheries models to include environmental variables as additional predictors of fish stocks in addition to historical catch records and catch effort for management and control of fishing efforts and permits. This study provided confirmation of the strong linkage between nutrient levels and productivity of coastal fisheries thus enabling investigation of runoff and rainfall related climate change effects on the KZN fisheries.

Keywords:

Coastal fisheries, Regulating services valuation, bio-economic modelling

Highlights:

- We extend a bio-economic fishery model to establish an explicit link between coastal and estuarine ecosystems composition and functionality and economic behavior
- We demonstrate the dependence of this system on nutrient deposition and rainfall
- We estimate the impact of climate change in fish stocks and harvests

2 Introduction

Gaps in current scientific knowledge of the interdependence between the coupled socio-ecological systems translate into misinformed decision making and adoption of wrong policies and actions that fundamentally result in unsustainable use of these natural assets and weak willingness to conserve them. Due to this knowledge gap human society recognizes only the value of a subset of services that are directly used as final products for consumption, production or recreation - *provisioning services* (MEA, 2005, 2007; TEEB, 2010). These are tangible products that are usually commercially exploited and traded in functioning markets and in many cases have defined property rights, e.g. food, fibre, water, medicines, etc. Accordingly, the shadow prices of these services are relatively easy to

estimate and hence the bulk of the environmental economics work on valuation of ecosystem services had gone into this category of ecosystem services – ES (MEA, 2005; Perrings, 2006; Barbier *et al.*, 2009).

On the other hand, the role and value of other more fundamental services that are not directly used as final products, but are crucial for the functionality of ecosystems and underlie the provision of directly used services, are not well understood and recognized. Examples of *supporting* ecosystem processes forming essential intermediate inputs in the production of final ecosystem goods and services include primary production, nutrient cycling and photosynthesis. Another set of services known as *regulating services* control and normalise ecosystem functioning and thus insures the benefits supplied by ecosystems. In spite of their crucial role as the basis of all other provisions of nature, the literature on valuing such regulating and supporting services is sparse, leaving an important gap in knowledge of sustainable management of ecosystems for human wellbeing (MEA, 2005; Barbier *et al.*, 2009; TEEB, 2010). Efforts to improve our scientific understanding of the complex nature of the involved dynamics of socio-ecological interactions are therefore necessary for prudent ecosystem management and development.

Various formulations and combinations of production function (PF) and bio-economic modelling approaches have been employed to measure marginal contributions of intermediate ES (*supporting and regulating*) to generation of final benefits to human society. Such applications include studies of nutrient cycling in seas and soils (Gren *et al.*, 1997; Nakhumwa and Hassan, 2003; Yerga and Hassan, 2010), biodiversity and carbon sequestration (Boscolo and Vincent, 2003) and pollination services (Ricketts *et al.*, 2004) of tropical forests. Other examples are studies of groundwater recharge for irrigation (Acharya and Barbier, 2000), tropical watershed protection services (Kaiser and Roumasset, 2002), and hydrological functions of wetlands (Jogo and Hassan, 2010). Intermediate ecosystem services in the fishery and coastal ecosystems literature include studies of the role of habitat quality (Acharya and Barbier, 2000; Barbeir, 2007; Rodwell *et al.*, 2003) marine reserves (Mardle *et al.* 2004; Sumaila 2002) and nutrients (Knowler *et al.*, 2001; Kasulo and Perrings, 2006 and Crafford and Hassan 2014) among many others.

The present study attempts to adapt a bio-economic fishery model to measure the contribution of regulating and supporting services of the Kwazulu-Natal (KZN) estuaries of South Africa to the dynamics of the KZN coastal fisheries. This will be achieved through establishing an explicit link between estuaries ecological composition (biodiversity) and functional attributes and provision of the final service (i.e. fish biomass) harvested for direct consumption. The study will accordingly enable establishing accounting prices for estuaries' ecosystem assets needed for deriving sustainability indicators to evaluate tradeoffs between future benefits of intact estuaries' ecological health and benefits from current and planned coastal management and development regimes in the study area and elsewhere.

The next section presents the analytical approach and how it is extended in this study to control for the effects of ecological attributes of estuaries ecosystems to coastal fishery dynamics. Section 3 describes the case study area where the developed model is applied to value the regulating and supporting ecosystem service of estuaries in KZN. The empirical model developed for implementing the intended analysis is presented in section 4. Section 5 presents and discusses empirical estimation

results. Simulations are performed in section 6 and implications for policy and future research are drawn in the concluding section 7.

3 Modelling contributions of intermediate estuarine ecosystems services to coastal fisheries production

Static fish production functions are typically specified to evaluate impacts of economic efforts on fish harvest and market outcomes. However, the importance of ecological structure and function of coastal and estuarine ecosystems (CEE) for the fishery have been studied and confirmed by many authors (Lynne *et al.*, 1981; Ellis and Fisher, 1987; Barbier and Strand, 1998; Barbier *et al.*, 2011). The said studies modeled the combined effects of economic inputs and ecological attributes of CEE on fish harvest H as follows:

$$H = h(E_i, X(S)) \quad (1)$$

Where E_i denote economic inputs (e.g. effort, costs, etc.) and X measures stock of fish biomass. S is a vector of CEE ecological attributes. Barbier (2003 and 2007) used habitat area (coastal wetland or mangrove areas) to represent S . However, in addition to physical characteristics such as habitat area many other ecological components and processes regulate the functioning of CEE. For instance, freshwater flows are known to be a major source of nutrients for primary production supporting key compositional elements (biodiversity) and important underlying ecological processes influencing fish production.

