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The Impact of El Niño/Southern Oscillation on Hydrology and Rice Productivity in the Cauvery Basin, India: Application of the Soil and Water Assessment Tool

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ABSTRACT

This study was performed to further understanding of the variations in hydrology and rice crop productivity during different El Niño/Southern Oscillation (ENSO) events in the Cauvery River Basin of Tamil Nadu, India using the Soil and Water Assessment Tool (SWAT). The entire Cauvery Basin was divided into 301 sub-basins and further subdivided into 3,601 Hydrological Response Units (HRU). Based on the National Oceanic and Atmospheric Administration (NOAA) official website, information on El Niño (1972, 1982, 1987, 1991, 1997, 2002 and 2004) and La Niña (1970, 1971, 1973, 1974, 1975, 1988, 1998, 1999 and 2000) years were obtained. The SWAT model was continuously run from 1970 to 2008, and a composite for El Niño, La Niña and normal years was constructed to understand their influence on hydrology and rice crop productivity in the study area. From the analysis, it was clear that an El Niño episode is correlated with rainfall, hydrology and rice productivity in the Cauvery river basin. The validation of the SWAT model indicated the capability of SWAT to accurately predict stream flow and rice productivity. It was evident from the investigation that the quantum of rainfall was more during El Niño years with high inter-annual rainfall variability (809.3 mm to 2,366 mm) compared with La Niña and normal years. As a result, the soil water recharge, including percolation and soil water availability in the surface layers, was increased in the El Niño years. Simulated rice productivity over 39 years in the Cauvery Basin ranged between 1,137 and 7,865 kg ha^{-1} with a mean productivity of 3,955 kg ha^{-1}. The coefficient of variation in rice productivity was higher during La Niña (21.4%) years compared with El Niño (14.7%) and normal years (14.6%). The mean rice productivity was increased in both El Niño and normal years, indicating the possibility of higher yields than those in La Niña years. An analysis of the hydrological data and rice productivity showed that the risk of failure was low during El Niño years compared with normal or La Niña years. This behavior could be utilized for forecasting rice crop productivity under different ENSO conditions and can provide information for policy makers when deciding on water allocation and import / export policies.

1. Introduction

Short-term climate variations exert large influences on hydrology and crop productivity. It is well recognized that El Niño/Southern Oscillation (ENSO) is the dominant mode of short-term climate variability, and its impacts are felt worldwide. The direct impacts of ENSO on the tropics are severe, particularly for countries that are affected by monsoons, such as Australia, India, Indonesia and Africa (Quinn 1987; Sikka 1980; Shukla 1987; Krishna Kumar et al. 1999). The 1997–98 El Niño, which is regarded as the "El Niño of the 20th Century", caused widespread droughts in the tropics leading to forest fires, with an estimated economic loss exceeding $20 billion USD in Southeast Asian countries (Stone et al., 1996). Due to its widespread global impact, understanding and modeling the processes and predicting ENSO have dominated climate research over the last two decades (Wallace and Thompson, 2002; Wang et al. 2004). The Indian Meteorological Department incorporates ENSO information into the statistical model used for forecasting monsoon rainfall (Rajeevan et al. 2006).

From observations, McBride and Nicholls (1983) and Nicholls (1988) found a useful predictive relationship between the ENSO index of a particular season and the regional rainfall over Australia and Indonesia in subsequent seasons. Similar relationships are also noticeable over the Indian monsoon region (Shukla and Mooley, 1987). For instance, Geethalakshmi et al. (2005) studied the linkage

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between ENSO and rainfall over Tamil Nadu, India during both the southwest (June through September) and northeast (October through December) monsoon seasons. The authors noted that during the summer monsoon, the relationship is negative, i.e., rainfall is less than normal during El Niño years, and the opposite is observed during La Niña years. In contrast, the relationship during the northeast monsoon is positive, i.e., rainfall is more than normal during El Niño years and less than normal during La Niña years (Geethalakshmi et al. 2009). Because rainfall variations have direct impacts on local agriculture, efforts have been made to utilize the ENSO-rainfall linkage for agricultural planning (Nicholls, 1988; Hansen et al., 1998; Mjelde and Keplinger, 1998; Hill et al., 1999).

A study conducted by Annamalai et al. (2007) revealed the uncertainty of the ENSO-monsoon relationship in future warming scenarios. This indicates that understanding and modeling the effects of ENSO, including changes in rainfall, on local hydrology and agricultural productivity are important both in current and future climates. Hence, this paper focuses on understanding the categorical ENSO influence on hydrology and rice productivity in the Cauvery River Basin, India.

The Cauvery River Basin is an important river basin in India in terms of agriculture and food security. The basin spans two southern Indian states, Karnataka and Tamil Nadu. The Tamil Nadu Cauvery Basin contributes 40% of the food grain production of Tamil Nadu. Rice is the major crop and is primarily irrigated using water from the Cauvery River. During the season of kharif (June-September), the beginning of crop activity depends upon the release of water from the Mettur Reservoir. Although the traditional Mettur Dam water release date has been June 12th since its construction in 1934, the water has only been released on the scheduled date fourteen times. In the other years, the release date has been delayed by the Chief Engineers of the Cauvery Basin, Public Works Department authorities and the District Collectors based on the amount of water in the reservoir. Due to large variations in rainfall in the catchment as well as in the delta area of the basin, water availability during paddy cultivation is becoming highly uncertain. Additionally, the possible anthropogenic effect of induced warming on increasing the variability of precipitation cannot be excluded. Hence, cultivating paddies in the kharif season is a challenging issue in the Cauvery Basin. In this context, a study was conducted with the goal of testing the impact of ENSO events on water availability in the Cauvery River Basin and its subsequent influence on rice production.

2. Materials and methods

2.1. Description of the study area

The Cauvery River Basin (Fig. 1) is located in southern India and covers an area of 81,155 km^2. Of this area, 44,016 km^2 lies in the state of Tamil Nadu in India from 10.00 to 11.30 °N and 78.15 to 79.45 °E; the rest is located in the state of Karnataka.

