AR-Sieve-based Prediction Interval for Sustainable Development Index

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We propose a procedure for monitoring progress of sustainable development measured by indices. AR-sieve-based nonparametric prediction interval is constructed to determine whether the movement of the indices is significant or not. Points outside the interval are considered significant and imply positive or negative movement of the indices. This method is used in the construction of prediction interval for sustainable development index for the Philippine. The interval is indeed capable of detecting significant movements that can be explained by policies and other factors.

Keywords: sustainable development index, AR-sieve bootstrap, nonparametric prediction interval

1. Introduction

(WCED,1987) defines sustainable development as meeting the needs of the present generation without compromising the ability of future generations to meet their own needs. Sustainable development integrates economic development, social development and environmental protection. It aims to reduce poverty, change unsustainable patterns of production and consumption, and protect and manage the natural resources (PCSD, 1997). Because of these, sustainable development has become an important concern in various countries, as manifested by their declaration to integrate the principles of sustainable development in their policies and programs.

The UN Commission on Sustainable Development promotes the national sustainable development strategy (NSDS) as a mechanism for translating goals of sustainable development into concrete policies and actions. NSDS covers situation analysis, formulation of policies and action plans, implementation, monitoring and regular review. An important element of monitoring is the development of indicators, benchmarks or thresholds. Indicators show the status and trend of a particular process. Appropriate indicators can be used to measure and monitor the effect and impact of different policies on sustainable development (UN Division for Sustainable Development).

In the Philippines, (Barrios and Komoto, 2006) constructed indices that were able to provide an adequate summary of sustainable development indicators. Time plot of these indices reveals the movement of sustainable development indices. In monitoring sustainable development, it is important to have a sound interpretation of the trend of indices and determine which increase or decrease in indices is significant. One approach is to set upper and lower limits for each index. This interval works similarly as a confidence interval for a parameter in a model. This interval, at some degree of confidence, will give the region where the true value of a sustainable development index lies. Hence, a score that is not within the interval will be considered as significantly high or significantly low.

Analyzing time series data and building prediction interval around each index using parametric inference through ARIMA models entail assumptions that need to be met and necessary procedures are sometimes mathematically intractable. According to (Mooney and Duval, 1993), applying inappropriate distributional assumption of statistic of interest may worsen Type I or Type II error rates. Also, an ARIMA model requires an adequate sample size (Wei, 1990). Alternatively, construction of prediction interval for forecast from time series data can be performed through nonparametric approaches, like bootstrap, which make distributional assumptions unnecessary and avoid analytical formula for parameter estimation (Mooney and Duval, 1993).

Bootstrap is a method that simulates the empirical distribution of a statistic from an estimated distribution on the basis of resample. (Bühlmann, 1997) developed sieve bootstrap as a method of generating a bootstrap sample by resampling from the residuals of a time series model. The sieve bootstrap produces consistent estimators of the variance of time series statistics, like the process mean. Previous studies illustrate applications of sieve bootstrap for time series data. (Campano and Barrios, 2011) proposed an AR-sieve estimation procedure which yields robust estimates of time series model with structural change. (Mancenido and Barrios, 2011) proposed a methodology for constructing control charts using AR-sieve bootstrap and concluded that the sieve bootstrap trivialized the issue of sample size on parametric inference. With bootstrap, there is no need to perform the iterative process of model building which complicates the analysis of time series data.

This study explores the use of sieve bootstrap in the construction of prediction intervals for sustainable development indices and compares the results with that of ARIMA models.

2. Sustainable Development

The essence of sustainable development is the harmonious integration of a sound and viable economy, responsible governance, social cohesion and ecological integrity to ensure human development for present and future generations. Philippine Agenda 21 is the nation's blueprint for sustainable development. It has laid the action plan for various sectors of society and the government to work towards sustainable development (Philippine Commission on Sustainable Development, 1997).