Changes in CEE structure and functionality however, represent stock changes (adjustments in the ecological infrastructure) over time, which cannot be described by static formulations. Accordingly models accounting for the dynamic linkages between changes in CEE stock attributes and harvest over time have been developed. The commonly used dynamic fishery system follows the general form:

$$X_t - X_{t-1} = F(X_{t-1}; S_{t-1}) - h(X_{t-1}; E_{t-1}) \quad (2)$$

Which specifies change in fish biomass X as a function of biological growth $F(X_{t-1}, S_{t-1})$ less harvesting $h(X_{t-1}, E_{t-1})$ realized through application of economic efforts E_{t-1} . This model assumes that CEE assets' attributes S_t (structure and function) influence fish stocks X_t through the biological growth function F . Employing the well known Schaefer model (Schaefer, 1954) specification of logistic biological fishery growth (equation 3) and harvest-economic effort fishery yield (production) functions (equation 4):

$$F(X_{t-1}, S_{t-1}) = rX_{t-1}[1 - X_{t-1}/K] \quad (3)$$

$$H_t = qX_tE_t \quad (4)$$

Where the intrinsic growth rate r , the biological carrying capacity K , and fish density dependent harvesting coefficient q are the drivers of this system. The yield/production function in equation 4 is based on the assumption that potential harvesting per unit effort (H_t / E_t) depends on fish abundance (level of X) (Clark, 1985).

Due to the typical problem of lack of appropriate data on fish biomass (i.e. levels and change in X over time are rarely monitored and recorded) the above system has been alternatively specified as function of observable fish catches (annual harvest H_t) and efforts E_t instead (Shnute, 1977). Equation 4 is therefore used to substitute for the fish biomass variable defined as:

$$X_t = (1/q) (H_t / E_t) = (1/q) c_t \quad (5)$$

Back in the dynamic fishery system in model 2 above will transform the dynamic fishery model into a relationship between catch per unit and effort:

$$(c_t - c_{t-1})/c_{t-1} = r - (r/qK)(c_{t-1}) - qE_{t-1} \quad (6)$$

Where c_t measures catch per unit effort (H_t / E_t). Accordingly parameters of the dynamics of the fishery system (r , K and q) can be estimated from a regression of data on fish catches H_t and effort E_t using transformation equation 6. Most model estimates based on above specifications and data used to analyze such dynamic linkages were derived under assumptions of long-run equilibrium of the studied fishery¹.

Barbier (2007) modeled the effect coastal ecosystem structure on the fishery through the carrying capacity parameter (K). In his specification of a dynamic coastal habitat-fishery model he made K a function of coastal ecosystem stock attributes (S):

$$K(S_t) = \alpha \ln S_t, \quad (7)$$

This changes the catch per unit and effort transformed relationship of equation 6 to:

$$(c_t - c_{t-1})/c_{t-1} = r - (r/\alpha q)[c_{t-1} / \ln S_{t-1}] - qE_{t-1} \quad (8)$$

Following Bjørndal and Conrad (1987), Barbier (2007) dynamic habitat-fishery model specified a fishing efforts function that adjusts in response to profits realized in previous periods as follows:

$$E_t - E_{t-1} = \phi [P * H_{t-1}(X_{t-1}, E_{t-1}) - wE_{t-1}] \quad (9)$$

Where H , X , and E as defined above, P and w refer to fish prices and unit cost of fishing efforts, respectively and $\phi > 0$ is the fishing effort adjustment coefficient.

¹ Barbier (2007) discusses key methodological problems with models attempted to value intermediate CEE services under such assumption.

We adapt the above dynamic fishery system analytical framework to empirically specify the relationship and value the contribution of CEE composition and functional attributes to KZN coastal fishery production in subsequent sections.

4 Study area coastal and estuarine ecosystem and coastal fishery

This study uses data collected on the ecological structure and function of the CEE of the east coast of South Africa within the KZN Bight between Cape St Lucia and Durban (Figure 1). This system plays an important functional biodiversity role in connecting terrestrial and estuarine system processes and components to marine-based species dynamics. This CEE consists of approximately 70 estuaries that have sub-tropical characteristics. Since the early 1980s, many researchers have conducted studies on the physical components, processes and human use of these systems, and thus a rich database exists to support the current study.

Twenty rivers flow via estuaries into the ocean along the KZN Bight (Thukela Bank). The oceanography of the Thukela Bank is dominated by the Agulhas Current (AC), which induces sporadic upwelling of colder water bringing somewhat higher concentrations of inorganic nutrients in the surface waters near the coast that is substantially greater than delivery of nutrients by rivers. While Shelf waters in this section carry higher plankton biomass than oceanic waters seaward there is periodic oscillation between low-nutrient surface waters, and somewhat richer upwelled waters, but generally the water is nutrient-poor along the Thukela Bank section. The AC, coastal topography and wind together create a fairly complex system of predominantly wind-driven inshore currents and topographically driven “semi-permanent eddies of expanded cooler inshore water, with predominantly north-going currents on their inshore edges” (Connell, 2007). The semi-permanent eddies act as important stages for fish migrating up the coast as “their inshore edges have predominantly north-going currents” (Connell, 2007).

The KZN coast is part of a recognized area of fish endemism within the Indo-Pacific region of high fish species diversity, with 16% of the approximately 200 fish species are endemic to the KZN coast, a number of which are considered endangered by the IUCN Red List of Threatened Species (van der Elst, 1988; Weerts, 2002). The majority of these species are strongly associated with estuaries (Whitfield, 1998). Sea surface temperatures between 20°C and 25°C (falling below 20°C fairly regularly); limited extent of reef-building corals; surface salinity that is generally higher (>35 ppt) than in other parts of the Indo-Pacific; and water bodies and eddies that regularly remain localised further restrict the distribution of fish contributing to the high endemism in the region.

