

SIMULATING CLIMATE CHANGE IMPACT ON SOIL EROSION AND SOC SEQUESTRATION IN AGRO-ECOSYSTEM OF HIMALAYAN LANDSCAPE USING GEPIC MODEL

Suresh Kumar¹, Patel N. R.¹ and Akarsh A.²

¹Indian Institute of Remote Sensing, 4- Kalidas Road, Dehradun (India)

Email: suresh_kumar@iirs.gov.in

²Ph. D. Scholar, Indian Institute of Technology (IIT), Gandhinagar, Gujrat (India)

Email: akarsh.a@iitgn.ac.in

KEYWORDS: Soil Carbon Sequestration, GEPIC Model, Climate Change

ABSTRACT: GEPIC, a GIS based EPIC model was used to simulate the variability in topography, soil and climatic on SOC sequestration and soil erosion processes. The present study was carried out to study the impact of climate change on soil erosion and soil organic carbon (SOC) in agro-ecosystem of Himalayan landscape of Doon valley of Uttarakhand state, India using GIS based Environmental Policy Integrated Climate (GEPIC) model. For erosion assessment, the model predicted rainfall erosivity index factor adjusted to the observed monthly values of the study area ($R^2 = 0.95$). The current SOC stock for top 30 cm for three dominant soil series namely Barwa, Doiwala and Jassuwala representing the agricultural landscape were simulated. Jassuwala soil series in the study area showed an improvement of 6.3 t ha^{-1} SOC over 12 year period (2000 to 2012). The GEPIC model after calibration was used to assess climate change impact on soil erosion and SOC sequestration under different climatic scenarios. The climate change impact on SOC and erosion process under A2a50 scenarios were assessed and the results show that the soil erosion rate will be double than that of the baseline period mainly due to increased rainfall of about 20 per cent during the time period. The study showed a decline in soil carbon in the soil series of Barwa ($0.80 \text{ t ha}^{-1} \text{ yr}^{-1}$) and Doiwala soil series ($0.59 \text{ t ha}^{-1} \text{ yr}^{-1}$) whereas increase in Jassuwala soil series ($0.31 \text{ t ha}^{-1} \text{ yr}^{-1}$) for A2a50 scenario. GEPIC model simulated quite well and helped in assessing spatial variability of soil carbon sequestration in the varying topography and soil types.

1.0 INTRODUCTION

Soils are the third largest pool of global carbon after oceans (38,400 Pg) and fossil fuels (4500 Pg). The Soil carbon pools are divided into two classes namely, organic carbon (1500- 2000 Pg) and Inorganic carbon (700 -1000 Pg) (Lal, 2004). The soil organic matter maintains soil structure, upgrades soil tilth, rejuvenates root development, boosts water retention and nutrient availability, and enhances microbial processes. The SOC reduces soil erosion by managing aggregates and reducing erodibility, upgrading water infiltration rate and decreasing the amount and rate of overland flow (Blanco and Lal, 2008). Any increase in soil organic carbon content due to changes in land management, with the implication which increase soil carbon storage, mitigates climate change is known as Carbon sequestration (Powlson et al. 2011). Soil erosion removes and redistributes the soil carbon sediment and accelerates the process of mineralization and alters the SOC flux. Out of the eroded soil carbon 10 % is transported to the ocean, 20- 30% is emitted to the atmosphere and 60- 70 % are redistributed over the landscape (Blanco and Lal, 2008). Various modeling approaches are used to measure the erosion induced changes in soil organic carbon pools by estimating the gains in carbon storage under different management scenarios. The changes in land use and precipitation patterns lead to soil erosion, the key element in land degradation, will alter the fluxes of soil organic carbon (SOC). Soil act as the important source and sink of atmospheric CO_2 and the erosion process affects the carbon dynamics due to detachment, transportation distribution and deposition. The disturbed SOC further contributes to greenhouse gases and thus global warming. Therefore, the soil erosion and SOC flux demands for the continuous monitoring and modeling approach to assess the spatial distribution and variation of SOC under various management and landscape systems.