The Tamil Nadu Cauvery Basin receives an annual average rainfall of 956 mm, and over 4.4 million people are employed in the agricultural sector in this basin. Major rivers in the Cauvery watershed are Cauvery, Vennaru, Kudamuruti, Paminiar, Arasalar and Kollidam. Most of the upstream and catchment areas of the Cauvery River Basin receive rainfall during the southwest monsoon season, filling up the Mettur Reservoir on the Cauvery River, which supplies water to the Tamil Nadu Cauvery Basin. However, the Cauvery delta area of Tamil Nadu receives most of its rainfall during the northeast monsoon season. Because this river basin receives rainfall from both the monsoons, rice is cultivated in both the kharif (southwest monsoon) and rabi (northeast monsoon) seasons.

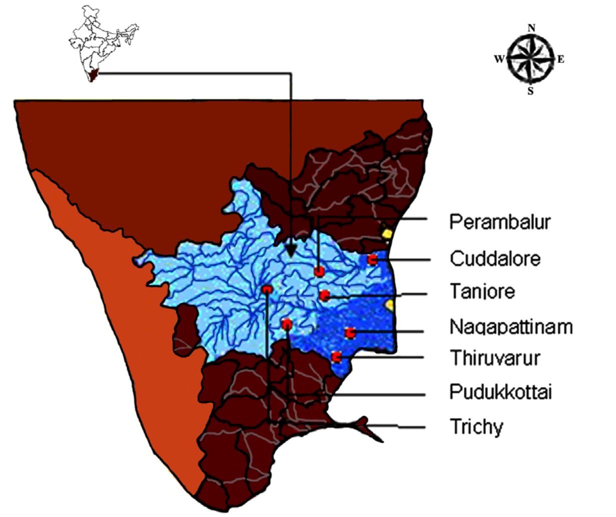

Fig. 1. Location of Cauvery river basin in India.

2.2. SWAT model description and model setup

The Soil and Water Assessment Tool (SWAT) is a GIS (Geographic Information System)-based decision support tool that has been successfully applied in many watersheds around the world including the United States, the United Kingdom and Africa (Arnold et al., 1993, 1998). In the current study, SWAT was used to understand the variations in hydrology and rice crop productivity of the Cauvery River Basin during different observed ENSO events. The SWAT model can be used for assessing the impact of strategic decisions such as changing the crop pattern, identifying new crop areas, selecting the best sowing time, improving irrigation water management, developing optimum fertilizer schedules for better economic results.

For running the SWAT model, a Digital Elevation Map of the study region was derived from the STRM 90 m elevation dataset. The elevation in the Cauvery Basin varies from zero to 2,674 m above MSL. Automatic delineation of the watersheds was performed to explain the spatial variability of various input parameters. In this study, the basin between the Mettur reservoir of Tamil Nadu and Coloroon was modeled. Information on soil was based on the soil map at 1: 50,000 scale obtained from the Remote Sensing Unit of Tamil Nadu Agricultural University. Although the Cauvery Basin has a variety of soils, the majority of the study area has sandy clay loam and sandy loam soils. A sizable area also possesses sandy clay and clay soils. The land use data were obtained from the Indian Space Research Organisation (ISRO), Bangalore. In the Cauvery Basin, 77.8% of the area is covered by rice crop, 9% by rice fallow pulses and 8.5% by forest cover. A marginal area is occupied by corn, cotton, grain sorghum and other crops (Fig. 2). Most of the rice crop is grown on a slope between 0 and 3%, and forest occupies most of the high, steep areas. Because the rice crop occupies most of the cultivable area, we focused our study on the rice crop.

The entire Cauvery Basin was divided into 301 sub-basins for spatial aggregation, and each sub-basin was further divided into hydrological response units (HRUs), which have unique combinations of soil, slope, land use and weather. For each land use in every HRU, management practices, including time of sowing, harvest, intercultural operations and different inputs, were specified. In total, there were 3,601 HRUs in the study area.

Observed daily rainfall (Fig. 3) and temperature data from 1970 to 2008 were obtained from the research stations of Tamil Nadu Agricultural University and the India Meteorological Department. For rice yield simulation, the SWAT Model uses maximum and minimum temperature, solar radiation, rainfall, wind speed and relative humidity prevails during the crop growing period.

In the absence of other daily weather data on solar radiation, wind speed and relative humidity, these weather parameters were generated using long-term statistics through the weather generator in the SWAT model. Verification of the weather parameters generated through the weather generator in SWAT was performed using the recorded weather data available at different research stations of Tamil Nadu Agricultural University located in the Thanjavur, Cuddalore and Nagapattinam districts of the Cauvery Basin. Error statistics, such as bias and root mean square error (RMSE), along with agreement statistics, such as the correlation coefficient (r) and index of agreement (d), were estimated for prediction against the observed data. The equations used to compute various statistics are given below.

$$\text{Bias} = n^{-1} \sum_{i=1}^{n} (P_i - O_i)$$

$$\text{Correlation coefficient } (r) = \frac{\sum P_i O_i \frac{\sum P_i \cdot \sum O_i}{n}}{\sqrt{\sum P_i{}^2 - \frac{(\sum P_i)^2}{n}} \cdot \sqrt{\sum O_i{}^2 - \frac{(\sum O_i)^2}{n}}}$$

$$\text{Index of agreement } (d) = 1 - \frac{\sum_{i=1}^{n} (P_i - O_i)^2}{\sum_{i=1}^{n} \left(|P_i - \overline{O}| + |O_i - \overline{O}| \right)^2}$$

$$\text{Root Mean Square Error } (RMSE) = n^{-1} \left[\sum_{i=1}^{n} (P_i - O_i)^2 \right]^{0.5}$$

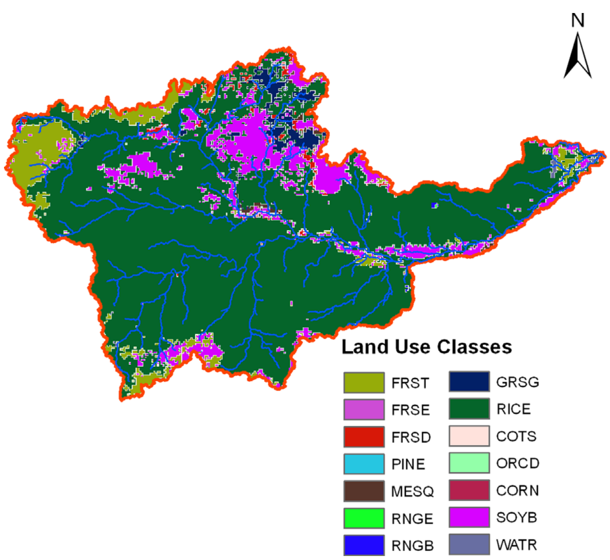

Fig. 2. Cauvery Basin modeled for the study and its land use pattern.