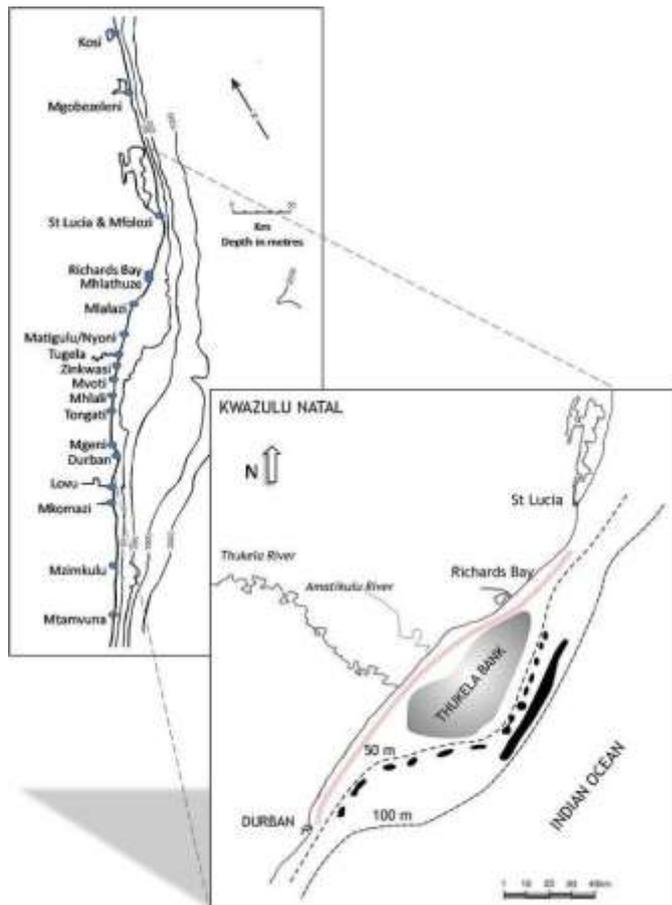


Figure 1. KwaZulu-Natal coastline showing the location of large estuaries (>100 ha) with an inset of the KwaZulu-Natal Bight (shaded pink), Thukela Bank (shaded grey), reef areas (black) and -50 m isobaths (adapted from Forbes and Demetriades 2005)

Large quantities of sediment and washed down terrestrial plant materials, together with decaying seaweed discharged into the sea by the numerous rivers entering the estuaries settle to provide important habitat and nutrients to benthic organisms (van der Elst, 1988). Mangroves, tidal flats, upper estuary areas, freshwater system of lakes and flowing rivers, papyrus swamps, secondary vegetation and coastal dune forests are key components of the type of CEE under study. The Mhlathuze Estuary has the largest mangrove swamp, consisting of approximately 1,200 ha. Tidal flats together with the upper estuary areas bear productive benthic faunas and are the important habitats of juvenile estuary-dependent fish for completion of their life cycle (Cyrus and Wepener, 1998).

4.1 Data sources and the empirical model specification

The system of equations 8 and 9 specifies the dynamic path of the fishery as a function of changes in CEE ecological attributes and consequent changes in fish production (harvest) and welfare given economic efforts applied at the time, i.e. independent of knowledge of (data on) X . Another data challenge relates to measuring the effects of CEE attributes on the carrying capacity of the fishery K specified in equation 7. As discussed above, the transformation of equation 8 allows for estimation of the dynamic fishery model parameters independent of data on X . While this also allows for an indirect derivation of an estimate of the ecological effects parameter α of equation 8, it does not specify an actual functional relationship for the ecological effects. Coastal wetland extent measured as mangrove area was used in Barbier (2007) to determine CEE effects on fish biomass through the system carrying capacity factor K in equation 7 above. Our study had access to an alternative data set that

allows estimation of ecological effects' parameters. The said data provides time series records of fish egg abundance collected by Dr Allan Connell since 1987. This consists of more than two decades of records, in 215 separate species data sheets, of fishes with pelagic eggs on the inshore shelf (within 5km of the KZN coastline (Connell, 2012). Annual spawning period and egg abundance trends are provided, as well as egg and larval descriptions. This activity is part of an ongoing research effort to increase the annual trend graphics for each species and to gather barcodes of currently unidentified eggs and larvae, so that they will be identified when adult material has been sequenced (The fish egg database of the website: www.fisheggsandlarvae.com). Fish eggs and larvae from each sample are collected by hand, counted and identified on a weekly basis. The number of eggs and larvae collected in each sample is used in our study as an index of fish egg abundance and considered a good proxy measure of fish biomass X.

Nutrient influx is one key attribute of coastal ecosystem function influencing fish biomass productivity particularly on the KZN coast which is highly nutrient-depleted and heavily reliant on nutrient influx from terrestrial runoff (Connell, 2012). This is supported by strong empirical evidence from recent research suggesting that nutrient influx into this system is closely tied to annual variations in runoff (Whitfield, 1998; Lamberth and Turpie, 2003; Turpie and Lamberth, 2010). We accordingly describe the relationship between the functional attributes of the KZN coast ecosystem and productivity of its fisheries by the following:

$$S_t = f(N_t(g(AR_t))) \quad (9)$$

Where N_t is an indicator of nutrient load in the fish production system and AR_t denotes annual runoff (AR). Data on AR into the KZN coast was also collected as part of the same fish egg data base described above which allowed estimation of the relation between nutrient influx and fish biomass (using the fish egg abundance index proxy).

Our empirical model of the CEE dependent dynamic fish production system (equations 7, 8 and 8) along the KZN coast is accordingly reduced to the following system:

$$E_t = \theta_1 H_{t-1} + \theta_2 E_{t-1} + \varepsilon_t \quad (10)$$

$$(c_t - c_{t-1})/c_{t-1} = \beta_0 + \beta_1 (c_{t-1}/\ln S_{t-1}) + \beta_2 E_{t-1} + \mu_t \quad (11)$$

$$S_t = \gamma_0 + \gamma_1 AR_t + \omega_t \quad (12)$$

Where E_t measures effort in crew hours per month (number of crew x number of hours fished) for vessel engaged in line fishing in period t; H_t measures total catch in Kilograms per month (kg/month) in period t, $(c_t - c_{t-1})/c_{t-1}$ was calculated from the catch per unit effort (kg/hour/month) data in periods t and t-1, respectively; $(c_{t-1}/\ln S_{t-1})$ was calculated using catch per unit effort data in period t-n and an our measure of S_{t-n} (number of fish eggs and larvae collected); MAR_t measures mean annual runoff in million cubic meters; θ_1 , θ_2 , β_0 , β_1 , β_2 , γ_0 and γ_0 are model parameters and ε_t , μ_t , and ω_t are residual error terms. As mentioned earlier, values of parameters of the structure of the

original dynamic fishery model can be recovered from estimates of the coefficients of above empirical system of equations (10-12) according to the following correspondences:

$$\varphi P = \theta_1; (1 - \varphi w) = \theta_2; r = \beta_0; (r/q\alpha) = -\beta_1; q = -\beta_2; \text{ hence } \alpha = -(r/q\beta_1) = (\beta_0/\beta_2\beta_1)$$

The system is estimated using data on commercial line fishing efforts E , their catch H and catch per unit effort collected by the Department of Agriculture, Forestry and Fisheries (DAFF) combined with above described data on fish egg biomass and annual runoff data.