The capabilities of dynamic simulation models to estimate the complex interaction of an ecosystem with weather or atmospheric parameters are utilized for climate change impact assessment. Earlier these models were used in site scale or watershed scale to assess the impact of climate change on crop productivity, soil processes etc. But in the current scenario the dynamic simulation models are applied to a larger extent such as regional or global level for a better assessment of the climate change impact. It will be useful to the policy makers to evaluate the adaptation strategies and hence, to identify the priority regions after considering vulnerability and socioeconomic aspects of that area. Remote sensing and Geographical Information System (GIS) technologies provides the prominent information for the large scale climate change impact assessment using dynamic simulation models. The integrated

use of GIS, remote sensing and Global Climate model (GCM) outputs with agro ecosystem model serve as a powerful tool for the spatial and temporal impact assessment of climate change. GIS provides a common platform for the input data preparation and database management for biophysical models, (Hodson et.al, 2010). There are different methods to integrate GIS with simulation models such as embedding method, loose coupling, and tight coupling approach, in which loose coupling approach is preferred in most of the cases to avoid redundancy in programming. “Environmental Policy integrated climate” (EPIC) is coupled with GIS platform by Liu (2009) termed as GIS based EPIC (GEPIC), and also known as spatial EPIC (Priya, 2000), which are examples of the loose coupling approach of an agro-ecosystem model.

The output of GCMs from various global and regional climate models now-a-days available in GIS data formats and it helps to analyze the spatial variability of crop system performance in current and future scenario (Neelin et. al, 2006; Lobell et. al, 2008). Local and regional conditions will devise the magnitude of the risk of soil erosion while the projected change in intensity and pattern of rainfall together with human activities will increase the risk of soil degradation (O’Neal et.al, 2005). To analyze the risk of soil erosion a large number of studies were conducted all over the world from micro to global level through macro and regional levels (Peeters et al., 2008). Rainfall acts as the prominent natural driving force for soil erosion and run off and hence any change in amount, intensity and erosivity will affect water flow and erosion process significantly. Simulation models play an important role in soil organic carbon assessment in varying scales. This helps to understand the processes of carbon sequestration and to develop management practices, (Izaurrealde et al., 1998). Process based multi-compartment models are widely used in SOC assessment and to study relationship between dynamics of C and N pools, (Paustian, 1994). EPIC, Century, APEX, Ecosystem and CQESTER are the common and well known models used for soil organic carbon simulation studies. Touré et al. (1994) recommended that EPIC had the best potential for analyzing climate change impacts on agricultural production by evaluating five well known models used at that time. Causarano et al. (2008) introduced EPIC model to study the impact of soil and crop management on SOC in corn and soybean crop lands of Iowa. The model estimated a decrease in of SOC (0-20 cm depth) with time due to soil erosion impact on soil depth. Zhang et al. (2005) evaluated the potential impact of climate change under three emissions scenarios on hydrology soil loss and crop production. They used HadCM3 derived future climatic conditions in Chengwu tableland region of southern Loess Plateau of China.

The present study was attempted to simulate climate change impact on soil erosion and soil carbon sequestration in the agricultural landscape on grid basis. The Doon valley, a complex hilly ecosystem has been selected for the current study. The study was carried out in a spatial resolution of $0.009^{\circ} \times 0.009^{\circ}$ (~1km X 1km) which accounts most of the spatial variability in soil type, topography and climate.

2.0 STUDY AREA

Agro-ecosystem of Himalayan landscape of Doon valley was selected as study area which lies in between $29^{\circ}57'30''\text{N}$ to $30^{\circ}31'40''\text{N}$ latitudes and $77^{\circ}34'50''\text{E}$ to $78^{\circ}18'50''\text{E}$ longitudes (Figure 1). It is a long and wide valley which covers an area of 1870 km^2 bounded between Lesser Himalayan mountain range at north east and Siwalik hill range at south-west. The Doon valley comprises of Himalayan and Shiwalik mountainous terrains in north and south respectively act as a sloping terrain composed of Piedmont material, which has been continuously reworked by organic and fluvial process to form terraces of varying age and elevation. The climate of the Doon valley region is subtropical to temperate. Soils in this area belong to soil orders of Inceptisols, Entisols, Alfisols and Mollisols in this region. The study area covers complex landscapes of the Himalayan region and the GIS based EPIC model is capable of taking into account the variability in topography soil and climatic conditions. The model can simulate crop yield as a combined effect of soil, weather and management practices.

Soil moisture regime is classified from Ustic to Udic and soil temperature from hyper thermic to mesic. Paddy is the prominent crop of Kharif season followed by sugarcane and maize. Wheat is the dominant crop in Rabi season.