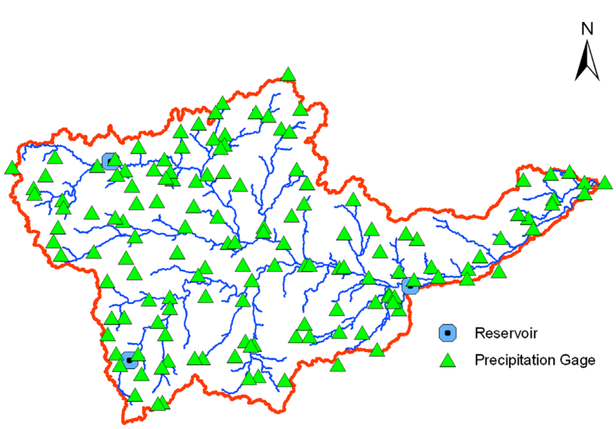

Fig. 3. Rainguage and Reservoir sites in the study region.

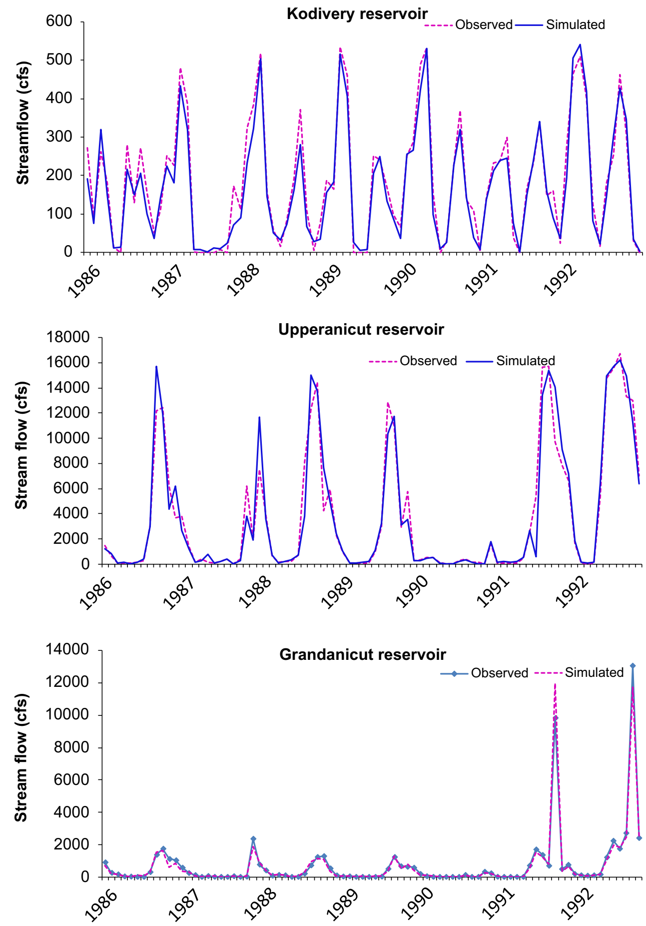

Fig. 4. Observed and simulated monthly mean stream flow (cfs) for the Cauvery basin over the calibration (1986–1989) and validation (1990–1992) time periods.

Table 1
Observed and SWAT predicted stream flow in different reservoirs of Cauvery basin.

Reservoirs	Average stream flow (cfs)		PBIAS (%)	NSE	R^2
Calibration	Observed	Simulated			
Kodivery	172.11	154.98	−9.95	0.74	0.80
Grand anicut	391.91	357.82	−8.70	0.86	0.88
Upper anicut	3188.64	3359.64	5.36	0.81	0.84
Validation	Observed	Simulated			
Kodivery	242.70	218.70	−9.89	0.78	0.80
Grand anicut	1250.0	1204.2	−3.67	0.89	0.89
Upper anicut	6250.64	6402.78	2.43	0.83	0.87

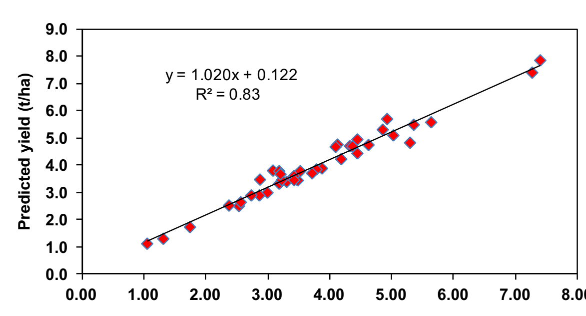

Fig. 5. Comparison of observed and simulated crop yield over Cauvery basin.

Validation of the results of the generated weather parameters (solar radiation, relative humidity and wind speed) using the weather generator is given in Appendix A. The error and agreement statistics for validating the solar radiation, relative humidity and wind speed generated through the weather generator indicated less bias, less RMSE, a high significant correlation

Table 2
Observed and SWAT simulated rice productivity in Cauvery basin.