4.2 Empirical model estimation results

Ordinary least squares (OLS) regression procedure has been used to estimate the biological and economic effects parameters of the above system of equations under the assumption that both X_{t-1} and E_{t-1} (hence c_{t-1}) are predetermined (Homans and Wilen, 1997). To allow for possible cross-equation correlations we employed both single equation and systems of equations econometric estimation procedures to measure above model parameters. The Zellner (1962) Seemingly Unrelated Regression Equations (SURE) procedure estimates of the system of equations 10-12 gave better statistical performance and hence we report and discuss hereunder (Annex 1 and Table 1) results of the SURE procedure.

Table 1. Estimates of model parameters with the SURE regression procedure

	Coefficient	Std. Error	t-Statistic	Prob.
θ_1	0.179113	0.078114	2.292972	0.0221
θ_2	0.810285	0.066065	12.26490	0.0000
β_0	0.129327	0.032052	4.034842	0.0001
β_1	-0.129161	0.087311	-1.479326	0.1394
β_2	-1.99E-07	4.87E-08	-4.075575	0.0001
γ_0	-42.32459	19.95174	-2.121349	0.0342
γ_1	0.293114	0.012656	23.15951	0.0000
γ_2	0.103226	0.008931	11.55843	0.0000
Determinant residual covariance		2.65E+10		

As Table 1 displays, all variables showed very high statistical significance (1% and 5% except the effect of the biomass proxy measure $\log S$ at 14%). The effect of S was statistically significant at 10% when estimated using the actual value instead of the log transformation but the sign of a key structural parameter (the measure of carrying capacity α in equation 7) changed to an infeasible negative value. With the $\log S$ transform we were able to recover all structural parameters of the system with expected signs (Table 2).

Results of the analysis of the relationship between runoff and spawning intensity show a strong effect of nutrient loading into the system in the current period AR_t (γ_1 in Table 1). Further exploratory analyses of this relationship indicated also very powerful lagged effects of nutrient input in preceding years. A one period lag (AR_{t-1}) however did not show statistical significance and hence estimation results for the statistically significant two periods lag (AR_{t-3}) are reported (γ_2 in Table 1). Both coefficients indicate a strong positive correlation between runoff and spawning intensity. The lagged effect is consistent with the life cycle characteristics of fish, which reach spawning maturity after 12-24 months. It is to be noted that improved condition of the spawning adults in the population, resulting from improved nutrition, contributes to the increased spawning (Crafford and Hassan, 2014).

Estimation results indicate that data supports the theoretical assumptions and that in addition to historical catch and economic efforts, functional (nutrients input) and compositional (in this case measured by egg and larvae abundance) attributes of the KZN estuarine and coastal ecosystems are also good key predictors of expected fishing catch and stocks and overall marine fishery system performance.

5 Simulation analysis

Parameter estimates generated were used to recover the structural parameters of the system described in equations 5 to 7, which are reported in Table 2. Estimates of these parameters were used to simulate the structural model to compute estimates of the KZN coastal fishery stocks (X_t) given observed values of AR (nutrient loading), the external driver of this system specification (determining the proxy of diversity measured in abundance of egg and larvae) and consequently the coastal fishery carrying capacity (K) and consequent system biological balances.

Table 2. Structural parameters of the KZN coast fishery

Structural parameter	Symbol	Estimating formula	Value
Intrinsic growth rate	r	β_0	0.12933
Catch ability coefficient	q	$-\beta_2$	1.99 E-07
Estuaries ES attributes effect on carrying capacity (K)	α	$-(r/qb_1)=- (b_0/b_2b_1)$	5,031.58
Carrying capacity	K_t	$\alpha * \log(S_t)$	Vary by t

Table 3. Harvesting and empirical Maximum Sustainable Yield (MSY) for 5 cycles in the KZN fishery over the 20-year period 1990-2009.

Period	Harvest (tons/month)	Empirical MSY (tons/month)
P1 1990-1994	21	-2
P2 1995-1999	15	33
P3 1999-2002	41	-5
P4 2002-2004	28	75
P5 2004-2009	35	31

Figure 2 and Table 3 depict the current situation of KZN coast fishery indicating periods of over-fishing and declining trend of fish stocks (1990-1994, 1999-2002, 2004-2009) and periods of stock recovery (1995-1999, 2002-2004).

Fishing pressure measured as harvest efforts exceeding the maximum sustainable biological Yield (MSY) of the fishery severely during 1990-1994 and during 1999-2002, and to a lesser extent during 2004-2009, driving fish stock down on a declining trend (Figure 2). These declining stock periods are associated with elevated harvests combined with lower rainfall (and AR). The converse is true for the periods of stock recovery (1995-1999 and 2002-2004). When this data is analysed over the long run data period (1990-2009), harvest was 86%-89% of MSY, indicating a sustainably fished system.

This analysis demonstrates that this fishery system is resilient and has, over the past 20 years, been able to recover from short periods of stress resulting from both over-fishing and natural variations in nutrient deposition.

Performance of the system was also simulated under a change in AR scenario, anticipating 10% reduction of AR scenario with climate change. This was implemented by simulating a 10% reduction in the rainfall trend of the past 10 years (1999 – 2009) for the next 10 years from 2011 to 2020. Impact of such reduction of nutrient inputs on the system works through egg & larvae abundance biology determining systems carrying capacity and productivity. The reduction in AR produced an impact of a 4.1% reduction in the system's carrying capacity lowering its MSY from about 28.5 to close to 27.4 Mt per month, and will reduce stock levels by 3.6% (from 4,300 to 4,150 Mt) by 2020. The results also indicate that a disinvestment will take place from fisheries through reduced fishing effort as a result of reduction in harvest by more than 50%.

This indicates the high importance of not only managing the system through managing fishing effort, but also monitoring nutrient inputs into the system and managing their flows and the allowable fishing efforts within the sustainable biological limits of the system to prevent possible collapse of this fishery.