The Organization of Economic Cooperation and Development created the Pressure-State-Response (PSR) Framework in 1993 to develop indicators for monitoring sustainable development. The pressure indicators refer to the underlying forces and direct stresses exerted on the environment. State indicators reflect the condition of the environment that results from human activities or pressure. Response indicators measure how the society responds to the pressure or changes in state of the environment (Department of Environment and Natural Resources, 1997).

Nalica and Barrios (2005) classified sustainable development indicators in the Philippines using PSR framework. Initially, there were 46 pressure indicators, 45 state indicators and 8 response indicators. With variable cluster method and principal component analysis, these indicators were reduced to 18 indicators. Barrios and Komoto (2006) constructed three sustainable development indices using these 18 indicators. They labelled the first component as 'Sustainable Development Index' since it is a representation of indicators from all categories (pressure, state and response). The second component is labelled as 'Pressure-Response Index' since it is a composite of pressure and response indicators. The third component is labelled as 'State Index' since it is an averaging of state indicators.

(UN Division for Sustainable Development) defines a NSDS as a coordinated, participatory and iterative process of thoughts and actions to achieve economic, environmental and social objective in a balanced and integrated manner at the national and local levels. Effective implementation of NSDS requires follow up and monitoring to know which policy or intervention works and which does not. This stage involves monitoring and evaluation of processes, outcomes and impacts. Process evaluation measures how effective implementation of action plans is done. Monitoring and evaluation (M&E) of outcomes involves measuring the immediate effect of the activities done. Impact assessment aims to determine the long term and widespread consequences of the intervention. Effective M&E for sustainable development needs to be participatory, practical and reflective. An M&E system should involve various stakeholders so that all ideas and concerns are considered. It should be relevant and able to provide needed information. Institutions involved should reflect and learn from the failures and successes of the process. Through M&E, institutions can improve the strategies and implementation process.

3. Methodology

This section presents the construction of sustainable development indices and the proposed nonparametric method of construction of the prediction interval that can be used in monitoring progress in sustainable development

Nalica and Barrios (2005) suggested a methodology of identifying indicators of sustainable development leading to 18 core indicators for the Philippines. Barrios and Komoto (2006) used these 17 of these indicators in the construction of sustainable development indices. However, they removed DIARR due to interpretability issue. The data used in this study are the time series data of the core indicators excluding DIARR from 1981 to 2005.

Since there are fewer observations than the number of variables, dimension reduction is used improve data visualization. However, since the indicators exhibit a natural trend, principal component analysis will result to averaging of the basic indicators. Sparsity is achieved while dimension is being reduced through the general algorithm of sparse principal component analysis (SPCA) by (Zou et. al., 2006) specially for case when the number of variables exceeds the sample size. After the loading for each indicator is obtained, we decide on the number of components or indices that will be used to summarize the sustainable development indicators. Express each index as linear combination of the indicators.

The indicators used in Nalica and Barrios (2005) and Barrios and Komoto (2006) are also used in this paper and summarized in Table 1.

Table 1. The Core Indicators of Sustainable Development (Philippines)

Indicators	Description and Unit of Measurement	Category
Economic		
GDPCAP	per capita gross domestic product (GDP), in pesos, at 1985 constant prices	State
EMPLOY	employment rate	Pressure
GVAAFFP	per capita gross value added (GVA) of agriculture, forestry and fisheries	State
Harvesting Water Resources		
FISHQ	quantity of fish catch, in metric tons per hectare	Pressure
COMMQ	quantity of catch in commercial fisheries, in metric tons per hectare	State
MUNQ	quantity of catch in municipal fisheries, in metric tons per hectare	State
Harvesting Land Resources		
IRRIG	area irrigated, in hectares	Pressure
FERT	total fertilizer consumption	Pressure
PALAYY	yield of palay per hectare, in metric tons	State
CORNY	yield of corn per hectare, in metric tons	State

REFTOT	total area of reforestation, in hectares	Response
REFTIM	area of reforestation among timber licensees, in hectares	Response
FORRES	area of forest land for reservation, in hectares	State
Health and Education		
EDUCSP	government spending on education, billion pesos at current prices	Response
HEALSP	government spending on health services, billion pesos at current prices	Response
DIARR	incidence of diarrhea per 100,000 persons	State
Air Quality		
VEHICLE	number of LTO registered vehicles	Pressure
Gender Sensitivity		
EMPFEM	percentage of female employed	State