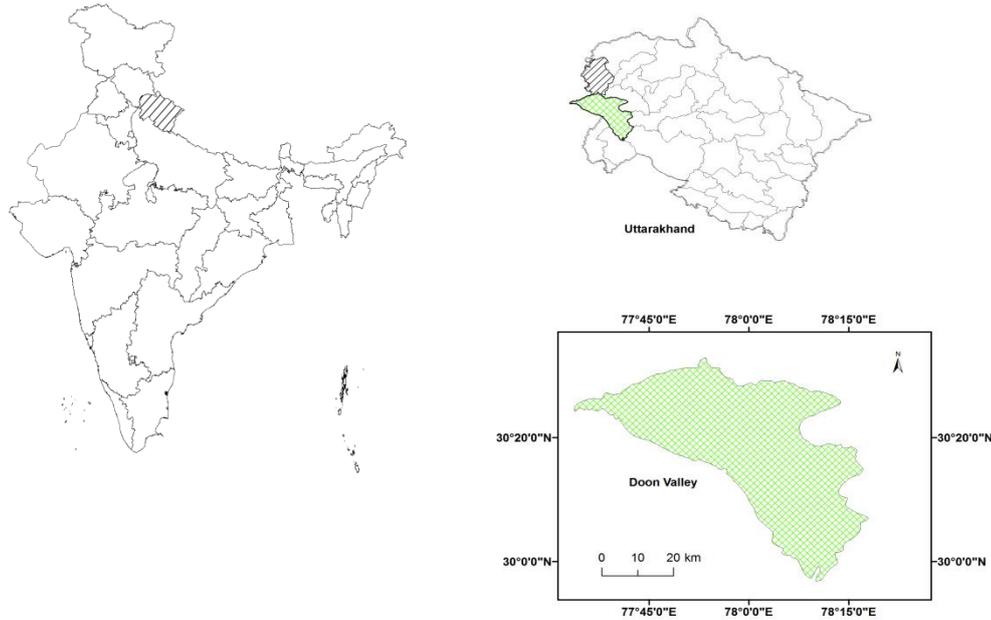


Figure 1. Study area – Doon Valley, Dehradun (Uttarakhand), India

3.0 DATA USED AND METHODOLOGY

3.1 GEPIC Model Description

GEPIC model is a GIS-based EPIC model developed and maintained by the Swiss Federal Institute of Aquatic Science and Technology (Williams, 1990). It is primarily Environmental Policy Integrated Climate (EPIC) Model. EPIC acronym now stands for ‘Environmental Policy Integrated Climate’, instead of earlier ‘Erosion Productivity Impact Calculator’. EPIC is a process based field scale model that operates in continuous basis using a daily time step and can perform long-term simulations of climate, soil and management interactions. According to Williams, (1990) EPIC is broad in terms of its components to model biophysical processes which include weather, hydrology, erosion, nutrients, soil temperature, plant growth, plant environment control, tillage, and economic budgets. EPIC model, the Arc GIS interface for EPIC v0509 are used in the most integrated way to investigate influence of anticipated climate conditions on various crop system processes over space and time. The model considers each grid cell as a site, and which is capable to simulate biophysical processes for all predefined grid cells with any spatial resolution (Liu 2009).

The GEPIC model simulations were performed on a grid basis, with a spatial resolution of $0.009 \times 0.009^\circ$ (~1kmX1km). In GEPIC, an input data translation module integrated with ArcGIS is used to transform raster datasets to text input files. The text file consists of latitude, longitude, elevation (m), slope per cent, LULC code, soil code, climate code, location code, Maximum fertilizer applied and maximum irrigation for each grid. It is generated using ArcGIS spatial analyst sample extraction toolkit and Microsoft Excel. A Universal Text Integrated Language (UTIL) is used to create input files in EPIC format.

3.2 Data Used

The spatial impact assessment requires spatial information on land use/ land cover (LULC), soil type and topographic data. LULC map, Soil physiography and Digital Elevation Model (DEM) derived through remote sensing are suitable to incorporate the spatial heterogeneity of landscape units to agro-ecosystem models. The methodology of the study and datasets used for the study is described as below:

3.2.1 Soil and Land use/Land cover (LULC) maps: The physiography-soil map and land use/land cover (1:50,000 scale) maps prepared, as part of NR-CENSUS prototype study for Dehradun district were used for the study. The soil analysis data of year 2000 for the study area was collected from NR-CENSUS report of Dehradun.