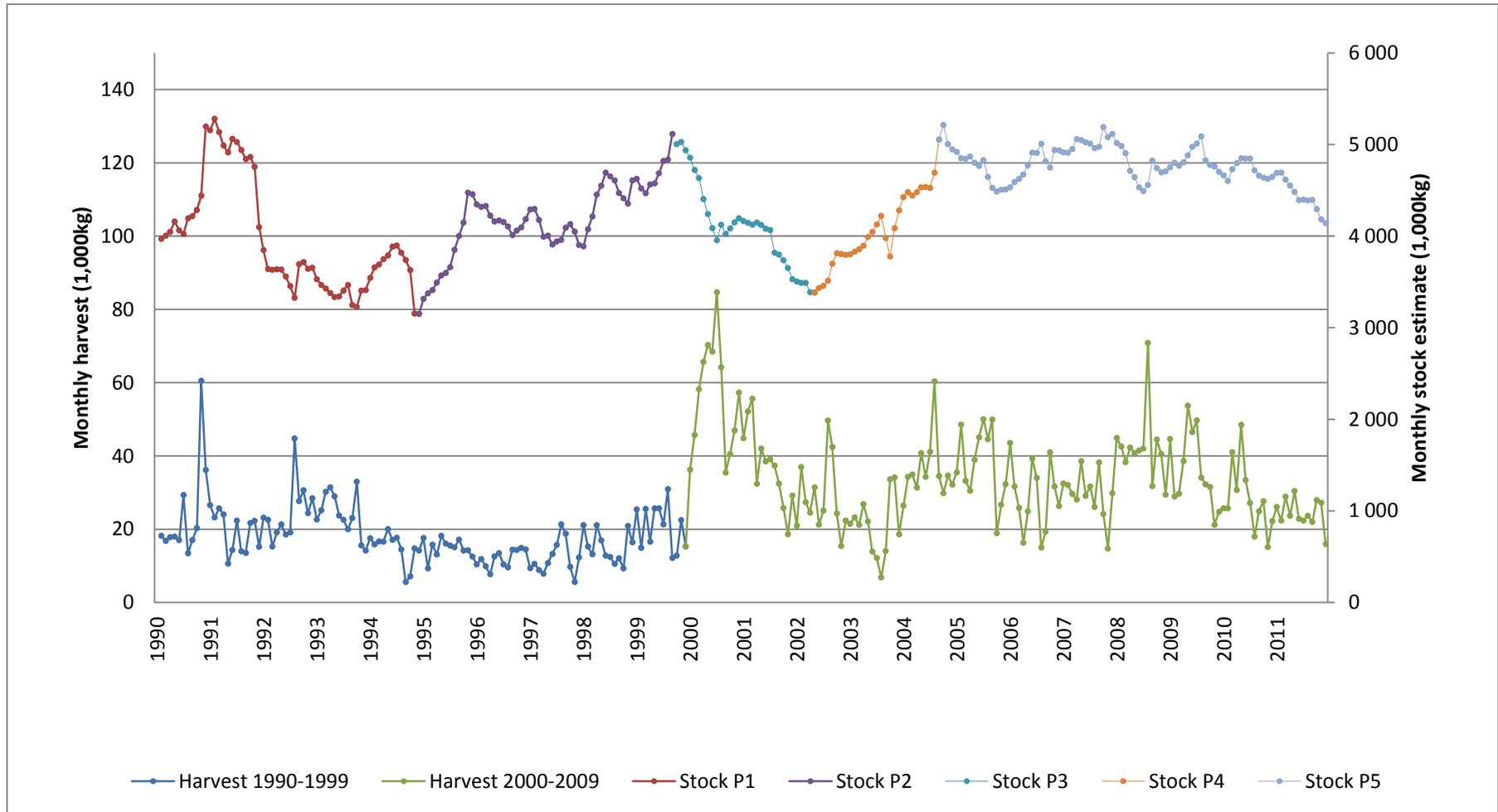


Figure 2. Stock levels and harvest volumes of the KZN line fishery for a 20 year period from 1990 to 2009. Declining trends of fish stocks (1990-1994, 1999-2002, 2004-2009) and periods of stock recovery (1995-1999, 2002-2004) are observed. Periods of stock decline are associated with elevated harvests combined with lower rainfall (and AR). The converse is true for the periods of stock recovery (1995-1999 and (2002-2004).