3.1 Construction of bootstrap-based parametric prediction intervals

An algorithm based on AR Sieve Bootstrap method for the construction of prediction interval is given, see for example (Campano and Barrios, 2008) or (Bühlmann, 1997) for details. AR-sieve bootstrap assumes that time series data y_t follows an autoregressive moving average [ARMA(p, q)] model, $\phi(B)y_t = \theta(B)a_t$, where $\phi(B) = 1- \phi_1\mathrm{B} - ... - \phi_pB^p$ and $\theta(B) = 1 - \theta_1B - ... - \theta_qB^q$ are polynomials in B, B is the backshift operator, and $\{a_t\}$ is a white noise process. Determine the best fitting ARMA model by examining the ACF and PACF graphs of the stationary time series data.

1. Estimate simultaneously the parameters in $\phi(B)y_t = \theta(B)a_t$ and obtain the forecasts and residuals.
2. Generate new residual series a_t at with mean 0 and variance equal to the mean square error (MSE) of the residuals in (1.2).
3. Generate new series y_t based on the estimates in (1.2) and the new residual series a_t in (1.3). Get the sum of y_t and a_t to form the series y_t^*.
4. Estimate the model equation using the generated series y_t^* in (1.4) and get the forecasts and residuals.
5. Repeat steps (1.3) to (1.5) B times, where B is a large number.
6. Get the average of MSE of B recreated series. This is the bootstrap estimate of MSE, denoted by $\hat{\sigma}_{bs}^2$.
7. For each time point, get the average of B forecasts from the recreated series. This is the bootstrap estimate of y_t, denoted by $\hat{y}_{t(bs)}$.

Compute the [(1–α)x100]% bootstrap-based parametric prediction interval using the formula $(\hat{y}_{t(bs)} - z_{\alpha/2}\hat{\sigma}_{bs}, \hat{y}_{t(bs)} + z_{\alpha/2}\hat{\sigma}_{bs})$.

3.2 Construction of nonparametric prediction intervals

Using the B forecasts for y_t in 3.3, compute the nonparametric bootstrap prediction interval by getting the $(\alpha / 2)^{\text{th}}$ and $(1- \alpha / 2)^{\text{th}}$ percentiles of B forecasts per time point.

Sustainable development is monitored by determining the significantly high or low index's scores based on the prediction intervals. The events that could have led to the increase or decrease in the indices' scores should be assessed for validation purposes.

4. Results and Discussion

The data was summarized using the first three components via principal component analysis (PCA) and sparse principal component analysis (SPCA). PCA yields higher percentage of variance explained than SPCA. In PCA, the first three PCs explain 80.7% of the total variance as opposed to 65.9% in SPCA. On the other hand, SPCA exhibits better dimension-reduction capacity than PCA. SPCs have sparser loadings as shown by high loadings on some indicators and zero loadings on other indicators. This results to non-overlapping of loadings of indicators between components. For instance, in PCA, the indicator GDPCAP has high loadings in second and third components while in SPCA, GDPCAP has high loadings in third component only. These observations on the explained variance and sparser loadings are consistent with the findings of (Barrios and Komoto, 2006).

Using the standardized values of the sustainable development indicators, the SPCs are represented as follows:

SPC1 = 0.357(FISHQ) + 0.375(COMMQ) + 0.395(VEHICLE) +
0.308(PALAYY) + 0.399(CORNY)+0.195(IRRIG)+0.274(FERT)+
0.348(EDUCSP) +0.297(HEALSP)
SPC2 = 0.574(REFTIM) + 0.531(REFTOT) + 0.624(EMPLOY)
SPC3 = 0.564(GDPCAP) + 0.826(GVAAFP)

The naming of SPCs follows the naming convention used by (Barrios and Komoto, 2006). Since the SPC1 is a composite of indicators which come from all categories (pressure, response, state), SPC1 is named as 'Sustainable Development Index'. SPC2 is named as 'Pressure-Response Index' (PRI) and SPC3 is named as 'State index'.