3.2.2 Shuttle Radar Topography Mission (SRTM) void filled digital elevation data with 90 m spatial resolution were acquired from USGS earth explorer archive to derive terrain slope map.

3.2.3 Spatial monthly climate data: Climate data of 30 arc-seconds (~1 km) for the baseline period and future projected scenarios were obtained from worldclim-global climate data archive. It consists of mean monthly maximum, minimum and means temperature and precipitation in generic or ESRI grid format with WGS84 datum. The datasets are available for baseline period (1950-2000) and future scenarios of HadCM3 A2a and B2a for the period of 2099. Daily weather data for the study area was obtained from the Global Summary of the Day dataset of US National Climatic Data Center. The climate data analysis are performed for baseline period and future A2a and B2a scenarios. Using the gridwise data extracted for monthly maximum and minimum temperature the possible changes in mean temperature with respect to baseline period were assessed. The scenarios used were HadCM3 A2a and B2a during the period viz. 2020 (2010-2039), 2050 (2040-2069) and 2080 (2070 – 2099).

The Monthly to Daily Weather Converter (MODAWEC) is an inbuilt weather generator along with GEPIC model was used to generate daily weather data and weather statistics file in EPIC file formats (Liu et al, 2009). The acquired monthly data were processed and average monthly maximum and minimum temperatures, monthly precipitation and numbers of wet days were extracted. The data extracted for 2155 grids were converted to MODWEC format using Excel VB macro programme.

3.2.4 Soil Data: Soil samples were collected based on physiographic-soil units and major soil group present in the study area. Main focus was given to agricultural land area. A total of 40 grids were identified for soil sample collection. From these locations, soil samples were collected at 0-15, 15-30 and 30 - 50 cm depths at 3 locations in a grid for analyzing soil organic carbon (SOC). SOC was analyzed using Walkley-Black method and total carbon using CHNS analyzer.

3.2.5 Soil Carbon Stock Estimation: The agricultural lands mainly represented by three soil series namely Barwa, Doiwala and Jassuwala soil series. The analysis results of samples collected from each soil series were compiled and top 30 cm SOC stock was estimated using equation given below:

$$\text{SOC stock} = (\text{SOC} * \text{BD} * \text{E}) * 100$$

Where SOC stock, is the Soil organic carbon stock in t ha^{-1} , SOC is the soil organic carbon in per cent, BD is the bulk density in Kg/m^3 and E is the thickness of soil layer in meter.

The SOC stock of top 30 cm were estimated for the year 2000 (NR-CENSUS report) and for the year 2012 based on soil sampling carried out in the area. Soil organic carbon sequestration (SOCS) rate of three soil series (Barwa, Doiwala and Jassuwala) were computed.

3.3 Model Calibration and Validation

Model simulations were performed on grid basis for crop yield, soil erosion and SOC assessments as explained in the following section.

3.3.1 Crop yield: Model calibration was performed for selected grids based on field observations of biophysical parameter of wheat crop. The crop yield was calibrated by adjusting selected parameters. The fine tuning are performed by adjusting crop parameters such as harvest index (HI), Maximum LAI (DMLA), PPLP1, PPLP2, plant population etc. After all adjustments the model is validated with observed yield and LAI (leaf area index).

3.3.2 Revised universal soil loss equation (RUSLE): The RUSLE model was used for the soil erosion simulation. Model simulations were performed under maize-wheat rotation one of the most common practice in the study area. After adjusting crop yield and soil erosion within observed range, simulations were performed for soil organic carbon assessment. The number of years of cultivation at start of simulation was defined as 100 years. This factor governs the fraction of mineralizable organic nitrogen pool present in the soil. The selected parameters of RUSLE model were adjusted to keep the soil erosion within the range of observed rate of soil erosion. One of the important factors that govern RUSLE soil erosion is rainfall erosive energy factor (EI). The peak runoff rate-rainfall energy adjustment factor (apm) was adjusted to obtain EI value within the observed range of the study area.