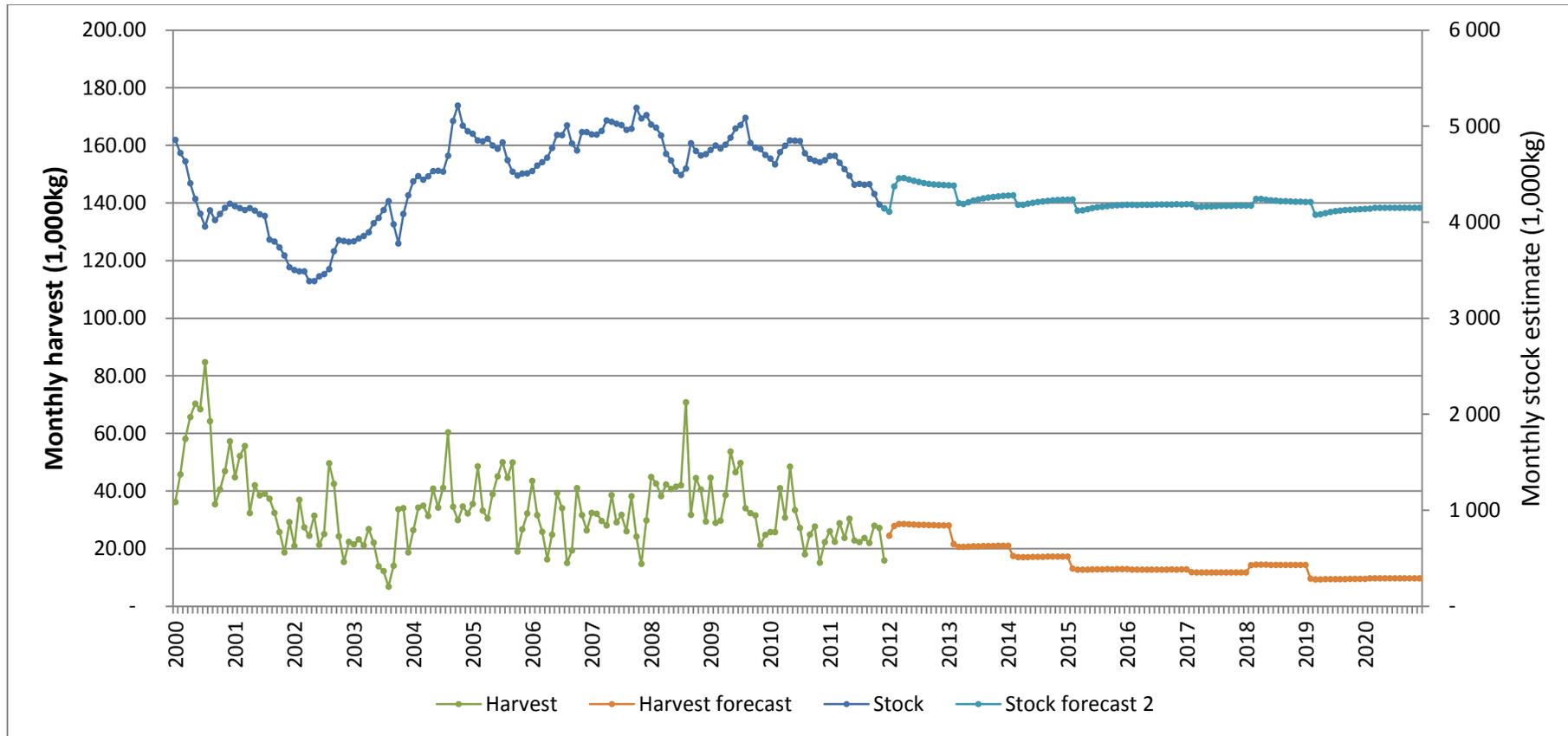


Figure 3. Performance of the system was also simulated under a change in AR scenario, anticipating 10% reduction of AR scenario with climate change. The reduction in AR produced an impact of a 4.1% reduction in the system's carrying capacity lowering its MSY from about 28.5 to close to 27.4 Mt per month, and is likely to reduce stock levels by 3.6%(from 4,300 to 4150 Mt) by 2020. The results also indicate that a disinvestment will take place from fisheries through reduced fishing effort as a result of reduced harvests.

6 Conclusions and implications for policy and research

This study adapted a bio-economic fishery model to measure the contribution of regulating and supporting services of the coastal and estuarine ecosystems in KZN to the dynamics and productivity of its coastal fisheries. The adapted model is based on a well-known dynamic fishery bio-economics formulation that has been widely used to study fishery systems. In this study however, the generic fishery bio-economic specification was extended to establish an explicit link between CEE ecological composition (biodiversity) and functional (nutrient supply) attributes and productivity of the coastal fishery (i.e. harvest of the final service, fish biomass). Other applications in the literature measured the contribution of other ecosystem attributes to fishery systems' dynamics and productivity (e.g. physical infrastructure such as habitat quality, extent of coastal wetland and mangrove area). We measured the contribution of other CEE asset attributes such as freshwater flows as the main source of nutrients for primary production supporting key compositional elements (species diversity) and important underlying ecological processes influencing fish production.

Choice of CEE attributes to include was dictated by available data. The study had access to data on counts of egg and larvae of fish species, which was used as the proxy indicator of biodiversity. The carrying capacity of the coastal fishery stock dynamics was accordingly specified to be a function of this measure of species density. The same data set also contained records of runoff flows into the KZN coast, which was used as a proxy indicator of nutrients input into this CEE and the major driver of species density, thus indirectly influencing carrying capacity and productivity of the fishery through the species composition variable. Above data was combined with available time series on economic efforts and catches of the commercial line fishing along the KZN coast to estimate the structural parameters of the developed dynamic fishery bio-economic model.

Results of the econometric specification of the model parameters showed good statistical fit to the data and supported the study hypotheses on the importance and strong contribution of the tested ecological attributes (diversity and nutrients loading) to productivity and dynamics of the studied fishery system in addition to economic efforts and biological factors. This new knowledge is of high value to coastal fisheries management and policy. It suggests modifying conventional fisheries models' approaches to estimation of fish stocks and management and control of fishing efforts and permits, to include environmental variables as additional predictors of fish stocks in addition to historical catch records and catch effort data.

The study has accordingly used estimated system parameters to generate estimates of stocks of this fishery over the years, which was lacking and hence provides basis for construction of resource accounts for this ecosystem and its assets. Parameter estimates were also used to simulate system performance through in-sample forecasting, which revealed very useful information for better policy and management of this resource. For example the in-sample simulation indicates that current fishing efforts and harvest rates exceed the MSY exerting pressure on the fishery the stock of which was shown to be on the decline.

This study provided further confirmation of the strong linkage between nutrient levels (using AR as a proxy) and fish egg abundance and thus enables the investigation of runoff and rainfall related climate change effects on KZN fisheries. The study has therefore also simulated out-of-sample system performance under a future scenario predicting potential climate change influences on runoff and predict consequent impacts on the fishery system under study. The simulation of futures suggests that a potential 10% reduction in AR will increase the pressure on the fishery carrying capacity leading to faster declines in stocks of up to 4% by 2020, accompanied by a contraction in the fisheries industry of more than 50% as fishing effort is reduced due to reduced productivity levels.

The study also confirms the critical role and benefits of instituting continued investment in long-term scientific monitoring programmes and systematic data collection. Such research efforts should address deficiencies of current efforts particularly the limitation of the available data for this study of lack of species specific information.

7 Acknowledgements

The authors gratefully acknowledge Dr Allan Connell of the *South African Institute for Aquatic Biodiversity* and the *Department of Agriculture, Forestry and Fishing of South Africa* for providing data for this study and for their inputs. We also acknowledge Transnet Ltd for their role initiating this study, the Water Research Commission of South Africa for partial funding and Prime Africa Consultants for funding the larger part of this work.