Figure 1 shows the trend of the three indices over the years. SDI has an increasing trend while PRI and SI show some fluctuations. (Barrios and Komoto, 2006) explained that an increasing index level happens when increasing harvest is balanced with the assessment of the current state of the environment and complemented with appropriate response. On the other hand, fluctuations may reflect current state of the environment and the responses being applied to address the pressure on the environment. The 95% prediction interval (PI) was computed for each index in order to determine whether this increasing trend or fluctuations are significant indication of progress towards sustainable development.

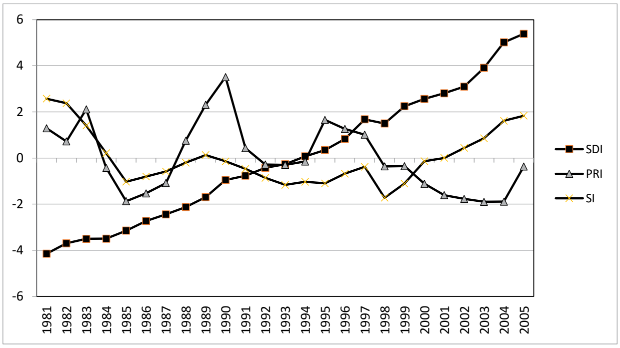

Figure 1. Scores of Sustainable Development Indices

4.1 Prediction interval for sustainable development index

There are three types of prediction interval (PI) computed for each index: bootstrap-based parametric PI, nonparametric bootstrap PI, and the parametric PI using ARIMA models. An integrated moving average (order 1) model is adequate for SDI. Figure 2 show the 95% bootstrap-based parametric PI for SDI and indicates that there are no significant movement in SDI within the period.

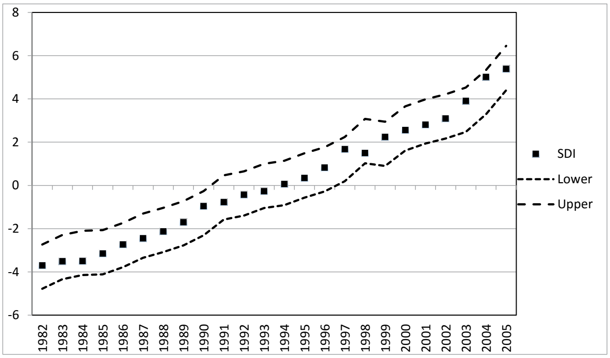

Figure 2. 95% Bootstrap-Based Parametric PI for Sustainable Development Index

Figure 3 show the 95% nonparametric bootstrap PI for SDI which indicates significant decrease in SDI score in 1998 and significant increase in 1997, 2003 and 2004. The drop in SDI scores in 1998 may be attributed to 7.9% decrease in

PALAYY and 24% decrease in FERT from the previous year. The low agricultural production was caused by El Niño (from 1997 to 1998), considered to be the worst El Niño in the 20th century. There was a 6.6% drop in agricultural production due to El Niño. Rice production exhibited a double-digit decline in the fourth quarter of 1998 (Jegillos et al., 2000).

Significant increase in 1997 may be attributed to 25% increase in FERT, 28% increase in EDUCSP and 33% increase in HEALSP from 1996 to 1997. The increase in FERT may be attributed to the implementation of the Ginintuang Ani for *Grains and Ginintuang Ani for High Value Commercial Crops* programs of the Department of Agriculture (DA) which started in 1996. However, this increase in FERT is not translated to good performance of agricultural sector. GVA grew only by 2.9% compared to 3.4% in 1996 due to the initial effect of El Niño (DA, 1998). Hence, only EDUCSP and HEALSP may have contributed to significant increase in SDI. In 1997, the Philippines reported a budget surplus of 0.1% of GDP while in the succeeding years until 2010, there was a fiscal deficit. The surplus in 1997 is the result of the comprehensive tax reform program of 1996 (DBM, 2003). This explains the increased budget allocation for education and health sectors.