3.3.3 Simulation of climate change impact on soil erosion process and SOC sequestration : Climate change impact on soil organic carbon (SOC) sequestration simulations were performed under baseline climatic conditions and future A2a scenario over 12 year period. The rate of change over this period was assessed for the selected

agricultural soil series namely Barwa, Doiwala and Jassuwala. The changes from baseline were assessed to understand the effect of climate change on soil erosion and SOC sequestration. Simulations for the baseline (BL) period were performed and changes from BL were analysed under A2a and B2a scenarios in different time scales (2020s, 2050s and 2080s).

To achieve high resolution spatial assessment of SOC, a module developed in VB programming language was added to GEPIC model. Which is capable to extract the information of Total Organic Carbon (TOC) from Annual cropman variable definition file (.ACM) produced during simulation. The output consists of a single text file with grid information (latitude, longitude and soil code) and year wise soil organic carbon present in total depth of the soil (here 2155 grids). This is useful for the spatial prediction of the rate of soil organic carbon changes under various management practices and climatic conditions. This module was utilized for Soil organic carbon sequestration (SOCS) assessment in the study area.

4.0 RESULTS AND DISCUSSION

4.1 Climate Change Analysis

The analysis of the key climate change indicator such as mean temperature and average rainfall for the study area were performed for A2a and B2a scenarios. The analysis of mean temperature shows an increasing trend in mean annual temperature in both scenarios. Upto 2050s the increase is almost same under both scenarios whereas high increase was observed for A2a (+4.1°C) compared to B2a (+2.97°C) scenarios by 2080s. The analysis of rainfall showed an increase from baseline period under both A2a and B2a scenarios. Analysis revealed an increase in rainfall of about 21, 23 and 18 per cent, respectively during A2a20, 50 and 80 and 3, 13 and 23 per cent during B2a20, 50 and 80, respectively.

4.2 Assessment of Current Soil Organic Carbon Stock

The current soil organic carbon stock of agricultural landscapes were estimated based on SOC content of soil samples collected during field survey. Soils of agricultural lands represented by three soil series namely Barwa, Doiwala and Jassuwala series. The current soil organic carbon stock of these soil series are shown in table 1.

Table 1. Current soil organic carbon stock of soil series in the agricultural land

Soil Series	SOC stock in top 30 cm (t ha ⁻¹)		Change in 12 years (t ha ⁻¹)	No. of profiles taken for averaging SOC
	Year 2000	Year 2012		
Barwa	52.10	51.35	-0.76	15
Doiwala	60.93	52.09	-8.84	9
Jassuwala	28.06	34.36	6.30	11

Barwa and Doiwala soil series showed reduction in soil organic carbon stock whereas Jassuwala series witness an increase of 6.3 t ha⁻¹ in top 30 cm over 12 year period.

4.3 Simulation of Soil Erosion Process and SOC Sequestration

Soil erosion and soil organic carbon for the study area were simulated for 12 year period with baseline climatic data under maize-wheat rotation where 10 t ha⁻¹ farmyard manure application was considered for the study.

4.3.1 Model calibration for soil erosion process: Rainfall erosivity index (EI) is one of the major factor that affects soil erosion. For proper estimation of soil erosion the model predictions for EI was adjusted for baseline period. The average monthly erosion index value for study area (Doon valley) was used for EI correction (Figure 2). The peak runoff rate-rainfall energy adjustment factor (apm) in EPIC model was set to 0.6 instead of default value 1. EI value adjusted with an R² value of 0.95. The results after incorporating this correction is given in table 2.

Table 2. Model adjustment for rainfall erosivity (EI)

Month	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Total EI
EI _{simulated}	4.0	1.0	3.0	0.0	0.0	51.0	400.0	432.0	115.0	10.0	0.0	1.0	1017.0
EI _{observed}	5.9	10.1	8.7	3.60	19.8	113.8	344.4	335.4	171.0	20.6	1.0	14.1	1048.4

Where, EI_{sim} is the simulated EI and EI_{obs} average observe value of EI for Doon valley from 1984-1992 (Narain et.al,1994).