Year	Average Rice yield of Cauvery river Basin (t/ha)		Standard Deviation		Range (t/ha)		PBIAS*
	Observed	Simulated	Observed	Simulated	Observed	Simulated	
1970	2.54	2.51	0.51	0.45	2.15–2.59	2.35–3.26	−1
1971	3.19	3.33	0.32	0.88	2.77–3.56	2.50–3.54	4
1972	4.13	4.76	0.10	0.75	2.54–4.61	2.57–4.94	15
1973	3.88	3.89	0.14	0.36	3.81–3.92	3.71–4.23	0
1974	1.32	1.31	0.46	0.36	1.10–1.49	1.16–1.58	−1
1975	1.75	1.74	0.08	0.36	1.42–1.84	1.88–2.10	−1
1976	3.31	3.40	0.16	0.36	3.2–3.74	3.45–3.93	3
1977	3.49	3.45	0.18	0.36	3.08–3.79	3.24–4.76	−1
1978	3.43	3.61	0.76	0.36	3.04–3.79	3.34–4.86	5
1979	3.00	3.00	0.33	1.05	2.78–3.15	3.01–4.19	0
1980	1.06	1.13	0.24	0.75	1.03–2.42	1.78–2.48	7
1981	3.43	3.46	0.28	0.84	3.64–3.92	3.13–3.79	1
1982	4.86	5.31	0.04	0.96	4.45–5.71	4.54–5.96	9
1983	3.79	3.85	0.10	1.09	3.11–4.15	3.58–4.16	2
1984	3.53	3.79	0.57	0.63	3.4–4.13	3.69–4.51	7
1985	4.19	4.23	0.13	1.10	3.54–4.25	3.64–4.70	1
1986	4.45	4.44	0.55	0.36	3.58–4.55	4.25–4.77	0
1987	5.03	5.10	0.47	0.36	4.47–5.19	4.93–5.35	1
1988	3.09	3.81	0.24	0.36	3.01–4.70	3.65–4.14	23
1989	3.19	3.79	0.64	1.17	3.29–4.23	3.97–4.20	19
1990	2.87	2.90	0.80	0.73	2.02–3.38	2.82–3.71	1
1991	7.40	7.85	0.14	1.24	6.67–6.16	6.34–7.88	6
1992	4.33	4.71	0.25	0.53	4.55–5.16	4.98–6.09	9
1993	4.45	4.95	0.33	0.53	3.84–5.04	4.31–5.32	11
1994	2.88	3.48	0.14	0.76	2.75–4.04	3.94–4.75	21
1995	4.10	4.68	0.58	0.65	4.03–4.69	4.93–6.45	14
1996	4.37	4.70	0.43	0.91	4.15–4.86	4.55–5.41	8
1997	4.93	5.70	0.18	0.92	4.88–7.18	6.46–7.96	16
1998	3.23	3.46	0.32	1.07	3.19–4.15	3.36–4.21	7
1999	3.72	3.71	0.27	0.99	3.38–3.91	2.45–3.91	0
2000	2.38	2.53	0.87	1.11	1.14–3.60	1.23–3.16	6
2001	7.27	7.40	0.60	1.12	6.79–7.40	6.35–7.78	2
2002	2.57	2.65	0.55	0.71	2.19–3.15	2.36–3.53	3
2003	3.21	3.68	0.48	0.63	2.85–3.73	3.36–4.21	15
2004	5.64	5.58	0.51	0.88	4.69–5.98	4.83–5.93	−1
2005	5.36	5.49	0.13	0.59	4.71–5.49	4.93–5.95	2
2006	5.30	4.83	0.35	0.91	4.88–5.18	4.46–5.06	−9
2007	2.74	2.90	0.16	0.79	2.42–3.58	2.72–3.51	6
2008	4.63	4.75	0.36	0.93	3.94–4.73	4.13–5.42	3
				RMSE	0.36	NRMSE	9.56

Where Si = Simulated yield, Oi = Observed yield, n = Number of observations

* PBIAS (Percentage of Bias) = (Si − Oi) / Oi × 100

$$\text{RMSE (Root Mean Square Error)} = \left[\sqrt{\frac{\sum_{t=1}^{n}(Si-Oi)^2}{n}}\right]$$

$$\text{NRMSE (Normalized Root Mean Square Error)} = \left[\frac{RMSE \times 100}{\overline{O}}\right]$$

Table 3
Observed and SWAT predicted rice productivity in different districts of Cauvery basin.

Districts	Average Rice yield of Cauvery river Basin (t/ha)		Standard Deviation		Range (t/ha)		PBIAS
	Observed	Simulated	Observed	Simulated	Observed	Simulated	
Thiruvalluvar	3.05	3.26	0.37	0.38	2.61–3.92	2.55–4.73	7
Trichy	3.82	4.11	1.03	1.08	2.59–4.19	2.59–6.21	8
Perambulur	3.79	4.03	0.59	0.61	2.69–3.94	2.59–5.12	6
Tanjavur	3.54	3.82	0.72	0.71	1.55–3.85	2.55–4.71	8
Nagai	3.54	3.84	0.83	0.81	2.16–4.16	2.16–4.96	8
Thiruvarur	3.36	3.47	1.03	1.07	2.86–3.84	2.86–4.77	3
Pudukottai	3.30	3.51	0.87	0.90	1.34–3.57	1.67–4.62	6

and the highest index of agreement (d) for both the annual and monthly scales.

Management practices, including details on tillage operations; time and method of sowing; quantity, method and time of fertilizer/irrigation application; and harvesting details, adopted at different districts of the Cauvery Basin were collected from the Department of Agriculture and from the Crop Production Guide issued for the state of Tamil Nadu and were fed as inputs into the SWAT; the model was continuously run from 1970 to 2008. The SWAT model has a unique module for defining the management practices in which all technological changes can be incorporated.

2.3. ENSO analysis

Operationally, ENSO conditions are defined based on sea surface temperature variations and their persistence along the equatorial Pacific Ocean. The NOAA defines El Niño and La Niña events based on a threshold of $+/-$ 0.5 °C for the Oceanic Niño Index (ONI) (3 month running mean of the Sea Surface Temperature (SST) anomalies over the equatorial eastern Pacific). As the kharif (June –September) and rabi (October-December) seasons are the rice growing seasons in the study area, years with ONI at or above $+0.5$ for 5 consecutive months between June-December are considered to be El Niño years; those with ONI at or below -0.5 are considered to be La Niña years (http://ggweather.com/enso/oni.htm). During the study period, there were seven El Niño years (1972, 1982, 1987, 1991, 1997, 2002 and 2004), nine La Niña years (1970, 1971, 1973, 1974, 1975, 1988, 1998, 1999 and 2000) and 23 normal years (years other than El Niño/La Niña). A composite for El Niño, La Niña and normal years was made from the SWAT model outputs to understand the influence on the hydrology and rice crop productivity of the study area.