Significant increase in 2003 and 2004 may be attributed to the increase in CORNY and FERT. In 2003, agricultural production grew by 3.77% mainly because of the improved performance of crops and fishery subsectors. In crops subsector, significant output increment was observed in corn farms at 6.86% and sugarcane at 15.54% (DA, 2004). In 2004, agriculture in general had a very good performance. The crop subsector, in particular, generated a 4.98% output increase. Production in corn farms grew by 17.28%. Increase in corn production was the result of expansion of harvest area, improvement of level of productivity, availability of quality seeds and having better market price which were all mechanism of the *Ginintuang Masaganang Ani* (GMA) program for corn (DA, 2005).

Using the parametric PI of the integrated moving average (order 1) model, only the SDI score in 2004 was identified to be significantly high, as shown in Figure 3.

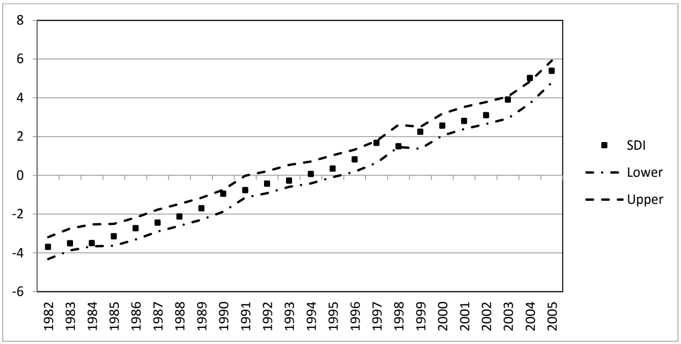

Figure 3. 95% Parametric PI for Sustainable Development Index

4.2 PI for pressure-response index

Figure 4 show the bootstrap-based parametric PI for PRI. There is no significant increase or decrease in PRI scores identified.

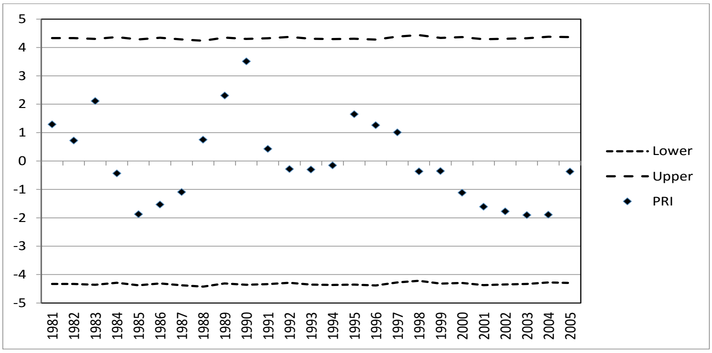

Figure 4. 95% Bootstrap-Based Parametric PI for Pressure-Response Index

Nonparametric bootstrap PI identified a significantly high PRI score in 1990, as shown in Figure 5. The spike in 1990 may be attributed to high value of REFTOT and REFTIM during that year. From 1981 to 2009, (NSCB, 2010) reported the largest area reforested at 191,663 hectares in 1990. Many programs of the Department of Environment and Natural Resources (DENR) for reforestation in 1980s and 1990s received support from different organizations. Among these programs is the National Forestation Program which operated from 1986 to 2000. This program was supported by loans from Asian Development Bank (ADB) and Overseas Economic Cooperation Fund (OECF). Another is the Community Forest Program which operated from 1989 to 1999 and was funded by ADB and the US Agency for International Development (USAID) (Harrison et. al., 2004). Beyond 1990, total reforested area was declining. The decreasing trend is attributed to the decreasing budgetary allocation for plantation establishment, maintenance and protection (UN FAO, 2010).