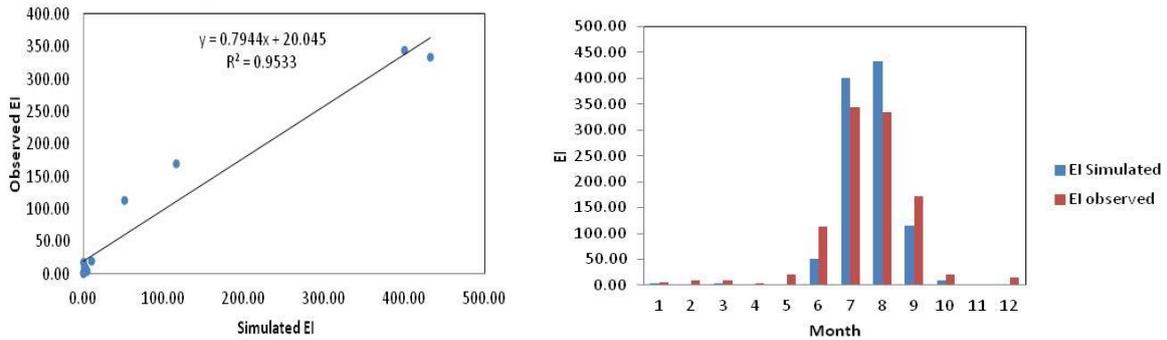


Figure 2. Model calibration for rainfall erosivity index in baseline simulations

4.3.2. Simulation for soil organic carbon (SOC) : Simulations were performed for 12 years period under baseline climatic conditions for soil erosion process with a spatial resolution of 1 km X 1 km. Model simulated change in SOC over 12 year period against measured change is given in table 3. Result showed that Barwa and Doiwala soil series witnessed the reduction in SOC by 8.99 t ha⁻¹ and 7.11 t ha⁻¹, respectively. The Jassuwala soil series showed an increase in SOC both by field measurements (6.30 t ha⁻¹) and model simulations (4.61 t ha⁻¹). The reduction in SOC was mainly due to soil erosion.

Table 3. Simulated SOC stock over 12 years period (2000 to 2012)

Sl No	Soil series	No. of grids	SOC stock (t ha ⁻¹)			Rate of change in SOC stock (t ha ⁻¹ yr ⁻¹)	Simulated soil erosion rate (t ha ⁻¹)
			Initial	Final	Change (12 yrs)		
1	Barwa	347	206.65	197.66	-8.99	-0.75	29.22
2	Doiwala	166	185.79	178.67	-7.11	-0.59	10.99
3	Jassuwala	186	69.82	74.43	4.61	0.38	8.13

4.3.3 Climate change impact on SOC sequestration and soil erosion: To understand the future trend in SOC sequestration affected by climate change and soil erosion process, analysis has been performed under A2a50 scenario with maize-wheat cropping system as performed for baseline scenario. The climate data analysis showed an increase in rainfall of about 20 per cent by A2a50. . Barwa soil series was predicted highest soil erosion rate (43.58 t ha⁻¹) followed by Doiwala series (22.42 t ha⁻¹) and Jassuwala series (14.33 t ha⁻¹). Simulation result showed that soil erosion will increase with increase in rainfall (Table 4). Figure 3 showed the climate change impact on SOC sequestration rate for baseline and A2a50 scenarios.

Table 4. Climate change impact on SOC sequestration and soil erosion rate in the study area

Soil Series	Rate of change in SOC stock (t ha ⁻¹)		Soil erosion rate (t ha ⁻¹)	
	Baseline (2000)	A2a50	Baseline (2000)	A2a50

Barwa	-0.75	-0.80	29.22	43.58
Doiwala	-0.59	-0.59	10.99	21.42
Jassuwala	0.38	0.31	8.13	14.33