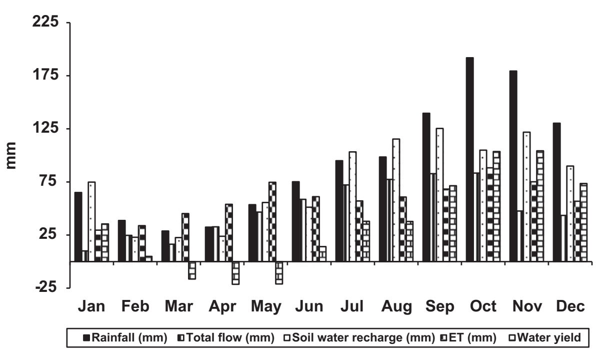

Fig. 6. Monthly water balance of the Cauvery river basin.

2.4. SWAT model calibration and validation

The SWAT model was calibrated and validated for the stream flow at major reservoirs (Kodivery, Upperanicut and Grandanicut) of the Cauvery Basin based on the datasets received from the Public Works Department (PWD) for 1986–1992. The first 4 years of observed data were used for calibration (1986–1989), and the remaining 3 years (1990–1992) of data were utilized for validation. The monthly statistical measures explained by Moriasi et al. (2007) were used in this study to calibrate and verify the model for stream flow including PBias (PBIAS), the coefficient of determination (R^2) and Nash-Sutcliffe Efficiency (NSE). There are reports that crop yield can be used as an alternative for evaluating the SWAT model as it generally account for both evapotranspiration and the soil moisture required for vegetative growth (Srinivasan et al. 1998). Hence, the model was also evaluated by comparing the predicted and observed rice yields of the basin for the years between 1970 and 2008, and a statistical test of significance was performed using statistical measures such as Normalized Root Mean Square Error (NRMSE) and the coefficients of determination (R^2). The rice crop productivity of the Cauvery Basin was obtained from the season, and the crop report of the Government of Tamil Nadu is published every year; the most recent available publication is for 2009–2010. The Cauvery Basin in Tamil Nadu is spread over seven districts of the state, Thanjavur, Thiruvarur, Nagapattinum, Trichy, Cuddalore, Perambalur and Pudukottai. The reported productivity data for these districts from 1970–2008 was taken from the Season and Crop Reports and was averaged to obtain the mean productivity of the basin. The average productivity of the sub-basins in each district predicted by the model was also compared against the reported observed productivity of the district.

3. Results and discussion

3.1. Calibration and validation of the SWAT model

3.1.1. Stream flow

SWAT was used to satisfactorily estimate the stream flow across all three reservoirs (Kodivery, Upperanicut and Grandanicut) during both calibration and validation (Fig. 4). The NSE, PBIAS, and R^2 statistic values for the calibration and validation (Table 1) indicated that SWAT was acceptable in simulating the stream flow. The model simulating stream flow values was in agreement with the measured stream flow values, and the values of the NSE, PBIAS, and R^2 statistics were within the ranges suggested by Moriasi et al. (2007). In fact, the SWAT prediction of the stream flow was more accurate during the validation period than the calibration period.

3.1.2. Crop yield

The performance of the SWAT model was evaluated by comparing the actual and predicted rice crop productivity of the basin between

Table 4
Annual summary of hydrological components of Cauvery basin (All years including El-Niño, La Niña and Normal from 1970 to 2008).

Particulars	Precipitation (mm)	Surface flow (mm)	Lateral flow (mm)	Ground water flow (mm)	Percolation (mm)	Soil water (mm)	ET (mm)	PET (mm)	water yield (mm)
30% Probability	1230.0	117.1	101.4	317.0	408.1	644.5	783.2	2575.4	523.6
50% Probability	1039.7	104.3	82.0	274.1	364.7	517.9	646.2	2268.1	473.3
80% Probability	855.4	87.4	63.4	179.6	237.1	426.8	551.9	1587.4	331.0
Mean	1124.0	168.0	120.3	307.2	307.3	601.7	703.2	2192.0	522.3
Median	1039.7	104.3	82.0	274.1	364.7	517.9	646.2	2268.1	473.3
Highest	2366.3	196.9	150.3	520.2	708.4	1097.5	1040.9	3488.5	800.1
Lowest	605.9	40.4	41.1	92.4	66.1	168.9	344.8	247.5	173.3
SD	307.1	30.9	27.7	99.0	125.6	28.3	191.4	759.6	143.5
CV	27.3	18.4	23.0	32.2	40.9	4.7	27.2	34.7	27.5

1970 and 2001, and the results are presented in Table 2. Based on the results, it could be inferred that the SWAT model predicted the rice yield reasonably well in most of the years under study, which was evident from the low Percentage of Bias (PBIAS), values. Interestingly, the extreme years affected by flood (1972, 1984, 1992, 1993, 1995, 1996 and 1997) or drought (1980, 1982, 1988, 1989, 1994 and 2003) exhibited higher PBIAS values. During the extreme years, the observed yields were significantly lower than the predicted yields, which resulted in higher PBIAS values. This signifies that SWAT can more precisely predict the yield under normal weather conditions compared with extreme event conditions. The NRMSE value was 9.6%, which shows a good match between the observed and predicted yield (Loague and Green 1991); a good R^2 (Fig. 5) proves the SWAT is capable of predicting crop yield.

The reported productivity data of the districts in the Cauvery Basin was compared with the average predicted productivity of the sub-basins falling in each district, and the results are presented in Table 3. The results indicated that the SWAT model can accurately represent the spatial variability of the rice productivity. In almost all districts, the PBIAS value between the predicted and observed yield was less than eight; the standard deviation values were also small and comparable.

3.2. Hydrology of the Cauvery Basin

3.2.1. Monthly water balance of the Cauvery Basin in Tamil Nadu

The average monthly summary of the hydrological components of the Cauvery River Basin (1970–2008) was obtained from SWAT model runs. Rainfall data used in the study is the observed mean monthly data for the entire basin obtained from rain gauges located across the Cauvery Basin. The SWAT model generates outputs on hydrological parameters such as surface flow, lateral flow, ground water flow, percolation, soil water, evapotranspiration and potential evapotranspiration based on the elevation, soil, land use, slope and weather data of the study area. Some of the sub-components of the water balance such as total flow (surface flow + lateral flow + ground water flow), soil water recharge (percolation + soil water), water yield (precipitation - evapotranspiration) and actual evapotranspiration were used to depict the general water balance of the Cauvery River Basin (Fig. 6).