References

- Acharya, G. and E.B. Barbier (2000). 'Valuing groundwater recharge through agricultural production in the Hadejia-Jama'are wetlands in northern Nigeria', *Agricultural Economics*, 22, 247–59.
- Barbier, E.B. (2003). 'Habitat-fishery linkages and mangrove loss in Thailand', *Contemporary Economic Policy*, 21(1), 59–77.
- Barbier, E.B. (2007). Valuing ecosystem services as productive inputs', *Economic Policy*, 177–229.
- Barbier, E.B. and I. Strand. (1998). 'Valuing mangrove-fishery linkages: A case study of Campeche, Mexico', *Environmental and Resource Economics*, 12, 151–66.
- Barbier EB, Baumgärtner S, Chopra K, Costello C, Duraiappah A, Hassan RM, et al. The valuation of ecosystem services (2009), in: Naeem S, Bunker DE, Hector A, Loreau M, Perrings C. *Biodiversity, Ecosystem Functioning, and Human Wellbeing: An Ecological and Economic Perspective*. Oxford University Press, Oxford.

Barbier, E., Hacker, S., Kennedy, C., Koch, E., Stier, A., and Silliman, B. (2011). The value of estuarine and coastal ecosystem services, *Ecological Monographs*, 81(2):169-193.

Bjørndal, T. and J.M. Conrad (1987). 'The dynamics of an open access fishery', *Canadian Journal of Economics*, 20, 74–85.

Boscolo, M. and J.R. Vincent (2003). 'Nonconvexities in the production of timber, biodiversity, and carbon sequestration', *Journal of Environmental Economics and Management*, 46, 251–68.

Connell, A. (2007). Marine fish eggs and larvae from the east coast of South Africa. Durban, South Africa, March 2007. At <http://www.fisheggsandlarvae.com/> as on 11 November 2008.

Connell, A.D. (2012). Marine fish eggs and larvae from the east coast of South Africa. Durban, South Africa. 2012 Dec. Available at <http://www.fisheggsandlarvae.com/>

Crafford JG, Hassan RM. Towards measuring relationships between ecological infrastructure and the economy: The case of a fishery. *S Afr J Sci*. 2014;110(7/8), Art. #2013-0139, 8 pages. <http://dx.doi.org/10.1590/sajs.2014/20130139>

Cyrus, D.P. and Wepener, V 1998. The enhancement and conservation potential of the 'mangroves and mudflats' area in Richards Bay Harbour, including recommendations for the development of a new sand spit within the area. Coastal Research Unit of Zululand (CRUZ) Investigation Report No. 56.

Ellis, G.M. and A.C. Fisher (1987). 'Valuing the environment as input', *Journal of Environmental Management*, 25, 149–56.

Gren, I-M., K. Elofsson and P. Jannke (1997). 'Cost-effective nutrient reductions to the Baltic Sea', *Environmental and Resource Economics*, 10, 341–62.

Homans, F.R. and J.E. Wilen (1997). 'A model of regulated open access resource use', *Journal of Environmental Economics and Management*, 32, 1–21.

Jogo W, Hassan RM. (2010). Balancing the use of wetlands for economic well-being and ecological security: The case of the Limpopo wetland in southern Africa, *Ecol. Econ.* (2010).

Kaiser, B. and J. Roumasset (2002). 'Valuing indirect ecosystem services: The case of tropical watersheds', *Environment and Development Economics*, 7, 701–14.

Kasulo, V. & Perrings, C. (2006) Fishing down the value chain: Biodiversity and access regimes in freshwater fisheries — the case of Malawi. *Ecological Economics*, 59, 106–114.

Knowler, D., E.B. Barbier, and I. Strand (2001). 'An open-access model of fisheries and nutrient enrichment in the Black Sea', *Marine Resource Economics*, 16, 195–217.

Lamberth SJ, Turpie JK. (2003). The role of estuaries in South African fisheries: economic importance and management implications. *Afr. Jnl. of Marine Science*, Vol 25: p 131-157

Lynne, G.D., P. Conroy and F.J. Prochaska (1981). 'Economic value of marsh areas for marine production processes', *Journal of Environmental Economics and Management*, 8, 175–86.

Mardle, S., C. James, C. Pipitone and M. Kienzle (2004). 'Bioeconomic interactions in an established fishing exclusion zone: The Gulf of Castellammare, NW Sicily', *Natural Resource Modeling*, 17(4), 393–447.

Perrings C. (2006). Ecological economics after the Millennium Assessment, *Int. J. Ecol. Econ.*, Vol. 6 No. F06: p. 8-22

Ricketts, T.H., G.C. Daily, P.R. Ehrlich and C.D. Michener (2004). 'Economic value of tropical forest to coffee production', *Proceedings of the National Academy of Science*, 101(304), 12579–82.

Schaefer, M.B. (1954), Some aspects of the dynamics of populations important to the management of commercial marine Fisheries. Inter-American Tropical Tuna Commission, Bulletin 1: 25-26.

Schnute, J. (1977). 'Improved estimates of the Schaefer Production Model: Theoretical considerations', *Journal of the Fisheries Research Board of Canada*, 34, 583–603.

Sumaila, U.R. (2002). 'Marine protected area performance in a model of a fishery', *Natural Resource Modeling*, 15(4), 439–51.

TEEB (2010) *The Economics of Ecosystems and Biodiversity: Ecological and Economic Foundations*. Edited by Pushpam Kumar. Earthscan, London and Washington.

Van der Elst, R. 1988. Shelf Ichthyofauna of Natal. In: Schuman, E.H. (ed) *Coastal Ocean Studies off Natal, South Africa*. Springer-Verlag New York Inc., Germany, pp 209-225.

Weerts, S.P. 2002. Habitat utilisation by juvenile fishes in Mhlathuze estuary and Richards Bay Harbour. MSc thesis. Department of Zoology, University of Zululand.

Whitfield, A.K. 1998. Biology and ecology of fishes in southern African estuaries, *Ichthyological Monographs of the J.L.B. Smith Institute of Ichthyology*, 2, 223 pp.

Yerga C, Hassan RM. (2010). Social costs and incentives for optimal control of soil nutrient depletion in the central highlands of Ethiopia, *Agricultural Systems* 103 (2010): 153-160

Zellner A. (1962). An efficient method of estimating seemingly unrelated regression equations and tests for aggregation bias. *J Am Stat Assoc.* 57:348–368

Annex 1: Alternatives to the normal Durbin-Watson statistics test for serial correlation

The following are valid alternatives to the normal Durbin-Watson (DW) statistic to test for serial correlation when lagged dependent variables are included in the right hand side of the estimated equation (Wooldridge, 2013).