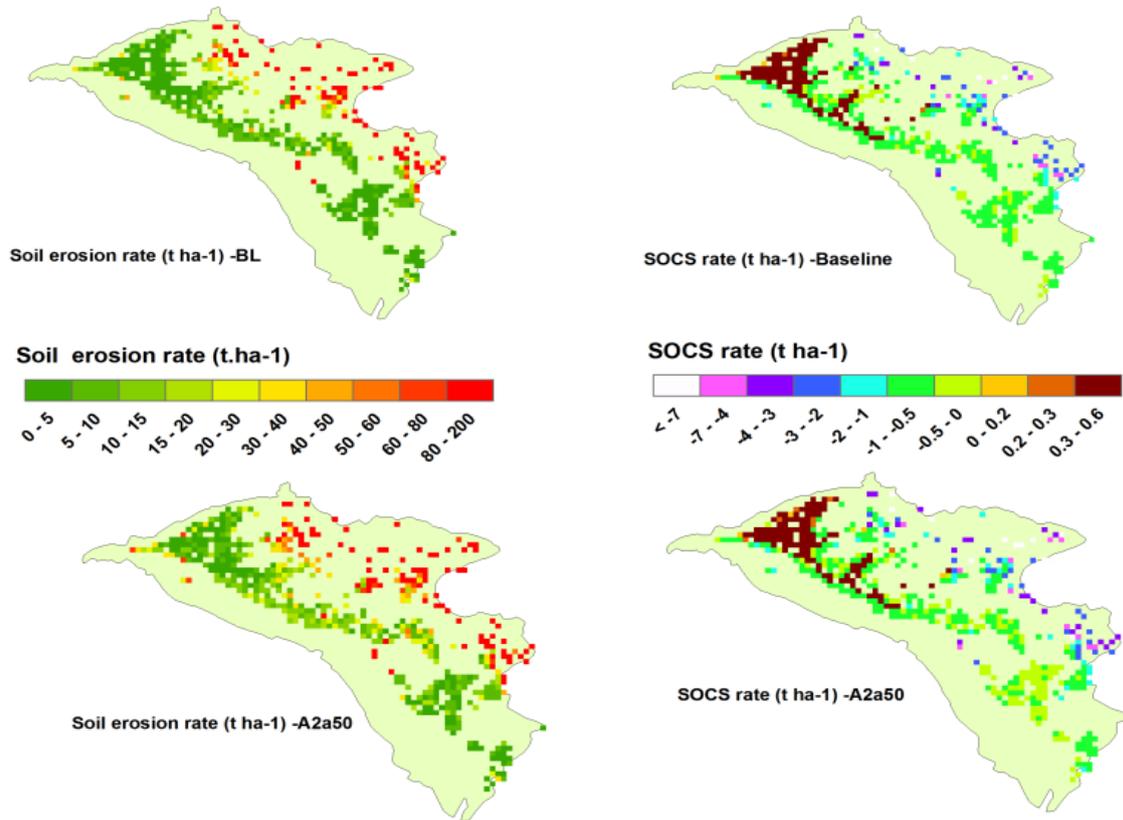


Figure 3. Climate change impact on SOC sequestration rate for baseline and A2a50 scenarios

5.0 Conclusions

The current study reveals the impact of climate change on soil erosion and soil organic carbon sequestration in the agro-ecosystem of Himalayan landscape of Doon valley of Uttarakhand state, India with the help of GIS based Environmental Policy Integrated climate model (GEPIC). Three soil series namely Barwa, Doiwala and Jassuwala representing dominant soil series in the agricultural landscape of Himalayan landscape were simulated. For erosion assessment, the model predicted rainfall erosivity index factor was adjusted to the observed monthly values of the study area ($R^2=0.95$). Result showed that Barwa and Doiwala soil series witnessed the decline in SOC by 8.99 t ha^{-1} and 7.11 t ha^{-1} , respectively whereas Jassuwala soil series showed an improvement of 4.61 t ha^{-1} SOC over period of 12 year (2000 to 2012). Barwa and Doiwala soil series were predicted to decline in SOC from base year (2000) to year 2050 for A2 scenario whereas Jassuwala soil series was predicted to increase in SOC sequestration. Analysis revealed that soil erosion rate has been doubled under A2a50 scenario due to 40 per cent increase in rainfall from baseline during that period. Climate change impact analysis revealed decline in soil carbon in the soil series of Barwa ($0.80 \text{ t ha}^{-1} \text{ yr}^{-1}$) and Doiwala soil series ($0.59 \text{ t ha}^{-1} \text{ yr}^{-1}$) whereas increase in Jassuwala soil series ($0.31 \text{ t ha}^{-1} \text{ yr}^{-1}$) for A2a50 scenario. The model predictions can be improved with the help of agronomic experiments and incorporating region wise data base of crop parameters. The current study conducted with statistically downscaled climate change scenario which may have inherent error in projection of climatic parameters.

Acknowledgement

Authors express their sincere gratitude to Director, Indian Institute of Remote Sensing (IIRS) for technical guidance and encouragement during the course of the study. Authors sincerely acknowledge the financial support under EOAM project of Mountain Ecosystem Services and Processes funded by ISRO, DOS, Govt. of India.