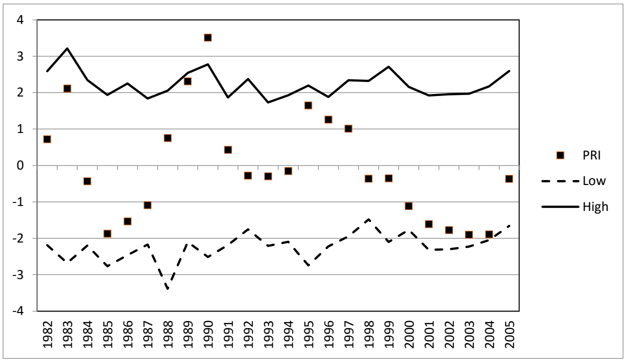

Figure 5. 95% Nonparametric Bootstrap PI for Pressure-Response Index

Parametric PI in Figure 6 yields the same result as bootstrap-based parametric PI, i.e., no significant points beyond the 95% PI.

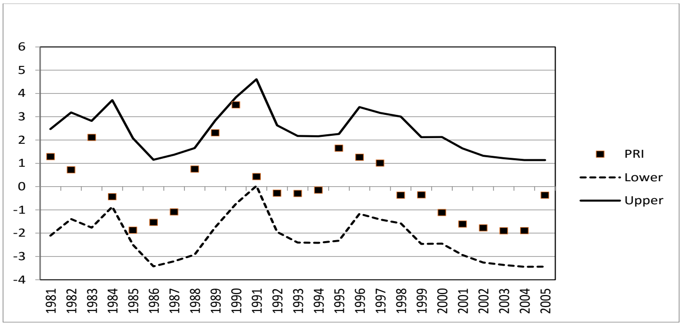

Figure 6. 95% Parametric PI for Pressure-Response Index

4.3 PI for state index

Figure 7 show the bootstrap-based parametric PI for SI, without any point exceeding the 95% PI.

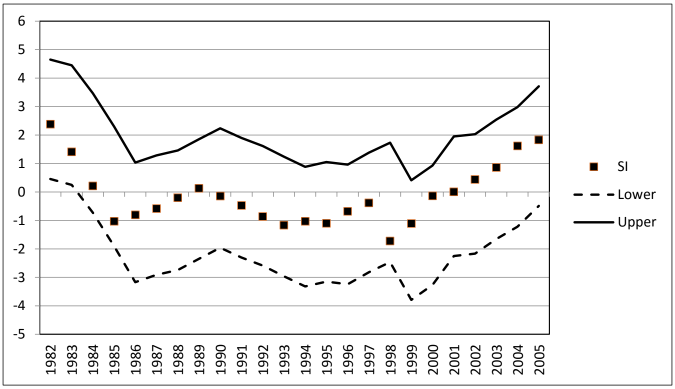

Figure 7. 95% Bootstrap-Based Parametric PI for State Index

Nonparametric bootstrap PI identified significantly low SI scores in 1984, 1985 and 1998. This may be attributed to the decline in GDPCAP in 1984 and 1985 and decrease in GVAAFP in 1998. The Philippines experienced a deep economic recession and decline in overall economic activity in 1984 to 1985 (Intal and Llanto, 1998). GDPCAP dropped by 9.58% in 1984 and another 9.54% in 1985 (NSCB, 2010). On the other hand, decrease in GVAAFP in 1998 is caused by El Niño. El Niño affects not only agricultural production but also marine production. In 1998, El Niño led to dried ponds, constricted production cycle, stunted growth and high mortality rates. As a result, fisheries sector suffered a P7.24B loss as of November 1998 (National Center for Atmospheric Research and United Nations Environment Programme, 2000). Figure 9 show the nonparametric bootstrap PI for SI.