Durbin h -statistic

The Durbin h -statistic is one option and it is constructed as follows:

$$h = \hat{\rho} \left[\frac{n}{1 - nS_{\hat{\beta}}^2} \right]^{\frac{1}{2}} \sim N(0,1) \quad (A1)$$

Where:

$$\hat{\rho} = \frac{2-d}{2}, \text{ with } d \text{ the normal Durbin-Watson statistic}$$

n : Number of observations in the regression

$S_{\hat{\beta}}^2$: Variance of the coefficient of the lagged dependent variable

One should note however, that the Durbin h -statistic can't be calculated using equation A1 above when $nS_{\hat{\beta}}^2 > 1$ since $x^{\frac{1}{2}}$ can't be calculated for negative values of x . The valid option in such case is to use the Breusch-Godfrey Serial Correlation Lagrange Multiplier (LM) test.

Breusch-Godfrey serial correlation LM (BG-LM) test

Like other tests of serial correlation, this test regresses the residual against itself lagged but includes all the explanatory variables from the original model in the residual regression:

$$e_t = \beta_0 + \sum_{i=1}^n \beta_i X_{it} + \rho e_{t-1} \quad (A2)$$

The test statistic of the BG-LM test is $nR^2 \sim \chi^2(1)$ and it's calculated from the results of the residual regression specified in equation A2 above. To perform hypothesis testing this value is compared to the critical value for a $\chi^2(1)$ distribution.

Annex 2: SURE estimation results

System: FINAL_2
 Estimation Method: Seemingly Unrelated Regression
 Date: 06/22/15 Time: 07:36
 Sample: 2 324
 Included observations: 323
 Total system (unbalanced) observations 1079
 Linear estimation after one-step weighting matrix

	Coefficient	Std. Error	t-Statistic	Prob.
θ_1	0.201483	0.077877	2.587177	0.0098
θ_2	0.793489	0.065873	12.04582	0.0000
β_0	0.195091	0.027186	7.176134	0.0000
β_1	-0.556974	0.170680	-3.263268	0.0011
β_2	-3.55E-06	4.78E-07	-7.434485	0.0000
π_1	0.025071	0.000394	63.66265	0.0000
γ_0	58.76243	18.31237	3.208892	0.0014
γ_1	0.251634	0.011831	21.26873	0.0000
γ_2	0.074804	0.008309	9.002466	0.0000

Determinant residual covariance 4.91E+15

Equation: 11: $E_t = \theta_1 * H_{t-1} + \theta_2 * E_{t-1}$

Observations: 323

R-squared	0.597993	Mean dependent var	29911.27
Adjusted R-squared	0.596741	S.D. dependent var	14968.05
S.E. of regression	9505.116	Sum squared resid	2.90E+10
Breusch-Godfrey LM Test F-stat = 27.6***			

Equation12: $(c_t - c_{t-1})/c_{t-1} = \beta_0 + \beta_1 * (c_{t-1}/\log SSEC_{t-2}) + \beta_2 * E_{t-1}$

Observations: 252

R-squared	0.186761	Mean dependent var	0.018626
Adjusted R-squared	0.180229	S.D. dependent var	0.137990
S.E. of regression	0.124938	Sum squared resid	3.886743
Breusch-Godfrey LM Test F-stat = 575.5***			

Equation 13: $SSEC_{t-2} = \pi_1 * STEC_{t-2}$

Observations: 252

R-squared	0.874496	Mean dependent var	1471.381
Adjusted R-squared	0.874496	S.D. dependent var	1561.046
S.E. of regression	553.0255	Sum squared resid	76765128
Durbin-Watson stat 0.104			

Equation14: $STEC_{t-2} = \gamma_0 + \gamma_1 * SAR_{t-2} + \gamma_2 * SAR_{t-4}$

Observations: 252

R-squared	0.756055	Mean dependent var	513.8190
Adjusted R-squared	0.754095	S.D. dependent var	296.1913
S.E. of regression	146.8777	Sum squared resid	5371690.
Durbin-Watson stat 0.1878			

System: EQ_14_15_16_LAG
 Estimation Method: Seemingly Unrelated Regression
 Sample: 2 324
 Included observations: 323

	Coefficient	Std. Error	t-Statistic	Prob.
θ_1	0.179113	0.078114	2.292972	0.0221
θ_2	0.810285	0.066065	12.26490	0.0000
β_0	0.129327	0.032052	4.034842	0.0001
β_1	-0.129161	0.087311	-1.479326	0.1394
β_2	-1.99E-07	4.87E-08	-4.075575	0.0001
γ_0	-42.32459	19.95174	-2.121349	0.0342
γ_1	0.293114	0.012656	23.15951	0.0000
γ_2	0.103226	0.008931	11.55843	0.0000
Determinant residual covariance		2.65E+10		

Equation 10: $E_t = \theta_1 * H_{t-1} + \theta_2 * E_{t-1}$

Observations: 323

R-squared	0.598150	Mean dependent var	29911.27
Adjusted R-squared	0.596898	S.D. dependent var	14968.05
S.E. of regression	9503.267	Sum squared resid	2.90E+10
Prob(F-statistic)	2.519967		

Equation 11: $(c_t - c_{t-1})/c_{t-1} = \beta_0 + \beta_1 * (c_{t-1}/\ln S_{t-1}) + \beta_2 * E_{t-1}$

Observations: 288

R-squared	0.041956	Mean dependent var	0.016936
Adjusted R-squared	0.035233	S.D. dependent var	0.133536
S.E. of regression	0.131162	Sum squared resid	4.903023
Prob(F-statistic)	0.186220		

Equation: $S_{t-1} = \gamma_0 + \gamma_1 * AR_{t-1} + \gamma_2 * AR_{t-3}$

Observations: 252

R-squared	0.780538	Mean dependent var	513.8190
Adjusted R-squared	0.778775	S.D. dependent var	296.1913
S.E. of regression	139.3123	Sum squared resid	4832573.
Prob(F-statistic)	0.188937		