References

References from Journals:

- Causarano, H. J., Doraiswami, P.C., McCarty, G.W., Hatfield, J.L., Milak, S., Stern, A.J., 2008. EPIC modeling of soil organic carbon sequestration in cropland of Iowa. *Journal of Environmental Quality*. 37, 1345-1353.
- Lal, R., 2004. Soil carbon sequestration impacts on global climate change and food security. *Science* 204: 1623-1627.
- Liu, J., 2009. A GIS-based tool for modelling large-scale crop-water relations. *Environmental Modelling & Software* 24: 411-422.
- Liu, J., Williams, J.R., Wang, X., Yang, H., 2009. Using MODAWEC to generate daily weather data for the EPIC model. *Environmental Modelling & Software* 24 (5): 655-664.
- Lobell, D.B., Burke, M.B., Tebaldi, C., Mastrandrea, M.D., Falcon, W.P., Naylor, R.L. (2008). Prioritizing climate change adaptation needs for food security in 2030. *Science* (319) :607-610.
- Narain, P., Khybri, M.L., Tomar, H.P.S. and Sindhwal, N.S., 1994. Estimation of run-off, soil loss and USLE parameters for Doon valley. *Indian J. Soil. Cons.*, 22 (3), pp. 129 - 132.
- O'Neal, M.R., Nearing, M.A., Vining, R.C., Southworth, J., Pfeifer, R.A., 2005. Climate change impacts on soil erosion in Midwest United States with changes in crop management. *Catena*, 6, 165-184.
- Peeters, I., Oost, K.V., Govers, G., Verstraeten, G., Rommens, T., and Poesen, J., 2008. The compatibility of erosion data at different scales. *Earth and Planetary Science Letters*, 265, 138–52.
- Powlson, D.S., Whitmore, A.P., Goulding, K.W.T, 2011. Soil carbon sequestration to mitigate climate change: a critical re-examination to identify the true and the false. *European Journal of Soil Science* 62:42-55.
- Touré, A., Major, D.J., Lindwall, C.W., 1994. Comparison of Five Wheat Simulation Models in Southern Alberta. *Can. J. Plant Sci.* 75(1): 61-68.
- Zhang, X.C., Liu, W.Z., 2005. Simulating potential response of hydrology, soil erosion, and crop productivity to climate change in Changwu tableland region on the loess Plateau of China. *Agric. For. Materol.* 131, 127-142.

References from Books:

- Blanco, H. and Lal, R., 2008. Principles of Soil Conservation and Management. Springer Science Business Media B.V., 513-534.
- Hodson, D., White, J., 2010. GIS and Crop Simulation Modelling Applications in Climate Change Research, in: Reynolds, M.P. (Ed.), *Climate Change and Crop Production*. CAB International, 245–262.
- Izaurrealde, R.C, McGill, W. B., Bryden, A., Graham, S., Ward, M., Dickey, P., 1998. Scientific challenges in developing a plan to predict and verify carbon storage in Canadian Prairie soils. In: Lal, R., Kimble, J., Follett, R.F., Stewart, B.A, (eds.). *Management of Carbon Sequestration in Soil*. Boca Raton, FL: CRC Press: 433–46.
- Paustian, K., 1994. Modeling soil biology and biochemical processes for sustainable agriculture research. In: Pankhurst ZE, Doube BM, Gupta VVSR, Grace PR, editors. *Soil Biota Management in Sustainable Farming Systems*. Melbourne: CSIRO Information Services: 182–96
- Williams, J.R., Wang, E., Meinardus, A., Harman, W.L., Siemers, M., Atwood, J.D., 2006. EPIC users guide v.0509. Texas A&M University, Texas Agricultural Extension Service, Texas Agricultural Experiment Station, Blacklands Research Center, Temple, TX.
- Williams, J.R., Izaurrealde, R.C., Steglich, E.M., 2008. Agricultural Policy / Environmental eXtender Model Version 0604 Agricultural Policy / Environmental eXtender Model Theoretical Documentation. BREC Report.

References from Other Literature:

- Neelin, J.D., Munnich, S.U., Meyerson, M.H., Holloway, J.E. 2006. Tropical drying trends in global warming models and observations. *Proceedings of the National Academy of Sciences USA* 103 (16): 6110–6115.
- Priya, S., 2000. National level spatial modeling of agricultural productivity: study of Indian agro ecosystem. *International Archives of Photogrammetry and Remote Sensing*, XXXIII, 1191–1198.