The Cauvery Basin exhibits a uni-model rainfall pattern, and the majority of the rainfall is received during the northeast monsoon season (44.44%). The southwest monsoon season also contributes 36.18% of the annual average rainfall. The total flow gradually increased from March to September; thereafter, it began to decrease. The soil water recharge increased from April and achieved its maximum during September through December. Computation of the water yield indicated that the actual evapotranspiration is met in most of the months (June – February) except during summer (March – May). This could be due to the high temperatures that prevailed during the summer season, which resulted in more evapotranspiration compared with precipitation.

3.2.2. Annual summary of hydrological components of the Cauvery Basin in Tamil Nadu

The statistics of the average annual hydrological parameters simulated using SWAT (for 39 years from 1970 to 2008) at the 30,

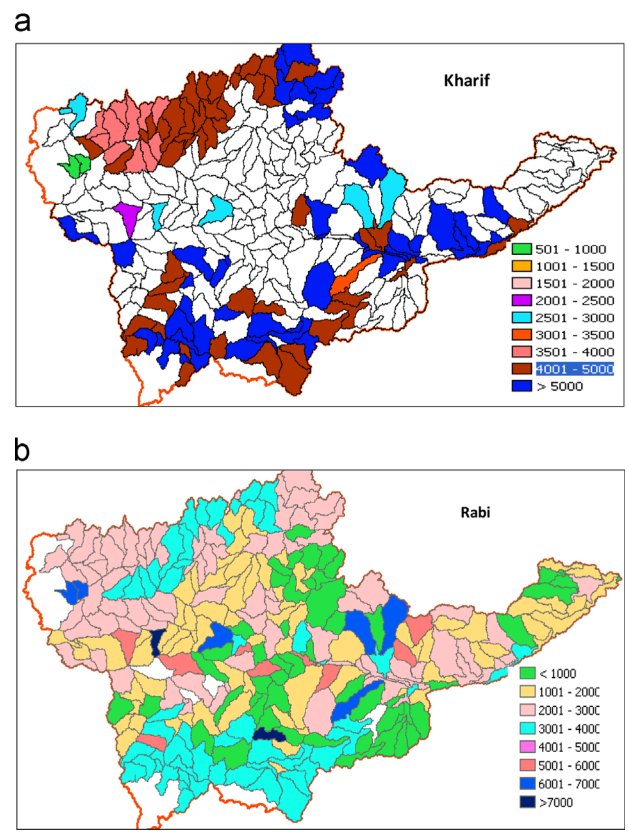

Fig. 8. (a) Rice growing areas and their productivity in Cauvery basin during kharif season and (b) Rice growing areas and their productivity in Cauvery basin during rabi season.

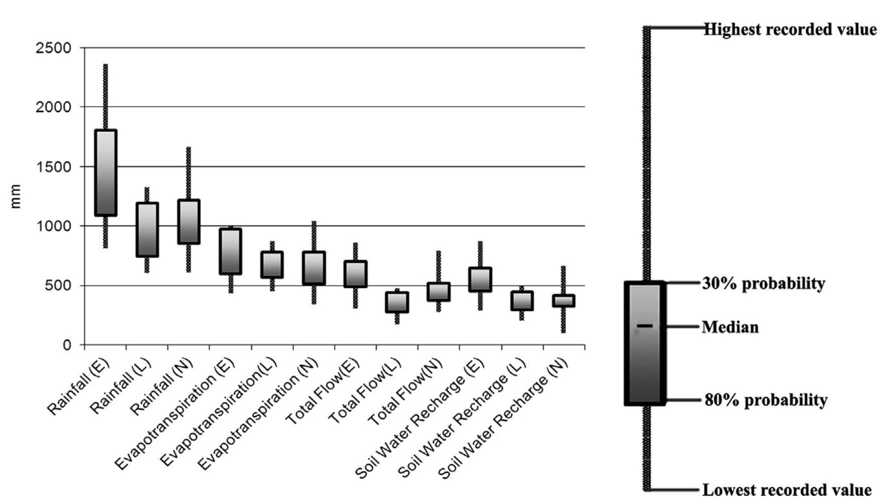

Fig. 7. Water balance of Cauvery basin as influenced by El-Niño, La Niña and Normal conditions.

50 and 80% probability levels of all hydrological parameters are presented in Table 4. Because the Cauvery Basin lies in a semi-arid tropical region, 30% probability values are reasonable for making farm decisions related to irrigation scheduling. However, for making critical decisions such as sowing time and choice of variety, 50 to 80% probability levels are required.

The inter annual rainfall variation in the Cauvery River Basin is high and ranges between 605.9 mm (1995) and 2,366 mm (1971) with a mean value of 1,124 mm. The mean annual water yield is 522.3 mm, accounting for 46.46% of the annual average rainfall. The mean annual evapotranspiration is 703.2 mm, which is 62.56% of the mean annual average precipitation. The atmospheric moisture demand (PET) of the basin is 2,192 mm, indicating a need for water from external / underground sources for successful crop production.

3.2.3. Impact of El Niño, La Niña and normal years on the Cauvery Basin water balance

From the SWAT model output runs between 1970 and 2008, a composite of El-Niño, La Niña and normal years was integrated for various hydrological parameters, and the results are presented in Fig. 7. During normal years in the Cauvery Basin, the rainfall ranged from 608.9 to 1,665 mm with a median value of 976 mm.

During El-Niño years, the mean annual rainfall was 1,340 mm; at 50% and 80% probability, the values were 1,352 and 1091 mm, respectively, which was more than the mean annual rainfall for any of the years. However, the rainfall variability during El Niño years was also higher (809.3 mm to 2,366 mm), and these results agree with the earlier findings of Geethalakshmi et al. (2005). In contrast, the amount of rainfall received during the La Niña years was lower than the rainfall in other years with minimum variability. The evapotranspiration values were higher during El Niño years, which could be due to more soil moisture availability as a result of increased rainfall. The total water flow (computed by adding surface flow, lateral flow and ground water flow) was lowest in the La Niña years due to the low quantum of rainfall, which primarily percolated into the soil. The soil water recharge (including percolation and soil water available in the surface layers) was also more in the El Niño years and indicated that the risk in crop production is significantly lower compared with normal or La Niña years.