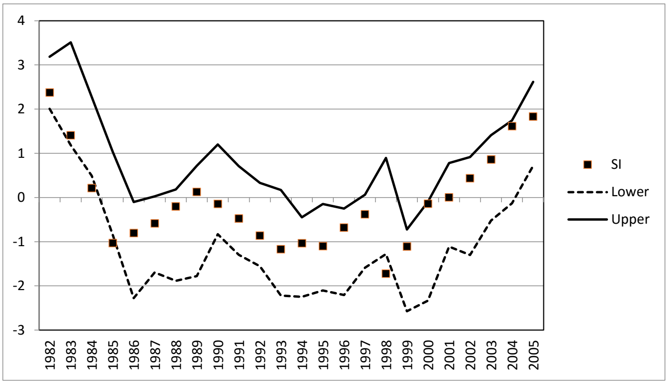

Figure 8. 95% Nonparametric Bootstrap PI for State Index

Parametric PI identified significant decrease in SI scores in 1998 and significant increase in 1999. The agricultural sector had slightly recovered from its loss in 1998. Despite the lingering effect of Asian financial crisis and El Niño, agricultural production increased by 6.49%. This growth was attributed to 37.78% increment in palay harvest and 19.92% increase in corn harvest. Major contributors for improvement in yield were the expansion in harvested area and rehabilitation of irrigation system (DA, 2000). Figure 9 show the parametric PI for SI.

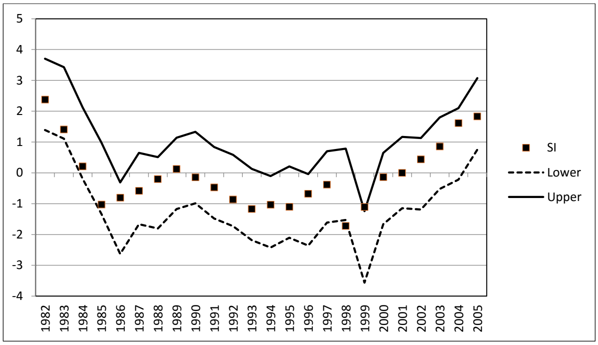

Figure 9. 95% Parametric PI for State Index

4.4 Comparing bootstrap PI and parametric PI

Table 2 summarizes the comparison of the three types of PI in terms of the significant points detected. Bootstrap-based parametric PI was not able to identify any significant points while nonparametric bootstrap PI identified the most number of significant points. All significant points identified are validated by plausible physical drivers of sustainable development.

Table 2. Detection of Significant Points with Plausible Physical Drivers by Bootstrap and Parametric PI

Index	Sig. Year	Bootstrap PI		Parametric PI	Plausible Physical Drivers
		Par	Nonpar		
SDI	1997	Not det	Det	Not det	National budget surplus
	1998	Not det	Det	Not det	El Niño
	2003	Not det	Det	Not det	GMA program
	2004	Not det	Det	Det	GMA program
PRI	1990	Not det	Det	Not det	External support for DENR's reforestation programs
SI	1984	Not det	Det	Not det	Economic recession
	1985	Not det	Det	Not det	Economic recession
	1998	Not det	Det	Det	El Niño
	1999	Not det	Not det	Det	Expansion of harvested area and rehabilitation of irrigation system

**sig – significant; det – detected; par – parametric; nonpar – nonparametric*

5. Conclusion and Recommendation

This study proposed a procedure for monitoring progress of sustainable development measured by indices. Prediction intervals are constructed to determine whether the movement of the indices is significant or not. The prediction intervals were able to detect significantly high and low sustainable development indices' scores that were validated and justified by some plausible drivers like the occurrence of El Nino phenomenon, implementation of programs, and other events that could have caused the increase or decrease in sustainable development indices. Nonparametric bootstrap PI is the most acceptable PI in terms of the number of significant points with plausible drivers detected.

The construction of AR-Sieve-based nonparametric PI is worth doing despite its complex computation because of its advantages over parametric prediction interval. Nonparametric bootstrap PI outperforms parametric PI in detecting the most number of significant points with plausible drivers. (Mancenido and Barrios, 2011) illustrated through a simulation study that AR-Sieve bootstrap control chart works even for small sample sizes and conditions of the near nonstationarity of the generating process. They concluded that AR-Sieve bootstrap control chart is free from distributional assumptions, model-based assumptions and potentially from model-based errors. Hence, AR-sieve-based prediction interval for sustainable development index can also possess these characteristics of AR-sieve bootstrap control chart.

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