3.3. Rice crop productivity in the Cauvery Basin

3.3.1. Seasonal impact of rice productivity

In the Cauvery Basin, rice is cultivated in the southwest as well as the northeast monsoon seasons, and there is a high variation in yield between the different rice growing areas of the basin. The variation in yield is primarily due to the soil, slope, and amount of water available for crop production and the prevalent weather

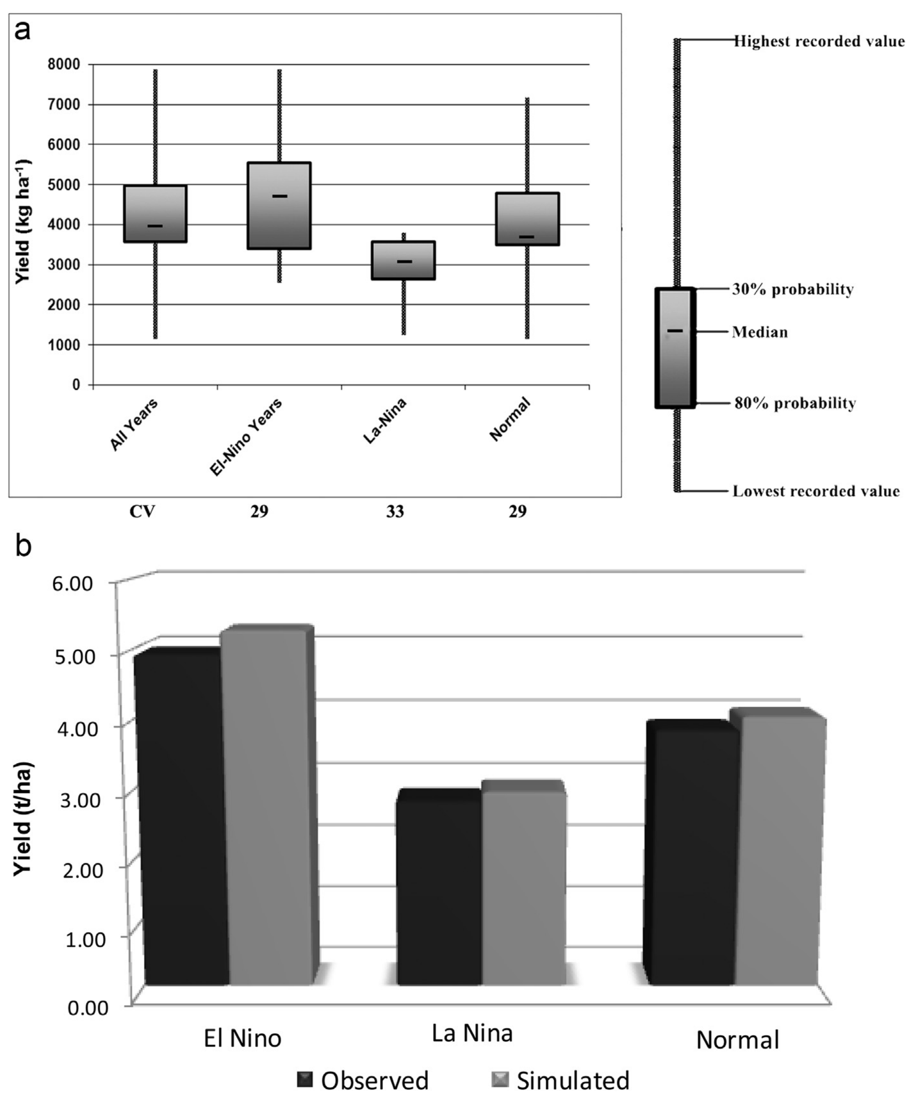

Fig. 9. (a) Productivity of rice crop (Kg ha-1) as influenced by ENSO and (b) Performance of SWAT in predicting rice productivity under ENSO event.

Table A1
Error and agreement statistics for solar ration, wind speed and relative humidity between weather generator data and observed data (1971-2000).

Locations	Bias		r^2		RMSE		d	
	Monthly	Annual	Monthly	Annual	Monthly	Annual	Monthly	Annual
Solar ration								
Cuddalore	1.8	1.8	0.70	0.76	2.3	2.3	0.61	0.64
Thanjavur	1.0	1.0	0.71	0.74	2.3	1.5	0.54	0.66
Nagapattinum	1.9	1.9	0.71	0.75	2.4	2.1	0.60	0.63
Wind speed								
Cuddalore	1.6	1.6	0.50	0.56	1.5	1.3	0.51	0.54
Thanjavur	0.9	0.9	0.74	0.76	1.7	1.3	0.63	0.65
Nagapattinum	1.7	1.7	0.81	0.85	1.7	1.1	0.59	0.60
Relative humidity								
Cuddalore	1.9	1.9	0.61	0.65	1.9	1.9	0.58	0.61
Thanjavur	1.1	1.1	0.61	0.64	1.7	1.4	0.51	0.63
Nagapattinum	1.8	1.8	0.60	0.65	1.7	1.4	0.57	0.60

during the cropping season, among other factors. The mean rice yield predicted for various sub-basins during the kharif and rabi seasons are presented in Fig. 8a and b. The area for rice increases during the rabi season due to the northeast monsoon and increased availability of water. Moreover, farmers in the coastal region are compelled to utilize paddy cultivation due to poor drainage during the northeast monsoon season.

Although the area for rice cultivation is increased during the rabi season, the average rice yields are less compared with the kharif season due to the torrential rains that result from frequent cyclic storms, the lack of adequate drainage facilities in the delta region and the prevalence of low light intensity during the growing season.

3.3.2. *Impact of ENSO on rice productivity*

Rice productivity was compared between the El Niño, La Niña and normal years, and the results are presented in Fig. 9a and b. The highest productivity with less CV was recorded in the El Niño years. The interannual variability of rice productivity in the Cauvery Basin is very high and ranged between 1,137 and 7,865 kg ha^{-1} with a mean productivity of 3,955 kg ha^{-1} (Fig. 9a). El Niño and La Niña events impacted rice productivity differently.

The coefficient of variation in rice productivity was high during La Niña years compared with El Niño and normal years. The median rice productivity was increased in both El Niño and normal years, indicating the possibility of higher yields. It is evident from Fig. 9b that SWAT is efficient in predicting the variation in rice productivity influenced by El Niño, and this behavior could be utilized for forecasting the rice crop productivity under different ENSO conditions, which can assist policy makers in deciding on import / export policies.

4. Conclusions

El Niño episode had a good linkage with rainfall, hydrology and rice productivity in the Cauvery river basin, India. Analysis of hydrology of Cauvery basin using SWAT model indicated that major share of rainfall is received during northeast monsoon (44.44%) followed by southwest Monsoon seasons (36.18%) and the total flow gradually increased from March to September. Soil water recharge increased from April and attained its maximum during September through December. Actual evapotranspiration is met in most of the months except during summer (March – May). El Niño years received more rainfall (with high inter annual rainfall variability of 809.3 mm to 2366 mm), which resulted in high soil water recharge including percolation and soil water availability in the surface layers. The mean rice productivity was shifted up in El Niño and Normal years indicating the possibility of getting more rice yields with less crop production risk compared to La Niña years. This behavior could be well utilized for forecasting the rice crop productivity under different ENSO conditions and can help the policy makers to decide on the water allocation as well as import / export policies.

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Appendix A

See Table A1.

References

Annamalai, H., Hamilton, K.P., Sperber, K.R., 2007. South Asian Summer Monsoon and its relationship with ENSO in the IPCC AR4 Simulations. J. Climate. 20, 1071–1092.
Arnold, J.G., Srinivasan, R., Muttiah, R.S., Williams, J.R., 1998. Large area hydrologic modeling and assessment, Part I. Model Development. J. American Water Resources Assoc. 34 (1), 73–89.
Arnold, J.G., Allen, P.M., Bernhardt, G., 1993. A comprehensive surface-groundwater flow model. J. Hydrol. 142, 47–69.
Geethalakshmi, V., Bride, J.M., Huda, A.K.S., 2005. Impact of ENSO on Tamil Nadu Rainfall. Vatavaran 29 (2), 9–16.
Geethalakshmi, V., Palanisamy, Akiyo Yatagai.K., Umetsu, Chicko, 2009. Impact of ENSO and the Indian Ocean Dipole on the Northeast Monsoon rainfall of Tamil Nadu State in India. Hydrol. Process. 23, 633–647.
Hansen, J.W., Hodes, A.W.J., Jones, W., 1998. ENSO Influences on Agriculture in the Southeastern United States. J.Climate. 11, 404–411.
Hill, H.S.J., Mjeldge, J.W., Rosenthal, W., Lamb, P.J., 1999. The Potential Impacts of the Use of Southern Oscillation Information on the Texas Aggregate Sorghum Production. J.Climate. 12, 519–530.
Krishna Kumar, K., Rajagopalan, B., Cane, M.A., 1999. On the weakening relationship between the Indian monsoon and ENSO. Science 284, 2156–2159.
Loague, K., Green, R.E., 1991. Statistical and graphical methods for evaluating solute transport models: Overview and application. J. Contam. Hydrol. 7, 51–73.
McBride, J.L., Nicholls, N., 1983. Seasonal relationships between Australian rainfall and the Southern Oscillation, Mon. Wea. Rev. 111, 1998–2004.
Mjelde, J.W., Keplinger, N., 1998. Using the Southern Oscillation to Forecast Texas Winter Wheat and Sorghum Crop Yields. J. Climate. 11, 54–60.

Moriasi, D.N., Arnold, J.G., Van Liew, M.W., Bingner, R.L., Harmel, R.D., Veith, T.L., 2007. Model evaluation guidelines for systematic quantification of accuracy in watershed simulations. Trans. ASABE 50, 885–900.

Nicholls, N., 1988. El Niño-Southern Oscillation impact prediction. Bull. Amer. Meteor. Soc. 69, 173–176.

Quinn, W.H., 1987. El Niño. In: Oliver, J.E., Fairbridge, R.W. (Eds.), Enclyclopaedia of Climatology. Van Nostrand, New York, p. 411.

Rajeevan, M., Bhate, J., Kale, J.D., Lal, B., 2006. High resolution daily gridded rainfall data for the Indian region: Analysis of break and active monsoon spells. Current Sci. 91 (3), 296–306.

Shukla, J., Mooley, D.A., 1987. Empirical prediction of the of the summer monsoon rainfall over India. Monthly Weather Review 115, 695–704.

Shukla, J., 1987. In: Fein, J.S., Stephens, P.L. (Eds.), Interannual variability of monsoons.Monsoons. John Wiley and Sons, pp. 399–463.

Sikka, D.R., 1980. Some aspects of the large scale fluctuations of summer monsoon rainfall over India in relation to fluctuations in the planetary and regional scale circulation parameters. Proc. Ind. A.cad. Sc, Earth and Plant Sci. 89, 179–195.

Srinivasan, R., Ramanarayanan, T.S., Arnold, J.G., Bednarz, S.T., 1998. Large area hydrologic modelling and assessment: Part II - model application. J. of American Water Resources Association 34, 91–102.

Stone, R.C., Hammer, G.L., Marcussen, T., 1996. Prediction of global rainfall probabilities using phases of the southern oscillation index. Nature 384, 1896–1909.

Wallace, J.M., Thompson, D.W.J., 2002. Annular Modes and Climate Prediction. Physics Today 55, 28.

Wang Jen-Chywan, Mika KakefudaDerynck, Daisuke F. Nonaka, Daniel B. Khodabakhsh, Chris Haqq, Keith R. Yamamoto, Chromatin immuno precipitation (ChIP) scanning identifies primary glucocorticoid receptor target genes, In. Proc. Of the National Academy of Science of the United States of America, 101, 2004. 〈http://www.pnas.org/content/101/44/15603.full〉.